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PREDICTING GOVERNMENT BOND PRICE RETURNS USING MACHINE LEARNING ALGORITHMS

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Predicting Government Bond Price Returns Using Machine Learning Algorithms

Devlet Tahvili Getirilerinin Makine Öğrenme Modelleri ile Tahmin Edilmesi

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ABBREVIATIONS

Abbreviation	Meaning	Page
U.S	United States	1
RIPPER	Repeated Incremental Pruning to Produce Error Reduction	2
RSI	Relative Strengh Index	2
RMSE	Residual Mean Squared Error	2
MAPE	Mean Absolute Percentage Error	2
ARIMA	Auto regressive integrated moving average	2
ANN	Artificial Neural Networks	2
k-NN	k-nearest Neighbors	2
SVM	Support Vector Machines	2
MAE	Mean Absolute Error	3
CEFLANN	Computational Efficient Functional Link Artificial Neural Network	3
FED	Federal Reserve	11
ISIN	International Securities Identification Number	11
CUSIP	Committee on Uniform Security Identification Procedures	11
ISO	International Organization of Standardization	11
NSIN	National Security Identifying Number	12
CBRT	Central Bank of Republic of Turkey	16
USDTRY	United States Dollar/ Turkish Lira	33
OLS	Ordinary Least Squares	44

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ABSTRACT

In this study, one-step, five-step, ten-step, thirty-step, sixty-step and ninety-step ahead daily close price returns of selected common long-end term bonds of Turkey, Germany and the United States are predicted with machine learning models, which namely are the linear regression, the random forest, gradient boosted regressor trees and support vector regressors. This study also provides information about how bonds' unique security codes (more specifically, how the National Security Identification Numbers and the International Security Identification Numbers) are determined, how the bond market and public debt evolved within the date range of the data set and the reasoning of the selection of the selected independent variables is provided: Explanatory variables are selected among other price series that are expected to be relevant with the dependent variable bonds. Selected performance metrics to evaluate each model and compare them with the baseline model, the random walk model, are the "Residual Sum of Squared Error", "Mean Absolute Percentage Error", and the directional accuracy. Results suggest that with the selected combination of models and independent variables, the gradient boosted regressor model and the linear regression model outperform other used machine learning models, while all models outperform the indicated baseline model, the random walk.

ÖZET

Bu çalışmada Türkiye, Almanya ve Amerika Birleşik Devletleri'nin uzun vadeli tahvilleri bir, beş, on, otuz, altmış ve doksan adım sonraki kapanış fiyatlarının günlük değişimleri, lineer regresyon, Rassal Orman, Gradyan Destekli Regresyon ve Destekçi Vektör Makineleri makine öğrenmesi modelleri ile tahminlenmiştir. Bu çalışmada aynı zamanda tahvillerin kendine özgü menkul kıymet kodlarının nasıl belirlendiği, veri setinin tarih aralığında tahvil piyasasının ve kamu borcunun nasıl geliştiği hakkında bilgi verilmekte ve seçilen bağımsız değişkenlerin seçilme gerekçeleri sunulmaktadır: Bu değişkenler, açıkladıkları bağımlı değişkenlerle ilişkili oldukları düşünülen başka fiyat serileri arasından seçilmiştir. Her bir modeli değerlendirmek ve bu modelleri baz model olan rassal yürüyüş modeli ile kıyaslamak için seçilen performans metrikleri Kök Ortalama Kare Hatası, Ortalama Mutlak Yüzde Hatası ve yön doğruluğudur. Sonuçlar, bu çalışmada kullanılan model ve bağımsız değişkenler kombinasyonuyla, Gradyan Destekli Ağaç ve lineer regresyon modellerinin diğer kullanılan makine öğrenimi modellerinden daha iyi performans gösterdiğini, tüm modellerin ise belirtilen baz model olan Rassal Yürüyüş’ten daha iyi performans gösterdiğini ortaya koymaktadır.

1. INTRODUCTION

The rise of computational power has been empowering quantitative finance as well as the use of “Machine Learning” techniques in the financial sector. “Machine Learning” is a sub-category of artificial intelligence, defined essentially as training available past data to either improve performance or make accurate predictions and it aims to accomplish these tasks by building algorithms that serve to capture accuracy as well as efficiency (Mohri, Rostamizadeh, & Talwalkar, 2012). Machine learning models find their usage areas in the financial sector in different ways, which are namely fraud detection, payment processing, risk modelling, regulation and investment (Emerson, Kennedy, O'Shea, & O'Brien, 2019). Regarding investment, it can be argued that quantitative trading has been drawing more attention recently. Quantitative trading is defined as “the trading of securities based strictly on the buy/sell decisions of computer algorithms” (Chan, 2009, s. 1). Quantitative trading has an intention the make use of past data and exploit it for the purpose of profit creation by finding patterns or hidden information. As opposed to traditional trading, which leans on heuristics, subjective personal opinions and “animal instincts”, quantitative trading ensures a more analytical framework to the business, thus the business leans on relatively more scientific methods. In this thesis, I analyze whether machine learning models are beneficial for bond trading. I focus on Turkish, Germany and United States (U.S) government bond markets.

In the literature, there is limited study on the application of machine learning for bond trading and prediction. However, there are numerous studies that analyze how machine learning models can be beneficial for the prediction and trading of other securities. For example, Gerlein, McGinnity, Belatreche and Coleman (2016) focus on relatively less expensive computational classification models to predict whether the market goes up or down in the following time frame. In their study, the USD/JPY currency’s upcoming time frame’s direction is predicted with Naïve Bayes, K-star, C4.5 decision tree algorithm, Logistic Model Tree, The Repeated

Incremental Pruning to Produce Error Reduction (RIPPER). The strategy consists of buying the currency pair when the direction is predicted up and selling it when the direction is predicted to be down. Additionally, used attributes to build the classification models are composed of two technical indicators used for similar purposes, the Relative Strength Index (RSI) and the %R Williams Oscillator, and some price information including the crude price data as well as its processed forms such as its lags, returns, returns' lags and moving average. Albeit numerous setups, the overall accuracy is almost always around 50%, that is not any better than a random guess. However, when only and only the best setup is considered, a cumulative return of %181.29 for a period of almost 2.5 years, which implies approximately an annual return of 50% appears.

