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Machine learning in the aviation industry and the potential of using air traffic as a real-time indicator of GDP

A study of how useful machine learning is to predict Norwegian air traffic and investigating the causal relationship between air traffic and GDP

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Abstract

Travel by air is an essential part of both the Norwegian society and its infrastructure, where Norway has one of the highest number of flights per capita in Europe. Nonetheless, the aviation industry is characterized by high uncertainty, with the Covid-19 pandemic being the most recent one.

This thesis has sought to investigate the use of machine learning in the Norwegian aviation industry and how the number of air passengers potentially can be used as a real-time indicator of GDP. Therefore, the thesis has been divided into two parts. The first part has aimed to use machine learning to predict the number of domestic and total passengers per capita in Norway. More precisely, we applied the methods OLS, elastic net, and random forest. The purpose of the second part has been to investigate the causal relationship between air passengers and GDP by conducting a strict linear Granger causality test. We particularly questioned whether air passengers could be used as a real-time indicator of GDP.

The findings suggest that machine learning is applicable for predicting the number of air passengers per capita in Norway, where elastic net yield the best results. In relation to the second part of the thesis, the findings reveal a causal relationship running from air passengers to GDP. Consequently, we find that there is a potential of using the number of air passengers as a real-time indicator of GDP in Norway.

Keywords – Machine learning, the Norwegian aviation industry, economic growth, causality, real-time indicators

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1 Introduction

1.1 Background

Norway is an elongated country in the outskirts of Europe, with challenging topography and a scattered population (NOU 2019: 22, p. 37). Hence, air travel is a vital part of the Norwegian infrastructure and the only realistic transport alternative for specific areas, particularly for the northern and western parts. To provide an example, the distance by car between the two largest cities in Norway and Sweden are relatively similar, at 464 and 473 kilometers between Oslo and Bergen, and Stockholm and Gothenburg, respectively. However, the corresponding travel times by car are seven and five hours. Similarly, train travel time is only three hours between the two Swedish cities and almost seven hours for the Norwegian city pair.

In 2019, the number of air passengers in Norway reached an all-time high with 54 million total passengers (Avinor, 2020b, p. 7). This amounts to an increase of approximately 93 percent from 2002 to 2019; the number of international passengers increased the most, with an increment of 185 percent. A significant part of this increase originates from leisure travel from *other* countries to Norway (NOU 2019: 22, p. 38). Domestic travel by foreigners have also increased rapidly, with 53 percent from 2015 to 2017.

Airports in Norway were historically classified as either main or short take-off and landing (STOL) airports (Engerengen, 2019; Thune-Larsen, 2019, p. 2). The latter was expanded from 1960 to 1980, aiming to connect the districts with central parts of Norway. In an interview conducted on October 29th, 2020, the managing director of Bergen Airport, Helge Eidsnes, argued that Norway made a deliberate choice of expanding the STOL network in the 1960s. Eidsnes further argues that this decision was made based on the cost associated with expanding other infrastructures, such as railways and roads. As a result, he claimed that the aviation structure in Norway is unique relative to other countries due to the scale of the aviation network compared to its population. This became clear when the Covid-19 pandemic struck Europe and made Widerøe the largest European airline in terms of movement in the first weeks of April (Nikel, 2020).

Prior to the pandemic, there was also a great demand for business travel, with typically more than 30 flights between Oslo and Bergen on a daily basis (Nikel, 2020). Although the pandemic naturally affects business travel in the short-run, there could also be long-term effects. As businesses become more adaptable to the pandemic, permanent solutions might be implemented, thus reducing or eliminating the need for business travel. In contrast, the editor of InsideFlyer, Martin Damm Laupstad, believes that domestic flights, in the parts of Norway with no other realistic transportation options, should return to pre-pandemic levels (Nikel, 2020).

Covid-19 has affected the aviation industry in more ways than those mentioned above. As a result of travel restrictions imposed by both the Norwegian Government and other countries, the number of passengers has decreased dramatically. This is especially true for the international segment, which decreased by 74 percent in the three first quarters of 2020, compared to 2019 (Avinor, 2020e). Likewise, the number of domestic passengers decreased by 50 percent. This has resulted in financial distress, in addition to temporary *and* permanent dismissals of staff in the aviation industry. As a result, this severe financial and structural stress may lead to airline bankruptcies. On November 9th, 2020, the Norwegian Government rejected the request for further financial aid for Norwegian Air Shuttle ASA.

The aviation industry has historically experienced similar uncertainties that have affected air travel demand in both a short and long-term perspective. Examples of such external shocks are the terror attacks on the World Trade Center in 2001, the volcanic outbreak in Iceland in 2010, and labour strikes, such as the SAS AB labour strike in 2019. Events like these are almost impossible to predict, and thus, entail uncertainty in the industry.

Another development and uncertainty in the Norwegian aviation industry, unrelated to Covid-19, is the announcement that the aviation heir, Eirik B. Braaten, is starting a new airline in 2021 (Granerud, 2020). Similarly, on October 6th, 2020, the Hungarian airline WizzAir announced that they were launching seven domestic routes in Norway (Giæver and Schultz, 2020). Through offering one-way prices as low as NOK 199 on selected routes, WizzAir effectively declared a price war on the incumbents.

In sum, the aviation industry has gone through a rapid development in the 21st century.

There is a clear long-term growth trend, but variation arises through external shocks, changing market dynamics, economic growth, and other factors. Thus, estimating the number of air passengers in Norway is valuable in numerous ways, both outside and within the aviation industry. In other words, predictions of air passengers can not only be relevant for airport operators and airlines, but also for the tourism industry, as well as the Norwegian society and economy in general, to mention some. Furthermore, a positive increment in air traffic volume can affect the economy both directly and indirectly (NOU 2019: 22, p. 22). Directly, as it creates jobs and generates revenue for industries, such as the aviation and the tourism industry. Indirectly, as it enables transportation of people and goods over long distances, and thus, increases efficiency. However, changes in the economy, usually measured in gross domestic product (GDP), can also impact air traffic volume.

1.2 Purpose and Research Question

On a broad scale, the focus of this thesis is the Norwegian aviation market. The area caught our attention as the industry is in constant change and under a lot of pressure due to the factors presented in the last section. We find the Norwegian aviation industry especially interesting, as it is a significantly more important part of the infrastructure compared to other countries. Based on this and the current uncertainties, we believe it is more important than ever to identify what factors are affecting air travel demand in Norway, and hence, be able to predict the number of air passengers with sufficient accuracy.

In this thesis, we ask two main questions. The first relates to whether it is possible to use machine learning methods to predict both domestic and total air passengers in Norway. Concerning this question, it is important to emphasize once again that there are a lot of uncertainties related to the long-term effects of the Covid-19 pandemic. During the process of writing this thesis, there have already been drastic developments in the industry, such as the possibility of Norwegian Air Shuttle declaring bankruptcy.

The second question relates to the relationship between the Norwegian aviation industry and its overall economy, where we question how they affect one another and in which direction. The two questions relate to each other, as economic growth is an important variable for predicting air passenger traffic. Therefore, in the second part of the thesis, the problem is somewhat reversed. We particularly question whether the number of air passengers is useful for predicting economic growth, measured in GDP.

More precisely, we want to investigate if there is a *causal* relationship between economic growth and air passengers in Norway. This is of interest as GDP is considered one of the most important indicators of the economy in a country. If we find such a relationship exists, running from air passengers to GDP, one can potentially use the number of passengers as a real-time indicator of GDP. Many key-statistics, such as GDP, are realized with a delay, and thus, policy-makers are forced to make real-time decisions based on high uncertainty (Aastveit et al., 2014, p. 48). Consequently, forecasting GDP in the present or very near future, referred to as nowcasting, is of great value to policy-makers and stakeholders. This is particularly true in uncertain times, such as the Covid-19 pandemic.

In sum, the research questions are:

1. How useful are machine learning techniques for predicting the number of air passengers in Norway?

2. Is there a causal relationship between air passengers and GDP in Norway, and can the number of air passengers potentially be used as a real-time indicator of GDP?

1.3 Structure

This thesis is divided into two parts, where we will, in Chapter 3 to Chapter 7, aim to answer the first research question, while the second research question will be answered in Chapter 8. Prior to the individual parts, Chapter 2 gives a brief introduction to the Norwegian aviation market. This entails an overview of the development in the Norwegian aviation industry in terms of air traffic volume, and a presentation of characteristics of the market and its participants.

In Chapter 3, we will present relevant literature, particularly focusing on factors affecting air travel demand. Chapter 4 presents the applied data set in the first part of the thesis and how data has been collected through several sources. Further, in Chapter 5, we will present the methodology used, which includes a description of the different machine learning methods applied in this thesis. The findings will be analyzed and presented in Chapter 6, mainly focusing on the performance of each method, before Chapter 7 provides a thorough discussion based on the findings presented in the previous chapter.

In the second part of the thesis, Chapter 8, we further investigate the relationship between air passengers and GDP, aiming to answer our second research question. Thus, the presented context from the first part is somewhat reversed. The chapter will start by presenting our motivation and interest in the topic before relevant literature is presented. Further, we will provide a walk-through of the methodology applied. Based on this, we will analyze the results before a discussion of the findings is given.

Lastly, in Chapter 9, we will give an overall conclusion, where both parts of the thesis will be summarized and concluded upon.

2 The Norwegian Aviation Industry

This chapter aims to provide an overview of central aspects of the Norwegian aviation market, as we find it useful to provide some context in order to get an understanding of the market structure and its characteristics. Firstly, we will present current market trends in terms of development in air traffic volume. Thereafter, we will give an overview of the market participants, followed by other characteristics of the Norwegian aviation market. Lastly, other usage of machine learning in the aviation industry will be presented.

2.1 Development in Air Traffic Volume

As previously mentioned, air transportation is an essential part of the Norwegian infrastructure. Based on data provided by Avinor, Figure 2.1 presents the development in the number of air passengers in Norway from 2002 to 2019. From this, one observes a rapid growth in the number of air passengers. The figure implies that the growth in international traffic exceeds the growth in domestic traffic, with an increment of 185 and 55 percent, respectively.

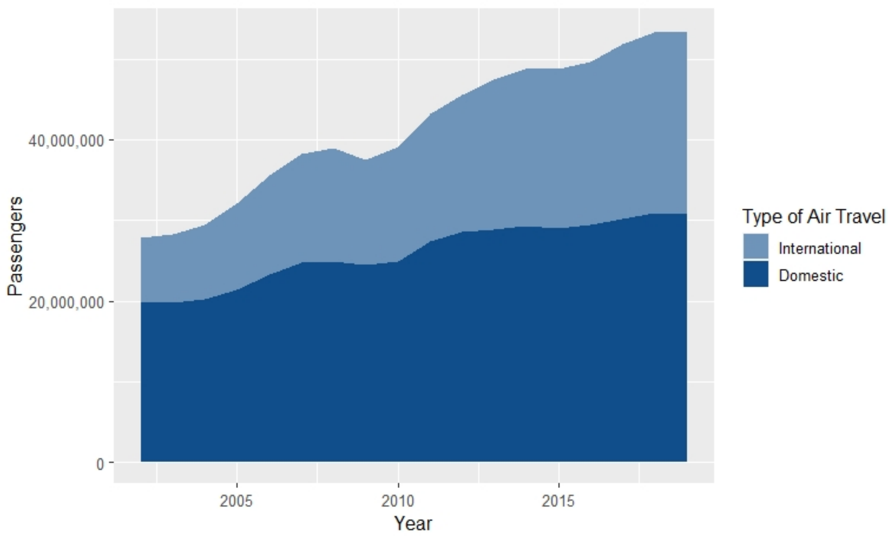


Figure 2.1: Development in the number of air passengers in Norway from 2002 to 2019 (Avinor, 2020)

Although international passengers have increased more than domestic passengers, Norway still had the highest domestic flights per capita in Europe in 2015 (Kristiansen, 2017, p. 3). In this year, Norway had an average of 2.9 and 7.3 flights per capita for domestic and total air travel, respectively. Compared to other countries, Norway were only outnumbered by the island countries Iceland, Malta, and Cyprus. To understand the uniqueness of Norwegian air travel habits, one can compare these numbers with the relatively similar country, Sweden. In 2015, Sweden had an average of 0.8 and 3.5 domestic and total flights per capita. Furthermore, some of the most trafficked routes in Europe are domestic Norwegian routes. In particular, the routes from Oslo to Trondheim and Oslo to Bergen were the sixth and ninth most trafficked routes in Europe (Kristiansen, 2017, p. 7).

Although the number of air passengers has increased, the number of flights has decreased (Christensen, 2020). This can be assumed a result of better capacity utilization, in addition to larger airplanes that accommodate more passengers. Based on data provided by Avinor, the number of flights has decreased by approximately 7 percent from its peak year in 2014 to 2019. The development from 2002 to 2019 is summarized in Figure 2.2.

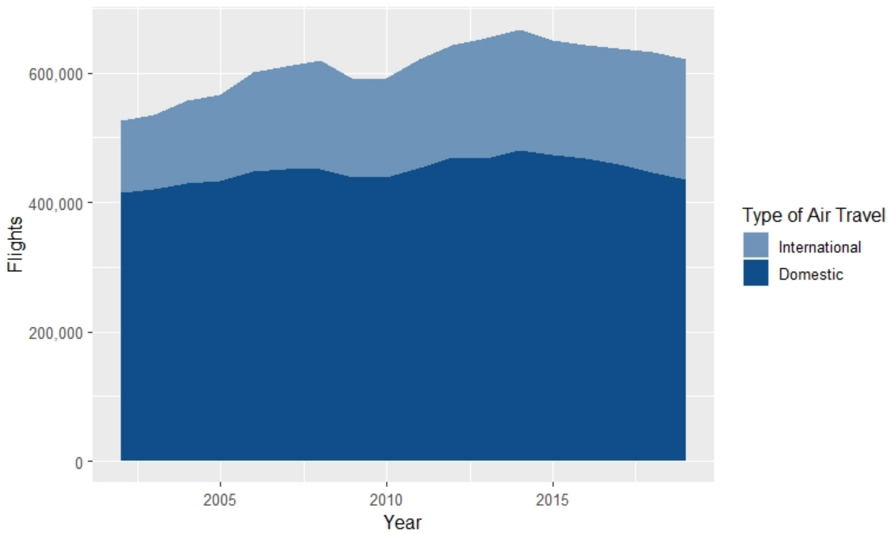


Figure 2.2: Development in the number of flights from 2002 to 2019 (Avinor, 2020)

2.2 Market Participants

Similar to other countries, the Norwegian aviation industry has historically been highly regulated (NOU 2019: 22, p. 57-61). In 1994, the Norwegian main route network was deregulated, which facilitated competition in the market. Likewise, the entrance of low-cost carriers in recent years has contributed to a reduction in airfares. Today, Norway has a deregulated aviation industry through the European Economic Area (EEA) agreement (The Norwegian Government, 2020). The agreement makes it possible for other EEA countries to establish and offer flights in Norway and between Norway and the EEA. In the following, we will present the main participants in the Norwegian aviation industry, both airlines and airport operators.

2.2.1 Airlines

The main participants in the Norwegian domestic aviation market are SAS, Norwegian Air Shuttle, and Widerøe AS, having a total market share of 99 percent in 2018 (NOU 2019: 22, p. 60). Moreover, SAS accounted for 43 percent of the domestic market, while Norwegian and Widerøe had a 35 and 21 percent market share, respectively. In short, SAS focuses on frequent travelers and reward customer loyalty through their EuroBonus program (SAS, 2020). Widerøe is the largest *regional* airline in Norway (Widerøe, 2020). Moreover, Norwegian Air Shuttle was founded in 1993 and started to operate as a low-cost carrier in 2002 (Norwegian, 2020). Furthermore, as mentioned in the introduction, WizzAir entered the domestic market as a low-cost carrier on November 5th, 2020 (Lorentzen and Bøe, 2020). As this is a relatively new development in the Norwegian aviation market, it is difficult to say how this entrance will affect the market structure.

