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Forecasting Foreign Exchange Rates Using Recurrent Neural Networks

The Role of Political Uncertainty

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ABSTRACT:
In June 2016, the majority of UK citizens voted to leave the EU (Brexit). The referendum outcome took both citizens and policymakers by surprise. No other member state has ever left the EU. As a result, the global stock and currency markets collapsed. The impact of uncertainty on financial markets has been studied for decades (Garfinkel, 1999). Studies show that political instability has a significant impact on economic performance. In addition to the market fluctuation, it has been found to increase the unemployment rate and decrease consumers' and companies' willingness to invest. Thus, prolonged political instability may lead to a scenario in which the capital moves less, the quality of public services decreases, and economic growth slows down. (Carmignani, 2003; Canes-Wrone et al., 2014).

Exchange rate forecasting is an important area of financial research that has recently received more popularity due to its dynamic nonlinear features. In the past, exchange rates have been analyzed using traditional financial models. However, recently academics have started to use artificial learning approaches alongside the traditional ones. In particular, neural networks have been used in time series modeling, and thus exchange rates have been modeled with neural networks. Machine learning aims to improve efficiency and make financial forecasting more automated.

The empirical part of this analysis is carried out using a recurrent neural network architecture known as the Long Short Term Memory (LSTM). The LSTM model enables the analysis of nonlinear data as well as the detection of diverse cause-and-effect relations. Therefore, it is reasonable to believe that accurate results can be obtained using this approach. The results are analyzed by comparing two different error values - the Mean Squared Error and the Absolute Mean Error.

The results prove that the LSTM model is capable of modeling exchange rate values even in times of high volatility. As the Brexit-related uncertainty is higher, the predictability of the Pound to Euro and Dollar decreases. This finding is consistent with previous studies that have shown that political instability reduces the predictability of exchange rates. On the contrary, as the uncertainty surrounding Brexit increased, the predictability of the Pound to Yen improved. This result can partly be explained by the Safe Haven effect, according to which the value of the Yen rises as the values of other developed countries' currencies fall. Finally, it can be stated that exchange rates are complex financial instruments whose volatility is influenced by a variety of factors and this study is able to produce new perspectives for further research.

KEYWORDS: Political uncertainty, foreign exchange rates, machine learning, neural networks

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TIIVITELMÄ :
Kesäkuussa 2016 enemmistö Iso-Britannian kansasta äänesti EU:sta eroamisen puolesta (Brexit). Kansanäänestyksen tulos yllätti niin kansalaiset kuin vallanpitäjätkin. Mikään muu jäsenvaltio ei ole aikaisemmin eronnut EU:sta. Tämän seurauksena valuutta- sekä osakemarkkinat romahtivat globaalisti. Epävarmuuden vaikutusta rahoitusmarkkinoihin on tutkittu jo vuosikausien ajan (Garfinkel, 1999). Tutkimukset todistavat, että poliittisella epävakaudella on merkittävä vaikutus taloudelliseen suorituskykyyn. Rahoitusmarkkinoiden heilunnan lisäksi sen on todettu lisäävän työttömyyttä sekä vähentävän kuluttajien ja yritysten investointihalukkuutta. Täten pitkittynyt poliittinen epävakaus voi johtaa tilanteeseen, jossa pääoma liikkuu hitaammin, julkisten palvelujen laatu heikentyy sekä talouskasvu hidastuu. (Carmignani, 2003; Canes-Wrone ym., 2014).

Valuuttakurssien ennustaminen on tärkeä rahoituksen tutkimusala, joka on kasvattanut suosiotaan sen haastavien ja epälineaaristen piirteiden vuoksi. Aikaisemmin valuuttakursseja on tutkittu perinteisillä rahoituksen menetelmillä, mutta lähivuosina tutkijat ovat alkaneet hyödyntämään yhä enemmän koneoppimista perinteisten mallien rinnalla. Erityisesti neuroverkkoja on hyödynnetty aikasarjojen mallintamisessa ja täten myös valuuttakursseja on mallinnettu neuroverkoilla. Koneoppimisen malleilla pyritään tekemään rahoitusmarkkinoiden ennustamisesta tehokkaampaa ja itseohjautuvampaa.

Tämä tutkimus hyödyntää empiirisessä osuudessa takaisinkytketyn neuroverkon arkkitehtuuria nimeltä pitkäkestoinen lyhytkestomuisti (Long Short Term Memory, LSTM). LSTM-arkkitehtuuri mahdollistaa epälineaarisen datan analysoinnin sekä monipuolisten syy-seurausketjujen hahmottamisen. Näin ollen on perusteellista uskoa, että tällä metodilla on mahdollista saavuttaa tarkkoja tuloksia valuuttakursseja analysoitaessa. Tulosten analysointi toteutetaan vertailemalla eri valuutoilla saatavia virhearvoja (keskihajonta sekä absoluuttinen keskivirhe).

Tulokset todistavat, että LSTM-malli on kykenevä mallintamaan valuuttakurssien arvoja myös epävakaina aikoina. Euron ja dollarin ennustettavuus heikentyy tutkituilla ajanjaksoilla, kun Brexitiin liittyvä epävarmuus lisääntyy. Tämä tutkimustulos on johdonmukainen aikaisemman tutkimuksen kanssa, jonka perusteella on todettu, että valuuttakurssien ennustettavuus heikentyy poliittisen epävarmuuden seurauksena. Jenin ennustettavuus taas päinvastoin paranee ajanjaksolla, kun Brexitiin liittyvä epävarmuus lisääntyy. Tämä tulos voidaan osittain perustella turvasatamailmiöllä, jonka mukaan jenin arvo nousee, kun muiden kurssien arvot laskevat. Lopuksi todetaan, että valuuttakurssit ovat monimutkaisia rahoitusinstrumentteja, joiden heilahteluun vaikuttaa useita eri tekijöitä. Tästä huolimatta, tämä työ onnistuu tarjoamaan uusia näkökulmia tulevaisuuden tutkimukselle.

AVAINSANAT: Poliittinen epävarmuus, valuuttakurssit, koneoppiminen, neuroverkot

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
CIP	Covered Interest Rate Parity
EMH	Efficient Market Hypothesis
EPU	European Policy Uncertainty
EU	European Union
IP	Interest Rate Parity
LSTM	Long Short Term Memory
ML	Machine Learning
NN	Neural Network
PPP	Purchasing Power Parity
RNN	Recurrent Neural Network
RW	Random Walk
UIP	Uncovered Interest Rate Parity

1 Introduction

"The value of sterling slumped to a 31-year low on currency markets and was on course for its biggest one-day loss in history as panicking investors contemplated the prospects of a vote to leave the European Union."
– The Guardian (2016)

On the 23rd of June 2016, the United Kingdom decided to leave the European Union (Brexit). The announcement of Brexit started a chain of events, which led to huge turmoil in the foreign exchange and global stock markets. The outcome of the referendum took many observers by surprise. No other member state had ever decided to withdraw from the EU. As the vote outcome became clear, the stock markets fell and the British Pound depreciated sharply. (Hobolt, 2016; Plakandaras et al., 2017). During the last decade, political events have been shaking the financial markets. Ever since the failure of Lehman Brothers and the financial crisis of 2008, the financial markets have been sharply fluctuating. Events like the European Debt Crisis, the election of Donald Trump as the president of the US in 2016 as well as the European immigration Crisis in 2014-2015 have caused uncertainty among market participants.

Uncertainty is a broad concept. From the economic point of view, uncertainty reflects consumers', firms', and policymakers' concerns about the future. Uncertainty may also be defined as macroeconomic uncertainty indicating concerns about the growth of GDP or microeconomic concerns about the growth rate of a firm. In addition to economic uncertainty, also social and other non-economic uncertainties may have a significant impact on the economic situation, such as wars or natural disasters. (Bloom, 2014). An extensive amount of literature has studied the impact of uncertainty and surprising shocks on the financial markets. Most of the previous literature has found a correlation between financial asset valuations and the degree of economic uncertainty. (Garfinkel, 1999; Bernhard et al., 2002; Bloom, 2009; Beckmann et al., 2017).

Political uncertainty has already been long recognized as a key determinant in the financial markets. Commonly, political uncertainty is understood as the uncertainty of future government policies and actions. Political instability may also be seen as social conflicts or overall dissatisfaction in the quality of institutions. (PIMCO, 2021). The challenge with political instability is its unique nature as it is not a standardized measure or factor that could be simply included in the traditional pricing models. Thus, it is challenging to determine how political uncertainty affects different financial markets in different situations.

Nevertheless, economic scholars have been creating models and metrics which attempt to provide accurate results of the impact of political uncertainty. Pastor et al. (2012) presented a risk premium that indicates that the markets tend to be more volatile during politically unstable times. Therefore, the stock prices tend to demand compensation for the taken risk. This risk premium has also been found from the option and currency markets (Bernhard et al., 2002; Kelly et al., 2016). In addition to these risk premiums, different kinds of indexes have been created to measure the magnitude of political shocks and events (Baker et al., 2016). For instance, a study conducted by Plakandaras et al. (2017) used The European Policy Uncertainty (EPU) index to measure if the depreciation of the Pound after the Brexit referendum could have been predicted. Their study provides evidence that most of the depreciation of the Pound was caused by political uncertainty caused by the Brexit referendum.

Inspired by the sharp depreciation of the British Pound, this thesis will study the role of political uncertainty on the foreign exchange markets. More precisely, this paper will study whether the forecasting accuracy of a neural network (NN) model varies during stable and politically unstable times. Accurate predictions of currency returns provide valuable insight for not only investors but also consumers and policymakers. Neural networks are one of the subsets of machine learning (ML) methods. Artificial intelligence and ML have begun to replace the traditional financial models which require data to be linear and stationary. Machine learning strategies aim to make models more accurate and efficient. In machine learning, the models can process dynamic nonlinear data, operate independently and find patterns from historical data.

Neural networks have been widely utilized as a promising approach for forecasting complex time-series data (Gradojevic et al., 2006; Panda 2007; Khashei et al., 2010; Dunis et al., 2012). Thus, a recurrent neural network architecture called Long-Short-Term-Memory (LSTM) will be implemented in this study. LSTM provides an effective technique that can model nonlinear data and make future predictions according to historical input values (Hochreiter et al., 1997). The utilization of neural networks is not a new innovation, yet surprisingly little research has focused on neural networks and how they perform with volatile currency data.

1.1 Brexit

The European Union (EU) is currently composed of 27 member states and its foundations lie in the European Economic Community (ECC). The main aim of ECC was to create a closer union and economic integration among the European countries. ECC was established already in 1957, but in 1993 as the European Union was established, ECC integrated into the EU. EU is a political and economic union that's laws and policies aim to create common rules that facilitate trade, investing and ensures better living conditions. (European Union, 2021).

Originally the UK became a member of the ECC, nowadays known as the EU, in 1973. Even though not being a founding member, the UK has historically had an important role as a leading member in the community and UK has been developing some of the key features of todays' EU, such as EU Regional Policy. However, UK never accepted some EU regulations, and they for instance declined to join the Schengen Area and rejected the common currency, Euro. During 47 years of membership, UK had two referendums of whether Britain should remain or leave the EU. The first in-out referendum was held merely two years after joining the community in June 1975, and the second was held in June 2016. The latter resulting in the withdrawal of the EU even though the prevailing

Prime Minister David Cameron had campaigned for the continuation of the membership. The Leave campaign turned out to be more successful. In the 2016 referendum majority of 51,9% voted in favor of leave and the rest 48,1% voted to remain. (Becker et al., 2017; Menon et al., 2016).

There were several reasons behind the increased dissatisfaction of the EU that led to the UK's decision to have the referendum. UK saw that as a country seceded from the EU, they would have a better chance to improve their global trade agreements, have more selective immigration policies and they would be able to secure their national economy. The UK now has an independent seat at the World Trade Organization (WTO) and they have more control of their laws and regulations than as a member state of the EU. Additionally, EU membership is extremely expensive and now Britain can contribute billions of Pounds directly to their own country instead of EU fees. (IG, 2021).

Despite these disadvantages, there are also benefits of the EU membership. The laws and policies of the EU are designed to ensure a wider union with better internal markets that enable free movement of people, goods, services, and capital. Free trade union reduces barriers between countries and enables companies to grow. Additionally, European businesses invest billions in other EU companies and the EU contributes to its member states' GDP. Lastly, the EU tries to achieve high employment rates and continuously improve living and working conditions. EU labor law ensures certain human rights, including discrimination against age, gender, religion, race, or sexual orientation. (European Union, 2021).

Many researchers have been keen to understand the difference between Leave and Remain voters. Studies show that different socio-economic characteristics like education, age, and ethnic diversity had an impact on voting behavior. Skepticism towards immigration and multiculturalism appeared stronger with voters that had lower levels of education and felt themselves threatened in the labor market. Studies show that there was also a correlation between the Leave vote and the geographical location. People living in the English countryside were more likely to vote “leave”, whereas people living in multicultural cities such as London voted for ”remain”. Highly educated young adults most likely voted for ”remain”. (Becker et al., 2017; Hobolt, 2016).

The day after the referendum, prevailing Prime Minister David Cameron promptly resigned and the Pound collapsed to its lowest since 1985 when the Pound was worth just 1,09 dollars. During one trading day, the GBP/USD exchange rate lost almost 10 per cent of its value (Plakandaras et al., 2017). Following Cameron’s resignation in 2016, Therese May became the leader of the Conservative Party and the UK’s second female prime minister. May started to work with the withdrawal and triggered Article 50 in March 2017. This started the negotiations of the UK’s withdrawal from the EU. Initially, the withdrawal was supposed to occur in March 2019, but the negotiations finally ended in January 2020. Officially Britain left the European Union on 31st of January 2020. The official resignation was the deadline for Article 50 and started the transition period which was due on 31st of December 2020. The purpose of this period was to help citizens and businesses to adapt to the new situation. During this period UK was not allowed to be present in EU institutions but continued to apply the EU law. The most relevant Brexit related events, starting from June 2016 ending to December 2020, are summarized in Table 1 (UK Parliament, 2021; The European Council, 2021).

Table 1. Brexit timeline – key events in the process

June 23, 2016: UK votes to leave the EU
March 29, 2017: Prime Minister Theresa May triggers Article 50
June 19, 2017: Brexit negotiations begin
December, 2017: EU and UK agree on the terms of Britain's EU exit
March 19, 2018: The UK and EU agree on transition phase
October, 2018: EU Council, Brexit deal is moved to European leaders
November 25, 2018: Draft withdrawal deal agreed
March 29, 2019: UK leaves the EU but remains signed up to many of its rules for a transition period
October 29, 2019: EU approves posting the Brexit date
January 31, 2020: UK officially left the European Union
December 31, 2020: The transition period ends

The withdrawal of a member state from the EU is unforeseen. The referendum surprised the media, politicians, and the financial markets even though the speculation and polls indicated for a "leave". As the vote outcome became clear, the financial markets fell and the Pound depreciated sharply against the Euro and the US dollar. (Hobolt, 2016; Plakandaras et al., 2017). Also, other international markets reacted to the outcome as the stock markets dropped by 10 per cent in France and by 9 per cent in German. The worst average declines were measured in countries with higher debt like Italy, Greece, and Spain, where the stock market declined by 14 per cent on average. (Burdekin et al., 2018).

A lot of questions arose after the Brexit referendum and researchers have been curious to study this topic. There is an extensive amount of papers studying the impact of Brexit on different financial variables such as the impact on stock prices and their volatility (Li et al., 2016; Sita, 2017). Also, the impact of Brexit on UK companies has received a lot of attention (Hill et al., 2016; Oehler et al., 2017). However, the exchange rates have received less attention even though the one suffering the most, has been the British Pound. Despite the fluctuation in the financial markets, British Sterling has been seen as a relatively strong currency. Even though the British Sterling has been a target of significant turmoil since the Brexit referendum, it still has one of the highest trading volumes in the foreign exchange (FX) market.

However, the future of the Pound is still unknown. Economists are sceptical of sterling's future. Sterling fell sharply in June 2016 and ever since it has remained close to "record low". However, it might be that Brexit will not have an as bad outcome as the current exchange rates predict. The British government and the EU succeeded in negotiations and in December 2020, UK and EU agreed on the trade and cooperation agreement. However, the trade agreement does not remove the fact Britain is no longer a member of the EU. Thus, most likely the bureaucracy will increase and the clearance obligations will be applied to British products. Therefore, it is hard to say what the long-term impact of Brexit will be. So far, the only fact is that the outcome of the referendum did have dramatic consequences on the stock and currency markets. (Broadbent, 2017).

1.2 Purpose of the study

The UK voted to leave the European Union on the 23rd of June 2016. This led to disarray in the exchange and global stock markets. Therefore, the purpose of this study is to analyze the impact of political uncertainty on foreign exchange rates. The foreign exchange market is one of the most complex financial markets due to its characteristics of nonlinearity and high volatility. Thus, foreign exchange rates have already for decades been in the interest of economists and policymakers. With accurate forecasts, it is possible to reduce uncertainty and make decision-making more efficient. Furthermore, exchange rates are one of the most prominent variables for forecasting economic growth.

Already for decades, several economists and scholars have been creating studies that provide evidence that machine learning methods, such as neural networks, tend to outperform the traditional financial models such as random walk and ARIMA (Zhang et al., 1998; Gradojevic et al., 2006; Ni et al., 2019). Furthermore, the motivation for the use of neural networks lies in a study conducted by Dunis et al. (2012). They provided evidence that neural networks are a superior method for forecasting exchange rates. Even during the financial crisis when the volatility was extremely high, the NN models outperformed traditional models. As a results, it is reasonable to believe that neural networks can provide significant results even during politically unstable times. Therefore, this study will use a recurrent neural network model called LSTM to see how forecasting accuracy differs before and after the Brexit referendum. The forecasting accuracy is evaluated with two different error values – the mean squared error and the mean absolute error.

Brexit-related events provide a unique framework since no other member state has ever decided to leave the European Union. Besides, most of the financial literature studying the impact of political uncertainty focus on major political events like the national elections (Pantzalis et al., 2000; Goodell et al., 2013). There has been surprisingly little research studying novel phenomena like Brexit-related events that do not count as the usual political uncertainty caused by election cycles. Thus, Britain leaving the EU provides an ideal setting to examine the impact of political uncertainty on foreign exchange rates.