McDonald, Coleman, McGinnity, Li and Belatreche (2014) use hybrid models that combine linear and non-linear models. First, linear models capture the linearity of given data. Then, remaining residuals that can not be explained by linearity, are modelled by non-linear models. Finally, linear and non-linear models are combined. This study shows that a combination may improve both accuracy for binary outcomes and other performance metrics such as residual mean squared error (RMSE) and mean absolute percentage error (MAPE). The linear component of all combined models is auto regressive integrated moving average (ARIMA), and the non-linear components vary across artificial neural networks (ANN), k-nearest neighbors (k-NN), support vector machines (SVM) and self-organizing fuzzy neural networks (SOFNN). Six major stock indices and 30 stocks are predicted: FTSE, S&P500, NIKKEI, CAC40, DAX, SSEC and the 30 stocks that make up the Dow Jones Industrial Average. Both prices and log returns are predicted in the study. For the log returns' direction prediction of the indices, hybrid models' accuracies have values of 48.67% for the combination of ARIMA and ANN, 53.29% for ARIMA and k-NN, 59.43% for ARIMA and SVM and 56.76% for ARIMA an SOFNN. These figures generally create an edge for a trading system set-up. While the respective RMSE figures are 0.0498, 0.0531, 0.0494 and 0.0497 for the log returns' predicted values, the respective MAPE figures stand at 9.45%, 10.28%, 9.51% and 9.44%. Evidently, for regression purposes, the combination of

ARIMA and SOFNN is better, as per RMSE and MAPE figures, whereas another performance metric, directional accuracy, suggests that, the combination of ARIMA and SVM is better performing.

In another study, Nikou, Mansourfar and Bagherzedah (2019) seek to evaluate the predictions of close prices of the Morgan Stanley Country Index United Kingdom Exchange Traded Fund for the time period between January 2015 and June 2018, made by four different machine learning models, which namely are the deep learning model, the support vector regression (SVR), NN and random forest. Data split is made such that 80% is the training data and the resting 20% is the testing data. Selected performance metrics are mean absolute error (MAE), mean squared error (MSE) and residual mean squared error (RMSE). After hyper-parameter tuning is taken care of, final comparison indicates that deep learning outperforms all three models in all aspects of performance metrics: For the residual mean squared error, the deep learning model outperforms random forest, support vector regressor and neural network models with a figure of 0.306543 against respective numbers of 0.3896482, 0.340657 and 0.454131.

Kara, Boyacioglu and Baykan (2011) use two classification techniques, which are artificial neural networks and support vector classifiers to predict the stock market's direction with numerous technical indicators as attributes, namely which are simple and weighted moving averages, stochastic oscillator, the relative strength index (RSI), the moving average convergence divergence (MACD), Williams R%, the accumulation/distribution oscillator and lastly commodity channel index (CCI) and the data set covers a time period of 11 years (from January 2, 1997 to December 31, 2007). Albeit different results for different parameters for each model, the support vector classifier with the best kernel and parameters averages less than all three averages of selected parameter combinations, which vary from 74.63% to 75.74%.

Dash and Dash (2016) create a classification model with the use of computational efficient functional link artificial neural network (CEFLANN) which has three class values, which are buy, hold and sell and consequently this model is compared with several others, which can be aligned as the support vector machine, the naïve Bayesian model, the K-nearest neighbor model and the decision tree model. The two stock indices used in the study are the S&P 500 and BSE SENSEX, with a time period starting from 4 January 2010 and lasting at 31 December 2014. In this study, they train the CEFLANN model with ELM learning instead of back propagation. The used technical indicators are simple moving average, moving average convergence divergence, the stochastic oscillator, relative strength index and Williams R%. Following the extraction of technical indicators, a trend analysis is performed with the use moving average. The trend is said to be existing if the close price leads or lags its moving average while moving average has been on the rise or fall for at least five consecutive days and if none of these tariffs hold, it is said that a trend does not exist. While the model produces a final signal of discrete values (buy, hold and sell as mentioned above), in the training process, a new generic number which is between 0-1 that reflects the price momentum is being generated. However, although this generated number gives more insight about the price, it should also be noted that the generation of these figures suffer from data snooping as it produces this number with future values of its own. Afterwards, technical indicators are being normalized, so that numbers with different natures and bases do not suppress each other. Hence, the model is trained. This model has been trained and tested on two stock indices, which namely are BSE SENSEX and S&P 500. The data range starts from 4 January 2010 and finalizes at 31 December 2014. For both indices, training set size is 1000 and the remaining is the testing data set. After parameter tuning and cross validation, results exhibit that the deep learning model produces better results for both indices in terms of profitability when compared to other models included in the study: For SENSEX, the profit is 47% and for S&P 500, the profit is 24.28%.

Theofilatos, Likothanassis and Karathanaspoulos (2012) aim to predict the one-day-ahead direction of the EURUSD exchange rate with five supervised classification techniques, which are K-Nearest Neighbors, Naïve Bayesian, Artificial Neural Networks, Support Vector Machines and Random Forests. Provided inputs only consist of autoregressive terms (from order 1 to 10) of

EURUSD fixings of the European Central Bank and it covers a time range between 17 January 2002 and 30 December 2010. The applied trading strategy is as simple as going long if the one-step ahead forecast is positive and going short if it is negative. Trading results suggest that the best algorithm with these inputs for this data set is the Random Forest model; both for the direction prediction accuracy and annualized return, which are 53.50% and 7.28%, respectively. However, it should be noted that prediction accuracies' minimum stands at 48.83% (Naïve Bayes); different provided inputs may have created more efficient accuracies compared to random and better returns.

Yasar and Kilimci (2020) use artificial intelligence by combining financial sentiment analysis with time series analysis to predict the USD Dollar/Turkish Lira exchange rate. For the financial sentiment analysis, deep learning models are used to process relevant text from social media and for the time series analysis, simple exponential smoothing, Holt-Winters, Holt's Linear and ARIMA models are used. Although a combination of both sentiment and time series analysis are missing, both exhibit separate promising results.

Machine learning techniques are also used for more of a statistical method, such as pairs trading and statistical arbitrage. Sarmento and Horta (2020) show how artificial intelligence can be used for primarily detecting two suitable securities for pairs trading and then how to stop avoiding prolonged decline periods by forecasting the upcoming value of the spread of the selected securities with making use of a model. Before clustering securities, dimensionality reduction is applied to the data with the Principal Component Analysis technique. Thereafter, an unsupervised learning clustering technique called OPTICS is applied for clustering. Having created the clusters from which the candidate securities are to be selected, further analysis is performed: A cointegrating relation is sought, the Hurst exponent is calculated as an extra validation step for the mean reversion characteristic, data with extremely short and long times for mean reversion is excluded and a minimum for number of trades for the pair is determined. After the pairs are selected, the trading model is built as follows: The next spread is predicted, and compared to a pre-determined threshold, which is based on spread percentage change distribution and the result of these thresholds' application on the validation set. Trained models for forecasting the spread are autoregressive moving average, a Long short-term memory (LSTM) and an LSTM Encoder-Decoder. Finally, the trading simulation is built such that all pairs are equally weighted in the portfolio and the cash arising from the short position is applied to the long position and all earned money from one pair is reinvested to that pair. The study's focused asset class is Exchange-Traded-Funds, and more specifically those which are related to commodities, either those which are linked to commodity indexes or those which track single commodities. With the final configuration, Sharpe ratio is 3.41 and return on investment is 11.3 %, maximum drawdown is 1.12% and out of 30 trades, 26 are profitable. Although numbers are not exaggeratedly good, numbers suggest that forecasting the spread ensures risk management while still having promising returns.

