Do Monetary Policy Measures Affect Foreign Exchange Rates during the COVID-19 Pandemic? Evidence from Turkey

Mustafa Tevfik Kartal*
Özer Depren**
Serpil Kılıç Depren***

Abstract

The study examines how foreign exchange (FX) rates in Turkey are affected by the pandemic considering the impacts of monetary policy responses to the pandemic. Selected FX rates are examined by using 10 independent variables containing monetary policy indicators and the pandemic figures. In this context, daily data from February 1, 2019 to August 31, 2020 that consists of the pre-pandemic and the pandemic periods are considered and machine learning algorithms are applied. The findings reveal that the pandemic and monetary policy indicators have a statistically significant and high effect on the FX rates, and the influence of independent factors on the FX rates vary according to the periods. According to the results of the study, it is emphasized the importance of the pandemic and monetary policy measures on the FX rates because monetary policy indicators have a statistically significant and high impact on the FX rates in Turkey for the pandemic period.

Keywords: FX rates; Machine learning algorithms; Monetary policy; Turkey.

JEL Classification: C14; C39; E44; E52; F31; N14.

Öz - COVID-19 Pandemi Sürecinde Para Politikası Tedbirleri Döviz Kurları Üzerinde Etkili mi? Türkiye'den Kanıtlar

Çalışma, pandemiye yönelik para politikası tedbirlerini dikkate alarak Türkiye'de döviz kurlarının pandemiden nasıl etkilendiğini incelemektedir. Seçilmiş döviz kurları, para politikası göstergeleri ve pandemi rakamlarını içeren 10 bağımsız değişken kullanılarak incelenmiştir. Bu kapsamda, pandemi öncesi ve pandemi dönemlerinden oluşan 1 Şubat 2019 ve 31 Ağustos 2020 arasındaki günlük veriler dikkate alınmış ve makine öğrenmesi algoritmaları uygulanmıştır. Bulgular, pandemi ve para politikası tedbirlerinin döviz kurları üzerinde istatistiksel olarak anlamlı ve yüksek bir etkiye sahip olduğunu ve bağımsız değişkenlerin döviz kurları üzerindeki etkisinin dönemlere göre farklılık gösterdiğini ortaya koymaktadır. Çalışmanın sonuçlarına göre, para politikası tedbirlerinin pandemi döneminde için Türkiye'deki döviz kurları üzerinde istatistiksel olarak anlamlı ve yüksek bir etkiye sahip olması nedeniyle, pandemi ve para politikası tedbirlerinin döviz kurları üzerindeki önemi vurgulanmaktadır.

Anahtar Kelimeler: Döviz kurları, Makine öğrenmesi algoritmaları, Para politikası, Türkiye.

JEL Sınıflandırması: C14; C39; E44; E52; F31; N14.

* Corresponding Author, Borsa İstanbul, Financial Reporting and Subsidiaries Directorate - E-mail: mustafatevfikkartal@gmail.com - ORCID ID: https://orcid.org/0000-0001-8038-8241.

** Yapı ve Kredi Bank, Customer Experience Directorate - E-mail: ozerdepren@gmail.com - ORCID ID: https://orcid.org/0000-0001-8948-5742.

*** Yildiz Technical University, Department of Statistics - E-mail: serkilic@yildiz.edu.tr - ORCID ID: https://orcid.org/0000-0003-4737-7131.

Article Received: 01.01.2021 Article Accepted: 15.07.2021 DOI: http://dx.doi.org/10.46520/bddkdergisi.987416

1. Introduction

Emerging countries aim to be developed countries while developed countries try to sustain their economic development via growth. The sustainability of economic growth is much more significant especially in emerging countries since they need more funding sources and stability by realizing much more commercial activities. Hence, the economic development of countries is mainly affected by the development and growth of the financial and real sectors (Kartal et al., 2020).

Financial sectors are very crucial because developments in the financial area have significant effects on economic and financial indicators and the real sector as well. There are a variety of economic and financial indicators that are quite crucial for economies. Credit default swap (CDS) spreads, economic growth rate, inflation, interest rates, unemployment, and the level of stock market index are some of these indicators that each emerging country should focus on for economic growth and development. That is why because each of these indicators has a significant role and functions in economies (Orhan et al., 2019).

Some indicators reflect the riskiness, soundness, and vulnerability of countries to shocks. They affect economies by affecting price stability, financial stability, and macroeconomic stability. For this reason, achieving and sustaining stability in these indicators is important (Kartal, 2020). In this context, FX rates takes place among the most important indicators for countries because changes in FX rates affect other indicators like inflation, interest rates, foreign investments including direct and portfolio, etc. Emerging countries aim to decrease inflation and interest rates while increasing foreign investments (Karikari, 1992; Zengin et al., 2018).

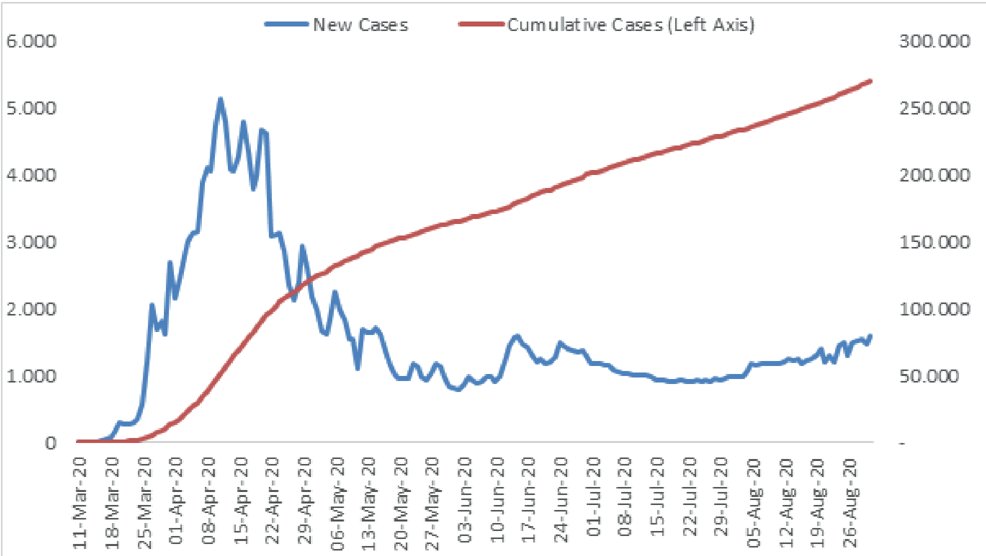
FX rates show mainly the value of a currency against other currencies. Generally, the values of national currencies are measured against FX rates that are mostly used and evaluated as reserve money. Although there are various FX rates like Sterling, Frank, Yen, Ruble, and Yuan, United States (US) Dollar (USD), and Euro (EUR) are the main FX rates that are highly used in most countries including Turkey (Khan et al., 2019; Atmaca & Karadaş, 2020). Therefore, the progress of the value of the national currency is examined against USD and EUR most of the time.

According to the literature, FX rates can be affected by various factors that are either global or national (macro and micro) indicators (Kartal et al., 2018). Therefore, effective factors on FX rates should be managed, directed, and followed up strictly by regulatory authorities to make FX rates stable and preventing the negative effects of FX rates on economies so that economic growth and development can be stimulated and sustained. Global variables should be taken into account that the beginning point should be national (macro & micro) indicators. In this way, emerging countries can benefit from stable FX rates.

Besides global and national factors that are effective, a recent issue, which is called COVID-19, should be considered in terms of the progress of FX rates. The COVID-19 emerged from China, spread to other countries in the following short time, and became pandemic on as of March 11, 2020 (World Health Organization-WHO, 2020a). Hence, all countries have been facing the COVID-19 pandemic crisis.

There are millions of confirmed cases, and thousands of deaths due to the pandemic (WHO, 2020b). The US, India, Brazil, and France are the most affected countries by the pandemic (WHO, 2020b). Also, as an important emerging country, Turkey is affected deeply from the pandemic. The first confirmed case and the death due to the pandemic occurred in 2020 March in Turkey (Ministry of Health of Turkey-MHT, 2020). Figure 1 shows the trend of the new and cumulative cases due to the COVID-19 pandemic.