Regarding international air travel from or to Norway, SAS and Norwegian Air Shuttle are the dominant providers, with a market share of 27 and 35 percent in 2018, respectively (NOU 2019: 22, p. 56). Other significant market operators in this segment are Wizz Air, KLM, Ryan Air, Lufthansa, and British Airways.

2.2.2 Airport operators

Avinor AS is the main operator of airports in Norway and also the provider of the air passenger and flight data applied in this thesis. The company is state-owned and operates 44 airports in Norway, including the subsidiary Svalbard Lufthavn AS and Værøy Heliport (Avinor, 2020b, p. 7). The airports have quite a wide variety in terms of size and traffic volume, with Oslo Airport being the largest by far. For example, the number of total air passengers in 2019 was 54,099,115, where Oslo Airport accounted for 28,572,060, which amounts to approximately half of the traffic volume. Other large Avinor airports are located in Bergen, Stavanger, and Trondheim. Amongst airports offered by other operators than Avinor, Torp Sandefjord airport, operated by Sandefjord Lufthavn AS, is the largest, with 2,073,228 passengers in 2019 (Torp Sandefjord Airport, 2020).

2.3 Profitability

The deregulation of the aviation industry and the entrance of low-cost carriers led to a reduction in global airfares. This resulted in low margins in the following years, whereas the market has experienced a positive development from 2004 (NOU 2019: 22, p. 29-30). However, there are regional differences in terms of profitability. For example, the North-American market is characterized by large, but few, airlines, which contrasts to the European market (CAPA, 2018).

Moreover, Professor Frode Steen at the Norwegian School of Economics, argues that the European aviation market consists of more airlines than what is sustainable for developing an efficient market (Kampevoll, 2019). As an example, several European airlines have declared bankruptcy in recent years. The market is also characterized by high operational costs, especially related to jet fuel and labour costs. A critical part of the survival of an airline is, therefore, related to operational optimization. This is also true for the leading market participants in Norway. In 2012, SAS was only minutes away from declaring bankruptcy due to high competition from low-cost carriers, in addition to a high deficit (Rønne, 2014). Similarly, Norwegian Air Shuttle is, as mentioned in the previous chapter, currently facing major financial distress.

2.4 Public Service Obligation

Although most of the Norwegian aviation market is operated commercially, the Government can provide subsidies on non-profitable routes to ensure a well-developed flight offering throughout the country (The Norwegian Government, 2020). The arrangement is referred to as public service obligation (PSO). Through a public competition among airlines, the Government can offer exclusive rights on a route for a specified period, with requirements for price, capacity, and the number of flights. The contract is usually given to the airline that offers the service at the lowest cost. Today, all PSO routes are operated by Widerøe, except the route between Oslo and Røros, which is operated by Air Leap AB (NOU 2019: 22, p. 63-67). Furthermore, no other European country operates as many PSO routes as

Norway, with 21 PSO routes. These routes are primarily operated in the northern and western parts of Norway, including routes between Svolvær and Bodø, and Sogndal and Bergen.

2.5 Machine Learning in the Aviation Industry

Although this thesis focuses on predicting the number of air passengers, machine learning methods are applicable to a wide range of problems within the industry due to the availability of Big Data. As an example, through its sensors, modern air crafts collect large amounts of data on fuel consumption, engine systems, and crew activity, to mention some (Maire and Spafford, 2017). Consequently, airlines can use machine learning methods to optimize operations in areas such as predictions of fuel consumption, in-flight food demand, and the number of delays.

Another application relates to price discrimination. In 1985, American Airlines developed one of the first revenue management systems, aiming to increase profits by offering different prices for different customer segments based on willingness-to-pay (Phillips, 2005, p. 6). At that time, they primarily distinguished between leisure and business customers. However, with the increased availability of customer data, machine learning methods and other new technologies, airlines can now more accurately predict willingness-to-pay for segments beyond just leisure and business. Lastly, machine learning methods can be used in other areas, such as runway utilization and airport security checkpoints.

Part I

Predicting Air Traffic in Norway Using Machine Learning Methods

3 Literature Review

Historically, researchers have mainly applied the basic linear regression model by fitting the model using ordinary least squares (OLS) to predict air traffic demand. Besides, the "Manual on Air Traffic Forecasting", prepared by the International Civil Aviation Organization (ICAO), suggests multiple linear regression and econometric analysis for quantitative causal methods (ICAO, 2006, p. 2).

However, other methods have been applied, as well. For example, Strisaeng et al. (2015, p. 476) developed two genetic algorithm models to predict quarterly domestic airline passenger demand in Australia based on data from 1992 to 2014. To test the performance of the two models, the data were divided into a training set and a test set, where the latter consisted of the last 13 observations (Strisaeng et al., 2015, p. 483). The results revealed that a quadratic form gave the best performance for both models.

In relation to research conducted on Norwegian data, Fridström and Thune-Larsen (1989, p. 213) developed a model with the aim of forecasting air traffic demand in Norway in 1989. In contrast to this thesis, their aim was to forecast demand for the entire Norwegian air network. Thus, the dependent variable was the number of passengers traveling from one airport to another during a year. Consequently, Fridström and Thune-Larsen (1989, p. 215) used a combination of cross-sectional and time series data. The corresponding predictors were the number of inhabitants in the zone of the departing airport, income per capita, average fares and travel time between two airports, and fares and travel time for alternative means of transportation. To our knowledge, research on predicting the number of air passengers by applying more advanced machine learning techniques have not been conducted.

In the following, we will provide an overview of relevant literature related to air travel demand. The chapter will mainly focus on factors affecting air passenger demand. We will present both the factors and the proxies used by researchers to capture these effects.

3.1 Factors Affecting Air Passenger Traffic

There is an established consensus among analysts that the two most important factors affecting air passenger demand in a country are price and income (Holloway, 2008, p. 87). The effect of income can be broken down into two questions. Firstly, how many potential customers are there, and secondly, what are their respective income levels? In the following, we will present an overview of proxies for airfares and income based on literature, as well as other relevant drivers.

3.1.1 Alternative price indicators

Despite price being a major driver of demand, it is often difficult to obtain. As a result, different literature uses alternative indicators to capture changes in price without having to retrieve actual prices. Both Chevallier et al. (2011, p. 15) and Strisaeng et al. (2015, p. 480) use world fuel prices as an indicator for airfares. They argue that a positive change in world jet fuel prices might force airlines to increase airfares due to an increment in operational costs, which can further negatively affect demand. Another study by Secilmis and Koc (2016, p. 417) looks at economic factors affecting airline demand in Europe, where the price index developed by the traveling service Omio is used as an indicator for airfares. The price index gives the global average airfares per 100 kilometers. This is calculated by obtaining the cheapest airfare between the two largest cities in a country, which is again averaged across the globe.

3.1.2 Air passenger traffic and gross domestic product

The relationship between air passenger traffic and economic activity is widely covered in the literature. According to Doganis (2010, p. 192), there is a strong correlation between changes in annual world GDP rates and changes in air travel growth rates. Similarly, Holloway (2008, p. 88) claims that there is a strong correlation between GDP per capita and the number of airline leisure trips per capita. He further argues that GDP is a good metric of income and can be used as a proxy, where the assumption is that the propensity to travel increases as the income of the population rises. Both Holloway (2008, p. 88) and Doganis (2010, p. 196) claims that personal disposable income is the ideal measure, but as it can be calculated differently across countries, per capita GDP is a better proxy. However, one potential problem is that GDP does not account for the income distribution in a country. Holloway (2008, p. 88) explains that this can be a problem in emerging economies particularly, as business and leisure travel of small elites tend to be less affected by incremental changes in income levels.

3.1.3 Demographics

According to Holloway (2008, p. 88), the number of potential air passengers in a country is affected by the demographics of a country. Both Strisaeng et al. (2015, p. 479) and Secilmis and Koc (2016, p. 414) include population as a predictor, where Secilmis and Koc also include age, gender distribution, and the level of education. In addition, Holloway (2008, p. 80) argues that air traffic demand within a country is not only dependent on its own population, but also on the population living within a certain hour of flight from the country. Holloway uses Emirates as an example, where he argues that their success is partly caused by the advantageous location of Dubai, as two billion people live within eight hours of flight. In other words, demand is also affected by the number of people living within a certain hour of flight. Other demographic factors discussed are unemployment rates, social rights and lifestyle (Wensveen, 2018, p. 31; Secilmis and Koc, 2016, p. 413).

3.2 Other Drivers

There are also other factors influencing air traffic demand. Holloway (2008, p. 92) claims that demand can be affected if the relative exchange rate changes at either departure or destination. However, the effect can go both ways, as a strengthened currency in the country of departure can increase the outbound flow of passengers, and vice versa. Strisaeng et al. (2015, p. 479) use real effective exchange rates as a measurement. Other drivers are also included in this study, such as interest rates and bed capacity in tourist accommodations in Australia. Moreover, exogenous shocks are included as dummy variables, like big sports events, and loss in capacity due to airlines running out of business. Secilmis and Koc (2016, p. 416) also include inflation rates and production indices.

Based on the presented literature, this thesis will contribute to the literature by applying machine learning techniques on Norwegian data.

4 Data

In this chapter, we will present the dependent variables and the predictors, where the chosen predictors are based on the literature introduced in Chapter 3. The variables are collected from various sources and are either observed on a quarterly basis or adjusted and transformed into quarterly data. Moreover, the dependent variables are observed from the second quarter of 2002 to the last quarter of 2019, amounting to 71 observations. In contrast, the predictors are observed from the first quarter of 2002 to the third quarter of 2019. That way, the predictors lag one quarter and models will be trained by using the dependent variable at time t and the corresponding predictors at time $t-1$. Although some observations from 2020 are available, we have chosen not to include these due to the Covid-19 pandemic.

4.1 Dependent Variables

The dependent variables comprise the domestic and total number of passengers, divided by the population, hence, passengers per capita. The corresponding data sets are provided by Avinor and obtained from Statistics Norway (SSB), respectively (Statistics Norway, 2020a). The former consists of quarterly numbers of terminal passengers, while the latter holds data on the Norwegian population at the beginning of each quarter. Avinor defines terminal passengers as the number of passengers at airports operated by Avinor either as a departing, transferring, or arriving passenger (Avinor, 2020c). Consequently, this infers that a passenger is counted twice, both at departure and arrival, given a domestic flight.

The data from Avinor are further divided into domestic, international, offshore, and total passengers, of which this thesis only builds on data for domestic and total passengers. Moreover, the data set only includes data from airports currently operated by Avinor. Consequently, the data set does not include information on the *total* number of air passengers in Norway, as Avinor is not the sole airport operator in the country. Nonetheless, the other operators are not of significant size. For example, in January, 2019, only 3.7 percent of all flights in Norway were associated with other airport operators. Out of these, Torp Sandefjord airport, operated by Sandefjord Lufthavn AS, was the dominant one, having approximately 3.6 percent of all flights. Unfortunately, passenger data from these operators in the period 2002 to 2009 are not available. Based on this, we find the benefits of a more extensive data set to exceed the disadvantages of not including all airports. Also, Haugesund Airport was leased to Lufthavndrift AS from 2019, and has therefore been excluded from the data set provided by Avinor (Avinor, 2020b, p. 7).

4.2 Predictors

Although this thesis distinguishes between domestic and total passengers due to the nature of some predictors, we will use the same database for both types. To clarify, it is, for example, not possible to distinguish between GDP for domestic and total passengers.

4.2.1 Gross domestic product

As a proxy for income, the quarterly seasonally adjusted GDP index is retrieved from the Organization for Economic Co-operation and Development (OECD), where 2015 is the base year (OECD, 2020a). All OECD member countries collect GDP data according to the 2008 System of National Accounts (SNA), but one should bare in mind that there are several ways to calculate and present the GDP in a country.

4.2.2 Price index

As a measurement for airfares, the passenger air transport price index has been obtained (Statistics Norway, 2020c). The index is developed by SSB and is part of the producer price indices for services. These indices measure the price development for different services over time. The passenger air transport price index measures the percentage change in price from the same period last year. The index is further divided into leisure and business travel.

Based on the literature, it is fair to assume that the price of leisure travel is closest related to air passenger demand. As a result, the subindex "Leisure travel, domestic and international traffic" has been retrieved for total passengers. In terms of domestic passengers, we use the subindex "Scheduled air transport domestic traffic." The ideal would have been to obtain "Leisure travel, domestic traffic", but since this is not available, we assess the chosen index as a suitable substitute. The index was developed in 2006; thus, values from 2002 to 2006 are missing. However, it is possible to estimate these through backcasting by estimating an ARIMA model, see Appendix A1.1 and A1.2 for backcasts. We consider this a weakness, as the estimations will not comply with the true values.

4.2.3 World jet fuel price

As presented in Chapter 3, an increase in world jet fuel prices can have a negative effect on air traffic demand as a result of airlines facing higher operational costs. Therefore, U.S Gulf Coast kerosene-type jet fuel spot price per gallon has been obtained from U.S Energy Information Administration as a measurement for world jet fuel prices (U.S. Energy Information Administration, 2020). As quarterly prices are not obtainable, we have retrieved monthly data and calculated the quarterly average.

Furthermore, changes in world jet fuel prices are often caused by changes in crude oil prices. This can be seen in Figure 4.1, which shows the average quarterly prices per gallon for both types from 2002 to 2019. From this, one can infer that the time series are highly correlated. This predictor is unique concerning Norwegian data, as its economy is highly susceptible to sudden and significant changes in oil prices (Cappelen et al., 2014).

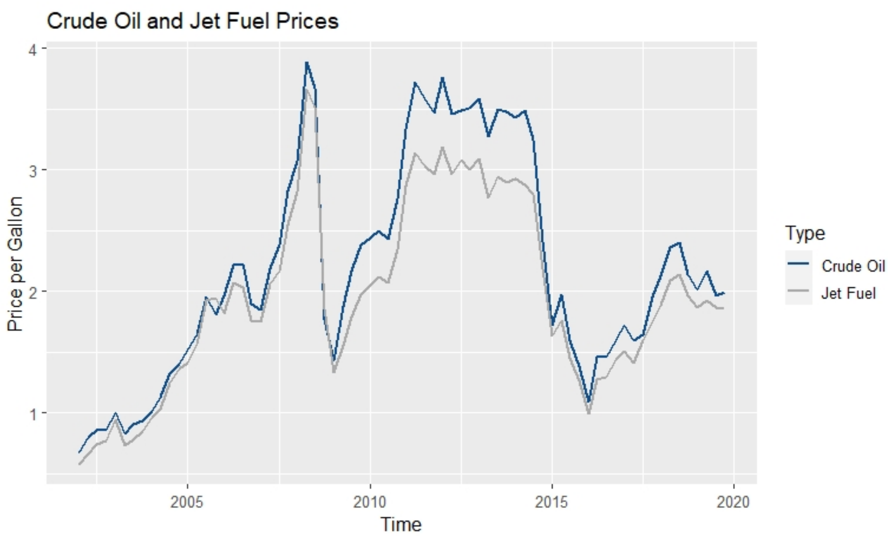


Figure 4.1: Crude oil and jet fuel prices (U.S. Energy Information Administration, 2020)

This correlation is of interest, as changes in world jet fuel prices can have conflicting effects. On the one hand, an increase in jet fuel prices could affect demand negatively due to a possible increase in airfares. On the other hand, this increase could be caused by an increment in crude oil prices, thus having a positive effect on demand. The opposite is true for a decrease in world jet fuel prices.

4.2.4 Unemployment rate

The Norwegian seasonally adjusted unemployment rate has been obtained from OECD (OECD, 2020b). The unemployment rate is based on labour force studies and amounts to the number of unemployed people as a percentage of the total labour force in the given country. Moreover, OECD defines unemployment as people of working age without work, who are both capable of working and have taken specific measures in trying to find work.

4.2.5 Real effective exchange rate

The real effective exchange rate (REER) of Norway has been retrieved from the Federal Reserve Bank of St. Louis, where the data are calculated as the weighted average of two-sided exchange rates (FRED, 2020). Moreover, the data are adjusted by relative consumer prices, and 2010 is used as base year. As the predictor is observed monthly, we have calculated the quarterly average.