Similarly, Krauss, Do and Huck (2017) investigate the effectiveness of deep neural networks, random forests, gradient-boosted trees and a combination (ensemble) of these methods on S&P 500 in the context of statistical arbitrage. In this study, one-day ahead trading signals for stocks of the S&P500 Index are generated, according to their probability forecast of outperforming the general market. A pre-determined number, k, of stocks are converted into long and short positions, with the top k probabilities being long positions and the bottom k probabilities being short positions. This method enables to eliminate the less mathematically certain part of the ranked probabilities. The study's findings suggest that a simple ensemble consisting of one deep neural network, one gradient-boosted tree and one random forest produces a daily return of 0.45 percent, excluding transaction costs, for k equaling to 10. The provided inputs consist of 31 lag values of the stocks, with the first twenty lags being daily consecutive lags and the following eleven lags being the following twenty-day consecutive periods. For each stock, a probability to outperform the cross-sectional median is calculated, and stocks are ranked according to their probabilities. Again, the top k stocks with highest probabilities to outperform the median are bought and the bottom k stocks with lowest probabilities are considered to underperform and therefore they are sold. As mentioned above, the ensemble model creates a daily return figure of 0.45 percent and that value is followed by random forest and gradient-boosted tree, with daily returns of 0.43 percent and 0.37 percent; respectively. Albeit reflecting returns with transaction cost not being involved, all three models mentioned above are both encouraging and promising.

Adegboye and Kampouridis (2021) use a directional change approach to predict the trend reversals and their continuation period for twenty different currency pairs, which namely are Australian Dollar / Japanese Yen, Australian Dollar/ New Zealand Dollar, Australian Dollar/ US Dollar, Canadian Dollar/ Japanese Yen, Euro/ Australian Dollar, Euro/ Canadian Dollar, Euro/ Czechoslavak Koruna, Euro/ Norwegian Krona, British Pound/ Australian Dollar, New Zealand Dollar/ US Dollar, US Dollar/ Canadian Dollar, US Dollar/ Norwegian Krona, US Dollar/ Japanese Yen, US Dollar/ Singaporean Dollar, US Dollar/ South African Rand, Euro/ British Pound for a time period of March 2016 – February 2017 and the Euro/ US Dollar, Euro/ Japanese Yen, British Pound/ Swiss Franc, British Pound/ US Dollar for a time period of June 2013 – May 2014. In their study, a primary classification is applied on the data to distinguish whether signaled directional changes are followed by over shootings (or continuations) or the signaled directional changes are followed by another directional change to the opposite way. If the classification output is such that the directional change is followed by a continuation of the reversed trend, a symbolic regression model associating the overshooting with the directional change is used to predict the ending point of the trend, at the end of the overshooting period. It is important to note that although the regression model follows the classification model, depending on the output of the classification and therefore by choosing which data to be applied on, while constructing the model, the regression is performed to the training data with a perfect foresight, meaning that the regression is applied to those directional change events known perfectly to be followed by a continuation. Thus, the regression model is built with the exclusion of noisy data that should have not be included at the first place. After the regression model is defined with its specifications, the classification model is built. An Auto-Weka process, which is an automatic model selection and hyperparameter optimization process, is applied only to the validation dataset, and a 10-k cross validation has been performed. The best model according to the F1 measure, the harmonic mean of those metrics called precision and recall, is selected. The trading strategy is a buy-only strategy, meaning that if initially an open position is not existent, a signal to buy is waited until a transaction is made, and sell signals are only used to close the open positions. All these strategies are applied to twenty currency pairs. When the classification results are examined, the average accuracy had a record of 81.7%. The average return of the proposed trading system generates a return of 22.5% in a time span of 10 months. The combination of classification and genetic programming outperforms other benchmarks, especially the buy and hold strategy, which has an average return of -12.8%.

Novak and Velušček (2015) suggest that close prices of stock are more volatile in comparison of daily high prices and therefore it creates more noise. Thus, they suggest the use of daily highs to build classification models instead of daily close prices. The study's date range is 31 October 2003 – 14 June 2013. The input variables consist only of technical indicators. The trading strategy is, to buy a stock whose current day high price is predicted to be higher than the previous day's high price and whose open price is less by a pre-determined threshold than the previous day's close price. The exit strategy is to sell the stock if the bought stock exceeds its previous day's high price or if the close price does not reach or exceed this level, to sell the stock at close at the close price. The used classifiers consist of linear discriminant analysis, the Naïve Bayes classifier, support vector machine classifier based on a Gaussian RBF kernel and a support vector classifier based on a linear kernel. The mean return for the selected stocks stand at 0.17% while the cumulative annual growth rate is an impressive 48.07% for the best classifier, which is support vector machine classifier based on a Gaussian RBF.

To the best of my knowledge, machine learning techniques have not been in the context of Turkish Government Bond trading or forecasting and overall, there is only limited work on the bond market.

In this study, bonds' price returns are being predicted with relevant securities' prices or derived series (such as return or daily difference) from these price series by using machine learning techniques. Bonds are selected from the long end of the curve. More specifically, the bonds with a 10-year maturity are intended to be predicted. However, it is important to note that different countries have yield curves of different length in years. Accordingly, for Germany and the United States, the then-current 10-year bonds' price series and their relative returns are being predicted. Contrarily, the predicted price return of the Turkish Government Bond is calculated with one constant bond, meaning it does not show the same sliding characteristic to reflect the actual then-current 10-year bond. This dichotomy has its unique and specific reasons and will come clear in section 2.1.1.

2. THE BOND MARKET

Bonds can be defined as financial instruments which provide the issuer (debtor) to borrow from the holder (creditor, investor) and they are debt securities, with specifics such as the principal, the coupon rate (either fixed or float with a link to a specific benchmark), maturity date, different types of measured yields depending on the price as well as coupon payment frequency, time to maturity, the coupon rate and so on. Bonds can be issued by sovereign entities as well as corporations. Bonds may have other specified attributes, such as call options (providing the issuer to the right to repay the bond at par on a call date before its maturity) or put options (providing the holder the right to receive the bond's payment on a put date before it maturity), making them "callable bonds" or "putable" bonds. There are other types of options on bonds as well. The scope of bonds and their attributes is beyond the content of this study, and as this study focuses on predicting the sovereign bonds of three specific countries with a certain focus on the yield curve. Therefore, the definition of a bond and its general attributes is enough for the context.

Treasury agencies issue debt with differing maturities. For the Turkish government debt securities, those maturing in less than a year are called "bills" while otherwise they are called "bonds". In the matter of German government debt securities, those with a maturity less than a year are called "Treasury Discount Paper" (or "Bubills"), those with a maturity of two years are called "Federal Treasury Notes" (or "Schaetze"), those with a maturity date of five years are called "Federal Notes" (or "Bobls") and finally the ones maturing in 7,10,15 or 30 years are called "Federal Bonds" (or "Bunds"). In Respect of U.S government debt securities, the distinction is three-fold: Debt instruments with an original maturity less than a year are called "bills", those with an original maturity with two to ten year are called "notes" and those with an original maturity over ten years are called "bonds".