No study has so far taken a comprehensive approach to compare the forecasting accuracy of exchange rates pre and post an unexpected political event. This paper addresses this gap by examining the forecasting accuracy of the LSTM model before and after the Brexit referendum. Therefore, each currency pair's dataset will be split into two time periods. The chosen currency pairs will be the main currencies against the British Pound, namely the US dollar, the Euro, and the Japanese Yen. The purpose is to highlight the strengths of neural networks in exchange rate prediction and examine the impact of political uncertainty on different exchange rates.

Therefore, the main purpose of this study is to examine how political uncertainty affects the behavior of foreign exchange rates. Previous studies have shown that uncertainty and surprising shocks tend to fluctuate the financial markets (Bloom et al., 2009; Bloom

2014). Furthermore, studies have shown a correlation between political uncertainty and the accuracy of currency forecasts. Surprising political events and the overall uncertainty are associated with forecasting errors. (Garfinkel, 1999; Bernhard et al., 2002; Beckmann et al., 2017). Therefore, the first research hypothesis of this paper believes that the political uncertainty caused by Brexit-related events does have a significant impact on the forecasting accuracy of the LSTM model.

H1: *The forecasting accuracy of the neural network model decreases during politically uncertain times.*

The purpose is also to investigate how the accuracy of the LSTM model varies between different currencies. Previous studies show that political events and policy shocks tend to cause a global effect (Colombo, 2013). Also, in this case, it can be noted that all the currencies (GBP/USD, GBP/EUR, and GBP/JPY) fell sharply in June 2016 when the outcome of the Brexit referendum became clear. Thus, it is clear that the referendum outcome caused an immediate reaction among market participants. However, it is interesting to study whether the overall political uncertainty related to the Brexit process impacted each currency pair equally. Therefore, the second research hypothesis of this study states that there are no significant differences in the accuracy of loss errors between different currency pairs.

H2: *The forecasting accuracy of the model does not vary among different currency pairs.*

In summary, this study aims to gain knowledge of how neural networks can be utilized in financial research. In addition, political uncertainty and its impact on currency movements will be studied. The purpose of the results is to broaden and clarify the overall picture of exchange rate forecasting using the LSTM model and then compare how the uncertainty caused by Brexit was reflected to different exchange rates.

1.3 Structure of the study

The remainder of this study is structured as follows: the next section provides an insight on the concept of political uncertainty and how this has been studied in the previous financial literature. The third section discusses exchange rates, their main features, and how exchange rates have been forecasted in the previous literature. Thus, the third section provides the basis for the empirical part of this study. The fourth section, on the other hand, briefly reviews the basic principles of neural networks and provides a better understanding of different types of neural networks and how these have been utilized in the financial literature. The fifth section introduces the collected data and explains the methodology which is used to evaluate the impact of Brexit events on the forecasting accuracy of neural networks. The performance measures which will be used to evaluate the forecasting accuracy will also be discussed in section five. The results are presented in the sixth section. Lastly, the conclusion section summarizes this study and provides recommendations and ideas for further studies.

2 Political uncertainty

It is generally accepted that the actions and decisions of governments can produce economic and political uncertainty. Political uncertainty and instability are generally defined as the uncertainty of future government policies and actions. Political uncertainty may be a consequence of (PIMCO, 2021):

- Government instability and changes in the political leadership
- Social conflicts (in the most extreme forms e.g. wars, terrorism)
- Policy decisions such as trade tariffs, taxes, and labor conditions
- Dissatisfaction in the quality of institutions (e.g. protests and strikes)

Political uncertainty is not necessarily restricted to country-level conflicts and changes. In today's global environments, major conflicts and political events may also have a significant impact on a national level.

Often literature that studies political uncertainty also discusses the concept of policy-related uncertainty. This concept is mostly describing the uncertainty related to fiscal, tax, and regulatory policy. Policy-related uncertainty is a significant factor when it comes to political instability since tax and foreign trade policies do have an impact on political uncertainty. However, political uncertainty is more a combination of policy-related uncertainty and an unstable political environment. This instability in the political field may lead to a scenario in which capital moves less, the quality of public services decreases, and the economic growth slows down. (Alesina et al., 1996; Carmignani, 2003).

Political instability is one of the biggest impediments to economic growth. Most people do not enjoy uncertainty so when investors are skeptical about the future, they tend to postpone their investment decisions. This risk-averse behavior can also be seen in the consumption of certain commodities such as new houses and cars. Therefore, during unstable times capital moves less as consumers tend to reduce unnecessary expenses.

Moreover, consumers tend to continue saving until the times are less uncertain. (Mody et al., 2012; Canes-Wrone et al., 2014).

In addition, political instability and sudden changes in the political field may disrupt companies' day-to-day business. In worst-case scenarios, unexpected changes can even disrupt companies performance and decrease its profitability. One of companies core business functions is risk management. One part of risk management is political risk analysis in which the purpose is to calculate probabilities of how likely a political change significantly impacts company's business or the profitability of its investments. Political decisions and sudden policy shifts may have a significant impact on companies' performance since governments can make new policies that are less business-friendly - for instance increases the amount of corporate taxation. Even small changes, for example, the increase of minimum wage may have a significant impact on companies' fixed costs and international competitiveness. (Berkman et al., 2011; Huang et al., 2015).

Additionally, companies' investment and recruitment decisions are highly correlated with the magnitude of uncertainty. Uncertainty makes companies less reluctant to new investments and thus they have a tendency to delay unnecessary projects. When prices remain stable, it is easier to plan future investment decisions without the fear that investments will lose their value. Stable prices are the basis for sustainable economic growth. In times of high uncertainty, companies' interest to expand into new markets may also decrease. Companies tend to continue this kind of behavior until uncertainty related to political issues has been resolved (Julio et al., 2012; Canes-Wrone et al., 2014).

As described, political instability is a factor that should not be underestimated. Studies show that it has a significant impact on several different sectors in the economy. Consequently, the negative effects of political instability in the economy have arisen the interest of several economists. Also, researchers and investors have been keen to understand the impact of political instability on different financial markets. As well as other unexpected changes, sudden political changes may have a significant impact on the performance of an individual asset or even the whole financial market. (PIMCO, 2021). An extensive amount of literature covers political uncertainty from the perspective of how the value and volatility of stocks, bonds, and exchange rates fluctuate during unstable times (Pastor et al., 2012; Goodell et al., 2013; Ulrich, 2013). Moreover, derivatives and commodities have received a lot of interest (Kelly et al., 2016).

From the perspective of an individual asset, sudden political change might cause an unexpected decline in the share price. This might be due to a policy change that concerns certain industry so only particular companies suffer from the change. On the other hand, wider political instability may increase anxiety among investors and could cause a decline in the market as a whole. (PIMCO, 2021). A market reaction like this was seen in 2016 when surprisingly, against all the odds, the British citizens voted to leave the EU.

This study will empirically examine the impact of Brexit-related uncertainty on foreign exchange rates. Therefore, later in this section, it will be discussed how the previous literature has studied the political uncertainty caused by Brexit. However, before that, table 2 provides a summary of the previous research related to different political events or policy shifts and their impact on different financial markets. This summary of previous literature related to political uncertainty and its impact on different financial markets can provide a useful perspective for this paper.

Table 2. Summary of previous literature - Political uncertainty and financial markets

Authors	**Purpose**	**Market**	**Methods**	**Results**
Goodell et al. (2013)	*The role of political uncertainty (US presidential elections) and implied volatility*	Stock market	VIX volatility index	Positive relation between implied stock market volatility and the election probability
Li et al. (2006)	*The impact of presidential election uncertainty on stock returns*	Stock market	Polling data (candidate preference) on US presidential elections	Stock prices tend to increase when the outcome of the election is unclear

Pantzalis et al. (2000)	*Behavior of stock markets around political elections*	Stock market	Behavior of stock markets around elections	Asset valuations tend to increase two weeks prior to the election due to the decreased amount of political uncertainty
Liu et al. (2017)	*The impact of Bo Xilai political scandal on asset prices*	Stock market	Bo Xilai poltical scandal/shock as a measure	An increase in political uncertainty causes a drop in the value of stock prices
Kelly et al. (2016)	*The impact of national elections and global summits on option markets*	Option market	Political risk premium	Political uncertainty caused by national elections and global summits are priced in the option market
Voth (2002)	*Political instability during the interwar period and stock market volatility*	Stock market	Panel data set on political unrest, demonstrations etc.	Positive relation between stock volatility and political instability during the interwar period
Gao et al. (2019)	*US elections and the municipal bond yeals*	Bonds	Yields on municipal bonds	Positive relation between municipal bond yields and US elections
Pastor et al. (2012)	*Uncertainty caused by government policies and how that impacts the stock markets*	Stock market	Equilbirum which includes uncertainty features	Political uncertainty requires a risk premium and stocks fluctuate aggressively during uncertain time
Ulrich (2013)	*The impact of policy changes on bond markets*	Bonds	Uncertainty of future government spending	Positive risk premium exists

Many studies have been able to document that political uncertainty has an impact on asset prices. Especially stocks are more volatile during uncertain times. (Pastor et al., 2012; Goodell et al., 2013). Particularly during the US elections, there has been a clear relation between political uncertainty and the performance of stock markets (Goodell et al., 2013). Pantzalis et al. (2000) conducted a study that included 33 countries and they also found a significant relationship between the stock performance and national elections. Their study shows that there are abnormally high stock returns two weeks before national elections. Li et al. (2006), on the other hand, found that in cases where the election does not have an obvious winner, the volatility and average returns tend to rise. This would indicate that in some cases political uncertainty might cause abnormal returns.

According to Voth (2002), there is a positive relation between stock market volatility and political instability. Their study focuses on the behavior of stock markets during the interwar period. Their study is able to prove that several political uncertainty factors such as political unrest and demonstrations have an impact on the volatility. Also, political shocks and scandals tend to have a significant impact on stock prices. An ideal event to study the impact of a political scandal on stock markets is the Bo Xilaio political scandal in 2012 in China. A study conducted by Liu et al. (2017) found that there is a strong relationship between political uncertainty and asset prices during the Bo Xilaio scandal.

Theoretical models indicate that a rise in political instability leads to a decline in the stock prices. Especially businesses that are vulnerable to changes in government policy, tend to suffer from political uncertainty (Liu et al., 2017). Due to political instability, investors' risk perception might increase, leading to a higher cost of capital. Thus, Pastor et al. (2012) suggested a political risk premium which states that political risk should be priced to the asset prices. Especially in countries, where the economic conditions are weak, there should be a risk premium which would cover the possibility of political uncertainty. Kelly et al. (2016) used the political risk premium in their study and found that political risk is also priced in the option markets. They studied the impact of national elections on option markets and found similar results as Pastor et al. (2012).

Gao et al. (2013), as well as Ulrich (2013), have studied bonds and political uncertainty. When it comes to bonds, a rise in political uncertainty tends to push bond yields higher. When there is a risk, there is a demand for compensation. This typically means higher returns. Ulrich (2013) developed a pricing model in which political uncertainty is one of the explanatory variables. This model predicts that government policies, which have an impact on business cycles, do create a positive risk premium for investors. Additionally, Gao et al. (2013) found consistent results of the risk premium on bond markets as they studied the impact of US national elections. Like previous studies, they also found results that indicate an increase in bond yields around US elections. In other words, during politically unstable times, there is a need for a risk premium.

As other financial markets also exchange rates react to political uncertainty. Usually, a rise in political uncertainty leads to a drop in the exchange rates. Therefore, several studies have been examining whether political events have a systematic impact on exchange rates. According to the efficient market hypothesis (Fama, 1970), the forward exchange rate should quite accurately predict the future value of the spot exchange rate. However, studies show that during political events, the forward rate tends to be a biased predictor of the future exchange rate (Pastor et al., 2012). This bias is said to be a consequence of the risk premium which investors demand as a compensation for holding a certain currency during politically unstable times. Moreover, political instability and the risk premia increase the likelihood that at least risk-averse investors will postpone their investment decision. During uncertain times, it is challenging to create accurate forecasts. (Bernhard et al., 2002).

Also, the impact of Brexit on the foreign exchange rates has been studied to some extent. Table 3 will provide some examples from the previous literature which has focused on studying the uncertainty caused by Brexit.

Table 3. Summary of previous literature - Political uncertainty caused by Brexit

Authors	Topic	Market	Methods	Results
Plakandaras et al. (2017)	*Could the depreciation of the Pound post-Brexit have been predicted*	Exchange rates	Linear and nonlinear econometric and ML methods, EPU index	Most of the depreciation is a consequence of the uncertainty caused by Brexit
Nilavongse et al. (2020)	*The relationship with the UK economy and EPU shocks*	Exchange rates	EPU index, SVAR framework	Brexit increased the amount of political uncertainty which decreased the value of Pound against dollar
Korus et al. (2019)	*The impact of Brexit-related news on the British Pound against the EUR and USD*	Exchange rates	Event study method, Brexit-related news	"Bad" news have a negative impact on the Pound, "good" news impact positively only in the short-run
Wu et al. (2021)	*Evaluating market reactions to the Brexit vote of 2016*	Exchange markets	Linear regression model	Results provide evidence of market inefficiency, which can be explained by investors behavior

Krause et al. (2016)	*The impact of Brexit on the British Pound*	Exchange markets	Poll survey data	Poll results indicating a result of Brexit led to the depreciation of the GBP

Plakandaras et al. (2017) included the Europen Policy Uncertainty Index (EPU) in their study and they found that due to Brexit the amount of political uncertainty has increased. This increased uncertainty has also caused the depreciation of the Pound against the US dollar. Nilavongse et al. (2020) conducted a similar study and included the EPU index in their study to see how the uncertainty affected the Pound. This study provided similar results which indicate that the EPU index could be used to forecast the movements of exchange rates.

Korus et al. (2019) took another perspective to their study and they studied the impact of Brexit-related news on foreign exchange rates. Thus, they focused on the impact of different kinds of Brexit-related news on GBP/USD as well as GBP/EUR exchange rate. They divided Brexit-related news into two groups – “bad” and “good” ones. The results indicate that “bad” news tends to correlate with the depreciation of the Pound, whereas “good” news tends to raise the value of the Pound against the Euro. Moreover, the study by Korus et al. (2019) showed that market participants tend to react with a delay. Especially when it comes to “bad” Brexit news. This would indicate that the markets are not that efficient as traditional EMH assumes. Wu et al. (2021) also found results that there exists inefficiencies in the financial markets. They evaluated markets’ reactions to the Brexit referendum and found that when the outcome of the referendum came clear, the markets reacted with a significant delay. Thus, this delay would indicate that market participants tend to behave irrationally during unexpected events.

Lastly, Krause et al. (2016) studied the impact of Brexit on the British Sterling. They used poll survey data as a tool to forecast the impact of the Brexit referendum on foreign exchange markets. Their study proves that poll results pointing towards Britain leaving the EU, caused a depreciation of the Pound. Thus, most of the discussed studies show that the impact of the Brexit referendum on currency markets could have been predicted. However, the challenge is that the Brexit referendum is just a unique case and not all political shocks cause similar reactions as this referendum did.

Furthermore, a crucial challenge in determining the effect of political uncertainty is the nature of political uncertainty. Among all the factors that might have an impact on the performance of financial markets, political uncertainty and risk might be one of the most challenging due to their complex nature. Uncertainty is related to investors' subjective thoughts about the future of the economy. It is not a direct measure or value that can be simply included in traditional pricing models. A key challenge in examining political uncertainty is the difficulty to isolate exogenous variation in uncertainty. In other words, it is a factor that is dependent on other factors such as macroeconomic uncertainty. (Kelly et al., 2016; PIMCO, 2021).

However, various indexes and variables have been developed to describe political uncertainty as accurately as possible. Studies show that it is possible to improve the predictability of different assets by adding political factors. As already stated earlier, Pastor et al. (2012) found that uncertainty commands a risk premium as stocks tend to be more volatile. Also, Kelly et al. (2016) and Bernhard et al. (2002) found that during politically uncertain periods, the option and currency markets tend to demand a risk premium. In addition to these risk premiums, for instance Baker et al. (2016) have developed a popular indicator that has been used as a measure of political instability. The EPU index developed by Baker et al. (2016) reflects the frequency of certain topics in newspapers. These topics can be anything related to economy, policy, or uncertainty. Thus, as the amount of these words increase, the value of the index increases as well.

Overall, it is clear that political uncertainty plays a crucial role when it comes to the volatility and performance of financial assets. In an unstable political environment, the determination of the net value of an asset is difficult. In most cases, the magnitude of uncertainty is hard to determine which again makes it difficult to calculate accurate rate of returns. Different index have been able to measure political uncertainty, however, the impact of different events remains still unsolved. The importance of political uncertainty will likely continue to be a significant factor in the global financial markets. The best way to hedge against political uncertainty is to ensure that the investment portfolio is sufficiently diversified, not only geographically but also to different industries and assets.

To conclude, political uncertainty is a broad concept that is usually defined as uncertainty caused by changes in the political system or as public dissatisfaction towards the prevailing government. Dissatisfaction often appears as unrest, strikes, and political protests. It is clear, that the impact of political uncertainty should not be ignored by consumers, businesses, or governments. Governments should address its root causes and seek to mitigate its impact through economic policies and their implementation. This way, governments are able to build more sustainable societies as well as economic policies that can lead to faster economic growth. (Aisen et al., 2013).

3 Exchange rates

Already since the publication of the pioneering study by Meese and Rogoff (1983), there has been a continuous debate of the predictability of exchange rates. A vast variety of studies have suggested several methods to forecast exchange rates. Some of these have found results in favor of the random walk model, whereas others have found economic models that outperform the traditional random walk model. These methods and techniques will be discussed in the following sections. The first and second sections introduce the fundamental concepts of foreign exchange rates and provide comprehensive understanding of the relevant theories and structures related to the determination of exchange rates. The last section provides understanding of how previous literature has succeeded in exchange rate forecasting and which are the traditional models that have been used to forecast future values.