4.2.6 Tourism

Although data containing information about the added value in the tourism industry as a share of GDP in Norway is available, it is only calculated on a yearly basis. On the one hand, the data could be transformed into quarterly observations, as we are not interested in seasonal effects. On the other hand, by obtaining this variable, it is not possible to predict the number of air passengers one quarter ahead, as one would have to wait until the end of the year to obtain this predictor.

On this basis, bookings for different accommodation types, such as hotels, have been used as an indicator for tourism. The data is retrieved from SSB and contains the total number of bookings for all accommodation types (Statistics Norway, 2020b). We consider this a weakness, as all our predictors are either normalized, shown as percentage changes, or indices. Nonetheless, we find the value of predicting one quarter ahead to exceed this disadvantage.

4.2.7 Number of departures

As a measurement of flight frequency, data on the quarterly number of departures have been provided by Avinor. Similar to the number of air passengers, the data only contain information about departures from Avinor airports, which is further divided into domestic, international, offshore, and total departures. As previously explained, both domestic and total departures are used. Lastly, the data are divided by the Norwegian population data, obtained from SSB.

4.2.8 Air passenger tax

As mentioned in Chapter 3, previous researches have included exogenous shocks when predicting air passenger demand. Based on this, we have created a dummy variable for the Norwegian air passenger tax, where observations before the tax equal 0, and observations after the tax equal 1. The Norwegian air passenger tax was introduced on June 1st, 2016, with the primary purpose of generating revenue for the Norwegian Government (NOU 2019: 22, p. 49). From June 1st, 2016, to 2018, the tax was NOK 80 per passenger but increased to NOK 83 in 2018. The tax was further reorganized on April 1st, 2019, where the tax was differentiated based on flight distance. This resulted in two types of taxes; a tax of NOK 75 for flights less than 2500 km from Oslo, and a tax of NOK 200 for flights more than 2500 km from Oslo. However, in our data set, we only distinguish between the period before and after introducing the tax and not the different types of taxes. Moreover, the air passenger tax is included to see if it can give better predictions, but we are not interested in the isolated effects of the tax, as such.

4.2.9 Other possible predictors

The aim of including predictors in the model is to predict the quarterly number of passengers. Other predictors could affect demand, but we have chosen not to include these for various reasons. Firstly, and most obviously, we do not include airfares. Although data for international airfares exist, such as statistics on US prices from the Bureau of Transportation Statistics, we find these airfares non-representative for Norwegian prices.

Secondly, we have chosen not to include the age and gender distribution in Norway.

As mentioned in Chapter 3, based on previous literature, these could affect demand. However, as they are relatively constant, and we are interested in how changes in a given predictor affect changes in demand, they would not provide additional information. Lastly, a seasonal dummy could have been included. Nevertheless, we are not interested in investigating how demand is affected by a seasonal component. Instead, other techniques will be applied to exclude the seasonal component in the data, which is further elaborated on in Chapter 6.

5 Methodology

This chapter introduces machine learning techniques towards predicting the quarterly number of air passengers in Norway per capita. The methods applied are classified as supervised learning, which (James et al., 2013, p. 1) defines as "building a statistical model for predicting, or estimating, an output based on one or more inputs." In this thesis, domestic and total air passengers per capita are the outputs, hereafter known as the responses Y. The corresponding inputs are the variables introduced in Chapter 4, in addition to a one quarter lag of the response, hereafter known as the predictors p. An overview of all variables can be found in Appendix A2. The assumption is that there is a fixed or unknown function f between the response, Y, at time t, and the predictors, p observed at time $t-1$.

Consequently, we will not consider any univariate time series forecasting methods. These methods are solely based on past observations of Y and assume that other variables are embodied (Moosa, 2000, p. 62). Moreover, we will only apply quantitative methods due to the nature of the response. In summary, the analysis aims to predict Y at time t by using different machine learning methods.

Both parametric and non-parametric techniques will be applied in this thesis, more precisely, OLS, elastic net, and random forest. In parametric methods, an assumption about the function form of f is made before the training data is used to fit the model (James et al., 2013, p. 21-23). The form of the function is often linear, and thus, these methods are often referred to as linear machine learning methods, such as OLS and elastic net. In contrast, a non-parametric method does not make an assumption about the form of the function. Instead, the methods seek to estimate f as close to the data points as possible.

Parametric methods are relatively simple to describe and implement. However, standard linear regression can have significant limitations in terms of predictive power (James et al., 2013, p. 265). Consequently, non-parametric methods can be used in order to give better predictions by reducing the variance. Examples of non-parametric methods are tree-based methods, such as regression trees, boosting, bagging, and random forest.

Furthermore, when training models, there is a risk of overfitting or underfitting the data. The former occurs when the machine learning methods are attempting too hard to find patterns in the data that, in reality, are just white noise, where the opposite is true for the latter (James et al., 2013, p. 32). In the cases of overfitting and underfitting, the model has high variance and bias, respectively. If this is the case, the trained model will predict unseen data poorly. We will further elaborated on the trade-off between bias and variance in Chapter 5.2.

Therefore, to test how well the models estimate actual values of the response, the data set is split into a training and a test set. The former consists of observations from 2003 to 2017, while the latter of observations from 2018 to 2019. Consequently, predictions for 2018 and 2019 will be made based on observations from all previous years. Before introducing the methods, we will, in the following, give some clarifications on the terminology used and explain how we will evaluate the accuracy of each method.

5.1 Clarifications

It can be useful to distinguish between statistical learning and machine learning, as these terms are often used interchangeably. James et al. (2013, p. 1) define statistical learning as a set of tools for modeling and understanding complex data sets. Although the terms are very similar, there is a perception that their purpose are somewhat different. Whereas machine learning will sacrifice interpretability for better prediction power, statistical learning will focus more on finding a relationship between variables (Stewart, 2019). However, this compromises their prediction power. In this thesis, we will use the term machine learning, as the main purpose is the prediction power.

5.2 The Bias-Variance Trade-Off

Moreover, it can be beneficial to look into how we will evaluate the performance of each model for a given technique. When assessing model accuracy, it is generally not essential to evaluate the ability to predict already seen data, referred to as the *training error* (James et al., 2013, p. 30). Rather, we are interested in evaluating the ability to obtain predictions from previously unseen data, referred to as the *test error*. In this thesis, the test error measurement will be the mean squared error (MSE), given by Equation 5.1.

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{f}(x))^2 \tag{5.1}$$

Through mathematical proof, it is possible to show that Equation 5.2 is the expected test MSE for a given value of x_0.

$$\mathrm{E}(y_o - \hat{f}(x_0))^2 = \mathrm{Var}(\hat{f}(x_0)) + [\mathrm{Bias}(\hat{f}(x_0))]^2 + \mathrm{Var}(\epsilon) \tag{5.2}$$

Consequently, in order to minimize the test MSE, a model that simultaneously achieves a low variance *and* a low bias is chosen, as $\mathrm{Var}(\epsilon)$ is the irreducible error (James et al., 2013, p. 34-35). Moreover, the variance is defined as the change in the estimated function f, referred to as $\hat{f}$, caused by estimations on different training data. Therefore, if a method has high variance, small changes in the training data result in a large change in the fitted model, which is not optimal. In contrast, bias is the error caused by attempting to estimate a real-life problem through a relatively simple model. Therefore, minimizing the test error is associated with finding the optimal bias-variance trade-off.

Generally, more flexible methods are associated with low bias (James et al., 2013, p. 34). However, as the flexibility of a method increases, so does the variance. OLS and the elastic net are considered to be inflexible methods, as they only generate linear functions f. Therefore, these methods will give high bias if the relationship between our response and its predictors is non-linear. In contrast, random forest is a flexible approach as it can generate a broader range of possible shapes when estimating f. The amount of preferred flexibility depends on the situation, and it is not easy to know prior to building the models. Thus, we have chosen to include both inflexible and flexible methods.

Although we will use MSE to evaluate performance, other accuracy measures are also calculated. As MSE is scale-dependent, it can not be used for comparisons across time series (Hyndman and Athanasopoulos, 2018). The same is true for RMSE, which is the squared root of MSE and represents the standard deviation of the residuals.

In contrast, the mean absolute percentage error (MAPE) can and will be used to compare performance between data sets, which in this case relates to a comparison of predictions of domestic and total passengers. The calculation of MAPE is given in Equation 5.3.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{f}(x_i)}{y_i}| \tag{5.3}$$

5.3 Time Series Cross-Validation

When the true f is not observable, it is difficult to calculate the test error discussed in the last section (James et al., 2013, p. 36). On this basis, numerous techniques have been developed to overcome this obstacle, where cross-validation is one example. Cross-validation is a class of methods that estimates the test error by holding out subsets of the training set. The remaining observations in each training set are used to train models, which are again tested on the hold-out samples, referred to as the test sets.

Therefore, before making predictions for 2018 and 2019, the performance of each machine learning technique will be tested through time series cross-validation. In this procedure, a series of test sets consisting of only one observation is taken out of the data (Hyndman and Athanasopoulos, 2018). The corresponding training sets, in which the models will be trained on, are observations occurring prior to each test set. The reasoning behind this is that, for time series objects, it is only relevant to test how well the model predicts future and not past values.

In this approach, a rolling window will be used, illustrated on the next page in Figure 5.1, where the blue dots represent the training sets and the red dots the test sets. This implies that for each new training set, one observation is added, and the oldest one removed (Hyndman and Athanasopoulos, 2018). Moreover, the test set is two observations ahead of the last observation in each training set. The figure is based on Hyndman and Athanasopoulos (2018).

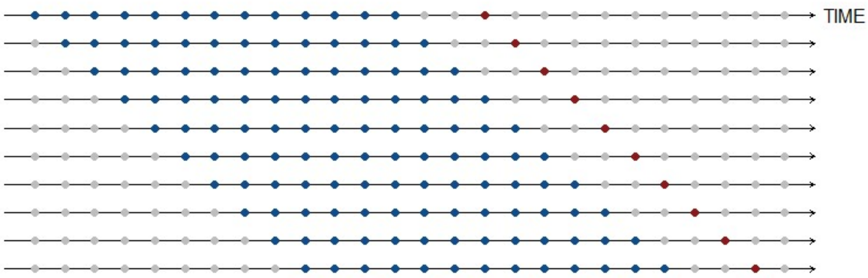


Figure 5.1: Rolling window time series cross-validation

5.4 Machine Learning Methods

In the following, we will present the machine learning methods. Firstly, we will present the standard multiple linear regression model, fitted by OLS, followed by elastic net. Lastly, random forest will be presented.

5.4.1 Ordinary least squares

The standard multiple linear regression model is given in Equation 5.4 (James et al., 2013, p. 71).

$$f(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon \tag{5.4}$$

The coefficients $\beta_0, \beta_1, \ldots, \beta_p$ for the p predictors are estimated by minimizing the sum of squared residuals (RSS), which is given by Equation 5.5 (James et al., 2013, p. 72).

$$RSS = \sum_{i=1}^{n}(y_1 - \hat{y}_i)^2 = \sum_{i=1}^{n}(y_1 - \hat{\beta_0} - \hat{\beta_{i1}} - \hat{\beta_{i2}} - \cdots - \hat{\beta_{ip}})^2 \tag{5.5}$$

In this method, all predictors are included in the model. As mentioned in Chapter 5.2, the test error can be reduced if it is possible to change the model such that the variance decreases for a smaller increase in bias or vice versa. Applying shrinking methods is one way to reduce the variance. In these approaches, the coefficients are shrunken towards zero, which has the effect of reducing the variance (James et al., 2013, p. 215). The two most common shrinking methods are ridge and lasso regression. However, as previously presented, the elastic net will be applied in this thesis, which is a combination of ridge and lasso regression. Therefore, in order to understand elastic net, we will give a walk-through of ridge and lasso.

5.4.2 Elastic net

Ridge and lasso regression both build on the principle of fitting the model using OLS. However, the methods also include a second term, known as the shrinking penalty, see Equation 5.6 and 5.7 (James et al., 2013, p. 215-219).

$$Ridge : RSS + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{5.6}$$

$$Lasso : RSS + \lambda \sum_{j=1}^{p} |\beta_j|. \tag{5.7}$$

Further, the tuning parameter λ is decided by the user and seeks to control what impact the shrinking penalty has on the estimations (James et al., 2013, p. 227). Consequently, both ridge and lasso regression estimate several coefficient sets, where OLS estimates $\hat{\beta}$ for each p predictor, ridge and lasso estimate $\hat{\beta}_\lambda^R$ and $\hat{\beta}_\lambda^L$ coefficients for each level of λ. Choosing the optimal λ value is critical, which we will do by minimizing the MSE obtained through time series cross-validation. In our estimations, λ values ranging from 10^{10} to 10^{-2} with the length of 1000 are tested.

The favorability these methods hold over OLS originates from the second term and comes from a better bias-variance trade-off (James et al., 2013, p. 215-217). This is because the coefficients $\beta_1 \ldots \beta_p$ will be shrunk towards zero in order to minimize Equation 5.6 and 5.7. The shrinking will lead to a reduction in variance, for a potentially smaller increase in bias. From Equation 5.6 and 5.7 one can see that if $\lambda = 0$, the model is estimated through OLS. Based on this, as λ increases, the flexibility decreases and the optimal λ is the level that optimizes the bias-variance trade-off.

One potential disadvantage of ridge regression is that although it shrinks the predictors towards zero, it never sets any predictors at exactly zero (James et al., 2013, p. 219). Hence, all p predictors are included in the model. In contrast, lasso both shrinks some predictors towards zero but also force some predictors to be exactly zero. The difference originates from the difference in the penalty term, see Equation 5.6 and 5.7. Lasso penalizes the absolute values of the coefficients, whereas ridge penalizes the squares of the coefficients. However, lasso is limited when the pairwise correlation between predictors are high, and for a $n > p$ situation where this is the case, ridge outperforms lasso (Tibshirani, 1996, p. 286). In order to overcome these obstacles, Zou and Hastie (2005) developed elastic net.

In elastic net, a second tuning parameter α is introduced. The parameter ranges from 0 to 1, where $\alpha = 0$ is ridge regression and $\alpha = 1$ is lasso regression James et al. (2013, p. 251). Consequently, a value ranging from $0 < \alpha < 1$ is chosen for elastic net. Similar to λ, α is chosen through the usage of time series cross-validation. Therefore, in this approach, a λ and a α value that simultaneously achieves the lowest MSE is chosen, where α values ranging from 0 to 1 with a length of 10 are tested.

In our approach, the optimal λ and α values are estimated to be 0.1 and 0.036 for domestic passengers, and 0.9 and 0.028 for total passengers, respectively. Appendix A3.1 and A3.2 shows MSE as a function of λ, given the optimal α values.

5.4.3 Random forest

As random forest builds on decision trees to construct more powerful predictions, we will give a walk-through of this method in order to understand the underlying mechanisms of random forest (James et al., 2013, p. 316). Decision trees can be applied for both regression and classification problems; however, as mentioned, due to the nature of the response, only the construction of regression trees will be described in brief. The process is nevertheless quite similar.

Regression trees consist of splitting rules and are constructed using recursive binary splitting, also referred to as a top-down approach (James et al., 2013, p. 306). Hence, at first, all observations are in the same region, before the trees are split into branches. When the trees are built, the set of possible values are divided into J non-overlapping regions $R_1, R_2, \ldots, R_J$, where the same prediction is given for observations that falls in region R_j. The objective is to minimize the RSS, given by Equation 5.8. The best split are made on each step; thus, future steps are not considered in the tree-building process.

$$RSS = \sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2 \tag{5.8}$$

Regression trees tend to suffer from high variance as well as poor predictive accuracy (James et al., 2013, p. 316-317). The predictive power of decision trees can be improved by using different techniques for aggregating trees, caused by a more optimal bias-variance trade-off. Bootstrap aggregation is such a technique and a central part of random forest. This technique builds B decision trees by using B different bootstrapped training sets and averaging all the estimations. Consequently, the estimated MSE is close to the true test error. Nevertheless, in our approach, we will also apply time series cross-validation to calculate the MSE.