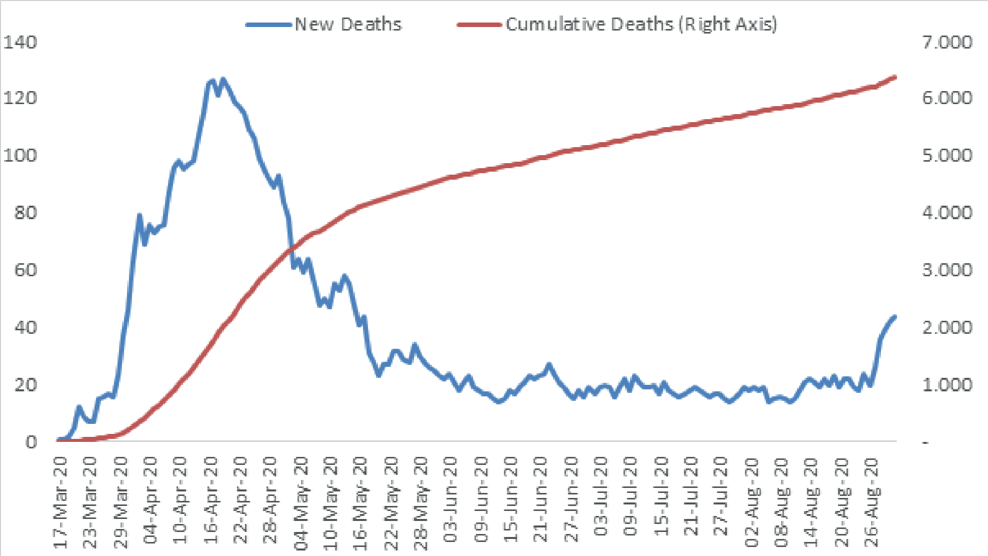
Figure 1. The Trend of the COVID-19 Pandemic New and Cumulative Cases in Turkey



Source: MHT (2020).

As Figure 1 shows, the first confirmed case was determined on March 11, 2020. There are nearly 270 thousand confirmed cases as of August 31, 2020, and the number of new cases has begun to increase recently. Besides, Figure 2 shows the trend of the new and cumulative deaths due to the COVID-19 pandemic.

Figure 2. The Trend of the COVID-19 Pandemic New and Cumulative Deaths in Turkey



Source: MHT (2020).

As Figure 2 shows, the first death occurred on 03.17.2020. There are 6.4 thousand deaths as of August 31, 2020, and the number of deaths has begun to increase recently. By considering the figures regarding new cases and new deaths, it can be said that the pandemic will continue in Turkey for a while and it will continue to create impacts on the Turkish economy.

With the spreading of the COVID-19 to countries, and continuing effects that cause new cases and deaths, negative developments on economic and financial have been seen and such indicators including FX rates have been deteriorating. Therefore, countries, where the pandemic continues, have been applying various measures so that the negative effects of the pandemic can be limited (Akhtaruzzaman et al., 2020). Mobility restrictions, lockdowns, quarantines, closures, and increasing funding provided by central banks are some measures that are frequently applied (Depren et al., 2021). Although various measures have been applied to prevent the spreading of the COVID-19, some negative effects have occurred on the economy, stock market indices, unemployment, welfare loss, etc. (Kartal, 2020; Phan & Narayan, 2020; Yılmazkuday, 2020).

FX rates for USD and EUR in Turkey have been increasing recently against Turkish Lira (TL). Also, there is a pandemic reality that should be taken into account in analyses of economic issues like FX rates. Moreover, other global and national factors like oil prices, gold prices, CDS spreads can be influential on FX rates. Even, applied measures, which countries have been applying against the pandemic, can be included in analyses. Negative developments in these issues can cause an increasing effect on FX rates. Therefore, various indicators as well as the COVID-19 pandemic and measures applied should be considered.

In summary, the COVID-19 pandemic has been continuing in Turkey since March 11, 2020, the number of cumulative cases and deaths due to the pandemic has been at serious levels, and the most used FX rates (i.e. USD and EUR) have been increasing and are quite high with regard to the pre-pandemic period. In addition to the fiscal policy actions of central governments, the Central Bank of the Republic of Turkey (CBRT) has been applying a variety of measures that provide the existence of much more money in the market. Although it is aimed to keep funding channels open with monetary policy measures that provide much more money in the market, unfortunately, they cause an increase in demand for alternative investment instruments. Such an environment can also cause an increase in FX rates. Hence, we expect that both the pandemic and monetary policy measures can affect FX rates and the importance of effective variables on FX rates can vary according to the period. That is why because the pandemic has caused a deep effect on almost every side of economies and financial markets. Moreover, there has been a high amount of national currency liquidity and low interest rates for a while by applying various monetary policy measures. All these caused a thought that the pandemic and monetary policy measures can have an effect on FX rates.

Increase and rapid changes in FX rates can damage the Turkish economy because Turkey has a high level of FX-denominated debt, export of Turkey depends heavily on imports of intermediary goods, and Turkey needs much more foreign investments including direct and portfolio for supporting economic growth and development. Therefore, understanding the relationship between the pandemic, monetary policy measures and FX rates are significant in order to develop appropriate policies. By considering these realities, an analysis examining the effects of monetary policy responses as well as other determinants on the FX rates in both pre-pandemic and pandemic times and whether the effects of influential factors vary according to period by including the recent data can provide contributions. Besides, the results of such an analysis can provide insights to regulators in developing policies to take measures for preventing the negative effects of FX rates in the pandemic times on FX rates. In this way, FX rates can be stabilized and Turkey can benefit from the stable FX rates in various ways such as attracting much more foreign investments. Such a development can be beneficial for the economic growth and development of Turkey in terms of money markets, financial markets, and macroeconomic indicators.

This study aims to present the importance of monetary policy measures and the COVID-19 pandemic as well as other selected variables on the main FX rates in Turkey because there is a deep relationship (and balance) among alternatives like FX rates, stock market, etc. and changes of FX rates can affect the allocation among financial instrument alternatives. In the study, 10 independent variables and the most recent daily data from February 1, 2019, to August 31, 2020, are used and the Random Forest and the Neural Networks machine learning algorithms are performed to examine the selected FX rates (USD and EUR) analyzed. The examination focuses on Turkey since FX rates in Turkey have been increasing rapidly. The results prove that the pandemic and monetary policy indicators have a statistically significant and high effect on FX rates. Also, the influence of independent factors on USD/TL and EUR/TL vary according to the period.

The main contributions of the study are to focus on an emerging market example (i.e. Turkey), consider USD and EUR as FX rates that have an increasing trend recently, adopt machine learning algorithms that are rarely used to examine FX rates and provide quite high prediction results, also consider the effects monetary policy responses applied upon the FX rates. Besides, the study includes Apple mobility data to examine FX rates for the first time in the COVID-19 pandemic times, and uses relatively long daily data from February 1, 2019 to August 31, 2020. The most significant finding is that the COVID-19 and monetary policy indicators have a significant effect on FX rates in Turkey.

The remaining parts of the study are organized as follows. Section 2 presents a literature review including variables. Section 3 explains the data used and the method performed. Section 4 explains the empirical results. Section 5 presents a findings-based discussion and conclusion.

2. Literature Review

The impacts of the COVID-19 pandemic on various indicators such as FX rates, gold, stock market, interest rate, etc. has been increasingly examined since the emergence of the pandemic. Also, the pandemic has still high effects on economies. However, studies that examine the effects of various indicators on FX rates in the pandemic times are very limited. On the other hand, various studies examine the effects of factors on FX rates.

We focus on mainly monetary policy measures and aim to examine whether these measures effective on the FX rates in Turkey because almost all countries including Turkey have been taking precautions to reduce negative impacts of the pandemic (Kartal, 2020; Kartal et al., 2021a; Kartal et al., 2021b). Although there are various monetary policy indicators, we prefer to using 3 main indicators as the amount of money issued by CBRT, the amount of securities bought by CBRT, and the weighted average cost of funding (WACF) (Kartal, 2020). We do not include one-week repo interest rate as a variable because times series data for this does not exist. Also, we do not include the total funding amount as a variable since the total funding amount provided by swap transactions is not publicly available. Hence, using either one-week repo interest rate or total funding amount as a monetary policy indicator cannot be the right choice. While the amount of money issued and the amount of securities bought by CBRT are expected to make an increasing effect, WACF is expected to make a decreasing effect on FX rates.