3.1 Exchange rates

An exchange rate is the value of one nation's currency in units of another nation's currency. This means that the exchange rate between two currencies is equal to the value of one currency needed to purchase another currency. The idea behind this concept is that no currency moves in isolation. Currencies are examined as currency pairs where the focus is on how much one currency is quoted against the other currency. The exchange rate between two currencies can be expressed as the price of foreign currency against the domestic currency or vice versa. Usually, the exchange rates are expressed as the price of domestic currency against the price of foreign currency. (Salvatore, 2019, pp. 370).

Exchange rates have been traditionally divided into three main categories: floating, managed floating, and fixed exchange rates. Fixed exchange rates are determined by the nation's central bank. Managed floating rate is a combination of fixed and floating exchange rate. The exchange rate floats freely between range of rates that the government has determined. (Mandura, 2020, pp. 187-188; Shapiro et al., 2019, pp. 37-38).

Floating exchange rates, on the other hand, are determined by the mechanism of the market, in other words through supply and demand. The demand and supply curves are impacted by several different factors. For instance, the demand increases when market participants want to invest abroad or domestic companies want to import from foreign countries. The supply, on the other hand, increases when the domestic country is an attractive investment for foreign investors and when domestic countries decide to export. Companies' decisions to export cause a sale of foreign currency and purchase of domestic currency and this increases the need for supply. (Salvatore, 2019, pp. 366.) When the demand and supply change, the exchange equilibrium changes according to the change. Decreased supply and increased demand is called appreciation whereas the increased supply and decreased demand is called depreciation. (Mandura, 2020, pp. 101; Salvatore, 2019, pp. 370).

Exchange rates are traded in the foreign exchange market (FOREX) which is a 24-hour market where individuals, banks, and firms can buy and sell foreign currencies (Salvatore, 2019, pp. 366). FOREX is known as the largest and most liquid financial market. According to a survey conducted by the Bank for International Settlement (BIS), the average daily turnover in April 2019 was 6,6 trillion US dollars (Triennial Central Bank Survey, 2019). Hence, it is no wonder that accurate forecasts of currency returns have received a lot of interest among market participants and economic agents.

Governments, individuals, and multinational corporations can trade two types of contracts: spot and forward contracts. The spot rate is the price of immediate delivery of the exchange rate. This delivery usually realizes within two days. (Bernhard et al., 2002). Forward rate, on the other hand, is determined as the amount of currency that investor agrees to purchase or sell at a predetermined day in the future. The amount of the forward contract is agreed beforehand and therefore forward contract can be used to lock in a currency rate. Thus, a forward contract is used when speculating that the rate will increase or decrease in the future. (Shapiro et al., 2019, pp.38; Bernhard et al., 2002).

However, when there is a future payment to be received or to be made, foreign exchange risk should be taken into account. This risk refers to the possibility that the investment might lose its value since the spot rate may fluctuate over time. This risk can be avoided by hedging with different currency derivatives such as forwards, futures, or options. Currency derivatives can also be used to speculate that the currency will depreciate or appreciate. (Salvatore, 2019, pp. 379-383). Therefore, futures and forwards can be used to manage risk.

But what are the main drivers for exchange rate movements? As already stated, floating exchange rates are determined by macroeconomic market forces. Supply and demand may fluctuate daily and several economic and geopolitical factors may cause changes in exchange rates. Major factors that cause variation and volatility in exchange rates are changes in inflation rates, interest rates, unemployment rates, and the amount of government debt. Additionally, political stability and economic performance may have a significant impact on the movement of currencies. Especially unexpected events may cause volatile reactions in the forex market. Usually, investors' assumptions and speculation cause turmoil in foreign exchange rates. (Salvatore, 2019, pp. 366-379).

To conclude, foreign exchange rates are part of an extremely active FOREX market. The behavior of the foreign exchange market is often seen as complex and volatile. Countless factors impact the determination of currencies and often attempts to predict exchange rates fail. The next part of this paper will explain the basic models that have been used in the determination of foreign exchange rates.

3.2 Exchange rate determination

Purchasing power parity (PPP) and Interest rate parity (IP) are fundamental cornerstones of exchange rate models in international economics. These parity conditions are used to explain both short-term and long-term behavior of exchange rates. In general, purchasing power parity is used to describe the long-term relationship, while interest rate parity is a more suitable model for analyzing the short-term relationship.

Macroeconomic exchange rate models rely on the assumption that, at least on some level, the PPP holds. PPP provides an estimate of the exchange rate that is needed to make the purchasing power of two countries equal. This estimate has especially been used to compare the performance and living standards of two countries. (Rossana, 2011, pp. 481-482). Purchasing power parity is further divided into two models - absolute purchasing power parity and relative purchasing power parity. Absolute PPP is based on the law of one price. According to this, the exchange rate between two nations should be determined with a ratio that is equal to the relation of the two nation's price levels expressed in a common currency. (Sarno et al., 2003, pp. 51-53). Thus, the purchasing power of a unit of one currency should be the same in both countries. Absolute PPP can be presented in the below formula:

$$S = \frac{P_{i,t}}{P^*{}_{i,t}} \tag{1}$$

According to the equation, the price level between two economies should be equal. Thus, an identical commodity basket expressed in a common currency should have same prices across different countries (Sarno et al., 2003, pp. 52-53). If the domestic price level P is higher than the foreign price level P*, rational consumers will consume more foreign products. This increased demand for foreign products will additionally increase the demand for the currency, which in turn strengthens the foreign currency compared to the domestic currency. Higher demand for foreign products will continue until the exchange rate settles to an equilibrium.

Absolute PPP assumes that the capital markets are fully efficient. There are no transaction costs, tariffs, or taxes. Relevant information should be equally accessible for all of the market participants so there is no opportunity for arbitrage. Arbitrage would be the purchase of currency in one market and an immediate sale with a higher price in another market. Due to this, there would be an opportunity for risk-free profit (Salvatore, 2019, pp. 373). Consequently, any violation from the absolute PPP assumption, such as the presence of tariffs, would violate the no-arbitrage condition and therefore the absolute model might not be that realistic in the real world. (Levich, 2001, pp. 113-144).

Instead, relative PPP provides a more accurate model since instead of assuming that the price levels across countries are equal, the model assumes that the changes in the price levels are the same. In relative PPP there is a relation between the exchange rate and the long-term inflation rate. Therefore, the model may be presented in the following form:

$$\frac{S_{t+1}-S_t}{S_t} = \frac{\frac{P_{t+1}^*}{P_{t+1}}-\frac{P_t^*}{P_t}}{\frac{P_t^*}{P_t}} = \frac{(1+\pi^*)}{(1+\pi)} - 1 \tag{2}$$

This equation states that the changes in nominal exchange rates during time t – t+1 are determined by the relation of domestic π_D and foreign inflation π_F. This model can also be denoted in logarithmic form:

$$\pi_D - \pi_F = S^* \tag{3}$$

In this formula, S* indicates the expected relative change in domestic and foreign currency. In addition, D presents the expected domestic inflation and F the inflation abroad. Thus, the model is the nominal exchange rate adjusted for the differences in the relative national price levels. According to this, the difference in inflation rates in two different countries will impact the changes in the exchange rate between these two countries. Inflation of domestic currency will reduce the PPP of the domestic currency. (Levich, 2001, pp. 113-144).

However, in the real world, PPP does not always hold. The reasons causing this deviation are the real-life transaction costs such as the trade barriers and other costs that the model does not take into account. In addition, PPP seems to be mostly valid in the long run. Empirical studies show that the PPP poorly predicts the exchange rates in the short run due to the high volatility. (Levich, 2001, pp. 132). Thus, it can be stated that the usage of PPP in real-life problems is not straightforward. Therefore, other models have been used to determine foreign exchange rates. One of these models is interest rate parity which will be discussed next.

One additional cornerstone theory in currency determination is the interest rate parity (IRP). According to IRP the difference in interest rates between two nations is equal to the difference between the spot and forward exchange rate. When IRP equilibrium holds, there is no opportunity for arbitrage and returns from investing in different currencies deliver the same payoff, regardless of the interest rates. (Sarno et al., 2001, pp. 5).

IRP can be further divided into two more specific concepts; uncovered interest parity (UIP) and covered interest parity (CIP). UIP is a fundamental parity condition which is widely used when testing the efficiency of the foreign exchange market. UIP refers to a theoretical condition where the difference in interest rates between two nations is approximately equal to the expected relative change in the exchange rate between two countries. The formula is presented in the following form:

$$\Delta_n S_{t+n}^e \; = \; i_D + i_F \tag{4}$$

In this equilibrium S_t presents the logarithm of the spot rate at time t, and $\Delta_n S_{t+n}^e$ presents the expected relative change. The spot exchange rate is the foreign currency converted into domestic prices. The right-hand side of the formula, in other words i_D and i_F, are the nominal interest rates in domestic and foreign securities. Thus, when UIP equilibrium holds, the nominal interest rates between two nations equal to the relative changes in the foreign exchange rates during the same period. (Sarno et al., 2001, pp. 5). UIP provides not only a way to study the short-term relationship between the interest rates of two different nations but also the ability to examine the expected changes in these two currencies.

However, more often the testing of exchange market efficiency focuses on the relationship between spot, forward, and interest rates. This parity, where the study includes forward, spot and interest rates, is known as covered interest rate parity. According to CIP, the interest rate differential between two currencies and the difference between the spot and the forward exchange rate should be equal. The equilibrium can be presented in the form of the below formula:

$$(1 + i_D) = \frac{F_t}{S_t} * (1 + i_F) \tag{5}$$

In this equation the left-hand side, $1 + i_D$, presents the continuously compounded risk-free interest rates in the domestic currency, and respectively on the right-hand side, $1 + i_F$, is the rate of return on investing in a foreign currency. To make these equal, term $\frac{F_t}{S_t}$ expresses the rate of depreciation in the forward market. The spot exchange rate S_t is the units of foreign currency per domestic currency at time t and F_t denotes the forward exchange rate in foreign currency per domestic currency at time t. The forward exchange rate is the exchange rate quoted today for settlement at some future date. An increase in S_t indicates an appreciation of the domestic currency and thus a depreciation in the foreign currency. (Du et al., 2018; Sarno et al., 2001, pp. 6-7).

Under these conditions, investors could either invest in domestic currency with rate of return $1 + i_D$ for n years or for the same time period exchange the domestic currency for S_t units of foreign currency in the forward market. With the latter option, the return would be $\frac{F_t * (1+i_F)}{S_t}$. Both of these investment strategies are equal since CIP assumes that the interest rate differential gained with a higher rate of return, will be lost on the exchange conversion when converting the foreign currency back to domestic currency. Thus both of the strategies deliver the same payoffs. (Sarno et al., 2001, pp. 6-7).

In both UIP and CIP equilibriums, variables move according to the market and therefore equilibriums remain in balance (Du et al., 2018). If one variable changes, other variables need to change according to it. Otherwise, there would be a possibility for arbitrage. However, if there appears to be an arbitrage opportunity, most of the time it is only temporary since the market inefficiencies return back to equilibrium when market participants try to take advantage of the risk-free returns. As a result of this, the opportunity for arbitrage in the currency markets disappear.

However, recent empirical studies show that there seems to appear persistent and systematic failures on both CIP and UIP conditions (Alexius, 2001; Du et al., 2018). For CIP these arbitrage opportunities have been explained by the fact that financial intermediation is expensive and there is an international imbalance between the supply of funding and the demand for investment (Du et al., 2018). Additionally, in nations where the nominal interest rates are high, the exchange rates tend to increase, whereas according to the CIP equilibrium, the exchange rate should depreciate. Empirical studies have also shown that the UIP fails at least in the short run. (Alexius, 2001). Under these conditions, where the UIP and CIP equilibriums do not hold, there is a possibility to gain risk-free returns in the foreign exchange markets. This again indicates that the foreign exchange markets violate the efficient market hypothesis.

Therefore, an important theory related to the determination of foreign exchange rates is the efficient market hypothesis and random walk model. According to the traditional investment theory, the markets are unpredictable and prices follow a random walk. The definition of the random walk was proposed by Kendall in the early 1950s and his study has worked as the foundation of several major models and theories in the financial industry. Kendall's (1953) study proposed that market prices cannot be predicted and thus the prices from the past cannot be used to predict the prices in the future. In other words, the prices occasionally move from the previous prices and it is impossible to find a predictable pattern in the price changes.

After the introduction of the random walk theory, the efficient market hypothesis (EMH) entered the financial vocabulary in the beginning of the 1970s. The original definition of the efficient market hypothesis was developed by Fama (1970). Ever since a huge proportion of academics have studied and tested the efficiency of financial markets. EMH has become the foundation of modern financial theories and it is used in almost every field of finance, from derivatives valuation to capital asset pricing.

In an efficient market, the price of the security "fully reflects" all the available information and the prices adjust instantly to publicly available information (Fama 1970). When this condition is satisfied, it is impossible to outperform the market since all the information is already incorporated into the prices so market participants cannot find overvalued or undervalued securities without accepting a higher risk. An efficient market is one in which deviations from the fundamental value can only be explained within information and transaction costs. Under these conditions, current exchange rates reflect their fundamental values, and investors and traders do not have the opportunity to consistently earn higher than average returns. It is therefore impossible to beat the market in the long run. The existence of the random walk model would confirm that currency prices are independent of past prices and thus markets would be efficient.

The efficiency of the foreign exchange market has been the subject of a comprehensive study. Fama (1970) introduced the theory that there are three forms of information - the weak, the semi-strong, and the strong form of information. The weak form reflects only historical data, semi-strong historical and publicly available information, and the strong form includes all the previous forms of information but also insider information. Due to this, if the weak form of market efficiency in exchange markets would hold, this would indicate that it is possible to predict the future values according to the development of historical price data. However, recent studies show that exchange rate models are consistently outperforming the random walk model, indicating that the markets are predictable and therefore not efficient (Moosa et al., 2014).

There is no common understanding of whether the currency markets are efficient or not. Traditional finance theories have been challenged with studies in which the findings prove that investors' attention plays a crucial role on markets' behavior (Goddard et al., 2015). During the last decades, models based on efficient market hypothesis have lost their credibility when many behavioral economists have begun to undermine the assumption of efficient markets.

Already in 1980 Grossman & Stiglitz studied the concept of EMH and found results indicating that perfectly efficient markets are an impossibility. If the markets would be perfectly efficient, they would reflect all the available information. However, gathering and processing information is not free. Due to this, if the markets would be efficient, there would be no financial gain in collecting information. There has to be abnormal returns that compensate investors for gathering and processing information which gives a purpose for trading. (Grossmann et al., 1980).

In addition, the historical financial models have ignored the fact that investors may behave irrationally, and their personal beliefs may have an impact on their investment decisions. Therefore, behavioral economists have gained interest to create new models which take cultural, social, and cognitive factors into account. One of the best-known papers that used cognitive psychology to explain economic decision-making was published in 1974 by Tversky and Kahneman. Their study proves that the efficient market hypothesis does not hold. They base their result on the logic that investors make decisions based on the potential value of gains and losses rather than on the outcome itself. Prospect theory is a behavioral model that takes a more humane perspective to financial decision-making. (Tversky et al., 1974).

Detecting inefficiencies and arbitrage opportunities in asset markets is an interesting yet challenging task. Several behavioral studies have been studying exploitable profit opportunities which provide evidence on market inefficiencies. These irregularities are often caused by investors' irrational behavior. This irrational behavior may cause deviations from equilibrium prices. These deviations are called anomalies and they refer to irregular patterns that tend to appear in the asset markets. With asset pricing anomalies there exists an opportunity for abnormal returns which means that either the traditional asset pricing model or the assumption of EMH is incorrect. (Bodie et al., 2014, pp. 366-367).

In addition, there is an extensive amount of literature on behavioral biases that explain the impact of human behavior in financial decision-making. Kumar and Goyal (2015) systematically reviewed historical literature on behavioral biases and found that investors do not behave fully rationally unlike the EMH assumes. The most common biases that impact investors' financial decision-making is overconfidence, familiarity bias, herding bias, and disposition effect. These biases are a direct violation of EMH since rational investors would not sell winning stocks and hold the losing ones (disposition effect). Additionally, rational investors would not let other investors' behavior impact their decision (herding) and they would not hold domestic securities rather than foreign ones (home bias). They would simply choose those securities which have the best risk-adjusted return. Lastly, investors tend to be overconfident about their knowledge and skills which may cause irrational investment decisions. (Kumar et al., 2015).

Lastly, several studies have found evidence that news announcements and unexpected events may influence investors' behavior which again impacts the volatility of foreign exchange markets. Studies show that news announcements tend to fluctuate the exchange markets. Especially unexpected news tend to have an impact in the short-run and these news tend to affect volatility more than the value of the exchange rate itself (Caporale et al., 2018). News announcements and media impact investors' expectations which again plays a crucial role during politically and economically uncertain times when investors are even more irrational.

To conclude, different exchange rate models are based on conflicting assumptions. Some models rely on the assumption that prices follow a random walk whereas other models rely on the assumption that prices fluctuate according to investors assumptions. Therefore, a question arises that how can investors know which model provides most accurate estimates? As previously stated, the foreign exchange market is a highly liquid and volatile market which correlates with several different factors and events. Therefore, it is not a surprise that the determination of foreign exchange rates has been and probably will continue to be an extremely difficult task.

3.3 Exchange rate forecasting

As already noted, currency markets are the largest and most liquid financial markets. Therefore, the importance of foreign exchange rates, for both policymakers and multinational firms, has evolved rapidly during the last decades. With accurate forecasts, decision-makers and companies are able to minimize risk and maximize returns. Therefore, accurate expectations of the future exchange rates and their movements can result in better risk management and as improvements in companies' overall profitability.

Thus, the predictability of exchange rates is an important yet challenging issue for international finance. Due to exchange rates' tendency to not only fluctuate according to the traditional economic factors but also political and psychological factors, the process of accurate currency forecasts is complex. The volatile and dynamic nature of currency markets makes it difficult for academics and practitioners to choose appropriate methods for forecasting exchange rates. This challenge has been addressed by a number of different methods that have been utilized in the process of forecasting currencies. The traditional models are usually divided into technical and fundamental models, but research has also developed linear and nonlinear models. In addition to these, even methods that utilize machine learning has been adopted to solve forecasting problems.