For each decision tree in random forest, a random sample of m predictors is used as split candidates from the set of p predictors (James et al., 2013, p. 319). Moreover, the split candidates only use one of the m predictors, where the default is $m \approx \sqrt{p}$. In our approach, time series cross-validation has been used to find the optimal m, where the chosen number is the one that minimizes the MSE. The results indicate that the optimal m for domestic and total passengers are six and five, respectively. Further, at each split, a new sample of m predictors is taken; thus, only a subset of the predictors is considered at each split (James et al., 2013, p. 319-320). Consequently, if there is a very strong predictor, random forest gives other predictors a greater opportunity to be considered and chosen in the top split. This characteristic of random forest refers to a process of decorrelating the trees.

A default of random forest, due to the large number of created trees, is that it can be difficult to interpret the model (James et al., 2013, p. 319). However, one can obtain an overall summary of the importance of the predictors by constructing a variable importance plot, where the plot is interpreted as the increase in MSE if we were to remove a given predictor.

6 Analysis

In this chapter, we will present our findings based on the methodology introduced in Chapter 5. As briefly presented in the previous chapter, the assumption is that there is a relationship between the number of air passengers per capita and the values of the predictors observed in the previous quarter. In other words, this analysis evaluates the capability the predictors, observed at time t, have to make prediction on the number of air passengers per capita at time $t+1$. Moreover, one of the predictors is a one-lagged value of the response. More precisely, this analysis will present how well the models predict the number of air passengers per capita for all periods in 2018 and 2019, which represents the test set. For clarification purposes, Table 6.1 summarizes the build-up of the training set, and thus, how the models are trained.

Table 6.1: Set-up of the training set

Response	Predictors
Q4 2017	Q3 2017
Q3 2017	Q2 2017
Q2 2017	Q1 2017
⋮	⋮
Q2 2002	Q2002

Before analyzing the findings, we will present descriptive statistics of the responses and the treatment of the seasonal component. Although we will only present the responses, descriptive statistics of all predictors are included in Appendix A4. Thereafter, we will provide a brief analysis of the parameters λ and α in the elastic net and present the MSE obtained from time series cross-validation of each machine learning method. Lastly, we will compare actual and predicted values for OLS, elastic net, and random forest. A more detailed discussion of both the predictions and the estimates will be given in the next chapter.

6.1 Descriptive Statistics

Figure 6.1, on the next page, exhibits scatter plots of the responses. Based on the plot, the quarterly data exhibit strong seasonal trends, particularly for total passengers.

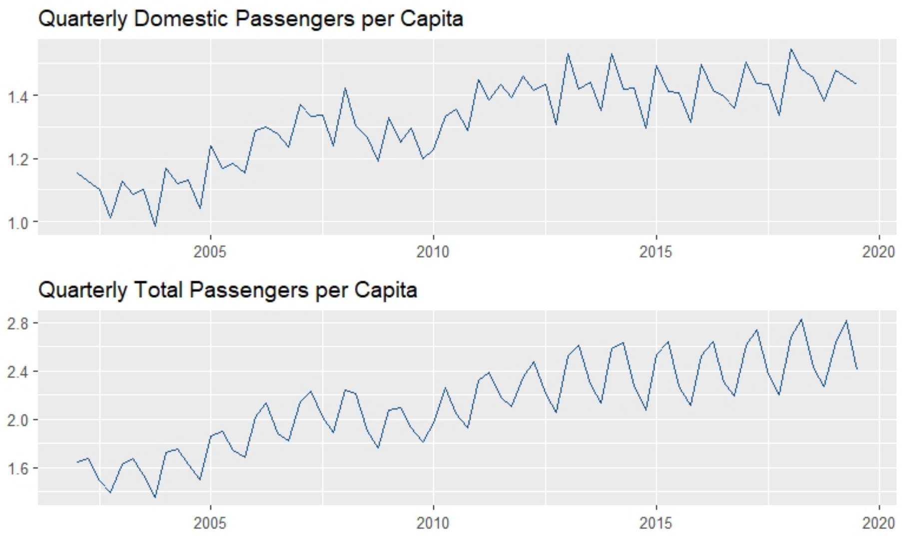


Figure 6.1: Quarterly passengers per capita

This can further be investigated through the seasonal plot in Figure 6.2. From this, the responses peak in Q2 and Q3 for domestic and total passengers, respectively. This is not a surprising finding as leisure travel occurs in these months. An explanation as to why the number of domestic passengers peak in Q2 and not in Q3 might be caused by the decrease in business travel during general staff holiday in July. Moreover, some passengers in Q4 could originate from travel related to Christmas, which could explain why these numbers are higher than Q1.

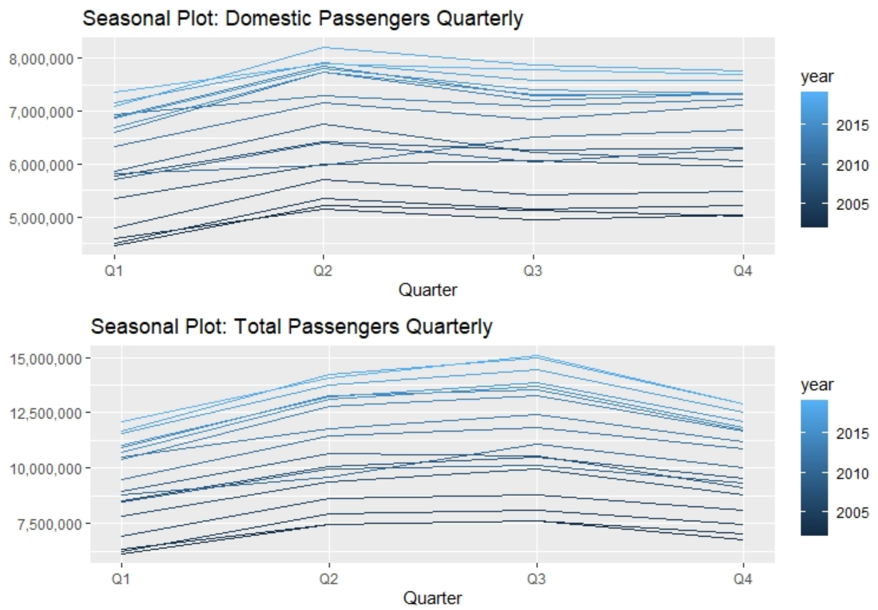


Figure 6.2: Seasonal plots

Furthermore, the seasonal pattern seems to be relatively periodic, particularly for total passengers. In addition, based on Figure 6.1 and 6.2, on the previous page, the seasonal effect seems multiplicative. In order to confirm this objectively, we performed a multiplicative seasonality test. As we are interested in how the predictors, and not the seasonal component, affect air passengers, we seasonally adjust the response and predictors where the obtained data were not seasonally adjusted. In order to do this, an *x11* decomposition was performed. This procedure originates from the US Census Bureau and Statistics Canada and builds on classical decomposition (Hyndman and Athanasopoulos, 2018). We have chosen this method as it both allows multiplicative and non-periodic seasonality. The seasonal adjusted data obtained is shown in Figure 6.3. Similarly, *Nights* and *Traffic* were seasonally adjusted, using the same method.

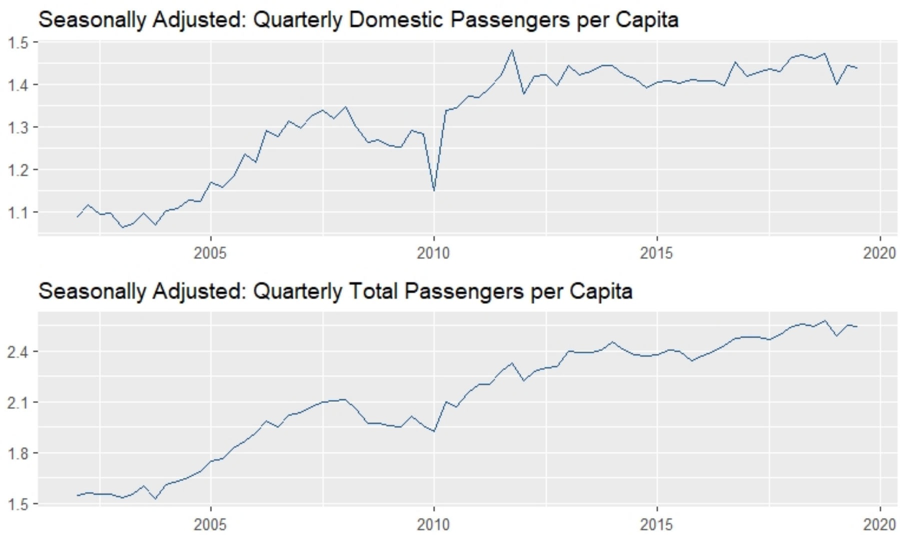


Figure 6.3: Seasonally adjusted quarterly passengers per capita

6.2 Performance

As previously discussed, in this approach, the machine learning methods will be evaluated by the MSE of the training data, obtained through time series cross-validation. The performance for domestic and total data are summarized in Table 6.2 and 6.3.

Table 6.2: Performance domestic passengers

Methods	MSE	RMSE
OLS	$4.00 \cdot 10^{-3}$	$6.33 \cdot 10^{-2}$
Elastic Net	$1.32 \cdot 10^{-3}$	$3.63 \cdot 10^{-2}$
Random Forest	$1.49 \cdot 10^{-3}$	$3.86 \cdot 10^{-2}$

Table 6.3: Performance total passengers

Methods	MSE	RMSE
OLS	$8.62 \cdot 10^{-3}$	$9.29 \cdot 10^{-2}$
Elastic Net	$4.37 \cdot 10^{-3}$	$6.60 \cdot 10^{-2}$
Random Forest	$8.21 \cdot 10^{-3}$	$9.48 \cdot 10^{-2}$

From Table 6.2 and 6.3, one observes that elastic net performs best on the training data for both domestic and total air passengers. Likewise, random forest and OLS rank second and third for both domestic and total passengers. Although the ranking is the same, random forest and OLS performs relatively similar for total passengers, whereas random forest performs almost as well as elastic net for domestic passengers.

Similarly, time series cross-validation was used to find the optimal parameters, λ, and α, in the elastic net, by simultaneously ranging through chosen values for each parameter and choosing the ones in which the MSE is at its minimum. For the domestic model, the optimal λ and α were 0.1 and 0.036, respectively. Likewise, for the total model, we found the optimal λ and α to be 0.9 and 0.028, respectively. These values and their implication will further be elaborated on in the next chapter.

Although the aim is to minimize MSE, the RMSE for each method is also summarized in Table 6.2 and 6.3 for interpretation purposes. RMSE represents the spread of the residuals and how much they differ from the response. For example, the elastic net deviates with $3.63 \cdot 10^{-2}$ and $6.60 \cdot 10^{-2}$ on average from the actual values for domestic and total passengers, respectively. In other words, the average difference between estimated and actual values of the number of air passengers per capita.

6.3 Air Passenger Predictions

In this part of the analysis, we will present the predictions for quarterly air passengers per capita. An overview of all predicted values can be found in Appendix A5.1 and A5.2. Although elastic net performed the best on the training data, predictions from all methods will be presented. Further, this part of the analysis is divided into two sections, where the first part presents domestic predictions, and the second part total predictions.

6.3.1 Domestic air passengers per capita

Figure 6.4 exhibits 2018 to 2019 predictions for quarterly domestic air passengers per capita, where the grey line represents the actual values. As previously stated, the elastic net is the best performing model on the training set with a MSE of $1.184 \cdot 10^{-3}$. From the figure, one can observe that elastic net also gives the best predictions on the test data. Nevertheless, values are overestimated for all quarters, and the predictive power decreases as t increases, the same holds for OLS. Both methods particularly perform poorly in Q2 of 2019, where the difference between predicted and actual values is 0.08 and 0.07 for OLS and elastic net, respectively. Accounting for the population in Q2 of 2019, this amounts to a difference of 431,194 and 391,154 passengers.

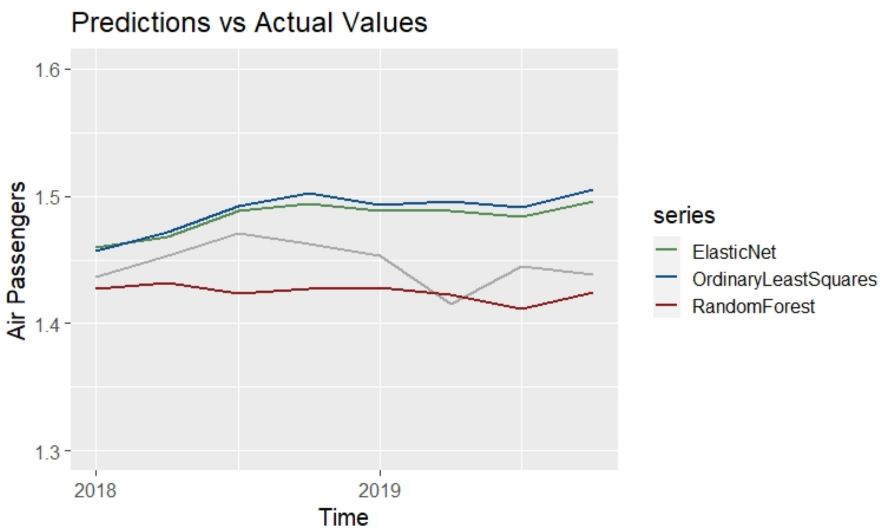


Figure 6.4: Quarterly predictions of domestic air passengers per capita

In contrast, random forest underestimates the values for all periods, except for Q2 of 2019, and the prediction power does not decrease as t increases. However, similar to the two other methods, random forest performs well in Q1 of 2018. Lastly, unlike the two other methods, random forest performs well in Q2 of 2019 and poorly in Q2 of 2018.

6.3.2 Total air passengers per capita

Figure 6.5 presents how the various machine learning techniques predict the total number of air passengers per capita in Norway in 2018 and 2019. Similar to domestic data, the elastic net performs best on the training set and yields the best predictions. The model performs particularly well in 2018, whereas it overestimates the actual values in the remaining periods, except for Q3 of 2019.

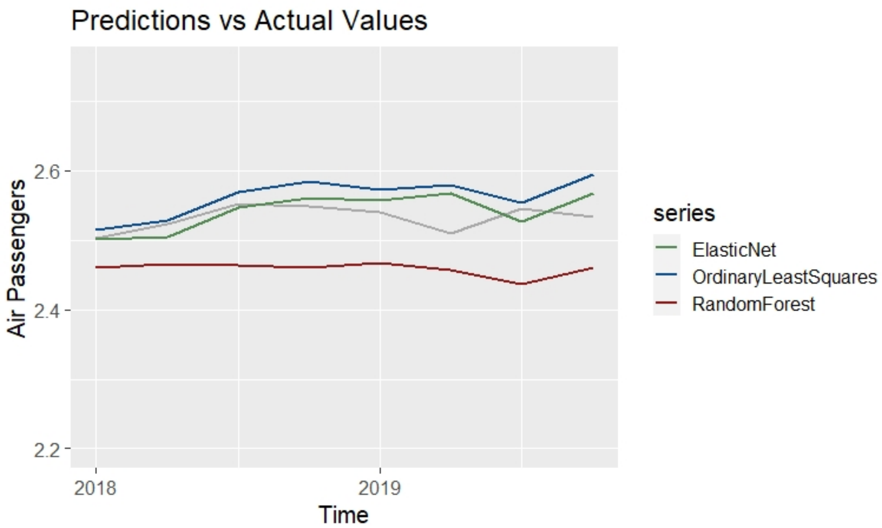


Figure 6.5: Quarterly predictions of total air passengers per capita

Similar to the domestic predictions, elastic net and OLS performs particularly poorly in Q2 of 2019. In this period, the difference between the predicted and actual value for OLS and elastic net are 0.08 and 0.06, respectively. This amounts to a difference of 431,194 and 312,975 passengers. Although random forest outperforms OLS on the training set, OLS makes better predictions on the test data. From Figure 6.5 one observes that random forest underestimates the values in all periods, whereas OLS overestimates all values. However, OLS is fairly close to the actual values, particularly in the three first quarters of 2018. As mentioned, random forest is the model with the least predictive power on 2018 and 2019 data, as it underestimates the actual values in both years.