According to the Debt Securities Market Daily Bulletins data which is provided by the Istanbul Stock Exchange's official website and has an origination date of 29 February 2000, the first ever Turkish 10-year government bond was issued on

27/01/2010 and had a maturity date of 15 January 2020. On the other hand, according to data provided by the Federal Reserve Bank (FED) of St. Louis, initial figure for 10-year US note interest rate appears on January 2, 1962.

In this aspect, the long end of the Turkish yield curve is relevantly new when compared to the other two sovereigns' yield curves of this study, namely which are the German Bunds' curve and the United States Treasury yield curve.

Every bond has an ISIN code, which is an abbreviation for "International Securities Identification Number". Following the explanations of the ISIN organization (ISIN Organization, n.d):

> The ISIN standard is used worldwide to identify specific securities such as bonds, stocks (common and preferred), futures, warrant, rights, trusts, commercial paper and options. ISINs are assigned to securities to facilitate unambiguous clearing and settlement procedures. They are composed of a 12-digit alphanumeric code and act to unify different ticker symbols "which can vary by exchange and currency" for the same security. In the United States, ISINs are extended versions of 9-character CUSIP (Committee on Uniform Security Identification Procedures) numbers; ISINs can be formed by adding a country code and check digit to the beginning and end of a CUSIP, respectively.

Following the same source (ISIN Organization, n.d), ISIN codes can be decomposed as the following:

- A two-letter country code, drawn from a list (ISO 6166) prepared by the International Organization for Standardization (ISO). This code is assigned according to the location of a company's head office. A special code, 'XS' is used for international securities cleared through pan-European clearing systems like Euroclear and CEDEL. Depository receipt ISIN usage is unique in that the country code for the security is that of the receipt issuer, not that of the underlying security.

- A nine-digit numeric identifier, called the National Securities Identifying Number (NSIN), and assigned by each country's or region's. If a national number is composed of less than nine digits, it is padded with leading zeros to become a NSIN. The numeric identifier has no intrinsic meaning it is essentially a serial number.
- A single check-digit. The digit is calculated based upon the preceding 11 characters/digits and uses a sum modulo 10 algorithm and helps ensure against counterfeit numbers.

National Securities Identifying Numbers (NSIN) are issued by national numbering agencies, and they indicate a nine-digit code that serves to identify the security.

For the Turkish government bonds, the national numbering agency that is in charge of issuing the NSIN codes is called “Takasbank”. The NSIN codes’ structure for the bonds is as follows: The nine-digit code is generated such that the first letter signifies the security’s type, whether it is a bond, a bill, a corporate bond and so on; and the following six numbers indicate the maturing date; the following letter indicates if the security corresponds to a stripped bond’s either coupon or face value, or if it corresponds to the bond in full coupon and face value while it can also indicated a foreign currency denomination. The ISIN code is the expanded version of this: The first two digits are the country code characters, as indicated in the ISO 6166 list, and then follows the just described NSIN code and finally there is a single check-digit. At last, the selected Turkish Government Bond’s ISIN code is TRT110226T13 in this study.

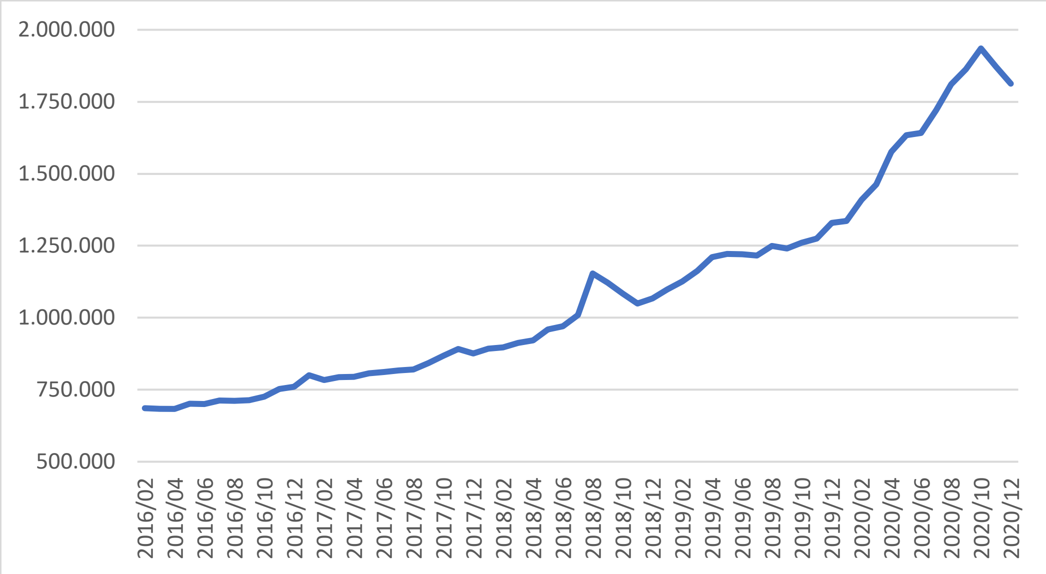
For the German Bunds, the national numbering agency which oversees the issuances of NSIN codes is called “Wertpapier-Mitteilungen”. The NSIN codes’ structure for German securities is as follows: The Wertpapierkennnummer is a German securities identification code where the first two to four digits indicate the issuer. The NSIN code is obtained simply by putting three zeros in front of the WKN number. The national numbering agency which is in charge of issuing the NSIN codes is called “Wertpapier-Mitteilungen”. The ISIN code then can be obtained by expanding the NSIN code, by simply putting two letters which indicate the country code to the beginning and a single check-digit. Securities that have been used for modelling purposes for the German Bunds could be seen above.

The national numbering agency that is in charge of issuing is called the CUSIP Global Services and it is operated by the S&P Global Market Intelligence (CUSIP Global Services, n.d). The word CUSIP is an abbreviation for “Committee on Uniform Security Identification Procedures” and CUSIP’s role serve as the national security identifying number in Canada and the United States. CUSIPs are nine-digit identifiers, and their role where the first six characters identify the unique name of the security issuing entity, and the following two characters identify the type of the security (whether it is a bond or equity etc.) and a check digit in the end. For the treasury bonds, ISIN is generated by adding the country code extracted from the ISO list to the beginning of the CUSIP code and adding a final check digit to the very end.