Besides, the COVID-19 pandemic indicators are included because the study examines the development of the selected FX rates in pandemic times. In this context, the number of new cases and new deaths resulting from the pandemic is selected as variables (Kartal et al., 2020). Because we think that these figures reflect the pandemic much better than using cumulative figures.

Moreover, as an innovative approach, we include mobility data as a potential determinant of FX rates. There are mobility data issued by Google and Apple. Some studies like Wang & Yamamoto (2020), Wielechowski et al. (2020), Zhu et al. (2020), Kartal et al. (2021b), Nouvellet et al.(2021), Yılmazkuday (2021) consider Google mobility data. On the other hand, Kartal et al. (2021a), Kartal et al. (2021b), Nouvellet et al. (2021) use Apple mobility as a variable in their studies. In this study, we prefer to use Apple data by considering that there is a high correlation between Apple and Google mobility data, these correlation result high representation of the mobility of the society. Also, we use walking mobility instead of driving mobility because it is much more important for the spreading of the pandemic.

It is expected that the pandemic has spread much more rapidly as mobility increases. Hence, an increase in mobility reflects the probability of the spreading of the pandemic and hence the occurrence of negative effects on FX rates via different economic and financial indicators and possible effects of measures taken on the mobility. Hence, we expect that these three variables related with the COVID-19 pandemic make an increasing effect on FX rates in Turkey because increases in these indicators would cause the spreading of the pandemic and increase uncertainty and volatility that all cause an increase in FX rates in turn.

In addition, we include gold prices, oil prices, CDS spreads, main stock market index (XU100 index for Turkey) as control variables in the analysis.

Gold prices and oil prices would be related to rates since they are substitute investment instruments. Sjaastad (2008) and Gangopadhyay et al. (2016) consider gold prices and define a positive correlation between FX rates and gold prices. Hence, a positive correlation is expected between FX rates and gold prices. Similar to gold prices, a positive relationship is also expected with oil prices because oil prices and FX rates are both alternative financial investment instruments.

As an indicator reflecting the riskiness of countries, CDS spreads can be related to FX rates. Ertuğrul & Öztürk (2013), Fontana & Scheicher (2016), Hassan et al. (2017), and Kartal (2020) consider CDS spreads in their studies and determine a positive nexus between FX rates and CDS spreads. 5-year CDS spreads are considered because this maturity is the most liquidity one (Hasan et al., 2016).

The main stock market index is another factor that is possible to be related to FX rates. Clark & Berko (1997), Jebran & Iqbal (2016), and Demir (2019) consider stock market indices in their studies and determine a negative nexus between FX rates and stock market indices. Therefore, we expect a negative nexus between FX rates and the XU100 index.

Totally 10 independent variables are included in the analysis as a result of the literature review. Table 1 summarizes the details of the variables.

Table 1. Details of Variables

Group	Variable	Symbol	Description	Relation	Data
Dependent	USD/TL FX*	USDTL	USD/TL FX rates	N/A	Bloomberg
	EUR/TL FX*	EURTL	EUR/TL FX rates	N/A	Bloomberg
Global	Oil Prices	OIL	Brent crude oil prices (USD)	+	Bloomberg
	Gold Prices	GOLD	Gold prices per ounce (USD)	+	Bloomberg
National	CDS Spreads	CDS	Turkey's 5-years sovereign USD CDS spreads	+	Bloomberg
	BIST Main Index	XU100	XU100 price index	-	Bloomberg
	CBRT Emission Amount**	EMISSION	Amount of money issued by CBRT	+	CBRT
	CBRT Securities Amount**	CBRT_SEC	Amount of securities bought by CBRT	+	CBRT
	CBRT WACF**	WACF	CBRT weighted average cost of funding (%)	-	CBRT
COVID-19	COVID-19 Cases	CASE	Number of new cases due to the COVID-19	+	MHT
	COVID-19 Deaths	DEATH	Number of new deaths due to the COVID-19	+	MHT
	Mobility	WALK	Walking mobility of Apple users	+	Apple

*: dependent variables; ** monetary policy indicators.

In addition to these variables that are included, some other variables like confidence index, foreign trade, industrial production index, inflation, unemployment, etc. have been used to examine the nexus with the FX rates. But, including such variables requires using low frequent data like monthly or quarterly, and examining the reaction of FX rates to monetary policy measures in the pandemic times requires using high-frequency data like daily. For this reason, such variables cannot be included in this study.

Moreover, it is seen that generally econometric techniques are used to examine FX rates. On the other hand, examining FX rates with new or rarely used techniques like machine learning approaches by taking into account the pandemic and precautions of the monetary policy taken by central banks can contribute to the literature.

3. Data and Methodology

3.1. Data

In this study, it is preferred to consider USD/TL FX rate and EUR/TL FX rate as dependent variables by following the studies of Kartal et al. (2018), Khan et al. (2019), and Atmaca & Karadaş (2020). That is why because these are the most FX rates used in Turkey.

The data from February 1, 2019 to August 31, 2020 is covered in the study. Data regarding the pandemic period is started from March 11, 2020 because the first case due to the pandemic was confirmed on this date. Moreover, all data is split into two parts, which are the pre-pandemic period (February 2, 2019-March 10, 2020) and the pandemic period (March 11, 2020-August 31, 2020).

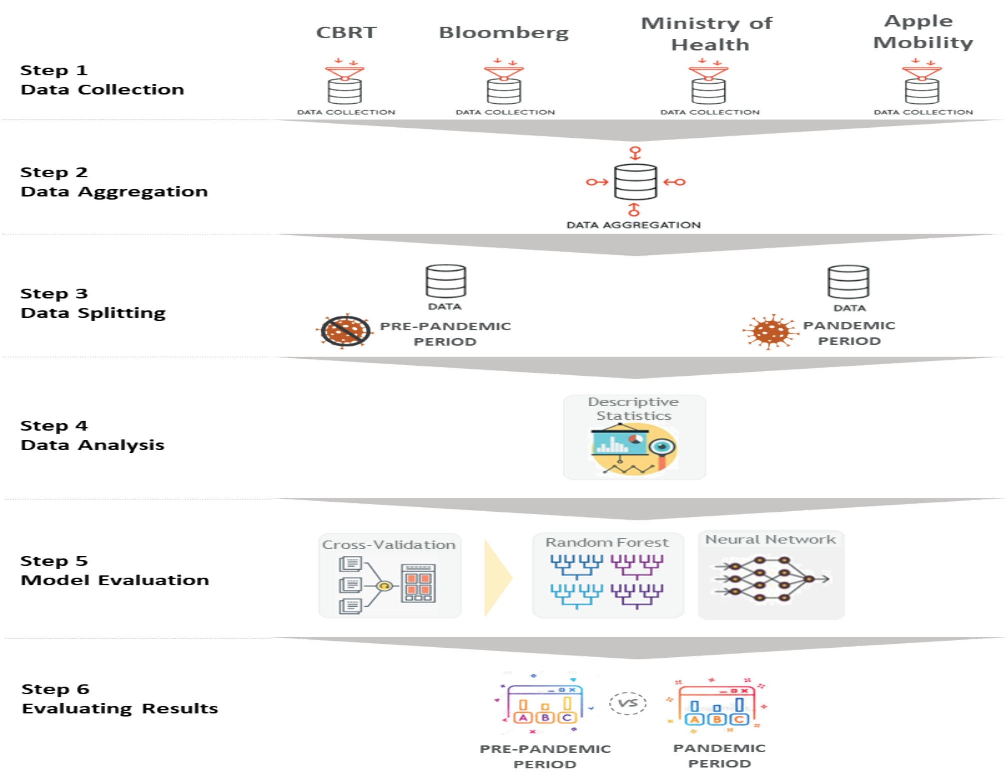
The daily observation of variables is obtained from Bloomberg (2020), CBRT (2020), MHT (2020), Central Securities Depositories of Turkey (CSD, 2020), and Apple (2020). Daily data are used because of investigating the reaction of the selected FX rates to the pandemic and monetary policy measures and this requires working with high-frequency data.