6.4 Conclusion of Predictions

To conclude, OLS and elastic net yield quite similar results, and the predictions were quite close to the actual values, with some exceptions. In contrast, random forest underestimated the actual values in all periods, except Q2 of 2019 on the domestic data. In the following chapter, we will provide a more detailed discussion of the predictions and their performance. Although we will mainly focus on periods in which the methods performed poorly, a discussion of the predictions as a whole will also be made. Moreover, a discussion of the predictors will be made. Here we will particularly comment on findings that differs from the literature and if this finding is surprising.

7 Discussion

7.1 Discussion of Predictions

As presented in the analysis, the machine learning methods yield quite different predictions. Elastic net and OLS mostly overestimated the values, whereas random forest underestimated for most periods. In the following, a discussion will be made on why the methods predicted different values and why their performance varied.

Before discussing domestic and total predictions separately, a comment on Q2 of 2019 predictions as a whole will be made. In the analysis, we found that the ability to predict Q2 of 2019 were poor compared to other periods, for OLS and elastic net. The SAS labour strike could explain this lack in predictive power. Over the course of seven days, SAS pilots went on a labour strike in April and May of 2019, which affected 370,000 passengers (Thommessen, 2019). As previously discussed, the aviation industry is vulnerable to events such as these, which can have an immense effect on the industry in the short-run. However, these events are almost impossible to predict, regardless of the method used.

7.1.1 Domestic passengers

As presented in Chapter 6, the elastic net model had the lowest test MSE on the training data, followed by random forest and OLS. Although the elastic net outperformed the random forest on the training set, the random forest predicts better on the test data. Their MSEs on the training set were also relatively similar. Therefore, it is not clear whether or not a parametric or non-parametric method is more suitable when predicting the domestic number of air passengers. Although the random forest outperforms the elastic net on the test data, this could be caused by the SAS labour strike. The random forest underestimates the response in all periods, *except* for Q2 in 2019. If the SAS labour strike had not occurred, random forest could have underestimated this quarter as well, and elastic net might have produced better predictions compared to random forest.

As mentioned in Chapter 5, the favorability elastic net holds over OLS originates from a reduction in variance, hence, a better bias-variance trade-off. Although the optimal λ

value is relatively small and the predictions are somewhat similar, a better bias-variance trade-off explains why the elastic net outperform OLS. Besides, OLS includes all predictors, whereas the elastic net sets some predictors at exactly zero, which could also explain the difference between the two models. Similar to elastic net, random forest reduces variance. Thus, their improved performance could come from a better bias-variance trade-off.

7.1.2 Total passengers

Similar to domestic data, elastic net performs the best for total data on the training set, followed by random forest and OLS. Consequently, the same holds for total passengers regarding the suitability of a parametric vs. a non-parametric model and a better bias-variance trade-off. In contrast to domestic data, the elastic net also yields the best predictions for total data. Although random forest performs better than OLS on the training data, OLS makes better predictions on 2018 and 2019 data.

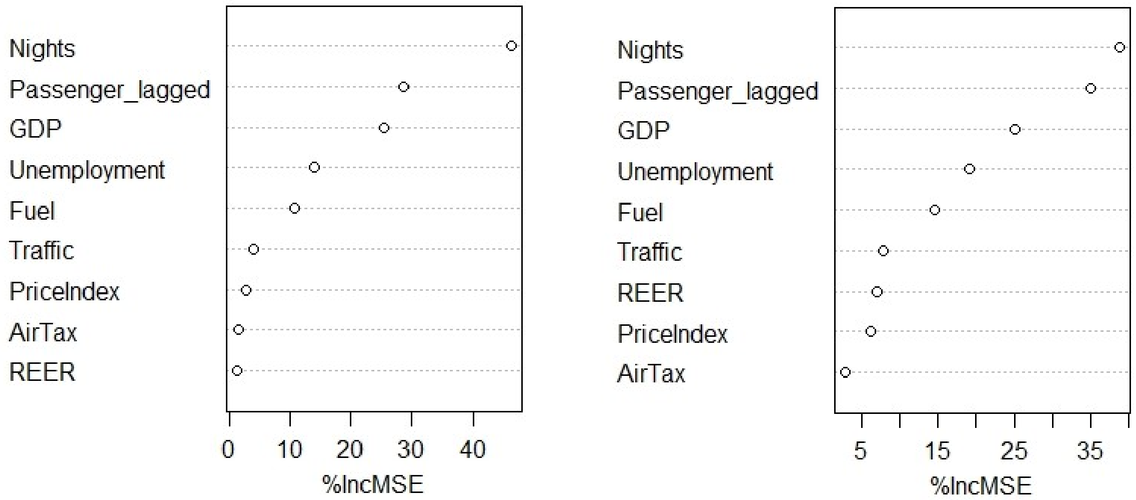
7.1.3 Comparing domestic and total passengers

In the following, we will compare the best model for domestic and total passengers. As elastic net performs the best for both data sets, we will compare these two estimations through MAPE, an in-dependent scale error measurement. On the training set, MAPE is 1.95% and 2.2% for domestic and total, respectively. However, on 2018 and 2019 observations, elastic net predicts total passengers better than domestic data. An explanation as to why could be the SAS labour strike, which based on Figure 6.4 and 6.5 in Chapter 6 seem to have affected domestic passengers more than international passengers, hence, total passengers.

7.2 Discussion of Predictors

Although the focus in this thesis is on prediction accuracy, we find it useful to include a discussion of the predictors. As random forest and elastic net had the lowest MSE, we will only look at their estimations.

The random forest variable importance plots for domestic and total passengers are presented in Figure 7.1a and 7.1b, respectively. The ranking determines the importance of each predictor, and as presented in the previous chapter, the plot is interpreted as the increase in MSE if we were to remove a given predictor. This is of interest as it can help us understand how important each predictor is when predicting the response, and thus, it could help understand potential deviations from actual values.



(a) Domestic passengers **(b)** Total passengers

Figure 7.1: Variable importance plots

From the figures, one observes that the two plots share some similarities, where only the three least important variables are ranked differently. As an example, *REER* is considered more important for total passengers than for domestic passengers. The finding is reasonable, as the decision to fly outside of Norway, or to Norway, could be affected by relative exchange rates. Moreover, both models select *Nights* as the most important predictor, followed by $Passenger_{lagged}$, *GDP*, *Unemployment* and *Fuel*. On the one hand, it seems reasonable that *Nights* is important as tourism and air travel are closely related. In addition, as mentioned in Chapter 1, a large amount of the increment in Norwegian air traffic is a result of increased tourism in Norway.

On the other hand, this does not comply with the literature presented in Chapter 3, which finds that income and price are the two most important variables. One explanation could be that this predictor is measured in number of nights, which is a weakness discussed in Chapter 4. Although the ranking is almost the same, the domestic model identifies *Nights* as the supreme predictor compared to the other variables. In contrast, the model for total passengers considers particularly $Passenger_{lagged}$ as almost equally important. This finding is reasonable as there is a clearer correlation between the number of domestic passengers and accommodation bookings in Norway. To clarify, outbound international travel is a part of total number of passengers, but these are not associated with accommodation bookings within Norway.

For the elastic net models, the coefficients for the domestic and total model are summarized in Table 7.1. As previously discussed, the ridge regression penalty is weighed more for the domestic model, and the opposite is true for the total model. As a result, in the domestic model only *AirTax* is set at exactly zero, whereas only *Fuel*, *GDP*, $Passenger_{lagged}$ and *Nights* are non-zero in the total model.

Table 7.1: Elastic net coefficients total passengers

Predictors	Domestic	Total
(Intercept)	$2.52 \cdot 10^{-1}$	$(1.51 \cdot 10^{-1})$
Fuel	$3.11 \cdot 10^{-2}$	$4.63 \cdot 10^{-3}$
REER	$(2.02 \cdot 10^{-4})$	.
PriceIndex	$(6.51 \cdot 10^{-5})$	.
GDP	$4.69 \cdot 10^{-3}$	$5.37 \cdot 10^{-3}$
$Passenger_{lagged}$	$3.08 \cdot 10^{-1}$	$7.41 \cdot 10^{-1}$
Traffic	(3.01)	.
Nights	$5.20 \cdot 10^{-8}$	$4.13 \cdot 10^{-8}$
AirTax	.	.

In contrast to previous literature, the *Fuel* coefficient in the elastic net is positive for domestic and total passengers, and thus, affects air traffic positively. Although this is in contrast to previous literature, it does not come as a surprise. As previously presented, this could relate to the dependency Norway has on the oil price. In addition, in practice, a decrease in jet fuel prices does not necessarily mean a decrease in airfares. As jet fuel is one of the largest cost drivers for airlines, they often buy crude oil futures to reduce the risk of significant and sudden changes (Rammen, 2019). Therefore, if the crude oil price changes, airlines could be bound to previous price agreements, and hence, it does not affect their operational costs.

It might seem surprising that the elastic net sets the predictor *Traffic* at exactly zero in the total model, as one would assume a positive correlation between the number of passengers and the number of flights. Likewise, in the domestic model, the coefficient for *Traffic* is negative, which is in contrast to previous presented literature. The variable importance plots also indicate that random forest identifies *Traffic* as one of the least important predictor. Although this might seem surprising, it can be a result of the better capacity utilization and larger air crafts in recent years, as presented in Chapter 2. For example, in 2013, Norwegian Air Shuttle launched that they were adding 10 Boeing 787-8 "Dreamliners" to their fleet, and thus, enabling long haul flights (Landre, 2013).

Another surprising finding is that the air passenger tax seems to have little or no affect on air traffic demand. One explanation could be that the additional cost is born by the airlines. In an article from 2019, Head of Public Affairs at SAS, Knut Morten Johansen, states that SAS are not able to increase its airfares, and hence, they will bear the additional cost imposed by the tax (Sørdal, 2019). Based on this statement, air passengers should not be affected by the tax, and if so, it will probably have a minimal impact on demand. Based on this, our findings seem reasonable.

Lastly, as expected, GDP has a positive effect on the number of air passengers per capita. It is difficult to say whether this effect is a result of changes in income or as a result of the correlation between air traffic and the state of the economy. This relationship will be covered in further detail in Chapter 8, which represents the second part of the thesis.

7.3 Value Creation of the Predictions

Predictions of air passengers create value in several ways. First and foremost, it can generate value for the aviation industry. As previously mentioned, the Norwegian airline industry is characterized by varied margins among the established firms. Therefore, optimization of operations is crucial. Predictions could aid the airlines in decisions, such as scheduling the number of departures. However, the data possessed by airlines are most likely far greater than the publicly available data applied in this thesis. Consequently, it is somewhat naive to believe that these predictions are very valuable for airlines.

Furthermore, these predictions could be valuable for airport operators. In 2018, Oslo Airport had approximately 15,000 employees, employed by more than 100 companies (Avinor, 2020a). Therefore, it is reasonable to think that these predictions can facilitate better staffing at airports. This is not only valuable for jobs such as airport ground staff and security checkpoint guards but also convenience shops, restaurants, cleaning personnel, and duty-free shops, to mention a few.

Although we have not focused on long-term predictions, it is worth mentioning that predictions and forecasts, in general, are essential in relation to long-term planning and development. For example, the planning of the expansion of Oslo Airport began in 2007, where the new terminal officially opened in 2017 (Avinor, 2020d). Consequently, as the number of air passengers increases, airports need to have a long-term perspective to meet this demand.

Our findings could also be useful for other non-aviation industries. As previously discussed, tourism and air traffic are closely related and a lot of the growth in air traffic volume originates from the tourism sector. Therefore, air traffic volume predictions could aid the market participants in the tourism industry in its decision-making. Such predictions could give an indication of future levels of tourism, and hence, facilitate better capacity planning and estimate future revenue, to mention some.

Likewise, air traffic can have a positive effect on the economic growth in a country. As air transportation enables transportation of both people and goods, it can make the overall economy more effective. In addition, the industry itself contributes to GDP both directly and indirectly. Directly through generating revenue for the aviation industry, but also indirectly by generating revenue in other industries such as the tourism industry. On this basis, predictions of the number of air passengers could be used as an indicator of economic growth in Norway. As mentioned, this will be elaborated on in detail in the second part of the thesis.

However, due to the Covid-19 pandemic, we question the *current* value of these predictions. As mentioned in the introduction of the thesis, the pandemic has affected the aviation industry in several ways, where particularly travel restrictions naturally have decreased the demand for air travel. Although the pandemic has affected most of the predictors, we believe the travel restrictions are the dominant factor as to why demand has decreased.

7.4 Prediction Weaknesses

As discussed in Chapter 4, the data ranges from Q1 of 2002 to Q4 of 2019. Although most predictors are available before 2002, Avinor only started measuring the quarterly number of passengers in 2002. As we used out-of-sample data, we only trained the models on 64 observations, which could be considered a weakness. Moreover, at the beginning of the process, we made an assumption about which factors affect the number of passengers. Although these variables were selected based on previous literature, it is difficult to know whether these reflect the Norwegian aviation industry properly.

Another weakness is related to the backcast of *PriceIndex*, which random forest found to be one of the least important variables. Therefore, if data for all periods would have been available, one might have seen different results. Moreover, the other proxy for airfares, *Fuel*, also reflects the oil prices; hence, the Norwegian economy. Consequently, in this approach, there are some weaknesses related to both proxies for airfares. Similarly, as previously mentioned, the proxy chosen for tourism was not the optimal one, in our opinion. Consequently, if quarterly added value in the tourism industry as a share of GDP would have been available, the results might have been different.

Moreover, we included a dummy for the air passenger tax as a predictor in the data set. As previously mentioned, the Government reorganized the tax in 2018 and 2019. Consequently, we could have included two additional dummies; a dummy for the increased tax from 2018 and a dummy for the reorganized tax from 2019. However, 2018 and 2019 were used as the out-of-sample data. Thus, the potential dummies would not have been a part of the training set. As mentioned, in practice, airlines often bare the cost of this tax. Although we characterize it as a weakness, we do not believe the additional dummies would significantly affect the predictions.

7.5 Recommendations for Future Research

This thesis has applied the machine learning techniques OLS, elastic net, and random forest to predict the quarterly number of air passengers per capita in Norway. However, other machine learning methods could have yielded better predictions. As presented in

Chapter 3, to our knowledge, research on predicting the number of air passengers by applying more advanced machine learning techniques have not been conducted. Thus, a recommendation for future research is to apply methods such as support vector machine, other decision tree methods, and neural network, to mention a few. However, it is difficult to say if these methods will yield significantly improved results. Similarly, univariate time series forecasting methods could be applied.

Moreover, based on previous literature, we have made assumptions about which variables affect the number of air passengers in Norway. Consequently, one could apply machine learning by using other predictors or other measurements for the predictors applied in this thesis. For example, one could use other measurements for GDP and or a different proxy for tourism.

Furthermore, the methodology could be transferred to specific regions or routes in Norway. In relation to the former, Fridström and Thune-Larsen (1989), developed a method to forecast demand for Norwegian regions in 1989. Thus, it could be of interest to build a similar model for more recent data. One can also apply the same methods to data from other countries, such as Sweden. This is of interest, as it can provide information on how the Norwegian and Swedish aviation industry differs; thus, what kind of variables are important for predicting air passengers in the respective countries.

In general, in the wake of the Covid-19 pandemic, it can be valuable to research different aviation industry aspects. As previously mentioned, the pandemic has affected the aviation industry in several ways. For example, it could reduce business travel in the long-run; thus, the variables affecting air travel could change. However, as the pandemic is still ongoing, at this point, it is difficult for us to recommend future research related to the effects of Covid-19.