It is commonly suggested that the most common approaches for financial forecasting are the fundamental and technical approaches. Already decades ago, fundamental analysis has been widely used in the field of exchange rate forecasting. Technical analysis, on the other hand, has been considered as a secondary tool which provides supportive analysis when the information and results based on fundamentals are not comprehensive enough (Menkhoff, 1997). Fundamental analysis tries to determine the value of an asset-based on underlying economic conditions and different fundamental factors. Technical analysis, on the other hand, assumes that historical data can be utilized to forecast the future movement of exchange rates. (Oberlechner, 2001; Shamah, 2012, pp. 183-184)

Fundamental forecasts try to predict exchange rates based on the analysis of different fundamental economic variables. Traditionally, when conducting fundamental exchange rate analysis, the interest is at economic performance factors like the growth of GDP, unemployment rates, and the money supply. However, fundamental factors can be anything from macroeconomic factors like unemployment rates and GDP, to microeconomic factors like the profitability and growth of companies. Thus, the fundamental method includes the analysis of financial and economic reports. This analysis process attempts to find assets that are undervalued or overpriced. (Shamah, 2012 pp. 191-193).

In contrast to fundamental analysis, technical analysis attempts to predict future rates based on historical data. This is based on the assumption that currency markets tend to fluctuate in trends and these trends tend to repeat themselves. (Shamah, 2012 pp. 207-208). One main reason why these recurrent patterns appear in the markets is due to human nature. Currencies are highly correlated with human behavior, which can be assumed to be constant. This means that markets and investors tend to react to economic news similarly, which means that past behavior can be utilized for future predictions. Thus, the technical approach attempts to examine these recurring patterns and movements of foreign exchange rates to find predictable patterns. (Shamah, 2012 pp. 149). Predictable patterns violate the classical assumption of efficient market hypothesis and random walk model. Unlike the random walk model, technical models allow market participants to predict future values.

As described, fundamental and technical approaches are based on different assumptions. Fundamental forecasts provide more accurate forecasts in the long run, while technical analysis allows a more accurate evaluation of short-term changes. A combination of both of these models would probably be the best. Despite the assumption that these methods provide accurate forecasts with different time frames, studies have also shown that the size of the market has an impact on which approach suits best. Large markets tend to give more emphasis on fundamental analysis and smaller markets tend to use technical analysis. (Oberlechner, 2001).

In addition to these traditional models, much research has also been devoted to linear and nonlinear models. Academics, who want to estimate currency forecasts with the highest degree of reliability, have made extensive use of linear and nonlinear techniques. Linear models show the relationship between a dependent variable and a set of predictor variables. (Clements et., 2004). Thus, a linear model may be presented in the following form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_x X_x \tag{6}$$

A linear relationship is usually utilized in regression models as well as in variance analyzes (ANOVA). Probably one of the most common linear models is the ARIMA model which stands for Auto-Regressive Integrated Moving Average. It has been used to capture the relationship between different time series. Due to its success, it has been widely used as a benchmark for developing new models and examining different dependencies between time series.

However, linear models such as the ARIMA, are unable to capture nonlinearity from time series and therefore models that are able to capture nonlinearity tend to outperform linear models (Zhang, 2003). According to Clements et al. (2004), certain financial series follow nonlinear cycles which makes it difficult to predict future values and movements.

Therefore, more sophisticated methods that provide more accurate results when evaluating nonlinear models have been brought to the financial research.

Nowadays, a vast variety of economic applications have nonlinear and unpredictable features which fluctuate and change over time. Due to this, models that are able to capture highly nonlinear and rapidly changing problems have received interest among researchers (Clements et al., 2004). Nonlinear model allows the researcher to determine the relationship between the dependent and one or more independent variables. Therefore, the simplest form of nonlinearity can be presented in the following form:

$$y = F(x_1, x_2, \ldots, x_n) \tag{7}$$

Common models such as autoregressive conditional heteroscedasticity (ARCH) as well as general autoregressive conditional heteroscedasticity (GARCH) have been widely utilized to capture nonlinearity from different data sets. In addition to these, machine learning methods have also been utilized to capture nonlinearities. (Mostafa et al., 2017, pp. 6-7). The unpredictable behavior of foreign exchange rates had led to a growing interest in machine learning methods and how intelligence technologies can be used to forecast foreign exchange rates. Machine learning provides data-driven methods such as genetic algorithms, fuzzy logic, and neural networks (Binner et al., 2005). Especially artificial neural networks (ANN) have been used to provide accurate forecasts of foreign exchange rates. As with technical analysis, neural networks analyze historical data and then with algorithms form a function that is able to predict future values and movements in the foreign exchange markets. The next section of this paper will further discuss neural networks, their main characteristics, and applications.

To conclude, it is not easy to say which model should be used to forecast foreign exchange rates. Some studies indicate that random walk provides the most accurate outcomes and others state that the most significant results are provided by nonlinear models. The accuracy of the models depends on several factors like the type of financial data, sample period, and forecast horizon (Rossi, 2013). Another perspective is that models that incorporate properties from different models are most valid when studying real-world events (Zhang, 2003). The difficulty of forecasting foreign exchange rates can be concluded to a sentence that "forecasting how a currency will move is still an art rather than a science" (Shamah, 2012).

4 Neural Networks

The purpose of this section is to present general information related to neural networks. More specifically, this section describes what neural networks are, what kind of neural networks exist and what are the advantages and disadvantages of neural networks. Lastly, this section will present how these models have been used to study exchange rates. More in-depth understanding of neural network models such as data collection, implementation of architecture, training, and the evaluation of the neural network will be presented in section five.

4.1 Basic Principles

Neural networks (NN), also known as artificial neural networks (ANN), are machine learning algorithms that are widely used to process different kinds of data. These models have been used “from pattern recognition to optimization and scheduling” (Maren et al., 2014, pp.1). Neural networks are models that are able to analyze linear and nonlinear datasets. These models also have the ability to learn, adapt and generalize the processed data. As with other statistical models, also neural networks require appropriate and sufficient data in order to receive accurate results. (Yu et al., 2007, pp. 27). The aim of NN models is to automate the information analysis and, with complex algorithms, make these models more efficient and capable of detecting changes.

Neural networks are inspired by the structure of the human brain. The basic idea is that network consists of layers that consist of computational units called neurons. These neurons are individual processing units that are able to receive information and then transmit this information to other neurons. Therefore, neurons are always interconnected and they pass signals through the network. More precisely, an artificial neuron consists of the input values, weights, sum function, activation function, and output value. Figure 1 presents the most basic structure for a network.

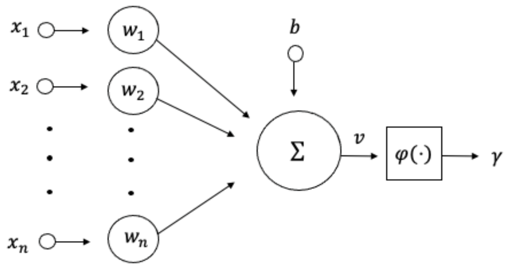

Figure 1. Neural Network (Haykin, 2009, pp. 10-11)

The figure shows that the network receives one or more input values $(x_1, x_2 \dots x_{n)}$ which it then processes with a set of coefficients $(w_1, w_2 \dots w_n)$. These coefficients are also called synaptic weights and each weight either amplifies or weakens the corresponding input. The network calculates a sum of all the received inputs and then multiplies each input with the corresponding coefficients ($\sum$). Threshold value (b) determines the appropriate value that the summation must exceed for the neuron to activate. V describes the activation potential and therefore it describes the difference between the sum function and the threshold. The neuron is activated when $V > 0$. After the activation potential is passed, the input is transmitted to the activation function ($\varphi(\cdot)$) which is designed to keep the values inside certain limit values. The output value (y) is the final value corresponding to the received inputs and their weights. (Haykin 2009, pp. 10-11).

The architecture of a neural network determines the structure, the number of neurons, the number of different layers as well as the direction of the signals that pass through the model. Figure 2 presents the general architecture of a neural network.

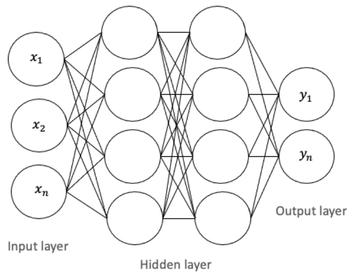

Figure 2. Basic architecture of neural network (Yu et al., 2007, pp. 27)

The basic architecture consists of an input layer, one or several hidden layers, and an output layer. These layers consist of neurons which are presented as nodes in the figure. All of these nodes interact with each other and therefore this connection is illustrated in the figure by arrows between the nodes. The function of the input layer is to receive data and signals outside the network. Often input layer also scales and normalizes the received data. The hidden layers, on the other hand, are responsible for the data analysis. The number of hidden layers varies depending on the complexity of the problem and the amount and quality of the data which is being processed. Finally, the function of the output layer is to produce and present the final outputs of the neural network. (Yu et al., 2007, pp. 27).

However, a neural network is not automatically an accurate model which knows how to process input data to a final output data. Neural networks gain the ability to provide accurate output values from a dataset with a training process. In this training process, the model is trained with examples that consist of the input value and a corresponding output value as well as the synaptic weights. With the synaptic weights, the aim is to minimize the difference between the target output value and the actual output value. The learning process continues until the model is able to identify patterns and therefore is able to provide estimate values for even input signals whose outputs are still unknown. Therefore, networks are able to learn from example data and then apply this knowledge to similar cases.

This learning ability is one of the main reasons why neural networks have been used to solve complex data problems. However, there are also several other benefits in neural networks. According to Maren et al. (2014) and Haykin (2009) the main advantages of neural networks are the following properties:

1. Input-output mapping
2. Adaptivity
3. Nonlinearity
4. Fault Tolerance

Input-output mapping refers to the ability to learn from examples. Then from these examples, the model is able to detect patterns that can be utilized when processing new input data. Nonetheless, networks are also adaptable so in case the environment changes the model is able to readjust. This adaptivity is one of the biggest benefits of neural networks. More particularly, adaptivity describes how the synaptic weights are able to change according to the environment with simple retraining. (Haykin, 2009, pp. 2-3; Maren et al., 2014, pp. 7-8).

The reason why neural networks have been especially utilized in the research of foreign exchange rates is due to their ability to handle complex and diversified data. One of the main properties of neural networks is flexibility as the model can process both linear or nonlinear data. Lastly, a neural network is fault tolerance which means that the performance of the model does not depend on individual information. In other words, the model may notice that some information is invalid or missing and despite this produce a valid output. (Haykin, 2009, pp. 3-4; Maren et al., 2014, pp. 7-8).

Given the above benefits, it is no wonder that neural networks are being used to process complex data and problems. The demand for time-effective machine learning methods is increasing and while it is possible to utilize these models in a more efficient and versatile way, also problems related to these models are being more and more detected. A common issue related to neural networks is the format of the data that the model requires. NNs require numerical data and in some cases, it might be extremely difficult to translate information to numerical values. (Mijwel, 2018).

Additionally, common disadvantages of neural networks are for instance the disability to explain the behavior of the model as well as the determination of an accurate network structure. The first is probably the most important since when it comes to neural networks the model does not provide information on how and why it has received certain output values. Therefore, in some cases, there might be uncertainty related to values that the network provides. However, the more the model is trained, the better results should be provided. The latter problem is related to this training process since there is no certain way to construct a neural network. Thus, only with trial and error it is possible to learn what kind of structure suits certain kinds of datasets. (Mijwel, 2018).

To conclude, there are many advantages with neural networks which make them a competitive option for different kinds of studies. There are naturally some challenges as well and therefore neural networks should be utilized in studies that are able to exploit its positive features and, on the other hand, control its challenges. These features that have so far been presented are general features related to NN. Thus, it is crucial to understand that there are different types of neural networks which have even more advantages and disadvantages. Hence, the next section of this paper will go through the most common types of neural networks.

4.2 Different Types of Neural Networks

There is a vast variety of different neural network types and each of them have their unique features and architectures. The most basic form of a neural network is called a feedforward neural network. As already the name indicates, in feedforward neural networks the data passes through the network to only one direction. The process starts from the input nodes and continues until it reaches the output nodes. Feedforward networks can be further divided into groups based on the number of layers. Hence, a feedforward NN might be grouped as a single-layered network or a multilayered network (Haykin, 2009, pp. 21). The simplest form of a feedforward neural network is presented below:

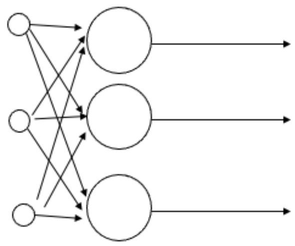

Figure 3. Feedforward Neural Network (Haykin, 2009, pp. 21)

As can be seen from Figure 3, the single-layered network consists of two layers: the input values and the output values. The multilayered network, on the other hand, includes the input layers, several hidden layers, and the output layer. (Haykin, 2009, pp. 21). A feedforward model which includes more layers is then practically identical to Figure 2, which was already presented earlier as the general architecture of a neural network. The number of layers depends on the complexity of the data and the function that will be used in the model. (Maren et al., 2014, pp. 85-91; Haykin, 2009, pp. 21-22). With a large number of neurons and several hidden layers, it is possible to create complex forecasting models. However, a prerequisite for a complex model is that there is a lot of teaching material available.

Feedforward types of neural networks have especially been utilized in supervised learning such as object or speech recognition. From a financial point of view, the feedforward method has been utilized for instance for classifying companies according to their financial statements (Serrano-Cinca, 1997) and as a prediction tool for future stock values (Thawornwong, 2004). A tool like this has been utilized in financial forecasting due to its ability to classify and provide estimates of the dependent variable.

Another noteworthy neural network type is the convolutional neural network (CNN). These networks are mainly used to analyze images and videos, but CNN can also be used for other types of data analysis such as stock price prediction (Tsantekidis et al., 2017). Convolutional networks are similar to multilayer feedforward networks, except they contain one or more convolutional layers. These models may also include normal hidden layers yet in order to fulfill the criteria of convolutional NN, there has to be at least one convolutional layer. For each convolutional layer, there is a need to determine the number of filters that the layer includes. Filters detect patterns and therefore for each filter there is a specific predefined objective that they are detecting. This could be for instance edges, shapes, or colors. As the layers get deeper, also the filters perform better so the filters can detect more complex objectives. (LeCun et al., 2015).

Shortly, the process of a CNN starts as with any other neural network, so the model receives data which it then transfers to the layers called convolutional layers and pooling layers. Convolution layers are placing a filter over an array of image pixels and create convolved feature map. Pooling, on the other hand, reduces the sample size of a particular feature map. This pooling makes the processing faster as it reduces the number of parameters the network needs to process. Then the sample is passed through an activation function called rectified linear unit (ReLU) which ensures nonlinearity. After the sample is flattened, it will flow to the last layer called the fully connected layer. (LeCun et al., 2015). An extremely simplified form of a convolutional neural network is presented in Figure 4.

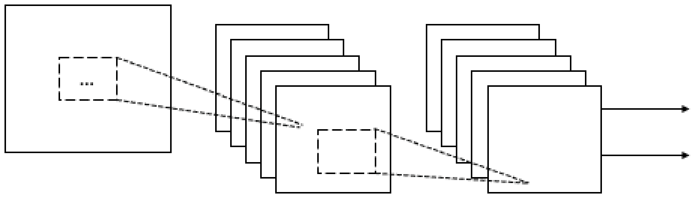

Figure 4. Simple form of CNN architecture

In CNN models (figure 4) and simple feedforward models (figure 3), the values flow from left to right. However, in addition to these feedforward neural networks, there is also a neural network model which may use feedback loops to process historical data. These models are called recurrent neural networks (RNN) and these models have internal memory to process sequences of input data. (LeCun et al., 2015).

RNN models are widely used in time series modeling. Recurrent neural networks are dynamic models in which the information flows in multiple directions. The speciality of this architecture is that each neuron can store information in its memory. Therefore, recurrent models are able to process more complex datasets than for instance simple feedforward models. In a simplified form, the recurrent neural networks can be presented as follows:

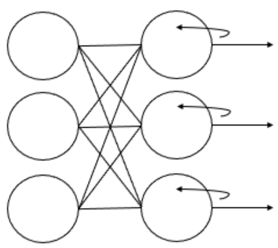

Figure 5. Simplified RNN architecture (Haykin, 2009, pp. 23-24)

As can be seen from Figure 5, a recurrent model with a simple architecture recalls the architecture of a single-layered feedforward model presented in Figure 3. In most real-life cases, the architecture of RNN is much more complex and they have several hidden layers. Therefore, Figure 5 should only be seen as a simplified example.

The main difference between feedforward and recurrent networks is that recurrent neural networks have at least one feedback loop. The feedback loop presents the model's ability to take information from prior inputs to influence further input and output values. RNN takes advantage of the entire history of input values while calculating current output values. The main advantage of recurrent networks is the ability to memorize past information and use it to generate new output values and improve its performance. (Haykin, 2009, pp. 23-24).

Despite the advantages, it is necessary to point out that recurrent neural networks have some limitations as well. They might have a challenge with the vanishing gradient which makes the training of a recurrent neural network complicated. The problem is that the longer the period gets, the smaller the gradient becomes. Since the gradients define how much the network is learning, if the value of the gradient gets close to zero, the parameter updates become insignificant. Due to this, the predictive power of the model becomes poor and it is difficult to learn cause-and-effect relationships. (Hochreiter et al., 1997; Hochreiter 1998).

The vanishing gradient problem has been solved by developing a network with long-short-term memory (LSTM). LSTM is a special case of RNN, and the LSTM model provides a long-term memory for the neural network. The LSTM model has already been created in 1997 by Hochreiter & Schmidhuber. Ever since its creation, the model has been widely used due to its ability to process sequences of data efficiently. Additionally, the model can maintain its memory for both output and hidden layers. Thus, LSTM architecture improves significantly the perception of the cause-and-effect relationship.

The LSTM networks might have quite complex architectures, yet their main components are:

- Cell
- Forget gate
- Input gate
- Output gate

The cell is also called the LSTM block which is responsible to remember the values. The gates, on the other hand, control the communication between the memory cell and the cells next to it. Forget gate is the vector which knows what information should be forgotten once the information is out of date and therefore irrelevant. Input gate, on the other hand, is called save vector as this gate determines which information passes to the long-term memory. The Output gate is responsible to choose which values are passed through to the next hidden LSTM unit. Overall, these gates and LSTM structures enable the LSTM networks to provide a steady and constant flow of gradients while backpropagating. As earlier stated, due to these features, LSTM models are able to learn and access information over a long period. (Graves, 2012, pp. 37-45).