3.2. Methodology

3.2.1. Preprocess of the Data

The six-step process is evaluated in this study as visualized in Figure 3.

Figure 3. The Working Flow of the Analysis Process



Source: Authors' construction.

Based on the literature, the variables that can significantly influence to USD/TL FX rate and EUR/TL FX rate are obtained from four different sources and combined to create one aggregated dataset of the model construction flow in the first two steps, respectively. The aggregated dataset is divided into the pre-pandemic period and the pandemic period in the third step. The descriptive statistics and the basic characteristics of the variables are given in the fourth step of the flow. In the fifth and sixth steps, Neural Networks and Random Forest algorithms with a cross-validation approach are evaluated and results are interpreted with performance criteria.

3.2.2. The Framework of the Algorithms

Nowadays, machine learning models have been used in various fields such as finance, education, tourism, and image processing to solve real-life problems. The Neural Networks and the Random Forest algorithms which do not have strict assumptions and produce robust estimations even if the presence of outliers, are the frequently used algorithms in these areas.

The details of the Random Forest can be described as (Wiener & Liaw, 2002):

- Determination of the number of trees to be built (n_{tree}).
- Determination of the number of the factors to be included in every split of the node (m_{try})
- Finding the significant factors to prune the tree.
- Aggregation of the results to reach the final tree.
- The algorithm process of the Neural Networks is as follows (Towell & Shavlik, 1993):
- Determination of the initial weight for the neurons
- Prediction of the dependent variable using the neural networks
- Calculation of the error function (the gap between the actual and the prediction of the dependent variable)
- Run the Backpropagation, which is a step to change the weights based on the error function.
- The run algorithm from steps 1 to 4 until the minimum acceptable level of error reaches.

3.2.3. Model Building

Once creating a machine learning model, overfitting or underfitting problems are the most important problems to be solved. In the literature, the dataset is split into two, which are training and testing datasets, to overcome the overfitting/ underfitting problems. In the training dataset, the model is enhanced while the testing dataset is used to test the model created in the training dataset. There are many techniques to reach this aim. In this study, a repeated cross-validation approach is used. The steps of this approach are as follows (Hastie et al., 1996):

Based on the dependent variable distribution, the dataset is separated into k equal size, randomly.

k-1 sub-samples are defined as training datasets and one sample is defined as a testing dataset.

k estimations are used to reach the final estimation.

In order to final estimations, the process from the first step to the third step is repeated t times.

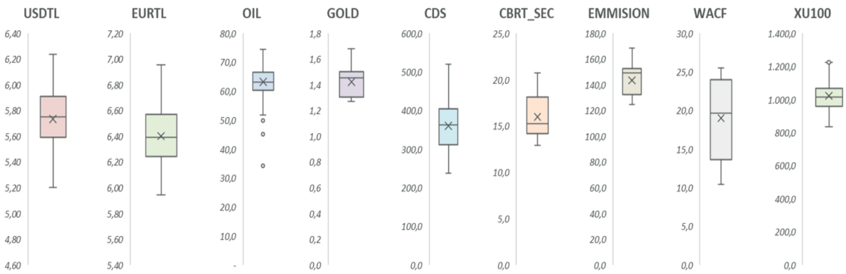
In this study, 5-fold cross-validation with a 5-repeat approach is used to build a robust model.

4. Empirical Analysis

4.1. Preliminary Data Analysis

The descriptive statistics and the Box & Whisker Plots, which is a proper way to analyze the data, are prepared for both the pre-pandemic and the pandemic periods in Figure 4 and Figure 5, respectively.

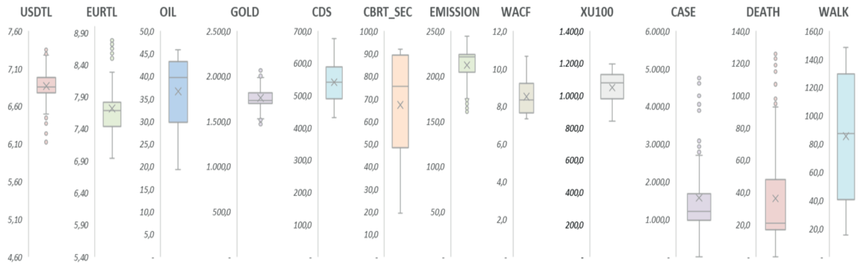
Figure 4. Descriptive Statistics of the Pre-Pandemic Period



	USDTL	EURTL	OIL	GOLD	CDS	CBRT_SEC	EMMISION	WACF	XU100
Mean	*5.73*	*6.40*	*63.27*	*1424.46*	*361.09*	*16.01*	*143.50*	*19.04*	*1022.97*
Standard Deviation	*0.24*	*0.23*	*5.11*	*111.80*	*68.21*	*2.19*	*10.82*	*5.43*	*89.41*
Coefficient of Variation	*4.21*	*3.55*	*8.07*	*7.85*	*18.89*	*13.68*	*7.54*	*28.53*	*8.74*
Minimum	*5.20*	*5.94*	*34.36*	*1270.69*	*237.85*	*12.95*	*124.73*	*10.46*	*836.75*
Q_{25}	*5.59*	*6.24*	*60.49*	*1306.27*	*311.68*	*14.24*	*132.52*	*13.69*	*961.42*
Median	*5.75*	*6.39*	*63.21*	*1455.26*	*363.20*	*15.25*	*149.41*	*19.64*	*1017.21*
Q_{75}	*5.91*	*6.57*	*66.52*	*1504.78*	*403.46*	*18.17*	*152.53*	*24.00*	*1065.88*
Maximum	*6.24*	*6.95*	*74.57*	*1680.47*	*520.06*	*20.73*	*168.45*	*25.50*	*1235.56*

In Figure 4, it can be observed that EUR/TL shows a greater average and median than USD/TL; however, the standard deviation of EUR/TL presents lower than USD/TL. Since Brent crude oil prices (OIL) have several outliers, the average and median values are very close. Moreover, the Coefficient of Variation (CV) of CBRT weighted average cost of funding (WACF) is relatively higher than others. To sum up, the standard deviation and coefficient of variation of all factors except WACF are relatively lower, thus it can be said that distributions of the factors in the pre-pandemic period are stable.

Figure 5. Descriptive Statistics of the Pandemic Period



	USDTL	EURTL	OIL	GOLD	CDS	CBRT_SEC	EMISSION	WACF	XU100	CASE	DEATH	WALK
Mean	6.87	7.72	36.64	1760.89	541.74	67.29	212.32	8.52	1050.88	1573.46	36.24	85.58
Standard Deviation	0.26	0.48	7.78	131.12	57.52	24.96	20.12	0.92	98.98	1111.23	32.90	42.35
Coefficient of Variation	3.85	6.20	21.23	7.45	10.62	37.09	9.48	10.82	9.42	70.62	90.79	49.49
Minimum	6.13	6.94	19.33	1471.24	432.00	19.27	160.55	7.34	842.46	0.00	0.00	15.66
Q_{25}	6.78	7.44	29.94	1696.65	492.00	48.76	204.86	7.66	981.80	972.00	17.00	40.61
Median	6.86	7.69	39.79	1730.27	541.00	75.60	221.24	8.34	1080.97	1212.00	21.00	87.46
Q_{75}	6.98	7.82	43.28	1810.42	588.00	89.42	224.19	9.22	1126.80	1639.00	48.00	129.56
Maximum	7.38	8.79	45.86	2063.54	677.00	92.01	244.24	10.65	1195.67	4801.00	126.00	148.62

The descriptive statistics and Box & Whisker plots of the factors for the Pandemic period are given in Figure 5. In the Pre-Pandemic Period, USD/TL and EUR/TL have many outliers and the standard deviation of EUR/TL is significantly higher than the Pre-Pandemic Period. Also, Gold prices per ounce (GOLD), the Amount of money issued by CBRT (EMISSION), the number of new cases resulting from COVID-19 (CASE), and the number of new deaths resulting from COVID-19 (DEATH) have several outliers in the pandemic period and the coefficient of variation of the amount of securities bought by CBRT (CBRT_SEC) is three times higher than the Pre-Pandemic Period. Moreover, the coefficients of variation values of CASE, DEATH, and walking mobility of Apple users (WALK) are significantly higher than others.