Part II

The Causal Relationship Between Air Traffic and GDP in Norway

8 Air Passenger Traffic and GDP

8.1 Introduction

In the first part of the thesis, we used GDP solely as a predictor of air passengers, as it can be used as a proxy of income. However, in this part, the problem is somewhat reversed. In August 2020, we read an article in Dagens Næringsliv (DN) about how investors use alternative real-time data to measure the state of the economy during Covid-19 (Christensen and Krattum, 2020). At this point, we were already researching the aviation industry and had come across literature that indicated a causal relationship between air traffic and GDP. This sparked an interest to further investigate the causal relationship between air passengers and GDP in Norway. If such a relationship exists, air passengers could potentially be used as a real-time indicator of GDP.

In the same article, the chief analyst in Nordea, Erik Bruce, explains how macro data observed on a monthly basis have its limitations during the ongoing pandemic (Christensen and Krattum, 2020). Consequently, investors were seeking alternative real-time data to understand the development of the Norwegian economy. The article provides an example, where Head of Credit Research at SpareBank 1 Markets, Pål Ringholm, used the number of toll passes by German trucks as an indicator of the economy. Similarly, he also used passengers passing through the airport security checkpoints in the US as an indicator.

The approach in this part of the thesis will *not* be to predict GDP, but rather investigate if a change in air traffic can signalize a change in GDP. Therefore, we will conduct a strict linear Granger causality test on the *total* number of air passengers. Hence, in contrast to the first part of the thesis, we will not distinguish between domestic and total passengers.

The structure of this chapter is similar to the first part. We will start by giving a brief description of the relationship between air passengers and GDP in Norway. Thereafter, we will provide an overview of relevant literature before presenting the chosen methodology. Lastly, the results will be analyzed and discussed.

8.2 Air Passenger Traffic and Gross Domestic Product

The relationship between air passengers and GDP is unique, as the number of air passengers is also important for the state of the economy in a country. As mentioned in the introduction to the thesis, the aviation industry creates jobs, generates revenue, and increases the efficiency in the economy as a whole, where Figure 8.1 provides an illustrative example.

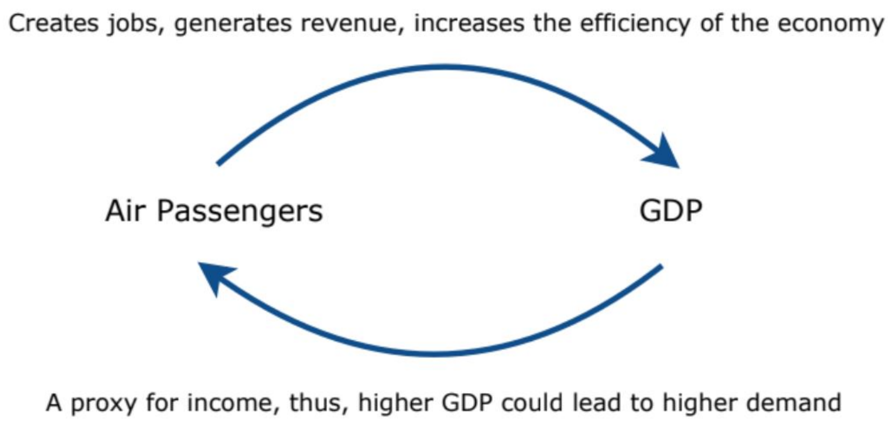


Figure 8.1: The relationship between air passengers and GDP

In the 20th century, changes in global air traffic were closely related to changes in GDP (NOU 2019: 22, p. 23). However, after the turn of the century, the increment in air traffic exceeds the increment in world GDP. The former increased by 140 percent from 2003 to 2017, while the latter had an increment of 40 percent. The difference in growth relates to the entrance of low-cost carriers, increased competition, and the improved efficiency in the aviation industry.

Regarding Norway, Figure 8.2, on the next page, represents the seasonally adjusted development in GDP and seasonally adjusted total air passengers per capita in the period 2002 to 2019. The figure is based on passenger data provided by Avinor, and the GDP is obtained from OECD. One can observe that the time series follow each other closely.

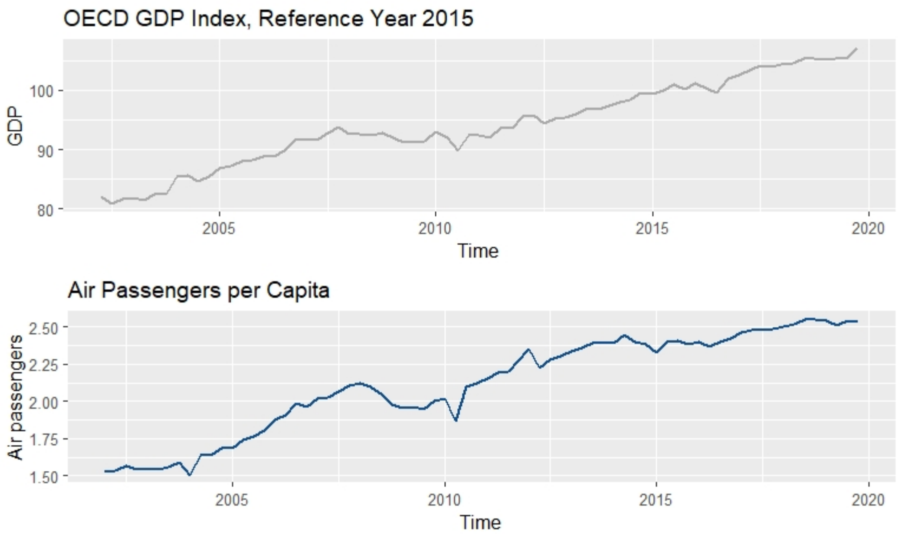


Figure 8.2: Development in GDP and air passengers per capita in Norway from 2002 to 2019

8.3 Literature Review

According to previously presented literature in Chapter 3, there is a correlation between air passenger traffic and GDP. Other research takes this even further and examines the causal relationship, both its existence and the direction.

Hu et al. (2015, p. 95) examined the causal relationship between domestic air traffic and economic growth in China based on quarterly panel data from 2006 to 2012. Through a Granger causality test, the study reveals a long-run bidirectional relationship. Similarly, Hakim and Merkert (2016) investigated the causal relationship in South Asia, based on annual data from 1973 to 2014. They found a long-run unidirectional causality, running from GDP to air passenger traffic and from GDP to air freight volumes (Hakim and Merkert, 2016, p. 125). In contrast to Hu et al. (2015), they do not find a long-run bidirectional causality. This is, according to Hakim and Merkert (2016, p. 126), related to the characteristics of these countries. As large populations and low income characterize countries in South Asia, Hakim and Merkert argue that incremental changes of a relatively small aviation sector do not significantly impact GDP. To provide an example of a South Asian country, due to its population, India has the third largest GDP in the world (Central Intelligence Agency, 2020). Nevertheless, its GDP per capita ranks 156th.

Fernandes and Pacheco (2010) and Chang and Chang (2009) investigated the causal relationship in Brazil and Taiwan, respectively. By conducting a Granger causality test based on domestic data from 1966 to 2006, Fernandes and Pacheco (2010, p. 580) revealed a unidirectional causality from economic growth to air passengers. Moreover, by using quarterly time series data from 1974 to 2006, the findings in Chang and Chang (2009, p. 265) suggests that there is a long-run bidirectional relationship between economic growth and air cargo expansion.

Lastly, Zhang and Graham (2020, p. 506) reviewed previous quantitative studies on the causal relationship between air transport and economic growth. They found that a bidirectional causal relationship is more common in less developed countries. In contrast, a unidirectional relationship is more prevalent for more developed countries, typically running from air transport to economic growth.

8.4 Methodology

In this section, we will present the methodology applied in this part of the thesis. As previously mentioned, we want to examine whether air passengers cause GDP, and vice versa, where the main focus is on the direction from air passengers to GDP. Firstly, we will give an introduction to Granger causality. To properly conduct a Granger causality test, we need to examine whether the data is stationary or non-stationary (Papana et al., 2014, p. 8). Therefore, we will present the concept of stationarity. Lastly, as we use a vector autoregressive model (VAR) to examine causality, we will also introduce the VAR model.

8.4.1 Granger causality

The Granger causality test examines the causal relationship in a bivariate time series; thus, whether one time series is useful for predicting another (Granger, 1969, p. 428). In other words, Y_t causes X_t if it leads to better predictions of X_t.

$F(X_t|I_{t-1})$ presents the conditional distribution given the information set I_{t-1}, where the set consists of lagged values of both X and Y (Hiemstra and Jones, 1994, p. 1644). If this is equal to $F(X_t|I_{t-1} - Y^{Ly}_{t-Ly})$, then Y_t does not strictly Granger cause X_t, where Ly is the length of the lagged values of Y. Equation 8.1 shows a situation in which there is *not* a strict Granger causality.

$$F(X_t|I_{t-1}) = F(X_t|I_{t-1} - Y^{Ly}_{t-Ly}) \tag{8.1}$$

Therefore, when investigating the relationship between air passengers and GDP, we test whether Equation 8.1 is not true. The corresponding null-hypotheses are:

1. H_0: The number of air passengers does not cause GDP
2. H_0: GDP does not cause the number of air passengers

We use an F-test to test the null-hypotheses presented above, and thus, to test for Granger causality. The alternative hypotheses are that air passengers cause a change in GDP (1), and that a change in GDP causes the number of air passengers (2).

8.4.2 Stationarity

A stationary time series is a time series where its statistical properties do not depend on the time at which the series is observed (Hyndman and Athanasopoulos, 2018). It is necessary to determine whether this is the case objectively. In this approach, the unit root test Kwiatkowski-Phillips-Schmidt-Shin (KPSS) will be applied (Kwiatkowski et al., 1992, p. 159).

In a KPSS test, the null-hypothesis is that the data are stationary. Hence, the alternative hypothesis is that it is not. To handle the issue of non-stationarity, one can difference the data. Differencing can help stabilize the mean of a time series, thus, eliminating trend or seasonality (Hyndman and Athanasopoulos, 2018). The process involves subtracting the observation at time $t-1$ from the observation at time t. Thus, the first-order differenced data y'_t can be written as $y'_t = y_t - y_{t-1}$.

8.4.3 The vector autoregressive model

For non-stationary data, a VAR model of first differences could be used in a linear Granger causality test (Papana et al., 2014, p. 1). In a VAR model, the p lagged values of the

k time series, in this case, $k = 2$, appears as regression (Hanck et al., 2015, p. 472). In other words, the VAR model is as expressed in Equation 8.2 and 8.3, where GDP and air passengers are denoted by X_t and Y_t, respectively. Here the βs and γs represents the estimated coefficients using OLS, and u_{1t} and u_{2t} are the error terms for the two models. Moreover, the right part of the equations represents the information set I_{t-1}.

$$X_t = \beta_{10} + \beta_{11}Y_{t-1} + \cdots + \beta_{1p}Y_{t-p} + \gamma_{11}X_{t-1} + \cdots + \gamma_{1p}X_{t-p} + u_{1t} \tag{8.2}$$

$$Y_t = \beta_{20} + \beta_{21}Y_{t-1} + \cdots + \beta_{2p}Y_{t-p} + \gamma_{21}X_{t-1} + \cdots + \gamma_{2p}X_{t-p} + u_{2t} \tag{8.3}$$

We will determine the optimal number of lags p, based on the Bayesian information criteria (BIC), as this approach is more suitable for VAR models (Hyndman and Athanasopoulos, 2018). The optimal number of lags is the one in which BIC is at its minimum.

8.5 Analysis

In this analysis, we will present the findings based on the methodology given in Chapter 8.4. As previously stated, we have tested both the causal relationship running from air passengers to GDP and vice versa. Similar to the first part of the thesis, this section will only analyze the results. Thus, a discussion of the findings and how they compare to the literature will be presented in the next section.

By conducting a KPSS-test, we get t-statistics of 1.79 and 0.11 for the time series *air passengers* and *GDP*, respectively. The corresponding 1% critical value is 0.74 . Thus, we conclude that *air passengers* is non-stationary, whereas *GDP* is stationary. On this basis, we first differentiate *air passengers*. Consequently, the order of integration $l(d)$ is $l(1)$ and $l(0)$ for *air passengers* and *GDP*, respectively.

The BIC metric finds the optimal number of lags to be one. However, as there are some issues with autocorrelation in the correlogram, we find it more appropriate to use two lagged values. Equation 8.4 and 8.5 show the corresponding VAR models, where "AP" is an abbreviation for air passengers.

$$GDP_t = \beta_{10} + \beta_{11}AP_{t-1} + \cdots + \beta_{1p}AP_{t-p} + \gamma_{11}GDP_{t-1} + \cdots + \gamma_{1p}GDP_{t-p} + u_{1t} \tag{8.4}$$

$$AP_t = \beta_{20} + \beta_{21}AP_{t-1} + \cdots + \beta_{2p}AP_{t-p} + \gamma_{21}GDP_{t-1} + \cdots + \gamma_{2p}GDP_{t-p} + u_{2t} \quad (8.5)$$

The Granger causality test reveals a causal relationship running from air passengers to GDP, but not from GDP to air passengers. The corresponding p-values are $1.888 \cdot 10^{-4}$ and $5.612 \cdot 10^{-1}$, respectively. Consequently, we reject the null hypothesis that *air passengers* does not cause *GDP*. Likewise, we keep the null hypothesis that *GDP* does not cause *air passengers*.

8.6 Discussion

Based on the findings presented above, we will discuss the results and their implications. The results indicate that there is a causal relationship running from air passengers to GDP. These findings are consistent with the study conducted by Zhang and Graham (2020), as they found that a unidirectional relationship is more likely to occur for more developed countries. It is reasonable to think that an increase in GDP does not significantly impact the number of air passengers in an already developed country. In contrast, the same reasoning does not hold for less developed countries, as a given increase in the income level could potentially affect demand for air travel on a larger scale. Therefore, as Norway is a highly developed country, with a GDP per capita of 46 percent above the European Union average in 2017, this finding is as anticipated (Statistics Norway, 2020d).

Moreover, in the interview with Helge Eidsnes on October 29th, 2020, he claimed that he did not believe a change in GDP would significantly affect the number of air passengers in Norway. He argued that this is partly due to the standard of living in Norway, but also the dependency on air traffic. This statement is in accordance with our findings, as we did not find a causal relationship running from GDP to air passengers. The last part of the statement could be the core reason as to why the Norwegian aviation industry is unique compared to other developed countries. If there are not any realistic alternative means of transportation, and if potential transportation are almost equally as expensive and time consuming, an increase in revenue will not have a significant affect, particularly for the domestic market. As an example, the price of train, city-rail roads and trams increased by 43.9 percent from 2003 to 2018 (Sandberg, 2019). In contrast, airfares only increased by 9.3 percent in the same period.

The findings in the analysis suggest that the number of air passengers is useful for predicting GDP. Therefore, passenger data can be used as a real-time indicator of the activity level in the Norwegian economy, thereby being an alternative measure of GDP. As mentioned in the introduction to the thesis, this can be of particular value for policy-makers and global traders. It is worth mentioning that this will only work as a signal and not a definite GDP measure. Alternative real-time indicators have been particularly valuable during the Covid-19 pandemic and in uncertain times in general (Christensen and Krattum, 2020). However, Chief Information Officer at Nordea, Robert Næss, states that these methods were also used prior to the pandemic. In sum, we believe our findings can be valuable, both in uncertain and certain times.

However, the Granger causality test has its weaknesses. Firstly, we have used a linear approach in this thesis; hence, assuming that the relationship between air passengers and GDP is linear. Moreover, despite its popularity, the linear Granger causality test is criticized for not reflecting the true *causal* effect (Stokes and Purdon, 2017, p. E7063). For example, due to either high bias or variance in the estimations, the test can give spurious results. Therefore, our findings do not necessarily imply a true causal relationship; thus, the results have their limitations.

Nevertheless, as previously presented, the relationship between air passengers and GDP is well documented in the literature. Moreover, the article from DN mentions how Ringholm uses passengers passing through the airport security checkpoints in the US as an indicator of the state of the economy (Christensen and Krattum, 2020). In sum, we believe our results are valuable but should be treated with caution.