2.1.Bond Market Overview

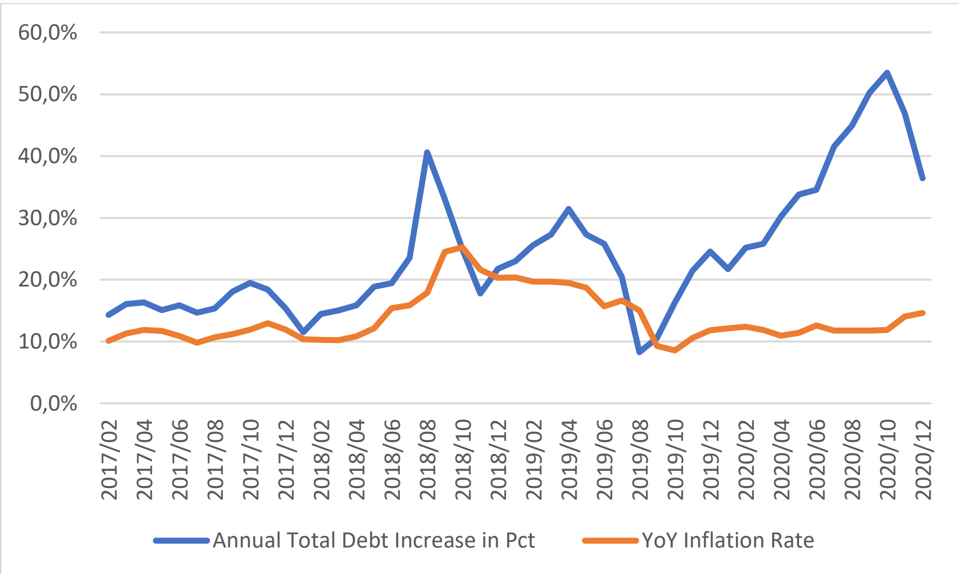
2.1.1. An Overview of the Turkish Bond Market

In February 2016, which is the beginning of the data set of this study, the central government’s gross debt stock totaled to an approximate 685.5 billion TRY, with 35.22% of it being foreign exchange denominated borrowings. At the end date of the date range of this study, total debt stock has increased to 1.81 trillion TRY, indicating a 164% in 58 months (Graph 1).



Graph 1: Total Debt Stock of The Turkish Government Agency in Million Turkish Liras (Republic of Turkey Ministry of Treasury and Finance Statistics, n.d)

As a matter of fact, there has been only three months where the annual rate of debt stock's growth did not exceed the year-on-year inflation rate (Graph 2).



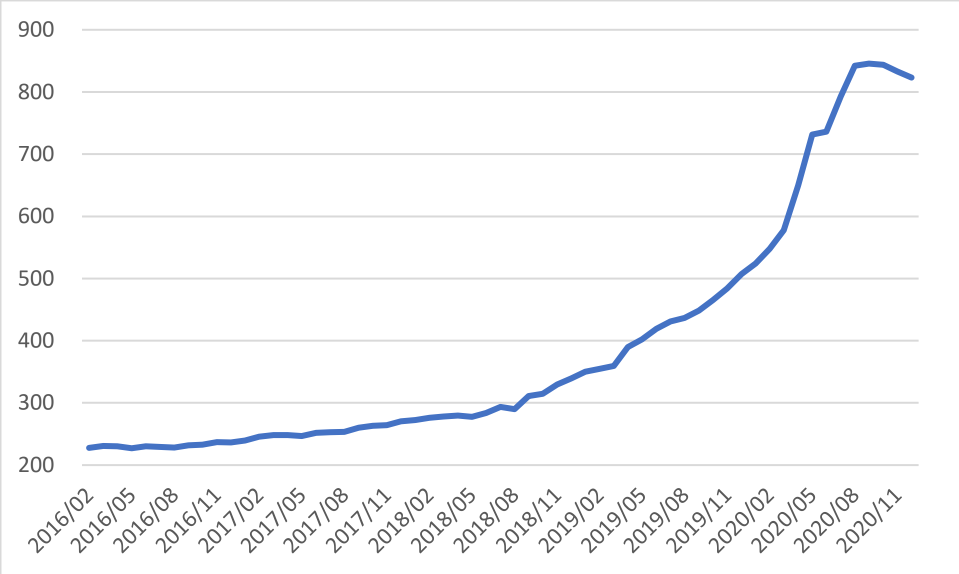
Graph 2: Year on Year Inflation Rate and Yearly Change in Total Debt

Liquidity in the bond market has become even more important than before, as non-residents almost dumped all their holdings of Turkish Lira denominated bonds issued by the government itself (Republic of Turkey Ministry of Treasury and

Finance, 2020). Within the date range of the study, the initial figure for non-resident holdings stood at 17.7% and peaked at 20.4% on September 2017 and has been declining almost ever since. The minimum figure, which is at the same time an all-time low of this data set that starts from 2004, is 3.0% on September 2020 and ends up at 4.0% in the end of the data set (Graph 3).

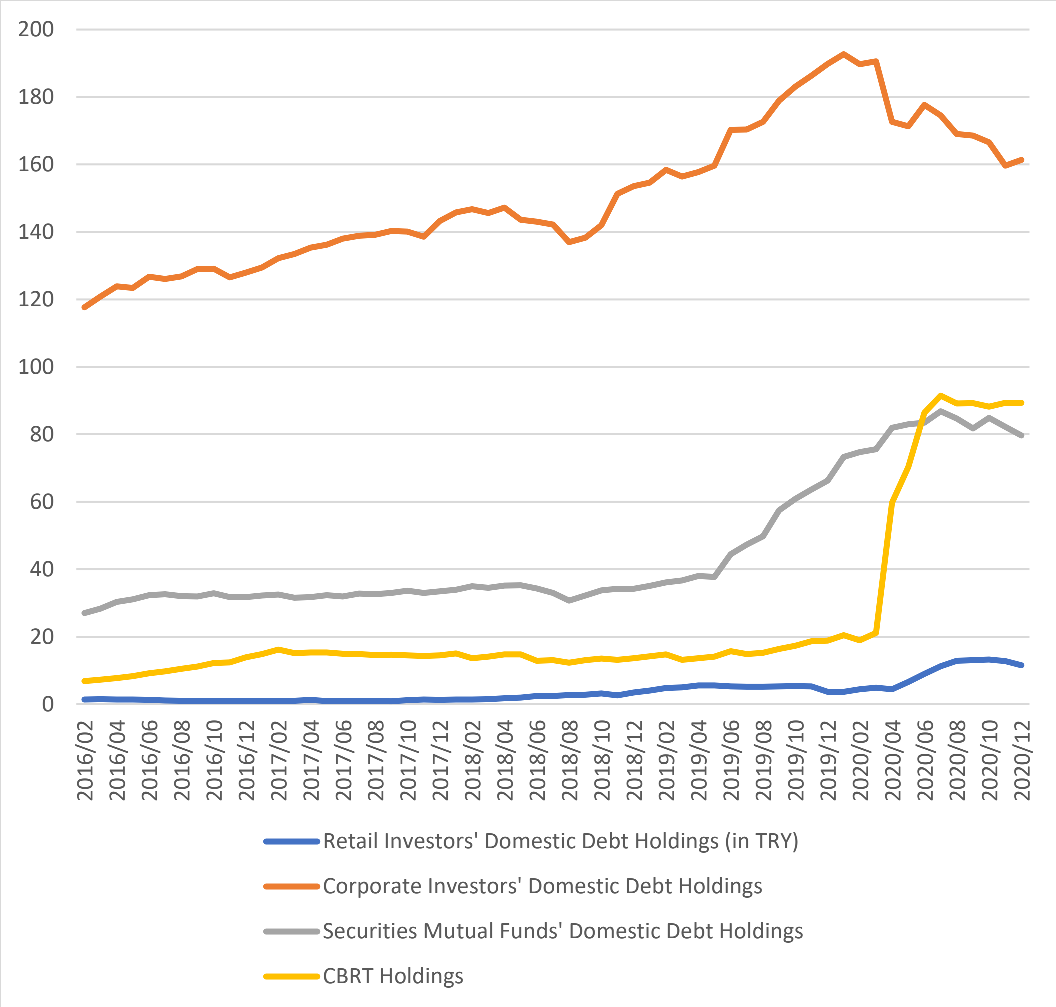
Graph 3: Ownership Rate of Non-residents of Turkish Government Domestic Debt (Republic of Turkey Ministry of Treasury and Finance Statistics, n.d)