4.2. Performance Evaluation Criteria for Prediction

In general, R^2, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) statistics are used to measure the performance of the model that has the continuous dependent variable. In this research, these criteria are given in Table 2 for the Random Forest and Multilayer Perceptron algorithm.

Table 2. Model Performance Criteria

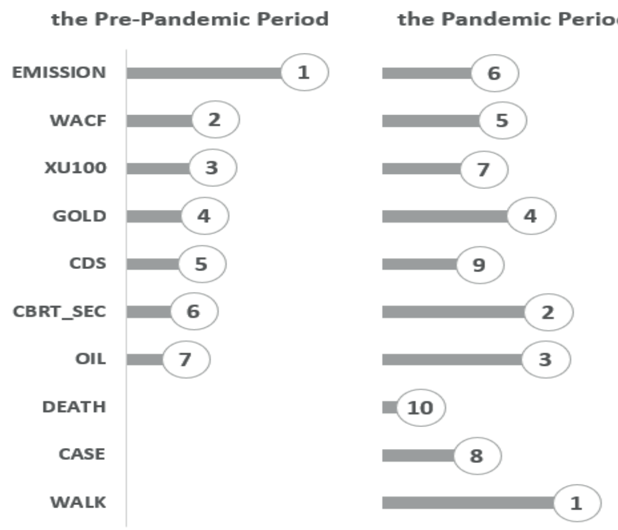
		The Pre-Pandemic Period			The Pandemic Period		
Target Variable	**Method**	**R^2**	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**
USD/TL	Random Forest	94.8%	0.0557	0.0406	94.7%	0.0632	0.0431
	Multilayer Perceptron	91.6%	0.2936	0.2232	93.7%	0.2568	0.1877
EUR/TL	Random Forest	92.6%	0.0631	0.0448	97.3%	0.0823	0.0594
	Multilayer Perceptron	85.7%	0.3849	0.2777	95.3%	0.1745	0.1397

Based on Table 2, the R^2 values are higher than 80% in the pre-pandemic period and higher than 90% in the pandemic period, which is very high. Thus, all models can be used to interpret the results. However, according to the goodness of fit criteria, the Random Forest algorithm, which has lower RMSE and MAE and higher R2 values, is used to explain the results in detail for both the pre-pandemic and the pandemic periods.

4.3. Analysis Results

Feature importance of the Random Forest in the pre-pandemic and the pandemic periods for USD/TL is given in Figure 6. With this analysis, factors can be ranked according to their importance level. Thus, the feature importance of the factors can be used to create action plans.

Figure 6. Feature Importance of Random Forest Algorithm in the Pre-Pandemic and the Pandemic Periods for USD/TL.

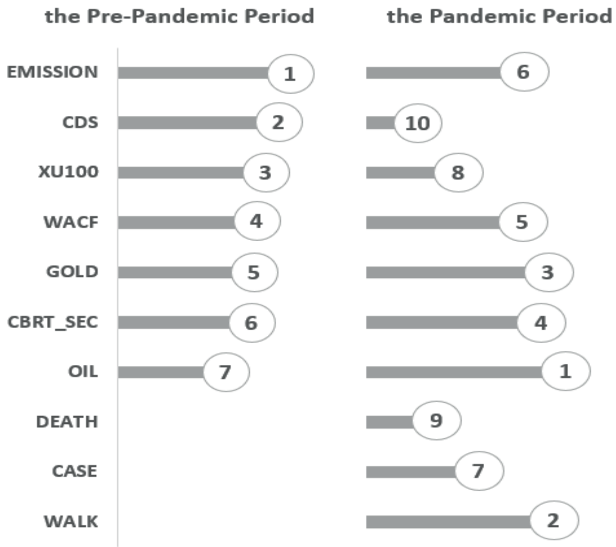


Note: 1 shows the most important factor whereas 10 implies the least important variable.

According to Figure 6, the most influencing factor on USD/TL is EMISSION in the pre-pandemic period. In addition, the effects of WACF, XU100, GOLD, CDS, CBRT_SEC, and OIL on USD/TL are not significantly differentiated in the pre-pandemic period.

On the other hand, USD/TL is strongly influenced by WALK in the pandemic period followed by CBRT_SEC, OIL, GOLD, WACF, EMISSION, XU100, CASE, CDS, DEATH, respectively. Although the 3 most important factors in the pre-pandemic period, which are EMISSION, WACF, and XU100, have lost their importance in the pandemic period.

Figure 7. Feature Importance of Random Forest Algorithm in the Pre-Pandemic and the Pandemic Periods for EURTL



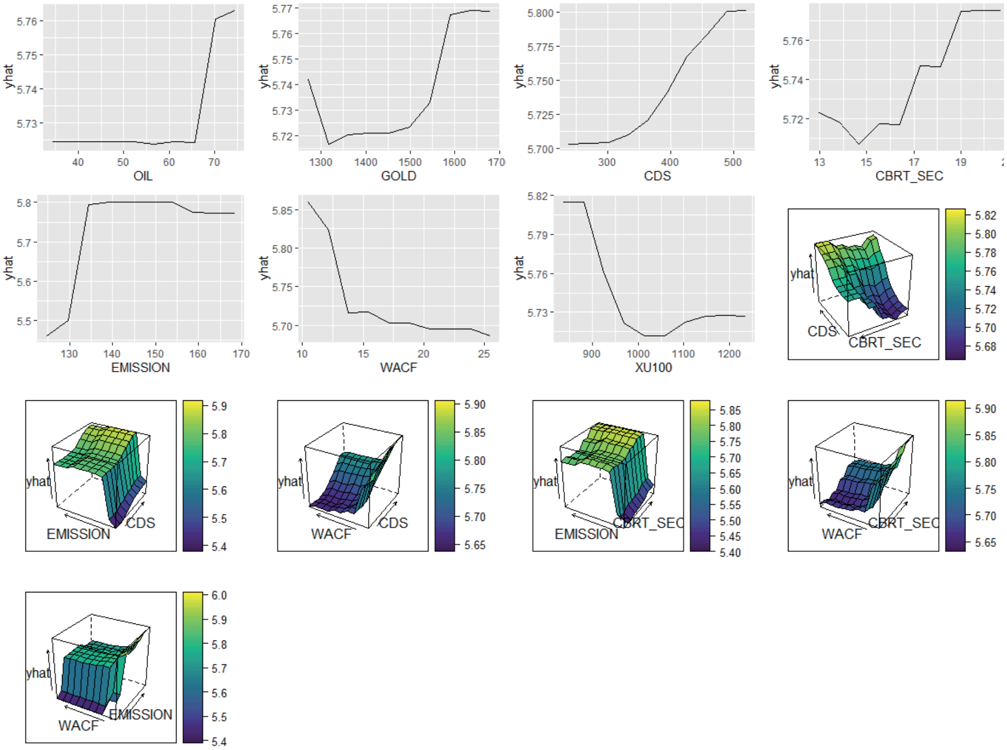
Note: 1 shows the most important variable whereas 10 implies the least important variable.

Based on Figure 7, EMISSION is the most influencing factor affecting EUR/TL in the pre-pandemic period. The other factors can be ranked from the most important to less important as CDS, XU100, WACF, GOLD, CBRT_SEC, and OIL.

On the other hand, OIL is the most influencing factor affecting EUR/TL in the pandemic period. Furthermore, the importance level of OIL and CDS has changed significantly in the pandemic period.