8.7 Recommendations for Future Research

The findings in this part of the thesis reveal a unidirectional causal relationship running from air passengers to GDP. Although this indicates that a change in air traffic volume can signal a change in GDP, this effect could be analyzed more in-depth. One example could be to use air traffic volume to nowcast GDP in real-time by applying machine learning techniques.

As the time series are observed on a quarterly basis, future research could investigate the same annual relationship. Research can also be conducted for other European countries and thereby compare the results with Norwegian data. Particularly, a comparison of countries like Sweden, Denmark, and Finland would be of interest, as they are all located in the outskirts of Europe but differ widely in terms of air traffic volume. Furthermore, we have not separately considered domestic and total passengers in this part of the thesis, which can be applied in future research.

9 Conclusion

In this thesis, we have discussed the following research questions:

1. How useful are machine learning techniques for predicting the number of air passengers in Norway?

2. Is there a causal relationship between air passengers and GDP in Norway, and can the number of air passengers potentially be used as a real-time indicator of GDP?

In order to answer the first question, we have trained six machine learning models with the aim of predicting quarterly domestic and total air passengers per capita in Norway for all quarters in 2018 and 2019. The models were trained on data from the second quarter of 2002 to the last quarter of 2017 using the machine learning methods OLS, elastic net, and random forest. To evaluate the prediction accuracy, we compared the predictions for each model with the actual values. The findings suggest that random forest has the highest prediction power on domestic data, whereas elastic net performed the best for total data.

Through our analysis, we found that OLS and elastic net performed particularly poorly in Q2 of 2019. We have reasons to believe that this is due to the SAS labour strike. In contrast, random forest performs particularly well in this quarter. Likewise, we found that random forest underestimates the actual values in all periods, expect for the second quarter of 2019 in the domestic model. On this basis, it is reasonable to believe that random forest does not necessarily predict the shock. Although we can not conclude that elastic net is the most suitable method for both domestic and total passengers, we have reasonable evidence to believe that this is the case.

We further compared domestic and total predictions by comparing the models with the lowest MSE on the training data. We found that the elastic net model for total passengers gave the best predictions on 2018 and 2019 data. In contrast, we found that the elastic net model for domestic passengers performed the best on the training set. It is therefore difficult to conclude which model is the most suitable, but again the SAS labour strike could have affected domestic passengers more than the total passengers.

Moreover, through the random forest variable importance plots, we found that the number of bookings for different accommodation types is the most important predictor for both domestic and total passengers. This differs from previous literature, and could be caused by the increased tourism in Norway, and the chosen measurement of tourism. We also have reasons to believe that the predictor, world jet fuel prices, is a measurement for the oil price, thus the Norwegian economy due to its dependency on the oil industry.

In sum, for the first research question, we find that machine learning is useful for predicting the number of air passengers in Norway, but has a significant shortcoming when it comes to events such as the SAS labour strike. However, we do not necessarily believe that other methods or an expert could have predicted such events, at least not in a long-term perspective. Based on our findings, we believe that machine learning could aid market participants both within and outside the aviation industry in its decision-making.

In order to answer the second question, we looked at the reversed relationship between air passengers and GDP in Norway to investigate whether a change in air passengers could signalize a change in GDP. The relationship was examined by conducting a strict linear Granger causality test. Through our analysis, the results indicate a causal relationship running from air passengers to GDP. Hence, based on the findings, we find that air passengers can potentially be an alternative real-time indicator of GDP. This is of value, as macro data are currently measured on a monthly basis, and thus, have its limitations in terms of reflecting the economy in real-time. As such, a real-time indicator can create value for both policy-makers and global traders in their decision-making process.

In summary, in this thesis, we have found that machine learning techniques are useful for predicting quarterly domestic and total passengers in Norway. However, we found that they have their limitations when facing external shocks. Also, due to the ongoing pandemic, we question the current value of these predictions. Similarly, we found that the number of air passengers is useful for predicting GDP, and can work as a real-time signal for GDP. We find these findings valuable, as both the aviation industry and the Norwegian economy are currently facing high uncertainty. This is particularly true for the last question as stakeholders are seeking real-time alternative measurements to navigate in an uncertain market.

References

Aastveit, K. A., Gerdrup, K. R., Jore, A. S., and Thorsrud, L. A. (2014). Nowcasting GDP in Real Time: A Density Combination Approach. *Journal of Business Economic Statistics*, 32(1):48–68. Retrieved from http://www.jstor.org/stable/43701629.

Avinor (2020a). About Oslo Airport. Retrieved from https://avinor.no/en/corporate/airport/oslo/about-us/about-oslo-airport/about-oslo-airport.

Avinor (2020b). *Annual and sustainability report 2019*. Retrieved from https://avinor.no/globalassets/_konsern/om-oss/rapporter/en/avinors-annual-report-2019_en.pdf.

Avinor (2020c). Hvor mye flyr vi? Retrieved from https://avinor.no/en/corporate/klima/hvor-mye-flyr-vi/.

Avinor (2020d). The New Oslo Airport 2017. Retrieved from https://avinor.no/en/corporate/airport/oslo/development/this-is-new/this-is-new.

Avinor (2020e). Traffic Statistics. Retrieved from https://avinor.no/en/corporate/about-us/statistics/traffic-statistics.

CAPA (May 16th, 2018). Airline mergers: why Europe needs blue sky thinking. *CAPA: Centre for Aviation*. Retrieved from https://centreforaviation.com/analysis/reports/airline-mergers-why-europe-needs-blue-sky-thinking-417376.

Cappelen, A., Eika, T., and Prestmo, J. B. (2014). Virkninger på norsk økonomi av et kraftig fall i oljeprisen. Retrieved from https://www.ssb.no/nasjonalregnskap-og-konjunkturer/artikler-og-publikasjoner/_attachment/180823?_ts=14662dc53a8.

Central Intelligence Agency (2020). The World Factbook: India. Retrieved from https://www.cia.gov/library/publications/the-world-factbook/geos/in.html.

Chang, Y.-H. and Chang, Y.-W. (2009). Air cargo expansion and economic growth: Finding the empirical link. *Journal of Air Transport Management*, 15(5):254–265. https://doi.org/10.1016/j.jairtraman.2008.09.016.

Chevallier, J., Chèze, B., and Gastineau, P. (2011). Forecasting world and regional air traffic in the mid-term (2025): An econometric analysis of air traffic determinants using dynamic panel-data models.

Christensen, H. (2020). (January 11th, 2020). Fullere fly på norske flyplasser. *Finansavisen*. Retrieved from https://finansavisen.no/nyheter/luftfart/2020/01/10/7487783/flere-passasjerer-og-faerre-fly-hos-avinor-i-fjor.

Christensen, J. and Krattum, H. F. (August 20th, 2020). Nå jakter de alternative data: - de tyske lastebilsjåførene er en utmerket indikator. *Dagens Næringsliv*. Retrieved from https://www.dn.no/marked/koronaviruset/makro/makrookonomi/na-jakter-de-alternative-data-de-tyske-lastebilsjaforene-er-en-utmerket-indikator/2-1-853950.

Doganis, R. (2010). *Flying Off Course* (4th edition). London: Routledge.

Engerengen, L. (February 11th, 2019). Kortbaneflyplass. Retrieved from https://snl.no/kortbaneflyplass.

Fernandes, E. and Pacheco, R. R. (2010). The causal relationship between GDP and domestic air passenger traffic in Brazil. *Transportation Planning and Technology*, 33(7):569–581. https://doi.org/10.1080/03081060.2010.512217.

FRED (2020). Real Broad Effective Exchange Rate for Norway [RBNOBIS]. Retrieved from https://fred.stlouisfed.org/series/RBNOBIS.

Fridström, L. and Thune-Larsen, H. (1989). An Econometric Air Travel Demand Model for the Entire Conventional Domestic Network: The Case of Norway. *Institute of Transport Economics*, 23B(3):213–223. https://doi.org/10.1016/0191-2615(89)90004-0.

Giæver, H. and Schultz, J. (October 6th, 2020). Lavprisselskapet Wizz Air starter innenriksflyvning fra Oslo. *Dagens Næringsliv*. Retrieved from https://www.dn.no/luftfart/wizz-air/lavprisselskapet-wizz-air-starter-innenriksflyvning-fra-oslo/2-1-888042.

Granerud, K. M. (October 6th, 2020). Erik G. Braathen starter nytt flyselskap. *Finansavisen*. Retrieved from https://finansavisen.no/nyheter/luftfart/2020/10/06/7574013/erik-g.-braathen-starter-nytt-flyselskap.

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *The Econometric Society*, 37(3):424–438. https://doi.org/10.2307/1912791.

Hakim, M. M. and Merkert, R. (2016). The causal relationship between air transport and economic growth: Empirical evidence from South Asia. *Journal of Transport Geography*, 56:120–127. https://doi.org/10.1016/j.jtrangeo.2016.09.006.

Hanck, C., Arnold, M., Gerber, A., and Schmelzer, M. (2015). *Introduction to Econometrics with R*. Pearson Education Limited.

Hiemstra, C. and Jones, J. D. (1994). Testing for Linear and Nonlinear Granger Causality in the Stock Price-Volume Relation. *The Journal of Finance*, 49(5):1639–1664. https://doi.org/10.2307/2329266.

Holloway, S. (2008). *Straight and Level: Practical Airline Economics* (3rd edition). Aldershot: Ashgate Publishing.

Hu, Y., Xiao, J., Deng, Y., Xiao, Y., and Wang, S. (2015). Domestic air passenger traffic and economic growth in China: Evidence from heterogeneous panel models. *Journal of Air Transport Management*, 42:95–100. https://doi.org/10.1016/j.jairtraman.2014.09.003.

Hyndman, R. J. and Athanasopoulos, G. (2018). *Forecasting: Principles and Practice, 2nd edition*. OTexts, Melbourne, Australia. Retrieved from OTexts.com/fpp2.

ICAO (2006). Manual on Air Traffic Forecasting. International Civil Aviation Organization.

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An Introduction to Statistical Learning: With applications in R*. New York: Springer.

Kampevoll, F. (February 25th, 2019). Norwegian er ikke alene - flere europeiske flyselskaper sliter. *E24*. Retrieved from https://e24.no/boers-og-finans/i/1kLO2J/norwegian-er-ikke-alene-flere-europeiske-flyselskap-sliter.

Kristiansen, T. (2017). *Norge på flytoppen*. Retrieved from https://www.framtiden.no/aktuelle-rapporter/811-norge-pa-flytoppen-2/file.html.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, 54(1-3):159–178. https://doi.org/10.1016/0304-4076(92)90104-Y.

Landre, E. (December 18th, 2013). Norwegian bestiller større Dreamliner. *E24*. Retrieved from https://e24.no/boers-og-finans/i/J1d8jX/norwegian-bestiller-stoerre-dreamliner.

Lorentzen, M. and Bøe, E. (October 7th, 2020). Den ungarske lavprisgiganten WizzAir inntar Norge: Vil starte en rekke innenlandsruter. *E24*. Retrieved from https://e24.no/naeringsliv/i/gW76A0/den-ungarske-lavprisgiganten-wizz-air-inntar-norge-vil-starte-en-rekke-innenriksruter.

Maire, S. and Spafford, C. (June 16th, 2017). The data science revolution that's transforming aviation. *Forbes*. Retrieved from https://www.forbes.com/sites/oliverwyman/2017/06/16/the-data-science-revolution-transforming-aviation/?sh=5a79d9817f6c.

Moosa, I. A. (2000). *Exchange Rate Forecasting: Techniques and Applications*. London: Palgrave Macmillan.

Nikel, D. (August 13th, 2020). The future of air travel in Norway after coronavirus. *Forbes*. Retrieved from https://www.forbes.com/sites/davidnikel/2020/08/13/the-future-of-air-travel-in-norway-after-coronavirus/?sh=659652444bce.

Norwegian (2020). Our story. Retrieved from https://www.norwegian.com/en/about/our-story/.

NOU 2019: 22. (2019). *Fra statussymbol til allemannseie - norsk luftfart i forandring*. Retrieved from https://www.regjeringen.no/no/dokumenter/nou-2019-22/id2680751/?ch=1.

OECD (2020a). Quarterly GDP (indicator). doi:10.1787/b86d1fc8-en.

OECD (2020b). Unemployment rate (indicator). doi:10.1787/52570002-en.

Papana, A., Kyrtsou, K., Kugiumtzis, D., and Diks, C. (2014). Identifying causal relationships in case of non-stationary time series. *Universiteit van Amsterdam, Center for Nonlinear Dynamics in Economics and Finance*, (14-09). Retrieved from https://EconPapers.repec.org/RePEc:ams:ndfwpp:14-09.

Phillips, R. (2005). *Pricing and Revenue Optimization*. Palo Alto: Stanford University Press.

Rammen, K. (December 22th, 2019). Oljeprisfallets innvirkning på drivstoff- og flybillettpriser. *Finanssans*. Retrieved from https://finanssans.no/oljeprisfallets-innvirkninger-pa-drivstoff-og-flybilletter.

Rønne, K. P. (January 31st, 2014). SAS var minutter fra konkurs. *Dagens Perspektiv*. Retrieved from https://www.dagensperspektiv.no/2014/sas-var-minutter-fra-konkurs.

Sandberg, T. (November 4th, 2019). Langt høyere prisvekst på tog enn fly: – Det er ikke rart at flytrafikken vokser. *Dagsavisen*. Retrieved from https://www.dagsavisen.no/nyheter/innenriks/langt-hoyere-prisvekst-pa-tog-enn-fly-det-er-ikke-rart-at-flytrafikken-vokser-1.1612177.

SAS (2020). Business model. Retrieved from https://www.sasgroup.net/about-sas/business-model/.

Secilmis, N. and Koc, A. (2016). Economic factors affecting aviation demand: Practice of EU countries. *Actual Problems of Economics*, 5(179):412–420. https://www.researchgate.net/publication/304807370_Economic_factors_affecting_aviation_demand_Practice_of_EU_countries.

Statistics Norway (2020a). 01222: Population and changes during the quarter (m) 1997k4 - 2020k3. Retrieved from https://www.ssb.no/en/statbank/table/01222.

Statistics Norway (2020b). 08403: Hotels and similar establishments. guest nights, by purpose of the accommodation (c) 1986m01 - 2020m08. Retrieved from https://www.ssb.no/en/statbank/table/08403.

Statistics Norway (2020c). 08408: Passenger air transport, price index (2010=100) 2006k1 - 2020k3. Retrieved from https://www.ssb.no/en/statbank/table/08408.

Statistics Norway (December 3rd, 2020d). Hva er egentlig BNP? Retrieved from https://www.ssb.no/nasjonalregnskap-og-konjunkturer/artikler-og-publikasjoner/hva-er-egentlig-bnp.

Stewart, M. (2019). The Actual Difference Between Statistics and Machine Learning. *Towards Data Science*. Retrieved from https://towardsdatascience.com/the-actual-difference-between-statistics-and-machine-learning-64b49f07ea3.

Stokes, P. A. and Purdon, P. L. (2017). A study of problems encountered in Granger causality analysis from a neuroscience perspective. *Proceedings of the National Academy of Sciences*, 114(34):E7063–E7072. https://doi.org/10.1073/pnas.1704663114.

Strisaeng, P., Baxter, G., Richardson, S., and Wild, G. (2015). A Forecasting Tool for Predicting Australia's Domestic Airline Passenger Demand Using a Genetic Algorithm. *Journal of Aerospace Technology and Management*, 7(4):476–489. doi:10.5028/jatm.v7i4/475.

Sørdal, K. (March 21st, 2019). Dette gjør flyselskapene med den nye flypassasjeravgiften. *Dagbladet - DinSide*. Retrieved from https://dinside.dagbladet.no/reise/dette-gjor-flyselskapene-med-den-nye-flypassasjeravgiften/70893152?fbclid=IwAR0o05yYSiufzghkfdZ_IyJVdAs_DP5uZp4PHimvZ_TLsqFeBghx88CuzjM.

The Norwegian Government (2020). (April 24th, 2020). Statlig kjøp av flytransport. Retrieved from https://www.regjeringen.no/no/tema/transport-og-kommunikasjon/luftfart/statlig-kjop-av-flyruter/id2076452/.