4.3 Neural Networks in Exchange Rate Forecasting

Financial forecasting has always been a prominent field of study. Machine learning algorithms have been able to improve the forecasting accuracy of stock and foreign exchange forecasts. Especially neural networks have been a profitable tool to forecast financial time series data. Thus, neural networks' ability to learn and model real-life phenomena has led to rapid utilization of these models. Due to the unique properties and the capability of powerful pattern recognition, neural networks have provided accurate models to predict and analyze foreign exchange rates. As stated in previous sections, neural networks are unique and efficient models due to their capability to process a large amount of nonlinear data. In addition to this, NN models are self-adaptive and have the ability to recognize complex relations (Yu et al., 2007). Due to these characteristics, neural networks have been a popular tool in currency analysis.

Table 4 provides a brief review of previous studies related to the utilization of NN models in the analysis of foreign exchange rates.

Table 4. Previous literature – Neural Netwoks and Exchange rates

Authors	**Purpose**	**Methods**	**Results**
Zhang et al. (1998)	NN forecasting of the GBP/USD exchange rate	Neural Networks	NN outperform linear models, especially in the short run

Zhang (2003)	Forecasting of GBP/USD exchange rate	ANN compared to random walk, ARIMA and hybrid model	Hybrid model outperforms ANN, ANN outperforms ARIMA
Gradojevic et al. (2006)	Forecasting exchange rates with nonlinear, non-parametric and non-fundamental models	ANN compared to random walk and linear models	ANN has consistently smaller RMSE compared to random walk and nonlinear models
Dunis et al. (2011)	Measuring EUR/USD rate with different NN architectures	Higher order NN, Psi Sigma network, RNN, Gaussian Mixture, MLP and softmax	Results show that MLP, HONN, Psi Sigma and RNN outperform traditional models
Zafeiriou et al. (2013)	Forecasting exchange rates with NN model that includes technical indicators	Neural network and technical indicators	NN model which includes technical indicators outperform traditional NN models
Ni et al. (2019)	Forecasting nine major currency pairs with C-RNN method	C-RNN, based on RNN and CNN	C-RNN method provides more accurate results
Zeng et al. (2020)	Forecasting USD/JPY with a hybrid model	Wavelet denoising, attention based RNN and ARIMA	The hybrid model combing three methods outperforms the traditional methods

Zhang and Hu (1998) ”Neural network forecasting of the British Pound/US dollar exchange rate”

Already a few decades ago, Zhang and Hu (1998) conducted a comprehensive study that analyzes neural networks and their ability to forecast exchange rates. More precisely, they were keen to understand what is the impact of the number of inputs and hidden nodes. Additionally, they were interested to evaluate what kind of role does the magnitude of the training sample play. They studied neural networks’ in-sample and out-of-sample performance and used GBP/USD exchange rate data. Their study provides evidence that NN is able to beat the traditional linear models, which is statistically significant when the time period is short. Additionally, they suggest that the number of input nodes has a more significant role compared to the number of hidden nodes.

Zhang (2003) "Time series forecasting using a hybrid ARIMA and neural network model"

The paper by Zhang (2003) compares the efficiency of auto-regressive integrated moving average (ARIMA), ANN, and a hybrid model. This hybrid model combines features from both ARIMA and ANN models. According to Zhang, models that are based on the assumption that the problem is either nonlinear or linear tend to fail in real-world situations. Therefore, a model that accepts both nonlinearity and linearity, provides the most accurate results. Zhang is able to empirically prove that the hybrid model provides significant results when suited to a real-life dataset. However, if the interest is simply in ARIMA and ANN model, their study shows that ANN provides more accurate results than an ARIMA model.

Gradojevic and Yang (2006) "Non-linear, non-parametric, non-fundamental exchange rate forecasting"

Gradojevic and Yang (2006) focus on investigating how neural network models perform compared to traditional linear models. In addition, they compare how NN models perform when it is compared to the random walk model. The random walk model is one of the grounding theories in the field of financial studies and it is generally stated that in efficient markets the random walk is the most accurate way to predict the movements. However, the paper by Gradojevic et al. (2006) prove that the most valid forecasts are received with neural networks. This evaluation is done by comparing the root mean squared errors and comparing how well the models are able to predict the direction of future values. ANN models are consistently outperforming linear and random walk models.

Zafeiriou and Kalles (2013) "Short-Term Trend Prediction of Foreign Exchange Rates with a Neural-Network based Ensemble of Financial Technical Indicators"

Zafeiriou and Kalles (2013) believe that models that focus on short periods, and technical indicators, are unable to provide significant results when it comes to foreign exchange rates. Therefore, their paper focuses on developing and conducting a neural network model which is able to forecast short-term buy and sell trends for currency markets. The reason why their model outperforms previous models is due to the technical indicators that they include as inputs. Therefore, neural network models do not only use prices or percentage changes as input values. By including different factors in NN models, the models are able to provide even more efficient and significant results.

Dunis, laws and Sermpinis (2011) "Higher order and recurrent neural architectures for trading the EUR/USD exchange rate"

As previously stated, there are several different neural network models. However, in addition to several NN models, there are also several architectures for these models. Therefore, Dunis et al. (2011) conducted a study in which they compared the forecasting accuracy for EUR/USD exchange rate with different NN designs and architectures. The chosen designs were Higher Order Neural Network (HONN), Psi Sigma Network, and a more typical recurrent neural network (RNN). In addition to these, there were three architectures chosen that were then compared – Gaussian Mixture (GM), Multilayer Perceptron (MPL), and SoftMax. The results show that MLP, HONN, Psi Sigma, and RNN models are able to outperform traditional forecasting models. When it comes to the comparison of these different architectures, the GM network is able to provide most accurate and significant results.

Ni, Li, Wang, Zhang, Yu and Qi (2019) "Forecasting of Forex Time Series Data Based on Deep Learning"

Ni et al. (2019) conducted a C-RNN model to predict foreign exchange rates. This C-RNN method is based on recurrent neural networks and convolutional neural networks. Their study combined the advantages of two algorithms and their aim was to further improve the forecasting accuracy. By studying nine different currency pairs, their paper provided evidence that the C-RNN method provides more accurate results than the LSTM model or CNN model.

Zeng and Khushi (2020) "Wavelet Denoising and Attention-based RNNARIMA Model to Predict Forex Price"

Zeng et al. (2020) proposed a forecasting model which combines wavelet denoising, attention-based recurrent neural network (RNN) model as well as autoregressive integrated moving average (ARIMA). They believe that the movements in foreign exchange rates play a crucial role as it can be a great opportunity or a big risk for the investors. Therefore, an accurate forecasting tool for currency markets is crucial. The purpose of wavelet denoising is to make the data structure more stable. ARNN tries to find nonlinear relationships whereas ARIMA finds linear correlations from the sequential data. By studying the USD/JPY exchange rate, they were able to prove that this hybrid model outperforms the traditional methods.

As previous literature indicates, already for decades neural networks have been used to study exchange rates. Despite this, the research of exchange rates and machine learning algorithms continues. Nowadays studies can provide more in-depth analysis, yet a perfectly accurate model is still to be found. The prediction of exchange rates is challenging due to their dynamic and complex characteristics. As currency markets react to several microeconomic and macroeconomic factors, it is no wonder that it is extremely challenging to find a forecasting model which would be able to predict how different events impact and how do investors and market participants react. Therefore, exchange rate forecasting has and most probably will continue as an important yet challenging research issue.

5 Data and methodology

This part of the paper describes the data and methods that are used to forecast foreign exchange rates. The first section will present a description of the data, how the data is collected, and then provide some pre-analysis related to the data. The second section, on the other hand, will provide a short description of the used tools and a more deep understanding of the chosen method. Therefore, the method part consists mainly of the preparation of the model, training, and generalization. Lastly, the loss metrics will be presented.

The main steps to build an LSTM model are:

- Prepare the data
- Preprocess the data
- Split data to train and test set
- Reshape data for implementation
- Building LSTM model
- Compile/train the model
- Evaluate the performance of the model

5.1 Data

A precondition for an accurate neural network model is preprocessed data. The quality of the data has a significant impact on the results and therefore properly prepared data is a crucial step in the process of constructing a neural network. (Sattler et al., 2001). This paper implements a recurrent neural network model, more precisely a LSTM model, using the Keras framework and a dataset that consists of closing values of three different currencies – GBP/USD, GBP/EUR, and GBP/JPY. The data of these three currency pairs is collected from Yahoo! Finance database. The collected data is daily closing values and thus the collected values present exchange rates between two currencies at the closing time of each trading day. With daily closing prices, it is possible to exclude some very short-term fluctuation and sudden behavior.

The datasets contain daily closing values from January 2010 to December 2019. To visualize the datasets, each dataset is plotted into a figure to show how the closing values have fluctuated over time. Additionally, for each dataset, the percentage change is calculated and then plotted as a figure. These logarithmic returns present how volatile the exchange market has been and how the volatility has fluctuated over time. Figures 6 and 7 present the historical closing values of the GBP/USD currency rate and the logarithmic returns for the same exchange rate during 2010-2019. Figures 8 and 9, on the other hand, consists of the historical closing values of GBP/EUR and the logarithmic returns for the same exchange rate. Lastly, figures 10 and 11 consists of historical data of GBP/JPY exchange rate and therefore present the historical closing values and logarithmic returns for GBP/JPY.

Figure 6. Closing price history GBP/USD

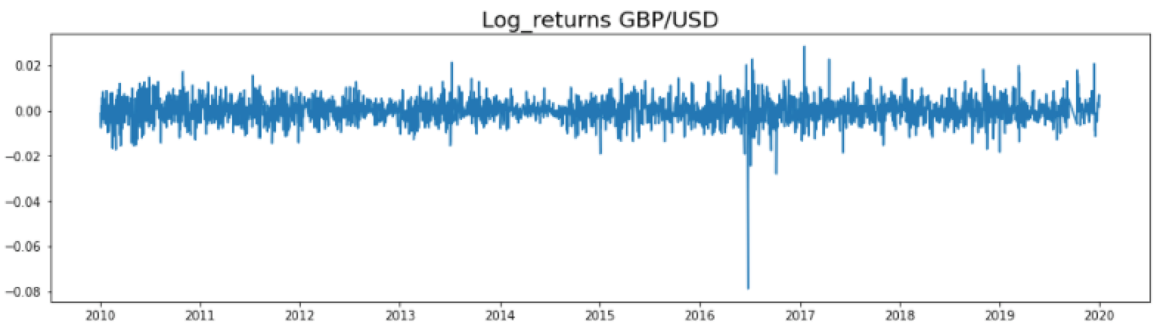

Figure 7. Logarithmic returns for GBP/USD

Figure 8. Closing price history GBP/EUR

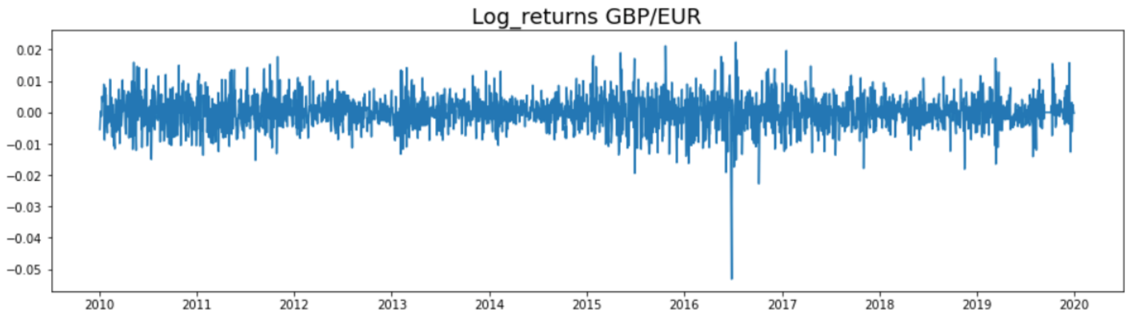

Figure 9. Logarithmic returns GBP/EUR

Figure 10. Closing price history GBP/JPY

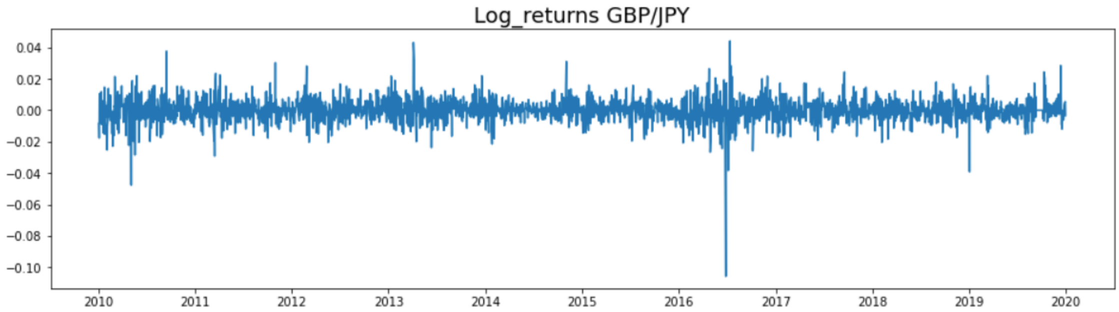

Figure 11. Logarithmic returns GBP/JPY

As the purpose of this paper is to seek for shifts in the predictability, each dataset is divided into equal-length periods – January 2010 to December 2014 ("set 1") and January 2015 to December 2019 ("set 2"). The aim of constructing two different datasets is to divide the data into two time periods. The first four years describing the time when the uncertainty caused by Brexit did not appear and the latter describing the time when Brexit-related events have occurred. Each of these subsets are presented in Table 5. This table shows how many observations are included in each subset and what are the mean, minimum and maximum values. Additionally, the last column shows the standard deviation for each subset.

Table 5. Statistical analysis of each subset

	Count	Mean	Min	Max	Standard deviation
GBP/USD set 1	1302	1.589465	1.429674	1.716090	0.052469
GBP/USD set 2	1281	1.359247	1.202198	1.588512	0.103715
GBP/EUR set 1	1304	1.194013	1.096800	1.286900	0.044089
GBP/EUR set 2	1282	1.204102	1.072430	1.440300	0.101484
GBP/JPY set 1	1302	143.38470	117.18000	189.22000	18.961093
GBP/JPY set 2	1282	153.07526	126.66600	195.74200	18.095405

The data collection of this study starts from 2010 which can be justified due to the financial crisis of 2007-2009. The most volatile impact of the financial crisis occurred during 2007-2009 and thus this period will be excluded from the dataset. However, the recession caused by the financial crisis may cause biases to the dataset. Moreover, when it comes to financial markets, also other factors may cause biases, such as the Eurozone crisis in 2009 and the US presidential elections in 2016. The period was chosen to end to December 2019 as the global pandemic Covid-19 began to cause volatile fluctuation in the markets at the turn of the year 2019-2020. Therefore, as the focus is on political uncertainty caused by Brexit, the fluctuation caused by Covid-19 is not in the scope of this paper.

It cannot be stated that the data from 2010 to 2014 would be completely unbiased. Additionally, it cannot be stated that the data from 2015 to 2019 would be fluctuating only due to Brexit-related events. However, when it comes to financial markets and real-life cases, the market will always be sensitive to several different factors and events. Therefore, it will always be a challenge to limit markets' reactions to one specific event. However, as the purpose of this paper is to study how the predictability varied during the time before Brexit compared to the time when Brexit-related events occurred, this paper will have to accept the fact that other factors may cause biases to the received results.

The next step after the collection and description of the used datasets is to preprocess the data. Currently, each dataset is presented in their original values and therefore they have completely different ranges. To make these currencies more comparable, these datasets should be scaled to a range between 0 to 1. This linear transformation is called normalization and in this process, each input value is scaled between a specific range. In this paper, a function called "MinMaxScaler" is used from a Python module called Scikit-learn (Pedregosa et al., 2011). This object scales each input variable between the default range [0, 1] according to the following formula:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{8}$$

The last step of the data preprocessing is to split each dataset into a training and testing set. Commonly the training set is 80% and the test set is 20% of all the input variables. The training set is used as the input variables for the neural network and the test set is used to test the accuracy of the neural network after the training part is finished. (Géron, 2019, pp. 30). Table 6 shows how each dataset is divided into training and testing sets.

Table 6. Training and testing sets

	Total amount	**Train size**	**Test size**
GBP/USD set 1	1302	1041	260
GBP/USD set 2	1281	1024	256
GBP/EUR set 1	1304	1043	260
GBP/EUR set 2	1282	1025	256
GBP/JPY set 1	1302	1041	260
GBP/JPY set 2	1282	1025	256

The last step in data processing is to reshape the data into an array shape which the LSTM model can then process. This reshaping can be done with the functionalities of the NumPy array.

5.2 Methodology

This paper implements an LSTM model to predict the closing price of foreign exchange rates. LSTM is a recurrent neural network architecture which has been widely used in time series analysis. The strength of this model is based on its ability to process not only individual data points but also larger sequences of data. In addition, the model has memory cells which enable the network to store information for a longer period. Unlike the standard RNN model, LSTM has three gates called input gate, forget gate, and output gate. The first one controls whether the information is updated, the second controls when the memory is set to zero and the output gate controls whether the output is made visible. Thus, the model can find long-term dependencies in the dataset. (Graves, 2012, pp. 37-45).

In order to build an LSTM model, this methodology part will utilize a vast variety of python libraries. The most important libraries are Keras and Tensorflow. Tensorflow is an open-source library which is widely used in machine learning applications such as neural networks. Keras, on the other hand, is an open-source library which can be used for building deep learning neural networks. Thus, Keras and Tensorflow are used in this study to develop accurate learning algorithms. In addition to these, libraries such as Pandas, Matplotlib, Numpy, and Scikit-learn are used to analyze the data more efficiently. These libraries are also used to preprocess the data as well as visualize the results. Already in the data section, Matplotlib was used to plot the closing values into a figure and Scikit-learn was used to scale the input variables to a range from 0 to 1. (Keras, 2021; Tensorflow, 2021).