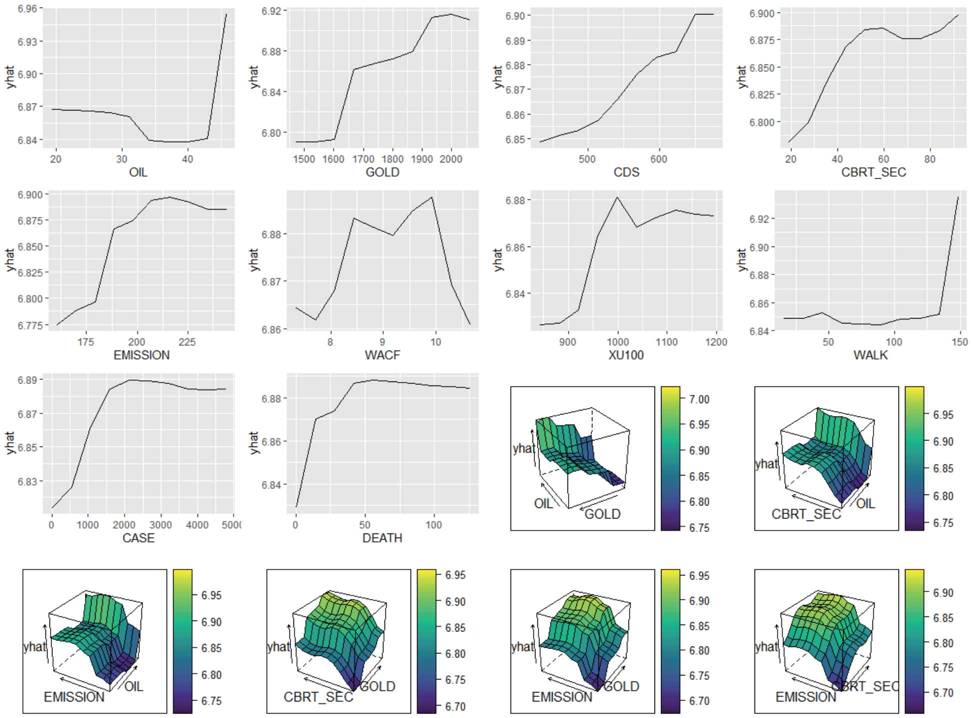
Results of feature importance analysis can help to determine the critical thresholds of the factors, which are visualized in Figure 8.

Figure 8. Singular and Interaction Effects of Influencing Factors in the Pre-Pandemic Period for USD/TL



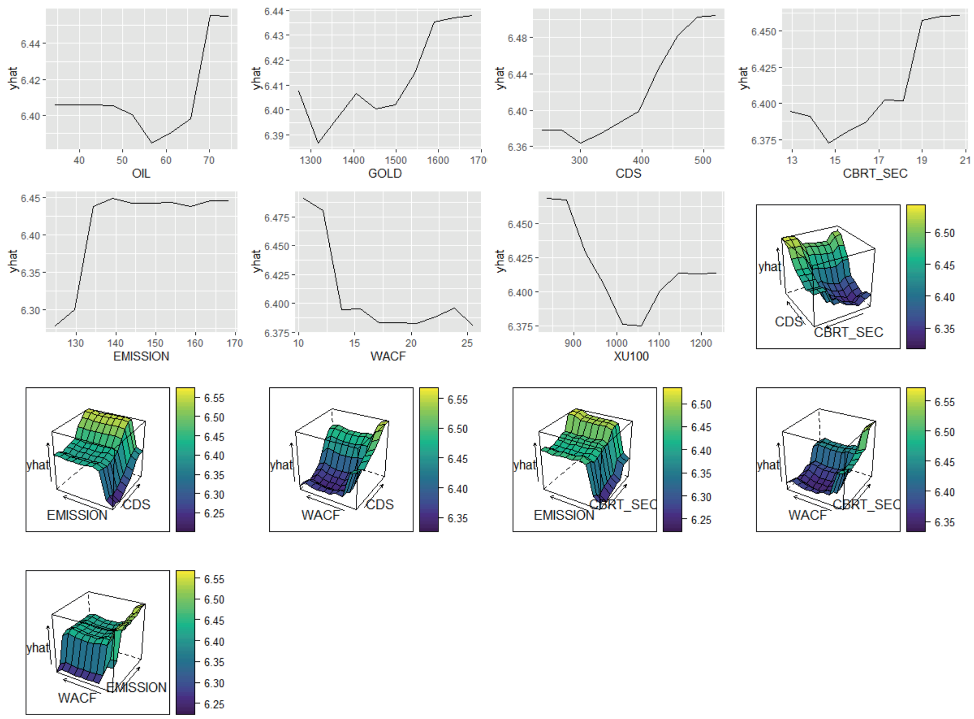
As a result of Figure 8, the USD/TL increases as the OIL, GOLD, CDS, CBRT, or EMISSION increase. In addition, critical thresholds are determined as 65 for OIL, 1600 for GOLD, 400 for CDS, 17 for CBRT_SEC, and 135 for EMISSION to reduce the USD/TL. On the other hand, USD/TL decreases as the WACF or XU100 increases. Moreover, it is revealed that the two-way interaction effects of CDS vs CBRT, EMISSION vs CDS, WACF vs CDS, EMISSION vs CBRT_SEC, WACF vs CBRT_SEC, and WACF vs EMISSION have a significant effect on USD/TL in this study. The optimal scenarios based on the two-way interaction effects are that CBRT_SEC should be lower than 17 and at the same time CDS should be lower than 350 to reduce USD/TL. Also, EMISSION should be below 135 and at the same time CBRT_SEC should be below 17 and WACF should be above 15 to reduce USD/TL.

Figure 9. Singular and Interaction Effects of Influencing Factors in the Pandemic Period for USD/TL



In Figure 9, the USD/TL increases as OIL, GOLD, CDS, CBRT_SEC, EMISSION, XU100, WALK, CASE, and DEATH increase in the pandemic period. Furthermore, the critical threshold of WALK is 130, which are 1000 and 25 for CASE and DEATH, respectively. However, the two-way interaction effects of OIL vs GOLD, CBRT_SEC vs OIL, EMISSION vs OIL, CBRT vs GOLD, EMISSION vs GOLD, and EMISSION vs CBRT_SEC have a significant impact on USD/TL.

Figure 10. Singular and Interaction Effects of Influencing Factors in the Pre-Pandemic Period for EUR/TL



The correlation between independent variables and EUR/TL and critical thresholds in the pre-pandemic period is similar to the results of USD/TL in the pre-pandemic period for all factors. However, WACF and XU100 should be higher than 13 and 1000 respectively to reduce the EUR/TL, respectively. Also, interaction effects of CDS vs CBRT_SEC, EMISSION vs CDS, WACF vs CDS, EMISSION vs CBRT_SEC, WACF vs CBRT, and WACF vs EMISSION are determined as significantly important to reduce EUR/TL.

Figure 11. Singular and Interaction Effects of Independent Factors in the Pandemic Period for EUR/TL