While non-residents have been dumping their holdings, the banking sector has been increasing both its proportional and nominal holdings. The banking sector’s total holdings of domestic debt is 227.7 billion TRY in February 2016 and increases remarkably to 823 billion TRY in December 2020 (Graph 4).



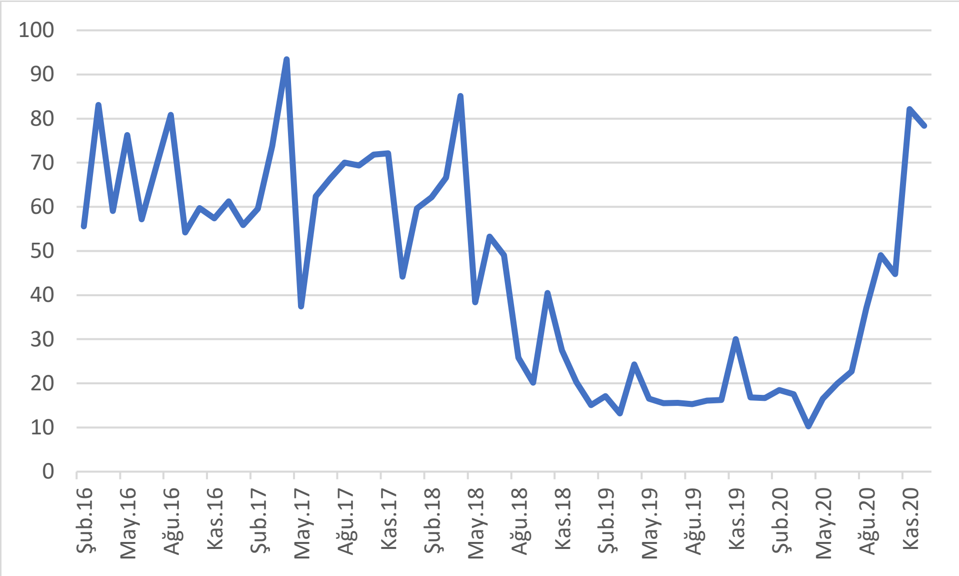
Graph 4: Banking Sector's Domestic Turkish Government Domestic Debt Holdings in Billion Turkish Lira (Republic of Turkey Ministry of Treasury and Finance Statistics, n.d)

Other than non-residentials and the banking sector, non-banking corporations, the Central Bank of Turkey (CBRT), securities mutual funds and households are other domestic debt holders. While the biggest component is the non-banking corporates, all other components' holdings has been increasing, where CBRT's rise after the outbreak of COVID-19 pandemic is quite significant: The CBRT holdings stood at 6.85 billion TRY in February 2016, and the final value in December 2020 is 89.3 billion TRY. The 68.2 billion TRY part of it is caused by the jump in April 2020. Securities mutual funds' holdings has risen to 79.7 billion TRY from 27.01 billion TRY in this time period, corporates' holding has risen to 161.4 billion TRY from 117.65 billion TRY and finally even retail investors's holdings have grown by 726% and reached to 11.6 billion TRY, albeit being insignificant compared to others (Graph 6).



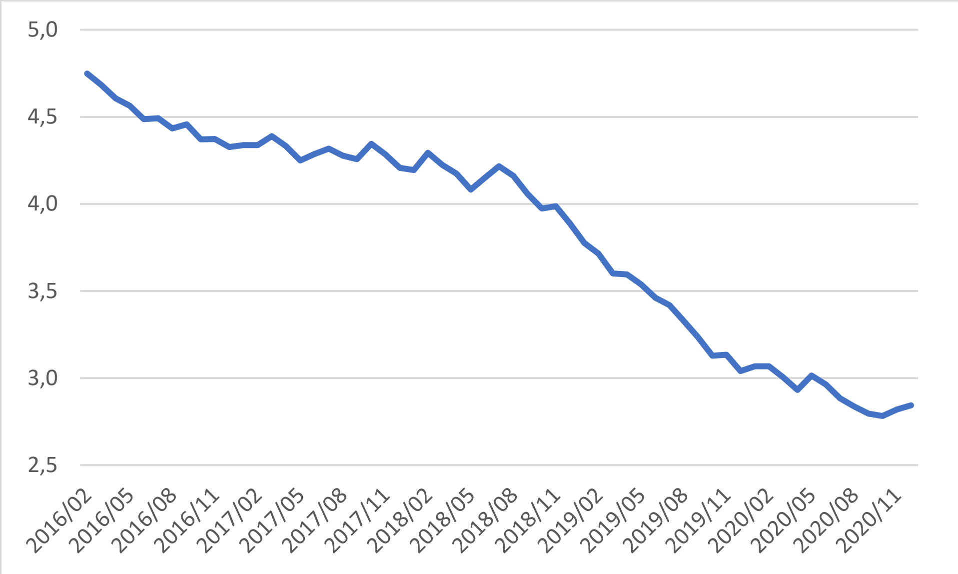
Graph 5: Nominal Turkish Government Domestic Debt Holdings According to Investor Types in Billion Turkish Liras (Republic of Turkey Ministry of Treasury and Finance Statistics, n.d)

In this period, it can be inferred from the fact that the latest ten-year bond issuance has had taken place in March 2018, the Turkish Treasury has reduced its duration on its borrowing program (or on its payers). This argument can easily be supported with data: According to the official website of the Republic of Turkey Ministry of Treasury and Finance, the monthly average maturity on fixed coupon bonds of the relevant month’s borrowing had started to decrease significanty after the inception of the devaluation of the Turkish Lira on August 2018, after which it stayed low and remained in their lows for approximately two years .With the fact that all Turkish Treasury bonds with fixed coupon rates paying coupons semiannually (albeit with different rates), it is almost mathematically certain that the lower the maturity the lower the duration. Thus, it can be argued that the graph below is sufficient enough the conclude with the argument that treasury shortened more its duration on borrowings than having it extended in this time period (Graph 6).