After the most prominent tools have been presented, it is time to build the LSTM model. This model will then be implemented in Keras utilizing the functionalities of Tensorflow. In order to build a functioning LSTM model, it is important to design an architecture which enables accurate data processing. Therefore, in the training part, it is necessary to define the right number of nodes and layers as well as choose the additional hyperparameters. As already discussed in the literature review, RNN models include an input layer, one or several hidden layers, and then an output layer (Yu et al., 2007, pp. 27). With Keras, it is possible to stack multiple layers with the “Sequential“ command. In this paper, a simple network with one LSTM layer including 50 memory cells will be combined with one dense layer. The main goal of the network is to map the inputs to target values. Then the efficiency of the learning process can be increased by picking a proper loss function, an optimizer, and other relevant parameters.

To ensure that the network performs as designed, the data used in the training process must be representative of the actual situation. It is incorrect to assume that the created model would inherently be an exact fit for future scenarios since the model might, for instance, assign too much weight to the noise in the training data. (Géron, 2017). A scenario in which the model describes the training data "too well" is called overfitting. Overfitting is a common challenge that neural networks deal with. In overfitting, the error of the training value continues to decrease yet the validation loss starts to increase. Thus, the overfitting starts to occur when the validation loss starts to get constantly worse. With early stopping it is possible to "stop early" so the model automatically recognizes when the model begins to over-fit and stops the learning process. (Keras, 2021; Goodfellow et al., 2016, pp. 241-242).

However, as this paper aims to compare how the forecasting accuracy of the implemented LSTM model changes during different periods and currencies, this study wants the structure and parameters to remain constant. Therefore, stopping early will not be utilized separately for each dataset. Yet, in this paper the first dataset (GBP/USD set 1) was tested with the early stopping function. The model stopped in epoch 470 with the patience of 10. Therefore, this paper uses 500 epochs to train each of the models.

Another tool to prevent the neural network from overfitting is a technique called dropout. The main aim of the dropout technique is to randomly drop units while training the model. Thus, the technique randomly chooses cells in a layer and then sets their output value to 0. With dropout, it is possible to improve the forecasting accuracy of the neural network. (Srivastava et al., 2014). This paper will use a dropout percentage of 20% and thus the probability of the technique to choose a cell and set the chosen output to 0 is 0,2. Lastly, this study will use an optimizer called "Adam". The optimizer is responsible for the neural network's target function minimization. The use of Adam is justified due to its successful performance in previous studies (Reimers et al, 2017; Kingma et al., 2014). The summary of the most important parameters is resented in Table 7.

Table 7. Summary of the parameters

Parameter	Value
Number of Epochs	500
Training Method	Adam
Hidden Layer Activation Function	Linear
Dropout percentage	0.2

How to design a model that performs well not only on training data but also on test data, is a common challenge in machine learning models. Therefore, defining the number of layers and hyperparameters is a crucial part. After this part is done, it is time to compile the model. Then a large amount of training data is fed into the adaptive LSTM model. Each training element also has a target value. This way the model can recognize relationships and weights between the input and target values. The aim in the learning phase is to teach the parameters to perform in an optimized way so that after the training phase the model could accurately predict target values for new input values.

5.3 Evaluation metrics

In this paper, the chosen performance evaluation techniques are the Mean Squared Error (MSE) and the Mean Absolute Error (MAE). The difference between an observed value and its prediction is referred to as the forecast error. The error does not indicate that there exists some inconsistency with the model, yet it refers to the unpredictability of the observation. (Hyndman et al., 2018, pp. 62-71).

Both MSE and MAE are common measures in the previous neural network research (Leung et al., 2000; Khashei et al., 2010). Hu et al. (2021) have recently conducted a survey in which they have collected dozens of machine learning studies focusing on currency and stock markets. They analyze what kind of ML algorithms have previous literature utilized, what different variables have been used, and what results these studies have provided. Thus, from their study, it is possible to conclude which performance parameters are most often used to measure the performance of neural networks. These measures are for instance Sharpe ratio, Accuracy, Error Percentage, and F-measure. However, the most popular metrics for evaluating LSTM models' performance are the MSE, the RMSE, and the MAE. However, as the RMSE is simply the root square of the MSE, will this study focus on simply the Mean Squared Error and the Mean Absolute Error. The chosen forecasting accuracy measures are listed below:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_t - \hat{y}_t)^2 \tag{9}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_t - \hat{y}_t| \tag{10}$$

The Mean Squared Error (MSE) is the average of the squared deviations. In other words, the average squared difference between the estimated value and its corresponding actual value. The Mean Absolute Error is the mean of the difference between the actual and predicted values. MAE tells what the distance is between the actual and predicted output. The disadvantage of MSE is the heavy weighting of outliers. Thus, single deviations will have a significant impact on the error value. In contrast to MSE, MAE penalizes large errors in the same proportion as small errors. For both of these error criteria, the smaller the error value, the better the forecasting accuracy.

As earlier discussed, in the neural networks preprocessing phase, the datasets are divided into training and testing datasets. Error-values are also calculated for both training as well as testing sets. In general, the training error is the error value that the model receives when the model runs on the training data. However, this error value does not provide much knowledge as this training data has already been used to train the model. Thus, a small training error does not necessarily mean that the same model would perform accurately on new data. Therefore, the testing error is a more valuable error value. The testing error is the error value received from the model when the trained model is fed with new input data, in other words, the excluded test data. (Hyndman et al., 2018, pp. 62-71). Thus, this error value tells how well the trained model performs with new data that it has not been exposed to.

In other words, when selecting models, it is a common practice to divide the available dataset into two subsets – the training data and the testing data. In this paper, the training data includes 80% of the observations whereas testing data includes 20% of the total observations. The first being used to train the model and the latter being used to evaluate the accuracy of the model. Since the test data has not been used to teach the model, the testing errors should provide good indicators of how well the model forecasts. This testing method is called out-of-sample validation since the model accuracy is based on data which has not been used when training the model. Out-of-sample validation is a generally agreed tool for evaluating forecasting methods. (Thashman, 2000).

To conclude, both the training and testing errors are important. These error values demonstrate how well the model can generalize from the training data. Generally, the training error will always decline. Testing error, on the other hand, may first decline but then it may start to increase. This so-called over-fitting occurs as the model learns "too well", and as a result, the testing error starts to increase as the forecasting accuracy decreases. Thus, a complicated model is not always the best model. It is crucial to develop a model which fits the actual situation. This means that the algorithm, the parameters and the training data have to be carefully chosen. If the training data does not accurately represent the actual situation, the model will produce incorrect results. In this case, the training data is nonrepresentative, which may be due to a wrongly selected sample size. If the training set is too large, the data may suffer from sampling bias. On the other hand, if the training set is too small, the training data may be biased due to noise in the training sample. (Géron, 2017).

6 Empirical results

This part of this paper will present the received results. For each currency and for each subset, the error values for both training and testing data are presented. Also, the loss values are visualized to show how the loss values developed as the number of epochs increased. The last figures will present how well the testing data followed the actual data. Lastly, there will be a discussion section in which the results will be critically evaluated and reflected in previous studies.

6.1 Results GBP/USD

Table 8. GBP/USD set 1 - training and testing evaluation

Training		**Testing**	
Parameter	**Value**	**Parameter**	**Value**
Number of observations	1041	Number of observations	260
MSE	0.00126169	MSE	0.00068745
MAE	0.02697517	MAE	0.01839239

Table 9. GBP/USD set 2 - training and testing evaluation

Training		**Testing**	
Parameter	**Value**	**Parameter**	**Value**
Number of observations	1024	Number of observations	256
MSE	0.00132558	MSE	0.00083907
MAE	0.02364593	MAE	0.02189644

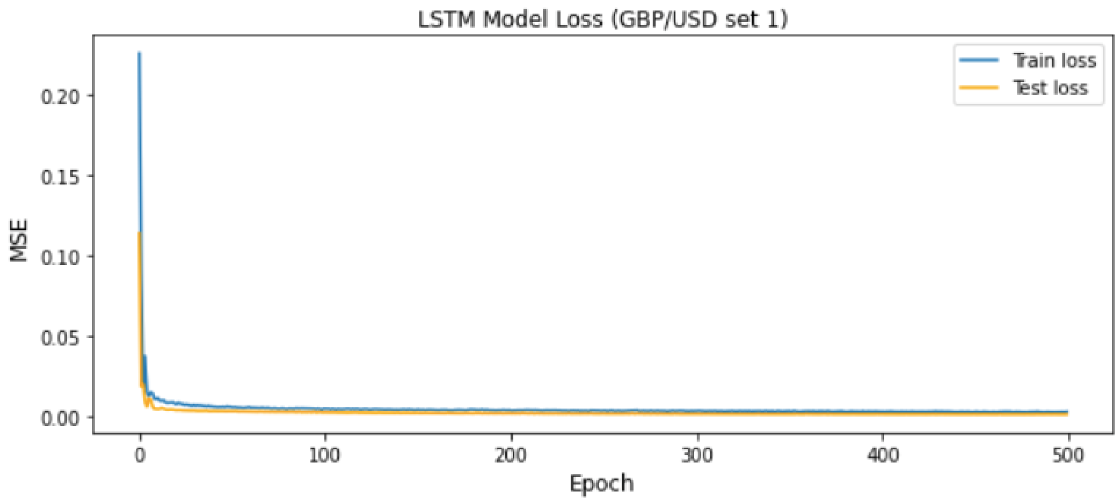

Figure 12. Loss visualization GBP/USD set 1

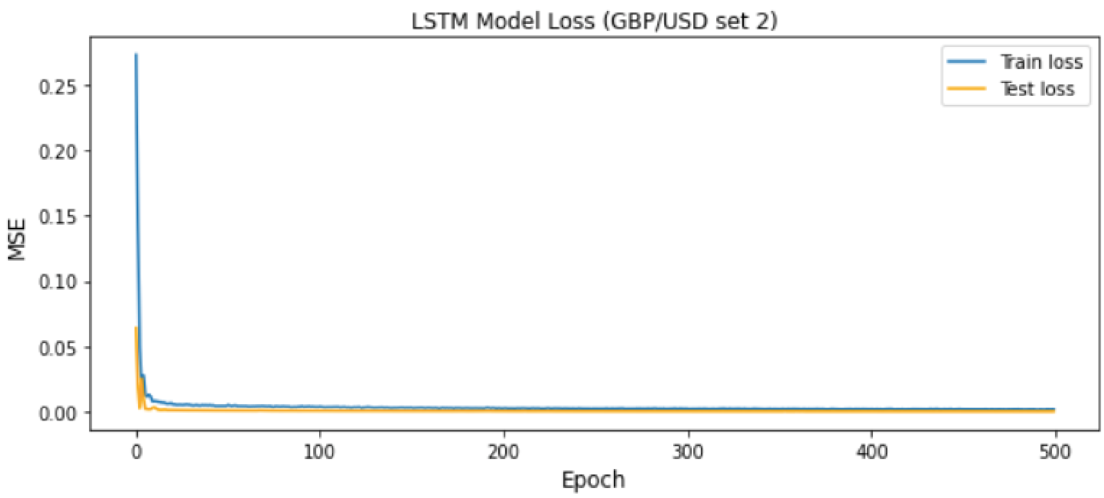

Figure 13. Loss visualization GBP/USD set 2

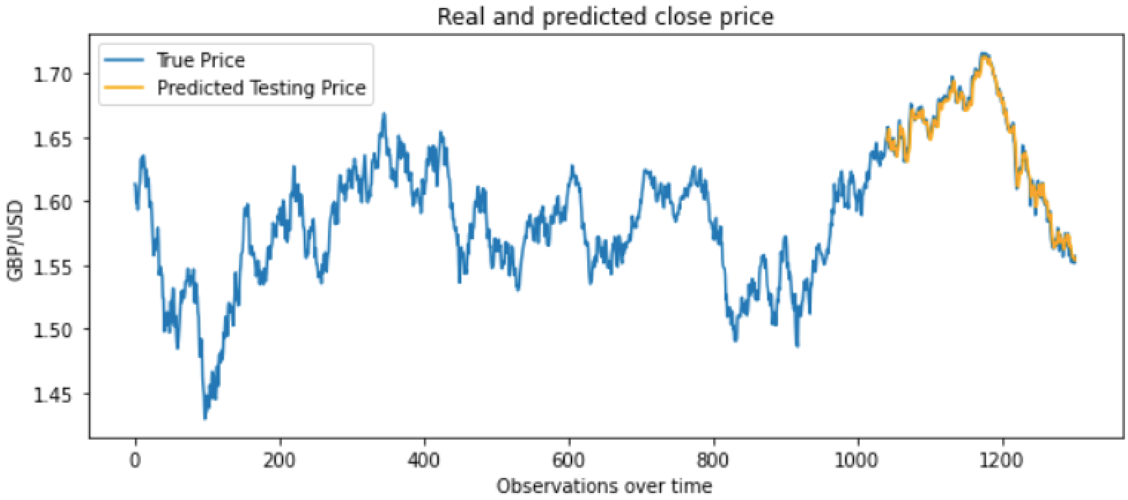

Figure 14. Real and predicted closing price for GBP/USD set 1 – full dataset

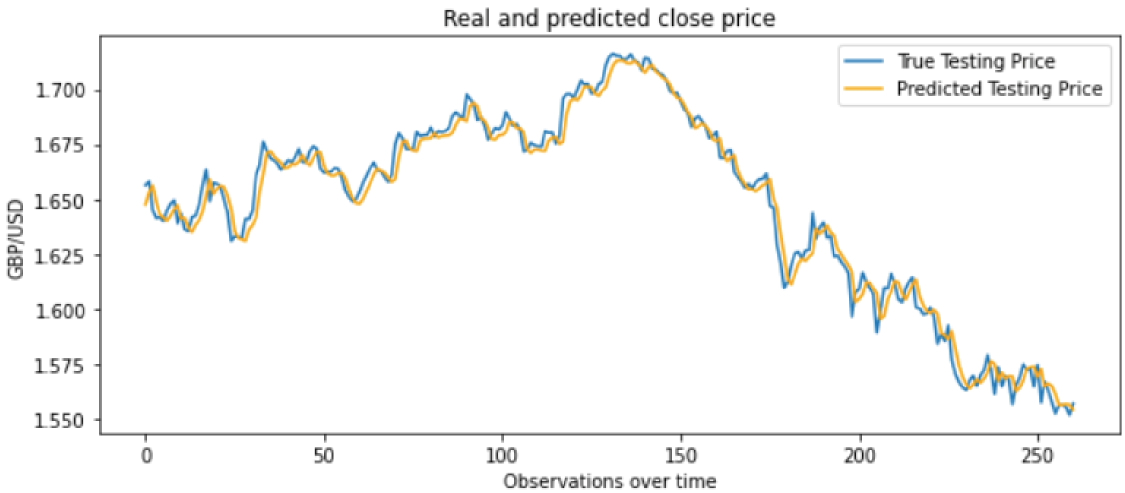

Figure 15. Real and predicted closing price for GBP/USD set 1 - testing set

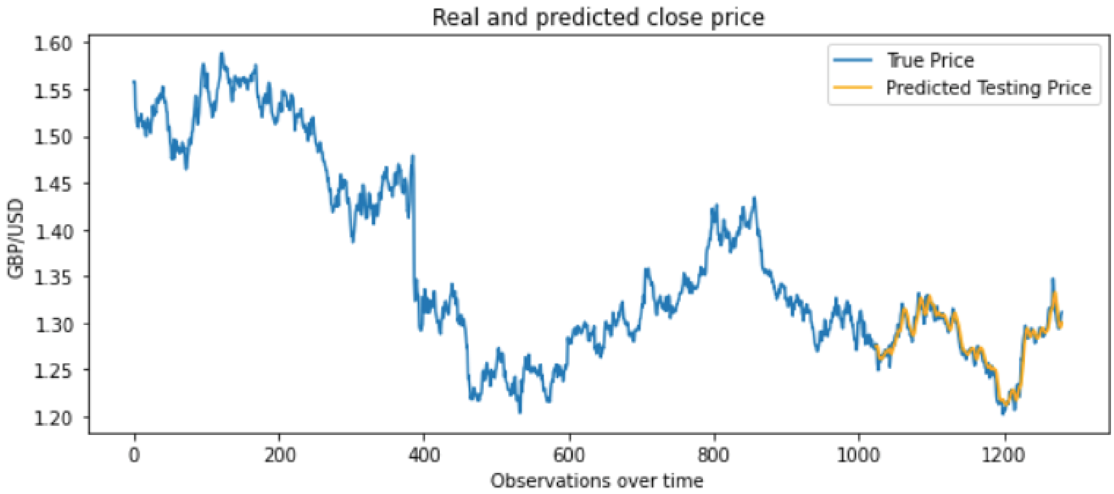

Figure 16. Real and predicted closing price for GBP/USD set 2 – full dataset

Figure 17. Real and predicted closing price for GBP/USD set 2 - testing set

6.2 Results GBP/EUR

Table 10. GBP/EUR set 1 - training and testing evaluation

Training		Testing	
Parameter	**Value**	**Parameter**	**Value**
Number of observations	1043	Number of observations	260
MSE	0.00108016	MSE	0.00054121
MAE	0.02446816	MAE	0.01889606

Table 11. GBP/EUR set 2 - training and testing evaluation

Training		Testing	
Parameter	**Value**	**Parameter**	**Value**
Number of observations	1025	Number of observations	256
MSE	0.00116383	MSE	0.00073512
MAE	0.02552009	MAE	0.02250179