Thommessen, J. K. (August 27th, 2019). Airhelp saksøker SAS etter pilotstreik. *E24*. Retrieved from https://e24.no/naeringsliv/i/zGbwx5/airhelp-saksoeker-sas-etter-pilotstreik.

Thune-Larsen, H. (2019). *Luftfartstilbudet i, til og fra Norge før og etter liberaliseringen* (TØI Report 1742/2019). Retrieved from https://www.toi.no/publikasjoner/luftfartstilbudet-i-til-og-fra-norge-for-og-etter-liberaliseringen-article35980-8.html.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the*

Royal Statistical Society. Series B (Methodological), 58(1):267–288. Retrieved from http://www.jstor.org/stable/2346178.

Torp Sandefjord Airport (2020). Nesten 2,1 millioner reisende på torp i 2019. Retrieved from https://www.torp.no/aktuelt/nesten-2-1-millioner-reisende-pa-torp-i-2019-article1657-281.html.

U.S. Energy Information Administration (2020). U.s. gulf coast kerosene-type jet fuel spot price fob. Retrieved from https://www.eia.gov/dnav/pet/hist/eer_epjk_pf4_rgc_dpgM.htm.

Wensveen, J. G. (2018). *Air Transportation: A Management Perspective* (7th edition). Taylor and Francis.

Widerøe (2020). About Widerøe. Retrieved from https://www.wideroe.no/en/home/about-wideroe.

Zhang, F. and Graham, D. J. (2020). Air transport and economic growth: A review of the impact mechanism and causal relationship. *Transport Reviews*, 40(4):506–528. https://doi.org/10.1080/01441647.2020.1738587.

Zou, H. and Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 67(2):301–320. Retrieved from http://www.jstor.org/stable/3647580.

Appendix

A1 Backcasts of Price Index

A1.1 Domestic passengers

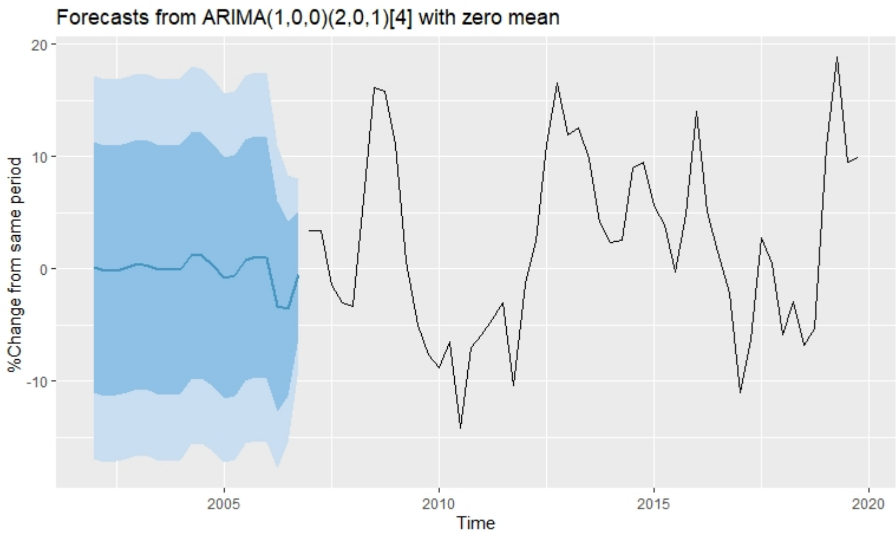


Figure A1.1: Backcasts for 2002 to 2006 domestic price index

A1.2 Total passengers

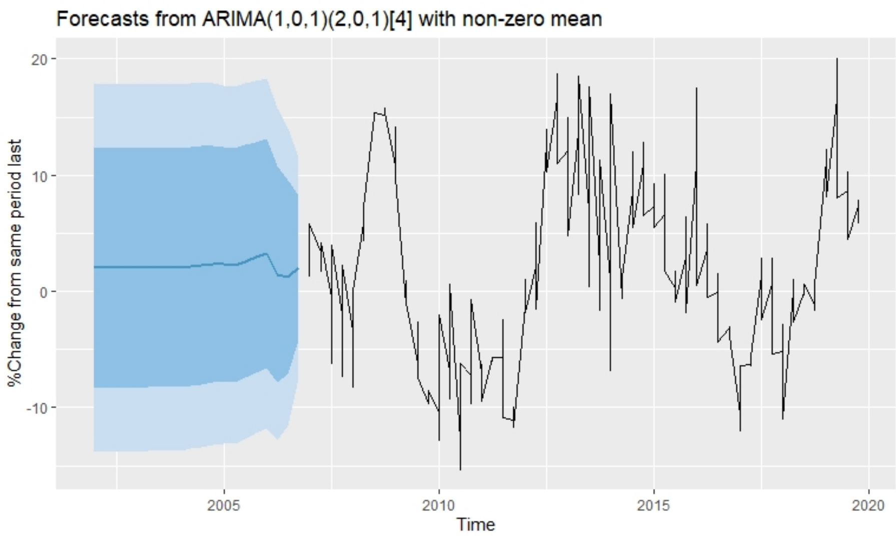


Figure A1.2: Backcasts for 2002 to 2006 total price index

A2 Variables

Table A2.1: Variable names

Variable Name	Description	Described in
Passengers	The number of passengers per capita	Chapter 4.1
Unemployment	Seasonally adjusted unemployment rate	Chapter 4.2.4
Fuel	U.S Gulf Coast kerosene-type jet fuel spot price per gallon	Chapter 4.2.3
REER	Real effective exchange rate	Chapter 4.2.5
PriceTax	Passenger air transport price index	Chapter 4.2.2
GDP	Seasonally adjusted GDP index	Chapter 4.2.1
Traffic	The number of departures	Chapter 4.2.7
Nights	Accommondation bookings	Chapter 4.2.6
AirTax	Air passenger tax	Chapter 4.2.8

A3 MSE as a Function of λ

A3.1 Domestic passengers

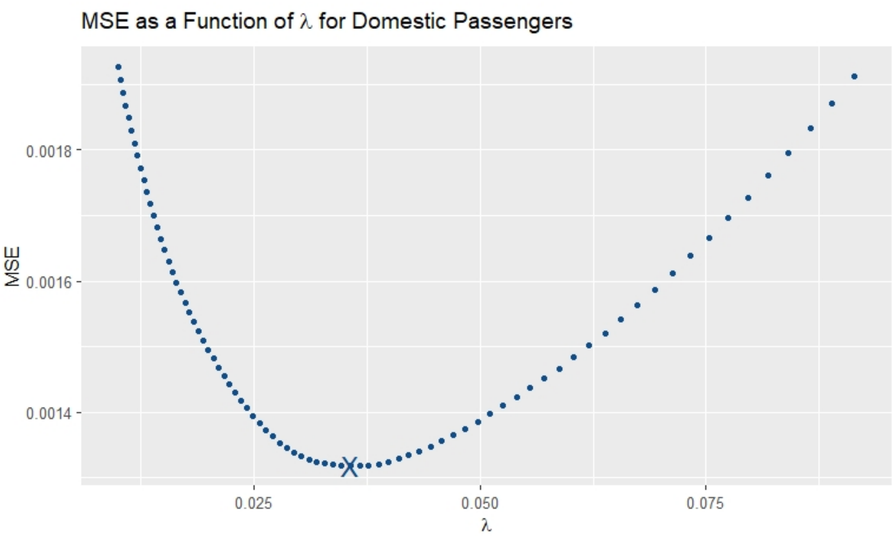


Figure A3.1: MSE as a function of λ given $\alpha = 0.1$

A3.2 Total passengers

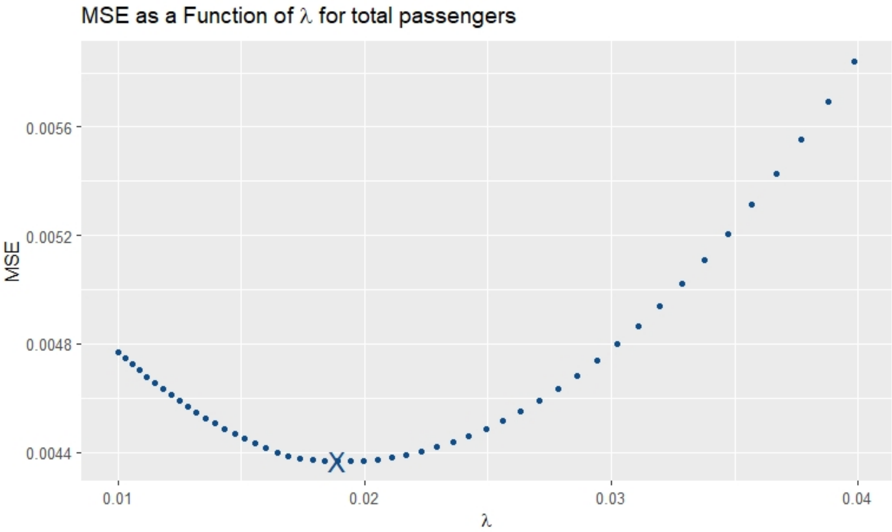


Figure A3.2: MSE as a function of λ given $\alpha = 0.9$

A4 Descriptive Statistics

Table A4.1: Descriptive statistics

	N	Mean	St.dev	Min	Median	Max
Domestic Passengers						
Passengers	71	1.318	0.13	1.054	1.367	1.474
Unemployment	71	3.75	0.61	2.47	3.77	5.03
Fuel	71	1.95	0.77	0.57	1.89	3.66
REER	71	95.03	6.58	81.88	96.80	106.93
PriceIndex	71	1.38	6.95	-14.20	0.27	18.80
GDP	71	93.80	7.08	80.40	92.70	105.40
Traffic	71	0.023	0.00	0.02	0.02	0.02
Nights	71	4,856,532.00	656,414.20	3,884,755.00	4,711,797.00	6,244,921.00
AirTax	71	0.14	0.35	0.00	0.00	1.00
Total Passengers						
	N	Mean	St.dev	Min	Median	Max
Passengers	71	2.13	0.32	1.50	2.15	2.553
Unemployment	71	3.75	0.61	2.47	3.77	5.03
Fuel	71	1.95	0.77	0.57	1.89	3.66
REER	71	95.03	6.58	81.88	96.80	106.93
PriceIndex	71	1.45	7.84	-15.30	0.46	20.00
GDP	71	93.80	7.08	80.40	92.70	105.40
Traffic	71	0.03	0.00	0.03	0.03	0.04
Nights	71	4,856,532.00	656,414.20	3,884,755.00	4,711,797.00	6,244,921.00
AirTax	71	0.14	0.35	0.00	0.00	1.00

A5 Predictions

A5.1 Quarterly domestic predictions

Table A5.1: Predictions of quarterly domestic passengers per capita

2018			
Period	OLS	Elastic net	Random forest
Q1	1.4569	1.4593	1.4274
Q2	1.4721	1.4681	1.4315
Q3	1.4925	1.4887	1.4233
Q4	1.5027	1.4936	1.4274
2019			
Period	OLS	Elastic net	Random forest
Q1	1.4935	1.4887	1.4281
Q2	1.4962	1.4887	1.4223
Q3	1.4925	1.4842	1.4117
Q4	1.5047	1.4956	1.4245

A5.2 Quarterly total predictions

Table A5.2: Predictions of quarterly total passengers per capita

2018			
Period	OLS	Elastic net	Random forest
Q1	2.5147	2.5016	2.4627
Q2	2.5284	2.5050	2.4678
Q3	2.5690	2.5471	2.4626
Q4	2.5847	2.5603	2.4617
2019			
Period	OLS	Elastic net	Random forest
Q1	2.5734	2.5016	2.4667
Q2	2.5793	2.5050	2.4593
Q3	2.5543	2.5273	2.4362
Q4	2.5939	2.5673	2.4617

A6 Packages in R

Table A6.1: R-packages

Package	Reference
boot	Canty and Ripley, 2020 Davison and Hinkley, 1997
car	Fox and Weisberg, 2019
dplyr	Wickham et al.,2020
dynlm	Zeileis, 2019
forecast	Hyndman et al., 2020 Hyndman and Khandakar, 2008
fpp2	Hyndman, 2020
ggplot2	Wickham, 2016
glmnet	Friedman et al., 2010
gridExtra	Auguie and Antonov, 2017
ISLR	James et al., 2017
MASS	Venables and Ripley, 2002
randomForest	Liaw and Wiener, 2002
seasonal	Sax and Eddelbuettel, 2018
tree	Ripley, 2019
tstools	Bannert and Thoeni, 2018
tsutils	Kourentzes et al., 2020
urca	Pfaff, 2008
vars	Pfaff and Stigler, 2018

A6.1 References

Auguie, B. and Antonov, A. (2017). *gridExtra: Miscellaneous Functions for "Grid" Graphics*. R package version 2.3. Retrieved from https://CRAN.R-project.org/package=gridExtra.

Bannert, M. and Thoeni, S. (2018). *tstools: A Time Series Toolbox for Official Statistics*. R package version 0.3.8. Retrieved from https://CRAN.R-project.org/package=tstools

Canty, A. and Ripley, B. D. (2020). *boot: Bootstrap R (S-Plus) Functions*. R package version 1.3-25. Retrieved from https://cran.r-project.org/web/packages/boot/boot.pdf

Davison, A. C. and Hinkley, D. V. (1997). *Bootstrap Methods and Their Applications*. Cambridge University: Cambridge University Press

Friedman J., Hastie, T. and Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinent Discent. *Journal of Statistical Software,* 33(1), 1-22. 10.1163/ej.9789004178922.i-328.7

Fox, J. and Weisberg, S. (2019). *An R Companion to Applied Regression*, Third Edition. Thousand Oaks CA: Sage. Retrieved from https://socialsciences.mcmaster.ca/jfox/Books/Companion/

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L, O'Hara-Wild, M., Petropoulos, F., Razbash, S., Wang, E. and Yasmeen, F. (2020). *forecast: Forecasting functions for time series and linear models.* R package version 8.13. Retrieved from https://pkg.robjhyndman.com/forecast/

Hyndman, R. J. and Khandakar, Y. (2008). Automatic time series forecasting: the forecast package for R. *Journal of Statistical Software*, 26(3), 1–22. Retrieved from https://www.jstatsoft.org/article/view/v027i03

James, G., Witten, D., Hastie, T. and Tibshirani, R. (2013). *An Introduction to Statistical Learning: With applications in R.* New York: Springer

Kourentzes, N., Svetunkov, I. and Schaer, O. (2020). *tsutils: Time Series Exploration, Modelling and Forecasting.* R package version 0.9.2. Retrieved from https://CRAN.R-project.org/package=tsutils

Liaw, A. and Wiener, M. (2002). Classification and Regression by randomForest. *R News,* 2(3), 18-22. Retrieved from https://cran.r-project.org/doc/Rnews/Rnews_2002-3.pdf

Pfaff, B. (2008). *Analysis of Integrated and Cointegrated Time Series with R* (2nd edition). New York: Springer.

Pfaff, B. and Stigler, M. (2018). *VAR Modelling.* R package version 1.5-3. Retrieved from https://CRAN.R-project.org/package=vars.

Ripley, B. (2019). *tree: Classification and Regression Trees.* R package version 1.0-4.0. Retrieved from https://CRAN.R-project.org/package=tree

Sax, C. and Eddelbuettel, D. (2018). Seasonal Adjustment by X-13ARIMA-SEATS in R. *Journal of Statistical Software*, 87(11), 1-17. 10.18637/jss.v087.i11

Venables, W. N. and Ripley, B., D. (2002). *Modern Applied Statistics with S* (4th edition). New York: Springer.

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis.* New York: Springer-Verlag.

Wickham, H., Francois, R., Henry, L. and Müller, K. (2018). *dplyr: A Grammar of Data Manipulation.* R package version 1.0.2. Retrieved from https://CRAN.R-project.org/package=dplyr

Zeileis, A. (2019). *dynlm: Dynamic Linear Regression.* R package version 0.3-6. Retrieved from https://CRAN.R-project.org/package=dynlm