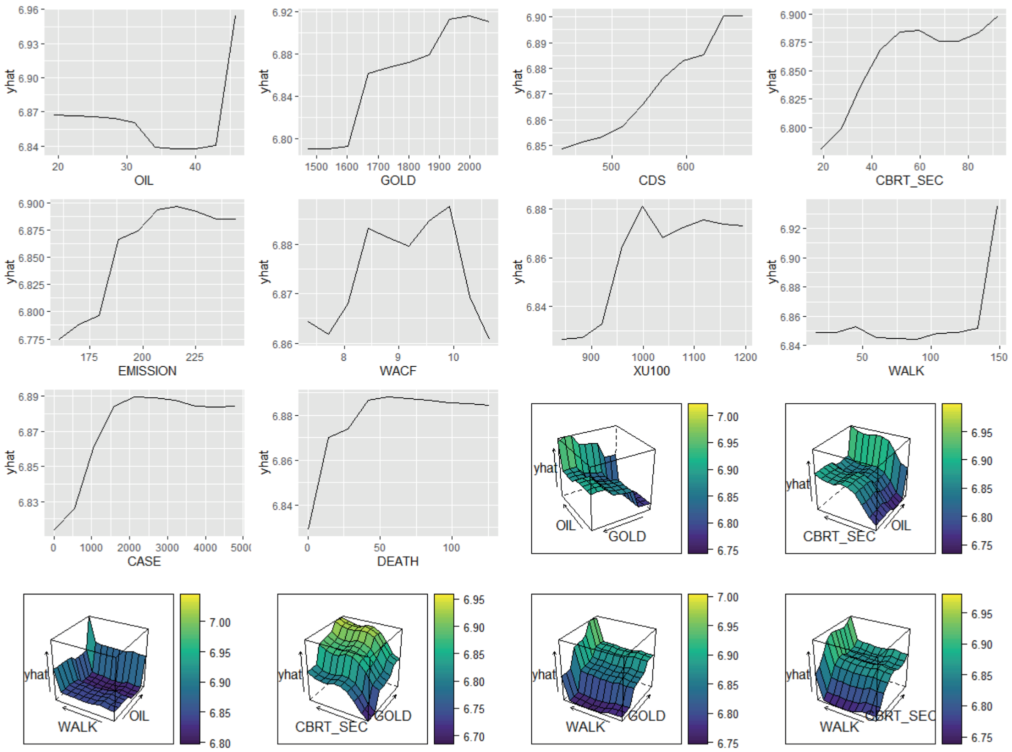
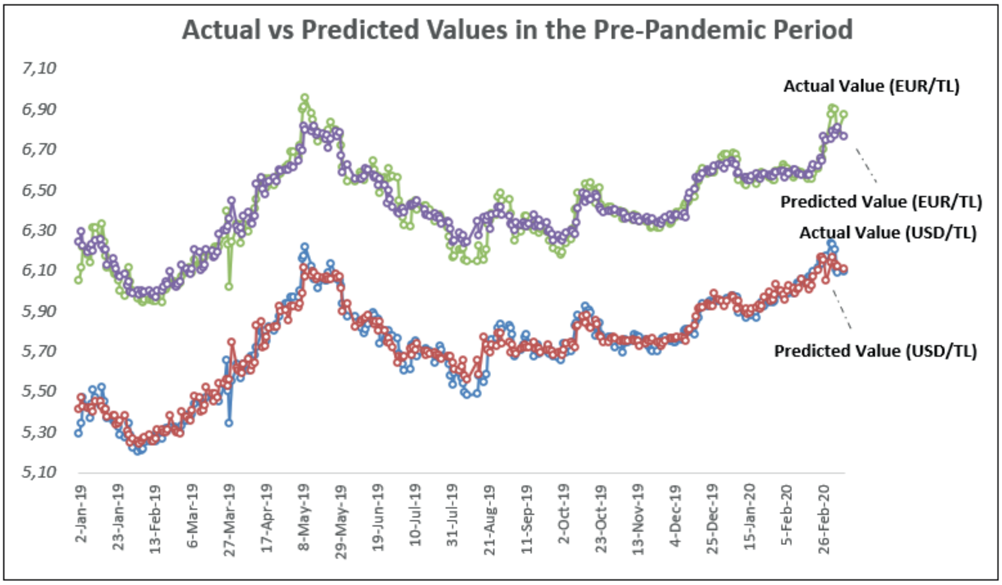


Figure 11 shows the singular and interaction effects of independent factors in the pandemic period for EUR/TL. According to Figure 11, it can be stated that the critical thresholds of all independent variables are not differentiated in the pandemic period for both USD/TL and EUR/TL. Furthermore, the following significant interaction effects are revealed: OIL versus GOLD, CBRT_SEC versus OIL, WALK versus OIL, CBRT_SEC versus GOLD, WALK versus GOLD and WALK versus CBRT_SEC.

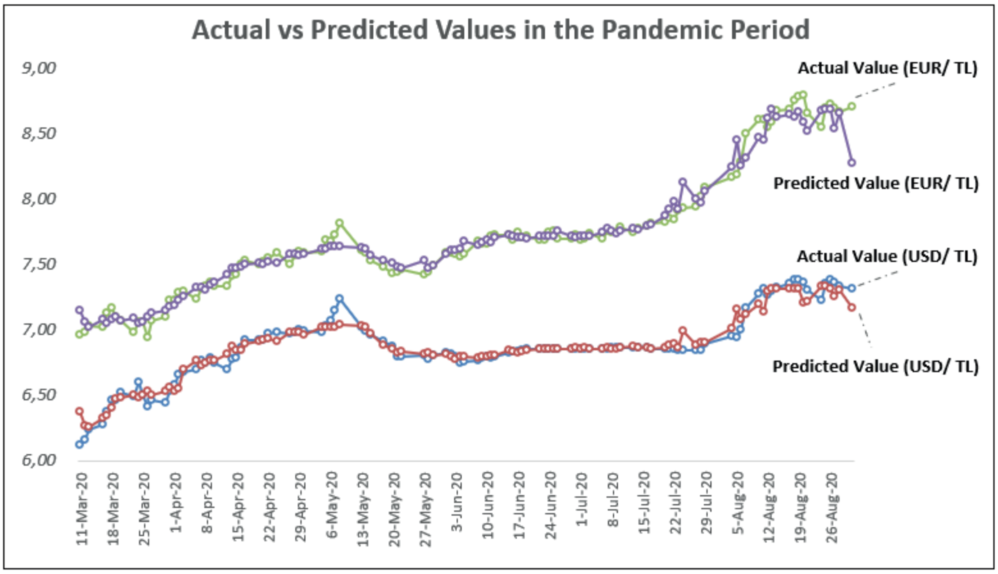
The actual versus predicted values of the USD/TL and EUR/TL predicted by the Random Forest algorithm in both the pre-pandemic and the pandemic periods are given in Figures 12 and 13, respectively.

Figure 12. Actual and Predicted Values in the Pre-Pandemic Period



In the pre-pandemic period, actual and predicted values are very close and moving together. The trend of actual and predicted values by time shows that the model can be interpreted.

Figure 13. Actual and Predicted Values in the Pandemic Period



Similar to the pre-pandemic period the trend of the predicted versus actual values are too close in the pandemic period.

5. Discussion and Conclusion

The study aims to measure the impacts of precautions on monetary policy on the FX rates by considering the potentially disruptive impacts of the pandemic on nearly all indicators. In this context, daily data from February 1, 2019 to August 31, 2020 is considered. Also, 10 (2 global, 3 monetary policy measures, 3 COVID-19 pandemic indicators, 2 global variables, 2 national) variables are included in the analysis. Moreover, Random Forest and the Neural Networks algorithms are performed. The accuracy of both algorithms is quite high, which is above 80%. Also, once the variable importance of the models is examined, the top 3 important factors are the amount of money issued by CBRT, CBRT weighted average cost of funding (%), and XU100 Price Index for the pre-pandemic period in USD/TL. In the pandemic period, the top 3 important factors are the walking mobility of Apple users, the amount of securities bought by CBRT, and oil prices. Similar to the determination of the important variable on the USD/TL FX rate, the variable importance analysis is performed for EUR/TL FX rate. The top 3 important factors are the amount of money issued by CBRT, CDS spreads, and XU100 Price Index for the pre-pandemic period in EUR/TL. In the pandemic period, the top 3 important factors are oil prices, Walking Mobility of Apple Users, and gold prices. The results obtained from the machine learning analysis are consistent with the pre-expectations and the literature.

The results of the analysis prove that the impacts and importance of significant factors on FX rates vary based on the periods. Taking into account this determination of the pandemic, Turkey should deal with the most important variables firstly. For this reason, main focus point should be on sustaining supportive monetary policy measures until pandemic ends and decreasing the effects of the pandemic indicators on the FX rates, respectively. Naturally, oil prices and gold prices are globally determining factors that cannot be fully controlled by Turkey, however, their adverse impacts can be limited by keeping FX rates under control (making FX rates stable). Hence, Turkey can benefit from the decreasing adverse effects of influential factors on FX rates. In total, every precaution related to making FX rates stable can be beneficial in providing a positive contribution to the variables used in the study and FX rates in turn.

The results of the study underline the significance of the pandemic and monetary policy measures on FX rates because monetary policy indicators have a statistically significant and high impact on FX rates in Turkey for the pandemic period. Re-evaluating the applied monetary policy measures like sustaining supportive activities with strict managerial supervision can be helpful to support the stabilizing FX rates and decreasing negative effects on the economy in turn. Besides, the central government and central bank authorities can develop other measures considering the economic realities of Turkey. Hence, the negative effects on the economy resulting from the high volatility in FX rates can be prevented by taking such measures.

It is a significant point which must be stated that precautions should be applied on time. In other cases, measures cannot be stabilizing FX rates in Turkey, which is crucial for the development of most of the other indicators, and Turkey cannot benefit from the measures applied. Also, following how the effective variables on FX rates change over time is quite crucial.