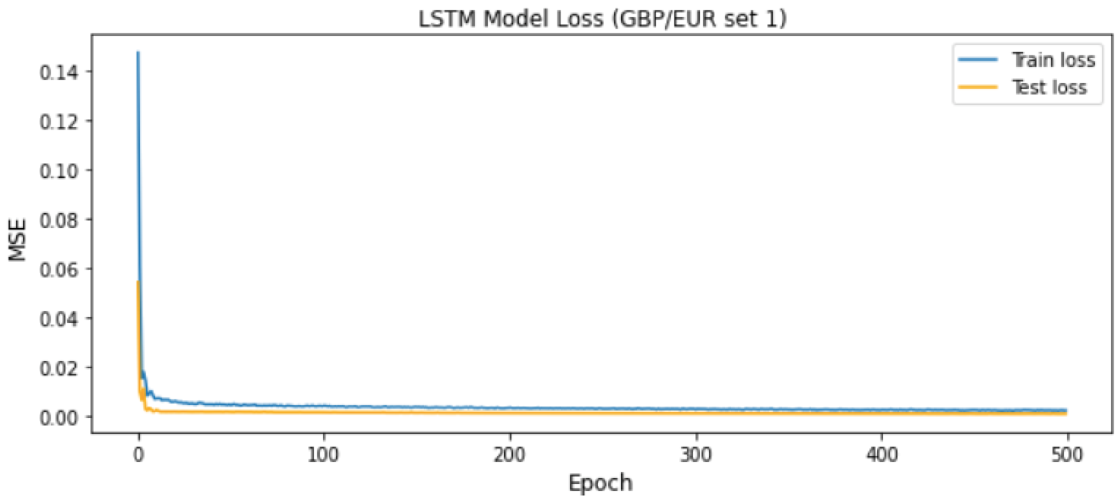

Figure 18. Loss visualization GBP/EUR set 1

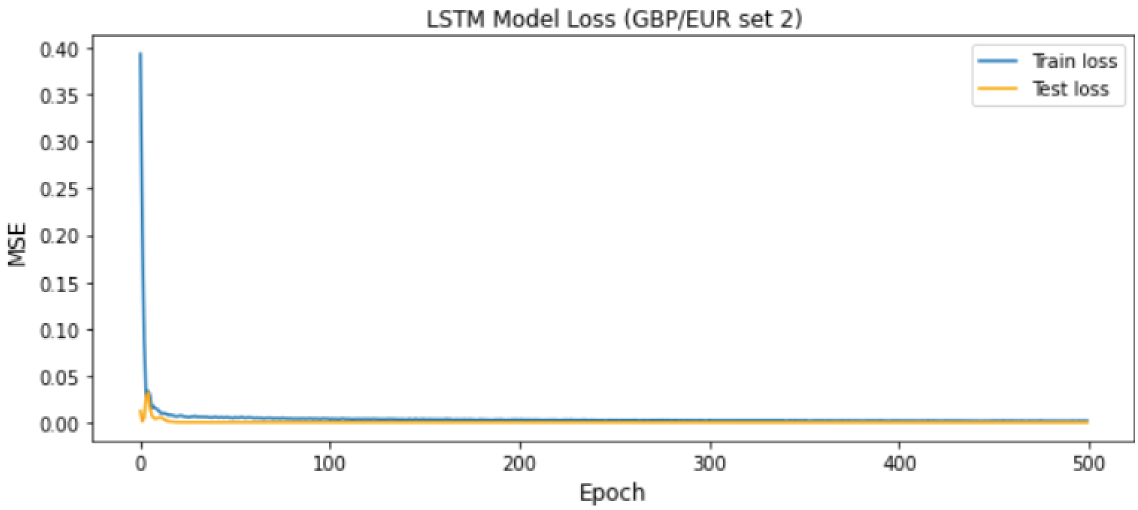

Figure 19. Loss visualization GBP/EUR set 2

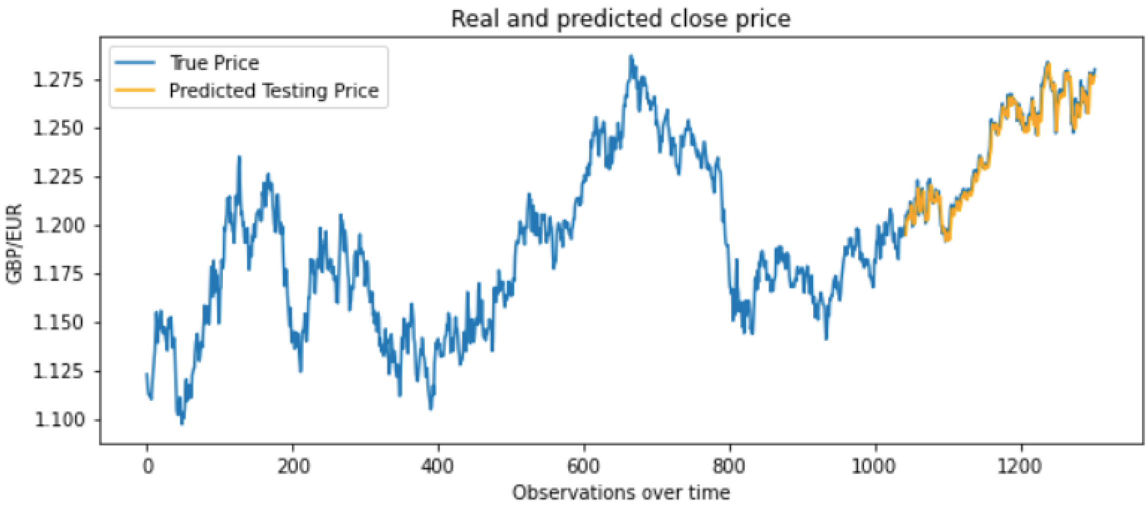

Figure 20. Real and predicted closing price for GBP/EUR set 1 – full dataset

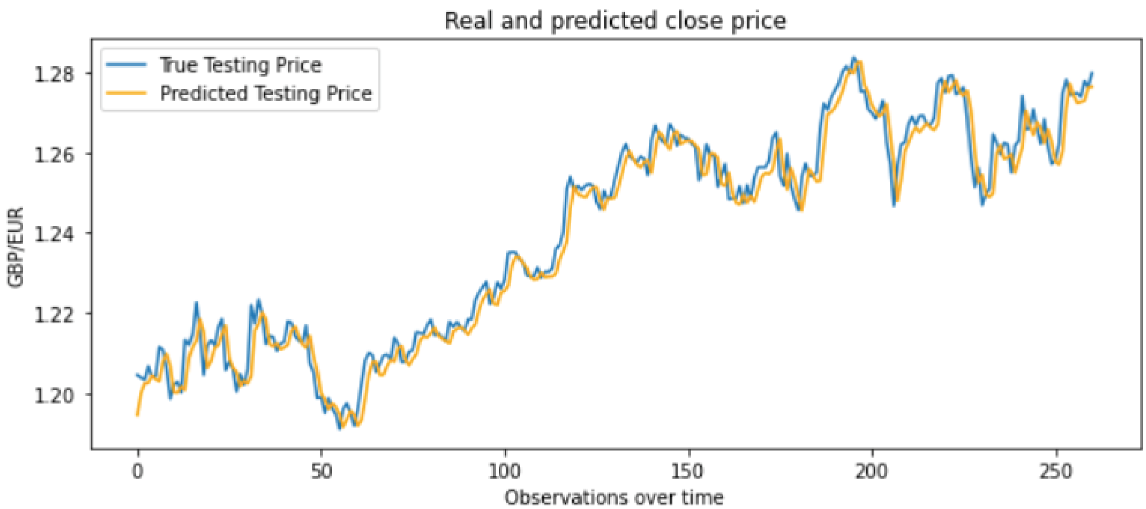

Figure 21. Real and predicted closing price for GBP/EUR set 1 - testing set

Figure 22. Real and predicted closing price for GBP/EUR set 2 - full dataset

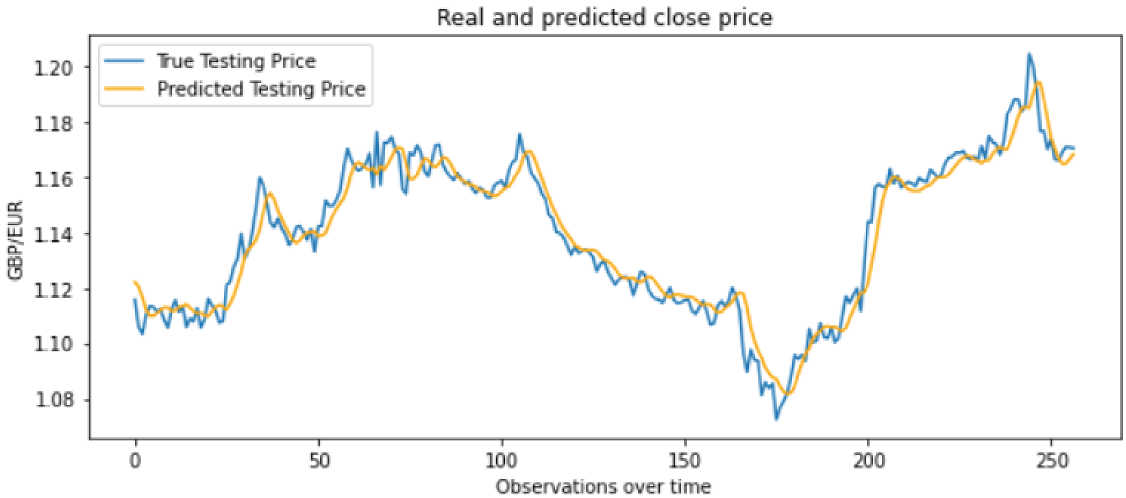

Figure 23. Real and predicted closing price for GBP/EUR set 2 - testing set

6.3 Results GBP/JPY

Table 12. GBP/JPY set 1 - training and testing evaluation

Training		Testing	
Parameter	**Value**	**Parameter**	**Value**
Number of observations	1041	Number of observations	260
MSE	0.00043861	MSE	0.00045872
MAE	0.01366948	MAE	0.01230264

Table 13. GBP/JPY set 2 - training and testing evaluation

Training		Testing	
Parameter	**Value**	**Parameter**	**Value**
Number of observations	1025	Number of observations	256
MSE	0.00053076	MSE	0.00029642
MAE	0.01378887	MAE	0.01084327

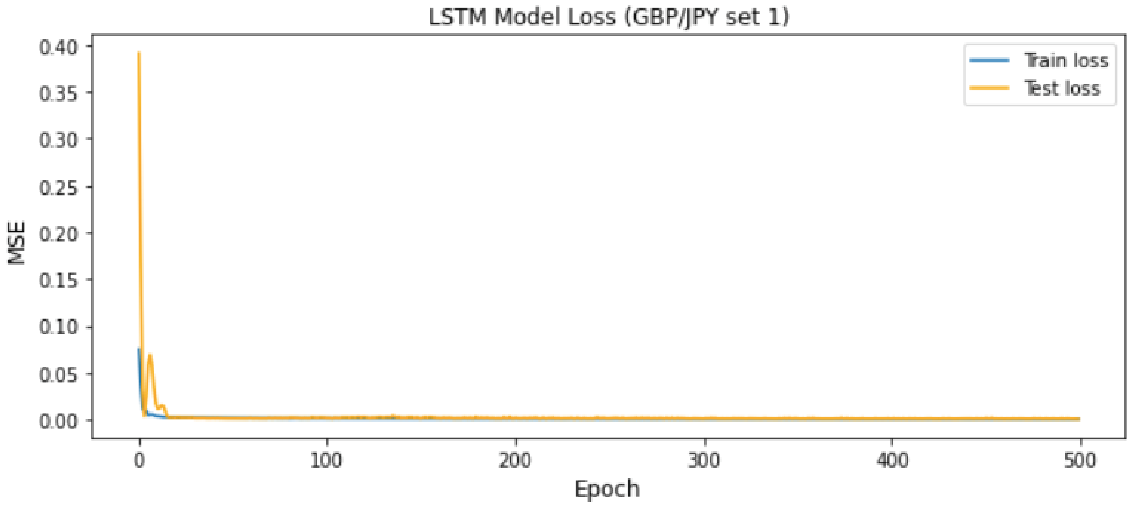

Figure 24. Loss visualization GBP/JPY set 1

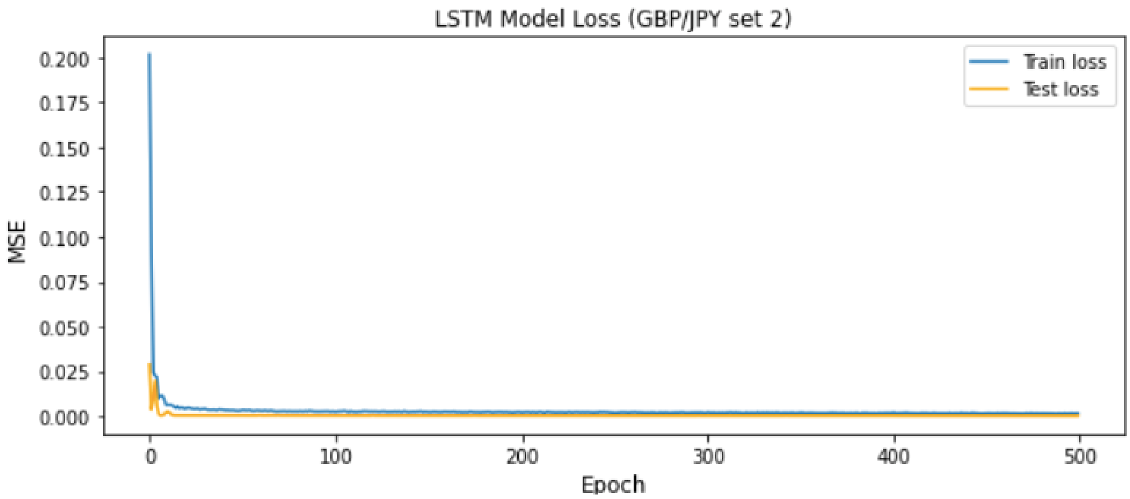

Figure 25. Loss visualization GBP/JPY set 2

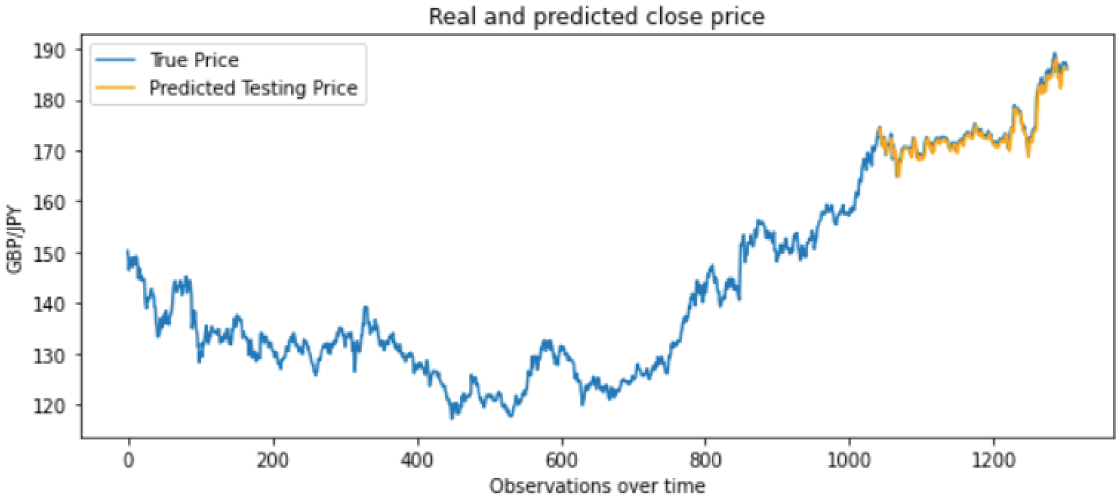

Figure 26. Real and predicted closing price for GBP/JPY set 1 - full dataset

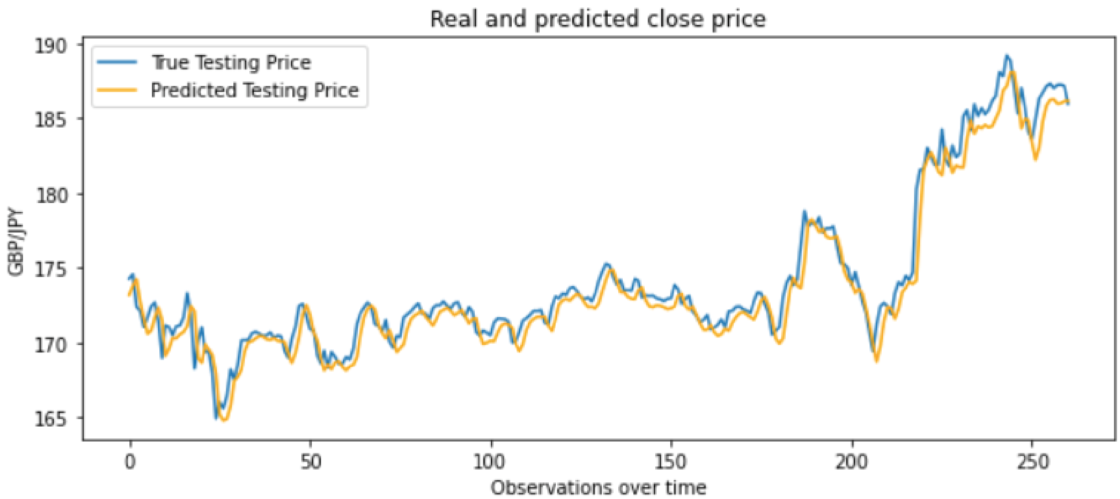

Figure 27. Real and predicted closing price for GBP/JPY set 1 - testing set

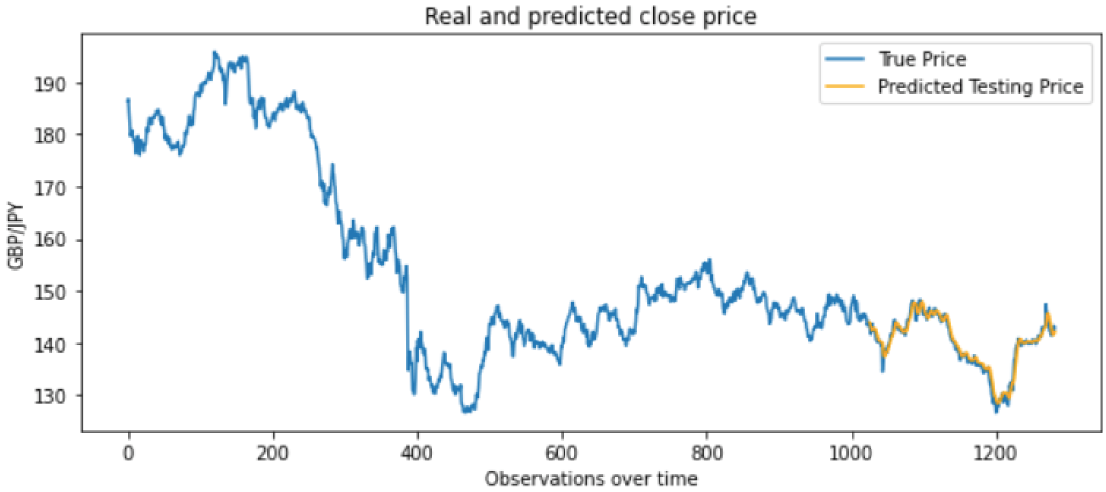

Figure 28. Real and predicted closing price for GBP/JPY set 2 - full dataset

Figure 29. Real and predicted closing price for GBP/JPY set 2 - testing set

6.4 Discussion

This paper has used a recurrent neural network architecture called LSTM for the prediction of three currency pairs – GBP/USD, GBP/EUR, and GBP/JPY. The purpose is to evaluate if there are differences in the model's performance before and after the Brexit referendum. In addition, the purpose is to analyze if the forecasting accuracy differs among the currency pairs. Thus, the purpose is to empirically evaluate if political shocks and overall, the uncertainty caused by political events impact foreign exchange forecasts.