Graph 6: Monthly Average Maturity on Fixed Coupon Bonds of Turkish Government Domestic Debt Stock in Months (Republic of Turkey Ministry of Treasury and Finance Statistics, n.d)

The shortened duration of treasury's borrowings can be further and directly seen in data provided by "Central Government Debt Stock Securities" (Republic of Turkey Ministry of Treasury and Finance Statistics, n.d), where the average time to maturity of central government debt stock is published. According to this data, in the beginning of this data set, the internat debt stock's average time to maturity was 4.7 years and at the end of the data set, this figure decreases to 2.8 years.



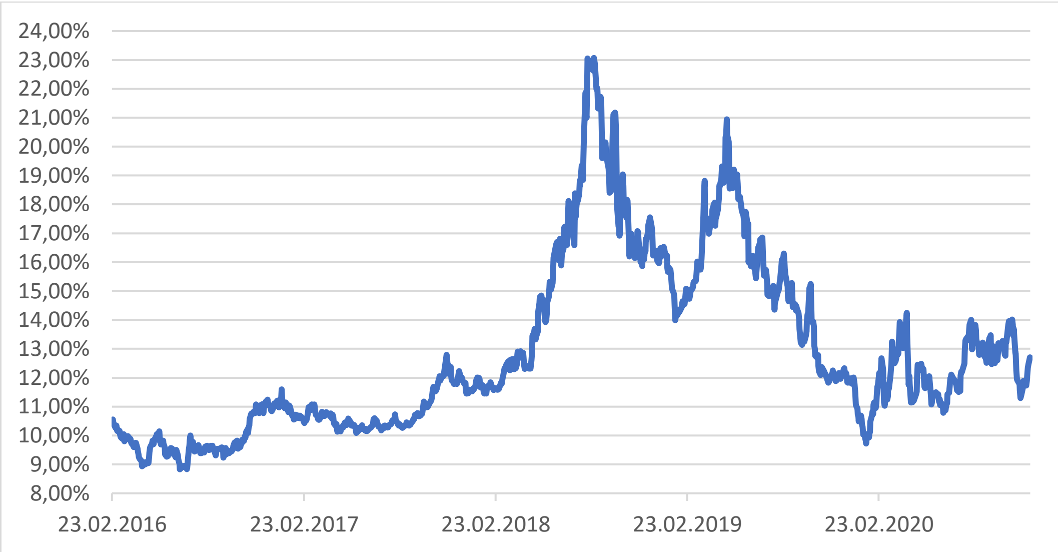
Graph 7: Average Time to Maturity of Central Government Domestic Debt Stock in Years (Republic of Turkey Ministry of Treasury and Finance Statistics, n.d)

By the time this study has started, the three longest-term bonds with fixed coupons were TRT080328T15, TRT110827T16, and TRT110226T13 (Following explanations above about ISIN codes, correspondent maturities for each bond are 08 March 2028, 11 August 2027 and 11 February 2026, respectively). A comparison including the number of days traded and average daily volume when traded is made: There have been 679 trading days since the first settlement date of TRT080328T15 on 20 March 2018 until the end date of this data set. Out of these 679 days, while both of TRT110827T16 and TRT110226T13 have been traded in 678 days, TRT080328T15 has been traded in 659 days. Thus, it can be clearly deducted that there have been days where the longest-term bond of the curve was not traded at all. Therefore, its ability to reflect market dynamics in a complete manner is questionable. While the number of traded days are the same for the other two bonds, the daily average volume for TRT110827T16 stands at 81.925.851 TRY in nominal where this figure is 288.439.233 TRY for the other one, TRT110226T13. It is clear that TRT110226T13 is the most actively traded and most liquid bond for this time period, and there is the reason of why this bond has been selected to reflect the long-end of the curve for Turkish government bonds, given that the shortened duration of debt enables this maturity to be considered as long-term for the Turkish government bonds.

		ISIN CODES		
		TRT080328T15	TRT110827T16	**TRT110226T13**
Attributes	Number of Days Traded	659	678	678
	Average Daily Volume (in TRY)	38.496.124	81.925.851	288.439.233

Table 1: Long-end Turkish Government Bonds' Trading

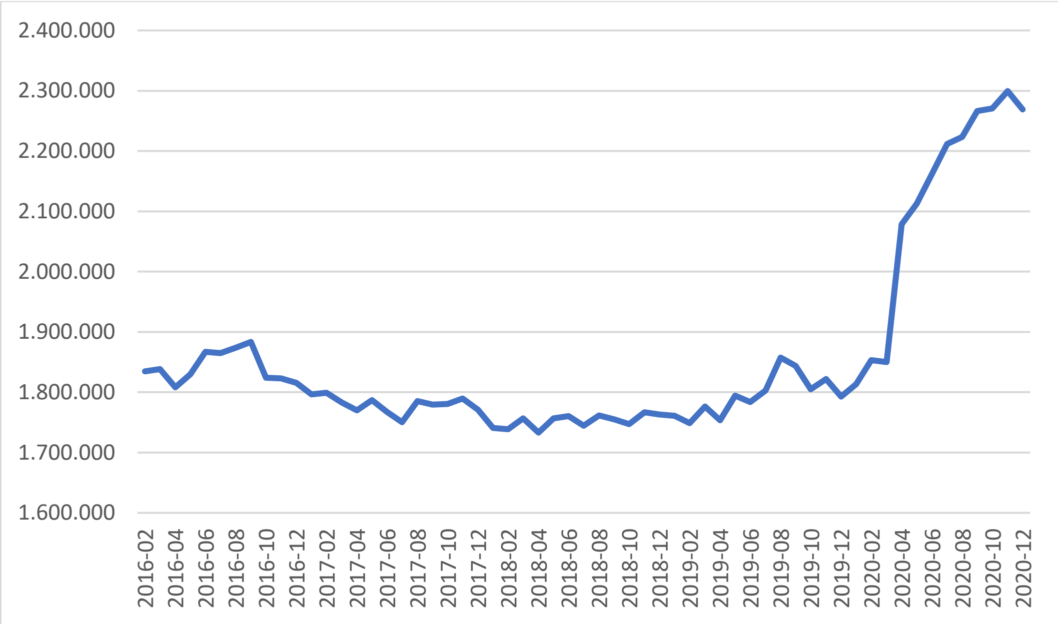
Finally, it can be argued that the path of the simple yield of the selected Turkish Government Bond, TRT110226T13, is highly volatile. The initial value, at the first ever settlement date, is 10.47%, after which the value peaks at 23.07% in late August 2018. Afterwards, it gradually decreases to 9.72% in 30 January 2020, both with institutional measures, falling interest rates and a shortened duration (Graph 8).