In this study, we focus on the reaction of the selected FX rates (i.e. USD/TL and EUR/TL) in Turkey since they have been quite volatile since 2020 beginning. Turkey can re-design the monetary policy measures and hence can affect the financial and economic development of the country in the pandemic period. Some policy recommendations are proposed based on findings of the analysis so that negative development on the FX rates can be decreased, and other economic and financial indicators can be steered up in turn.

The main limitation is that the study is only focused on Turkey. In new studies, other FX rates in Turkey and FX rates in other countries such as China (COVID-19 originated country), the US, India, Brazil, and France that are affected by the pandemic highly. Also, excluding some macro-level factors is another limitation of the study. Obtaining more data for macro-level factors, including such indicators to analyze in future studies can be possible and this extends the literature. Moreover, new methods for FX rates like Granger-causality on quantiles and quantile-on-quantile regression can be applied in new studies. Lastly, as an important contribution, this study includes Apple walking mobility data. However, it is possible to include Apple driving mobility data in future studies, and making this can provide new insights in analyzing FX rates in both Turkey and other countries.

References

1. Akhtaruzzaman, M., Boubaker, S., & Şensoy, A. (2020). Financial Contagion during COVID-19 Crisis. Finance Research Letters, 101604.

2. Apple. (2020). Mobility Trends Reports, https://covid19.apple.com/mobility, 09.05.2020.

3. Atmaca, S., & Karadaş, H. A. (2020). Decision Making on Financial Investment in Turkey by Using ARDL Long-Term Coefficients and AHP. Financial Innovation, 6(1), 1-22.

4. Bloomberg. (2020). Bloomberg Terminal, 09.05.2020.

5. CBRT. (2020). Electronic Data Distribution System (EVDS), https://evds2.tcmb.gov.tr/index.php?/evds/serieMarket, 09.05.2020.

6. CSD. (2020). Data of Foreign Investors' Net Buying Amount. Obtained from CSD of Turkey via e-mail on 09.05.2020.

7. Clark, J., & Berko, E. (1997). Foreign Investment Fluctuations and Emerging Market Stock Returns: The Case of Mexico. FRB of New York, Staff Report, No. 24.

8. Demir, C. (2019). Macroeconomic Determinants of Stock Market Fluctuations: The Case of BIST-100. Economies, 7(1), 8.

9. Depren, Ö., Kartal, M. T., & Kılıç Depren, S. (2021). Changes of Gold Prices in COVID-19 Pandemic: Daily Evidence from Turkey's Monetary Policy Measures. Technological Forecasting & Social Change, 170, 1-12.

10. Ertuğrul, H. M., & Öztürk, H. (2013). The Drivers of Credit Swap Prices: Evidence from Selected Emerging Market Countries. Emerging Markets Finance & Trade, 49, 228-249.

11. Fontana, A., & Scheicher, M. (2016). An Analysis of Euro Area Sovereign CDS and Their Relation with Government Bonds. Journal of Banking & Finance, 62, 126-140.

12. Gangopadhyay, K., Jangir, A., & Sensarma, R. (2016). Forecasting the Price of Gold: An Error Correction Approach. IIMB Management Review, 28(1), 6-12.

13. Hastie, T., Tibshirani, R., & Friedman, J. (1996). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer-Verlag.

14. Hasan, I., Liu, L., & Zhang, G. (2016). The Determinants of Global Bank Credit-Default-Swap Spreads. Journal of Financial Services Research, 50(3), 275-309.

15. Hassan, M. K., Kayhan, S., & Bayat, T. (2017). Does Credit Default Swap Spread Affect the Value of the Turkish Lira Against the US Dollar? Borsa Istanbul Review, 17(1), 1-9.

16. Jebran, K., & Iqbal, A. (2016). Dynamics of Volatility Spillover between Stock Market and Foreign Exchange Market: Evidence from Asian Countries. Financial Innovation, 2(1), 3.

17. Karikari, J. A. (1992). Causality between Direct Foreign Investment and Economic Output in Ghana. Journal of Economic Development, 17(1), 7-17.

18. Kartal, M. T. (2020). The Behavior of Sovereign Credit Default Swaps (CDS) Spread: Evidence from Turkey with the Effect of Covid-19 Pandemic. Quantitative Finance and Economics, 4(3), 489-502.

19. Kartal, M. T., Kılıç Depren, S., & Depren, Ö. (2018). Türkiye'de Döviz Kurlarını Etkileyen Makroekonomik Göstergelerin Belirlenmesi: MARS Yöntemi İle Bir İnceleme. MANAS Sosyal Araştırmalar Dergisi, 7(1), 209-229.

20. Kartal, M. T., Depren, Ö., & Kılıç Depren, S. (2020). The Determinants of Main Stock Exchange Index Changes in Emerging Countries: Evidence from Turkey in Covid-19 Pandemic Age. Quantitative Finance and Economics, 4(4), 526-541.

21. Kartal, M. T., Kılıç Depren, S., & Depren, Ö. (2021a). How Main Stock Exchange Indices React to Covid-19 Pandemic: Daily Evidence from East Asian Countries. Global Economic Review, 50(1), 54-71.

22. Kartal, M. T., Depren, Ö., & Kılıç Depren, S. (2021b). The Relationship between Mobility and COVID-19 Pandemic: Daily Evidence from an Emerging Country by Causality Analysis. Transportation Research Interdisciplinary Perspectives, 10, 100366, 1-10.

23. Khan, M. K., Teng, J. Z., & Khan, M. I. (2019). Cointegration between Mac-

roeconomic Factors and the Exchange Rate USD/CNY. Financial Innovation, 5(1), 1-15.

24. MHT. (2020). COVID-19 Numbers, https://covid19.saglik.gov.tr/TR-66935/genel-koronavirus-tablosu.html, 09.05.2020.

25. Nouvellet, P., Bhatia, S., Cori, A., Ainslie, K. E., Baguelin, M., Bhatt, S., ... & Donnelly, C. A. (2021). Reduction in Mobility and COVID-19 Transmission. Nature Communications, 12(1), 1-9.

26. Orhan, A., Kırıkkaleli, D., & Ayhan, F. (2019). Analysis of Wavelet Coherence: Service Sector Index and Economic Growth in an Emerging Market. Sustainability, (11), 6684.

27. Phan, D. H. B., & Narayan, P. K. (2020). Country Responses and the Reaction of the Stock Market to COVID-19-A Preliminary Exposition. Emerging Markets Finance and Trade, 56(10), 2138-2150.

28. Sjaastad, L. A. (2008). The Price of Gold and the Exchange Rates: Once Again. Resources Policy, 33(2), 118-124.

29. Towell, G.G., & Shavlik, J.W. (1993). Extracting Refined Rules from Knowledge-Based Neural Networks. Machine Learning, 13, 71-101.

30. Wang, H., & Yamamoto, N. (2020). Using a Partial Differential Equation with Google Mobility Data to Predict COVID-19 in Arizona. Mathematical Biosciences and Engineering, 17(5), 4891-4904.

31. WHO. (2020a). Coronavirus Disease (COVID-19) Pandemic, https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/novel-coronavirus-2019-ncov, 09.05.2020.

32. WHO. (2020b). COVID-19 Numbers, https://COVID19.who.int, 08.18.2020.

33. Wiener, M., & Liaw, A. (2002). Classification and Regression by randomForest. R News, (2)3, 18-22.

34. Yılmazkuday, H. (2020). COVID-19 and Welfare Costs of Reduced Mobility. Journal of Regional Science, Forthcoming.

35. Yılmazkuday, H. (2021). Stay-at-Home Works to Fight against COVID-19: International Evidence from Google Mobility Data. Journal of Human Behavior

in the Social Environment, 31(1-4), 210-220.

36. Zengin, S., Yüksel, S., & Kartal, M. T. (2018). Understanding the Factors that Affect Foreign Direct Investment in Turkey by Using MARS Method. Finansal Araştırmalar ve Çalışmalar Dergisi, 10, 1309-1123.

37. Zhu, D., Mishra, S. R., Han, X., & Santo, K. (2020). Social Distancing in Latin America during the COVID-19 Pandemic: An Analysis Using the Stringency Index and Google Community Mobility Reports. Journal of Travel Medicine, 27(8), taaa125.