Motivation for using neural networks lies in the previous literature (Zhang et al., 1998; Gradojevic et al., 2006; Khashei et al., 2010; Plakandaras et al., 2017).

As shown in the preceding sections, the conducted LSTM model has been implemented for three different currency pairs and two datasets for each currency. Thus, there are a total of six datasets. The results received from the LSTM model have been presented in the previous sections. The LSTM model's forecasting accuracy with different currencies will now be compared and evaluated using statistical error measures. This paper compares two error measures – the MSE and the MAE. These results will be compared to one another and the comparability of these findings with previous studies will be evaluated. Thus, it will be discussed how the results of this study support previous literature or, alternatively, question the previous literature.

First of all, it can be generally stated that the LSTM model of this study performed relatively well. If analyzing the visualization of the received results, it can be seen from the figures that the test values follow the actual values. These figures (16, 18, 22, 24, 28, 29) are already presented in the previous sections, yet, in order to easily compare these results, Figure 30 brings all these graphs together. The figures on the left-hand side are the series of GBP/USD, GBP/EUR, and GBP/JPY before the uncertainty caused by Brexit (2010-2014). Figures on the right-hand side present the same figures during the Brexit period (2015-2019).

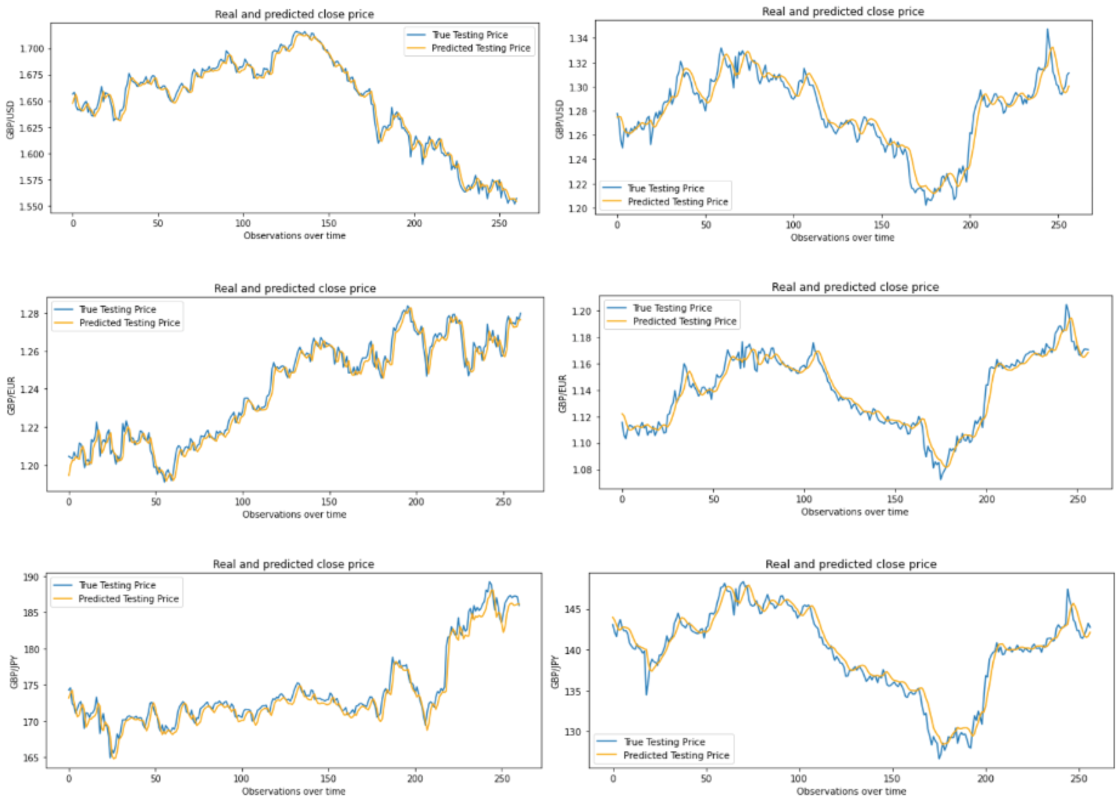

Figure 30. Summary of the visualized results

From the figures, it can be seen that the test values follow the actual values relatively well. However, the test values do not always accurately predict identical values as the actual ones. Particularly the second datasets are unable to predict large fluctuations in real-time. This would suggest that the model's forecasting accuracy decreases during politically unstable times.

When evaluating the performance values, the same effect can be observed. The precise error values of the models are presented in the preceding sections. For comparison purposes, the error values are visualized with bar graphs in Figures 31 and 32. As previously mentioned, the predictive power of a model should be evaluated based on the error values of testing data in order to determine how well it performs with datasets it has not used in the training phase. This way the testing error should be a good indication of how well the LSTM model forecasts. Therefore Figures 31 and 32 presents the out-of-sample Mean Squared Errors and the Mean Absolute Errors for test sets.

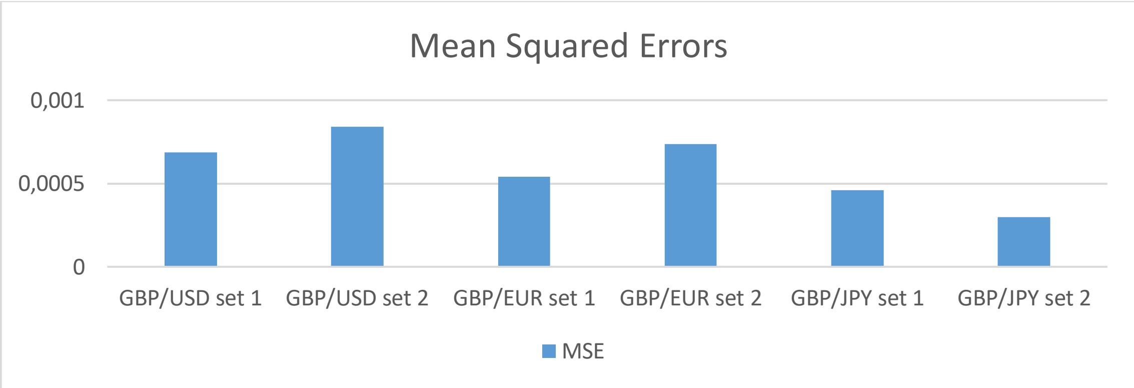

Figure 31. Mean Squared Errors

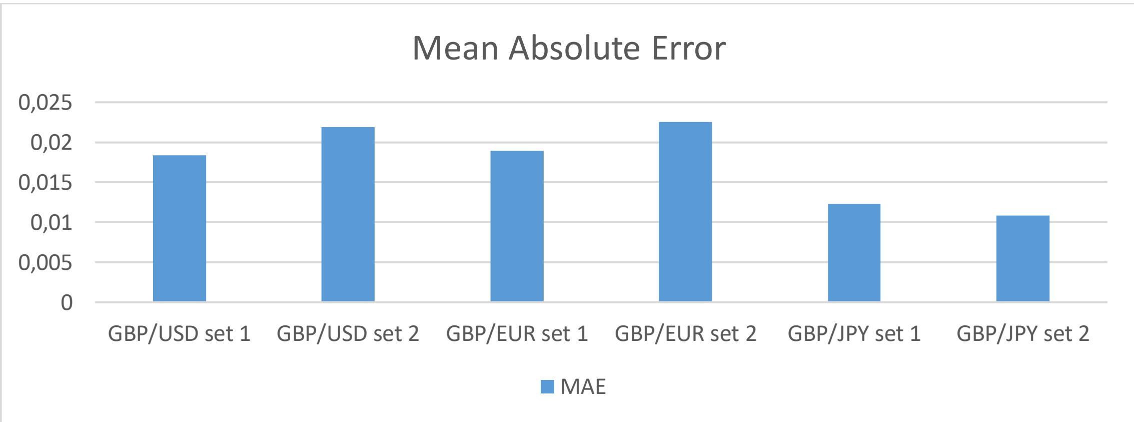

Figure 32. Mean Absolute Errors

The first research hypothesis of this paper states that the LSTM models perform less accurately during politically uncertain times. When evaluating Figures 31 and 32, it can be observed that with both performance values (MSE and MAE), the error value increases with the second dataset for GBP/USD and GBP/EUR. This would imply that the LSTM model's accuracy decreases during times of Brexit-related uncertainty. This conclusion supports previous literature that has found that political uncertainty weakens the accuracy of currency predictions (e.g. Garfinkel, 1999; Bernhard et al., 2002;

Beckmann et al., 2017). Economic agents find it difficult to predict exchange rate fluctuations when markets are unpredictable and volatile.

When analyzing the GBP/JPY, conflicting results are found. Unlike other currencies, the GBP/JPY has smaller forecasting errors after the Brexit referendum. This indicates that the Brexit referendum and the events during the Brexit process have less of an impact on GBP/JPY than they did on the GBP/EUR and GBP/USD. This could be explained by the safe haven phenomenon. Studies have found that the Japanese Yen tends to appreciate when the volatility and policy uncertainty increases in other countries (Ranaldo et al., 2010; Beckmann et al., 2017). Thus, the Japanese Yen is a safe haven currency whose value rises when other currencies value declines and indeed this phenomenon has been noticed after the Brexit referendum. The mean value of the JPY during 2010-2014 was 143,38 whereas during 2015-2019 the mean value was 153,07. This appreciation of the JPY does not fully explain the conflicting results found in this paper. However, this could partially explain why the Japanese Yen behaves in such a contradictory way.

The second research hypothesis of this paper states that the conducted LSTM model is able to forecast all the currencies equally. The results of this study show that the LSTM model is capable of modeling all the exchange rates successfully. However, there are some differences between the exchange rates' error values and thus the second research hypothesis does not hold. For instance, when evaluating the MSE values, the values vary between 0,0004 and 0,0006. The GBP/JPY has the most accurate forecast while the GBP/USD has the lowest. However, with such a simple model and with uncontrolled data, it is difficult to state that the comparison between the currencies would be significant. The main issue is that since exchange rates are the ratio of two different countries, the currency values are automatically impacted by the fluctuation of the other nations' currency. Thus, for instance, the lower forecasting accuracy of GDP/USD could be explained by the additional political uncertainty in the US markets. The election of Donald Trump as the US president in 2016 caused significant reactions in the financial markets. However, as earlier stated, despite the political uncertainty and fluctuation in the financial markets, the LSTM model performed successfully well for all the six datasets as can be seen in the visualizations (Figure 30).

Overall, the results are mainly consistent with previous studies. This study agrees with Dunis et al. (2012) who proved that neural networks are capable of predicting exchange rates. Even during politically unstable times, when the financial markets are volatile, neural network models are able to provide relatively accurate forecasts. This research result shows that with ML method it is possible to form models based on technical analysis which predicts the future values of exchange rates based on historical exchange rate data. This result is in contradiction with the efficient market hypothesis which assumes that the market participants behave rationally, and the markets follow a random walk.

Furthermore, this study supports the view of previous studies that have shown that uncertainty tends to have an impact on forecasting accuracy (e.g. Bernhard et al., 2002; Beckmann et al., 2017). Thus, it is no surprise that the accuracy of the LSTM model tends to decrease after an unexpected political event. To a large extent, the failure of the forecasts can be explained by the behavior of market participants. When there is uncertainty, there is no valid information available for the market participants who could then utilize this information for their decision-making process. Thus, they have to make predictions based on inexact knowledge which again might be biased based on the interpretations of the market participants. (Bloom 2009).

Conclusion

The purpose of this study was to investigate how political uncertainty affects the predictability of foreign exchange rates. An extensive amount of previous literature has studied the impact of uncertainty and unexpected political shocks on financial markets. However, the majority of previous work focuses on the stock markets and general elections such as presidential elections. Also, neural networks have been receiving a lot of attention among researchers. This thesis contributes to the existing literature by evaluating the impact of political uncertainty on foreign exchange rates. No study so far has taken a comprehensive approach to compare the forecasting accuracy of an LSTM model pre and post an unexpected political event. Therefore, this paper examines the forecasting accuracy of the LSTM model before and after the Brexit referendum. This study aims to combine two different branches of research – the behavior of currency markets during politically unstable time and the use of the LSTM model in forecasting exchange rates.

This study is divided into two parts – theory and empirical research. First, the theoretical section presents the concept of political uncertainty. Thus, section 2 helps to understand what political uncertainty is and how political uncertainty has been studied in the previous literature. Sections 3 and 4 provide the basis for the empirical part of this study. Section 3 discusses exchange rates as well as different models that have been used to study and predict foreign exchange rates. These models include for instance the traditional purchasing power parity, interest rate parity as well as the random walk model. These traditional models have been found to be insufficient and therefore the behavioral aspect is also included in the theory section. Section 3 concludes that the previous literature is not able to provide significant results on which model is most accurate for modeling exchange rates.

Section 4, on the other hand, provides understanding of neural networks and their main characteristics. This section provides insight as to why neural networks have been widely utilized due to their unique features such as the ability to process complex nonlinear data. However, neural networks have also their challenges. One of the biggest challenges with recurrent neural networks is the vanishing gradient problem. This challenge has been solved by creating the LSTM model (Hochreiter et al., 1997). This architecture is also utilized in this study. The last part of section 4 provides a comprehensive summary of the previous neural network literature. Previous literature proves that neural networks provide accurate forecasts for financial research.

The empirical part of this paper is implemented in Keras. The primary goal of the LSTM model is to automate the data analysis and make the forecasting process more effective. First, the collected data was preprocessed and then the actual model was built. This model was then used to estimate three currency pairs during the period of 2010 to 2019. The chosen currency pairs were GBP/USD, GBP/EUR, and GBP/JPY. All these datasets were further divided into two groups – the time before and the time after the Brexit referendum – the latter period describing the time of political instability. The model's accuracy was then evaluated with the Mean Squared Error and the Mean Absolute Error.

The results of this study are consistent with previous machine learning studies. The results prove that the conducted LSTM model is able to provide relatively accurate results, which indicates that the efficient market hypothesis would not hold in the foreign exchange markets. Also, the visualizations and relatively low error values of the testing sets show that the predicted values follow the expected values, indicating that the prices do not fluctuate randomly.

The main objective of this research was to study how political uncertainty impacts foreign exchange rates. The empirical results of this paper show that political uncertainty does have an impact on foreign exchange rates. Brexit had a negative impact on the forecasting accuracy of GBP/EUR and GBP/USD, indicating that the forecasting errors increased as the uncertainty related to Brexit appeared. On the contrary, the forecasting accuracy of GBP/JPY increased during the timeframe when Brexit-related events occurred. However, this finding is not entirely illogical since recent research has shown that the Yen is a safe haven currency, implying that it behaves differently from other currencies.

The second research hypothesis of this paper studied how the forecasting accuracy differs among currencies. As previously stated, the model was able to successfully perform for each dataset yet there were some differences in the results. The results indicate that the model performed most accurately with the GBP/JPY while the GBP/USD has the highest loss errors. However, with such a simple model and uncontrolled data, it is difficult to state that the comparison between the currencies would be significant since other factors impact the currencies fluctuation. Thus, it cannot be stated that the lower forecasting accuracy would only be due to Brexit-related events.

One of the most crucial limitation of this study is the problem of currencies interdependence. When statistically analyzing foreign exchange rates, it is often a challenge that the shifts in one currency are reflected in other currencies. Therefore, the evaluation of stock markets would make more sense when the purpose is to study the impact of a specific event. Changes in stock markets can be considered more fixed than the changes in currency markets because the changes in one share is not directly out of the return on the other.

The comparability of the datasets also impacts the reliability of the results. It is not possible to say that the first sets, which in this study are used as the less uncertain time periods, would not be impacted by other political events. Thus even though the focus is to compare how the LSTM model performs before and after the Brexit referendum, it is critical to remember that also the first time periods may have been impacted by other political events. When evaluating the impact of political uncertainty, it is a challenge to distinguish the cause from the effect.

Therefore, it can be concluded that despite the interesting results, this research needs to be further developed. Firstly, from the perspective of political uncertainty, it would be interesting to add political indicators to the study. As noted earlier, the market demands a risk premium and also different indices have been able to model uncertainty. Therefore, the possibilities for further research are almost unlimited. More complex studies could develop a more diverse LSTM model, which adds for instance political indicators such as the EPU index to the model and then compares how well the model performs.

Also forecasting and machine learning implementations are almost infinite. When there already exists a vast variety of different neural network models and new methods are constantly developed, it provides a lot of opportunities for further research. Thus, further studies could compare different neural networks performance and then evaluate which model performs best during times of higher uncertainty. These ideas are just few suggestions for the further research when in reality there are endless ideas to develop this research. This paper is able to provide interesting results and provides comprehensive understanding of political uncertainty and neural networks. Also this study is able to highlight some challenges with neural networks combined with political uncertainty, and provides a lot of possibilities for further research. Thus, this study can be concluded with a citation by Shamah (2012) - “forecasting how currencies will move is still an art rather than a science”.

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