Graph 8: TRT110226T13 Bond's Simple Yield Graph

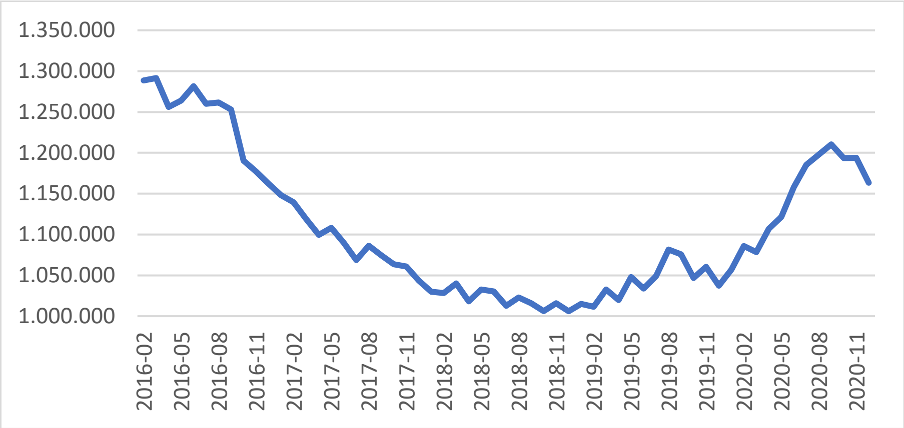
2.1.2. An Overview of the German Bund Market

According to data provided by the Bundesbank (Deustche Bundesbank Eurosystem Debt Securities Holdings Statistics, n.d), within the date range of this study, debt securities stock issued by the general government had an initial value of 1.83 trillion euros and the final value stood at 2.27 trillion euros. The local minimum of this value is 1.73 trillion, seen in April 2018. After the outbreak of the Covid-19 pandemic, there is a considerable increase in debt stock in a short time in the overall stock. After the recognition of the COVID-19 as a pandemic by the World Health Organization in March 2020, the issued debt security stock by the general government increased by a rapid 22.62%, generating an annualized growth rate of 30.17%.

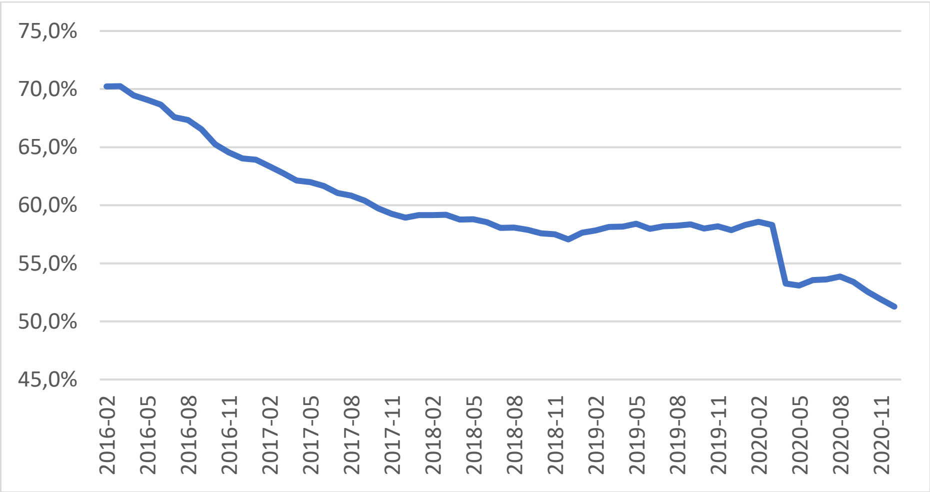


Graph 9: Debt Security Stock Issued by the General Government of Germany (Deustche Bundesbank Eurosystem Debt Securities Holdings Statistics, n.d)

The biggest proportion of the holders is composed by non-residentials with a varying ratio of 51.27% - 70.25%. However, despite being the biggest component, it is important to note that this rate has been declining steadily. Although the nominal difference is a negative 125.4 billion (Graph 10), the proportional difference in the overall debt security stock is almost 19%. Nonetheless, the change in non-residential holding is not as significant as Turkish Government bonds (Graph 11).



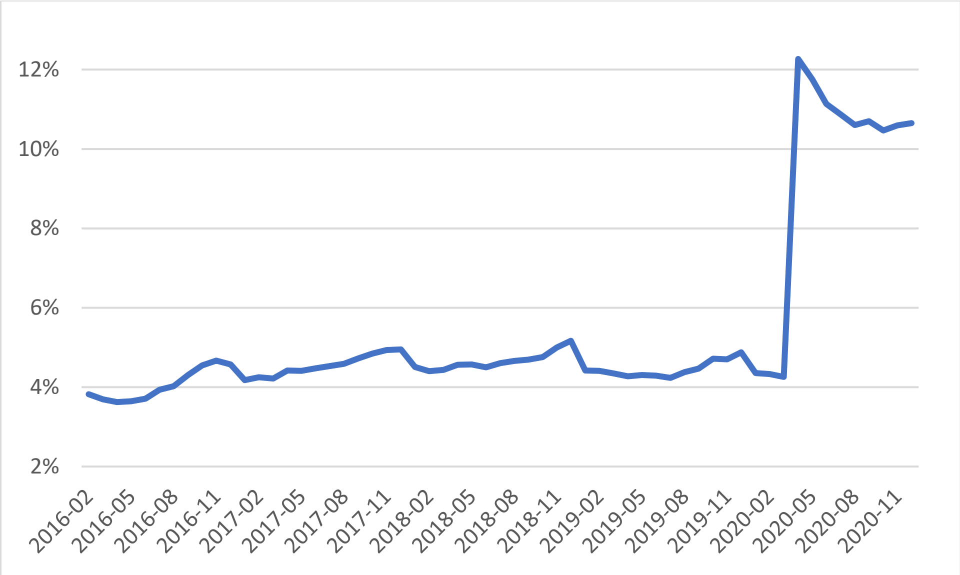
Graph 10: Non-residential Holdings of German Debt Securities in Million Euros (Deustche Bundesbank Eurosystem Debt Securities Holdings Statistics, n.d)



Graph 81: Ratio of Non-residentials in Overall Debt Security Stock Issued by the General German Government

It is also worth noting that monetary financial institutions' holdings have started at 485.46 billion euros and increased a significant 85.86% to reach 855.02 billion euros; in other words, it increased by a 394.93 billion euros. The proportion of financial institutions' holdings has raised to 37.7% in the end of this study's date range from an initial rate of 25.1%.

The change in government holdings is at least as remarkable as the financial institutions, showing a similar behavior to the Central Bank of Turkey. The initial value of government holding stands at an approximate 70.10 billion euros and the ending value is an approximate 241.65 billion euros, suggesting a 244% increase. The timing is coherent with the outbreak of COVID-19 pandemic. With the contribution of this, the proportion of government holdings in all holdings has risen to 10.7% in the end, where the beginning value stood only at 3.8% (Graph 12).



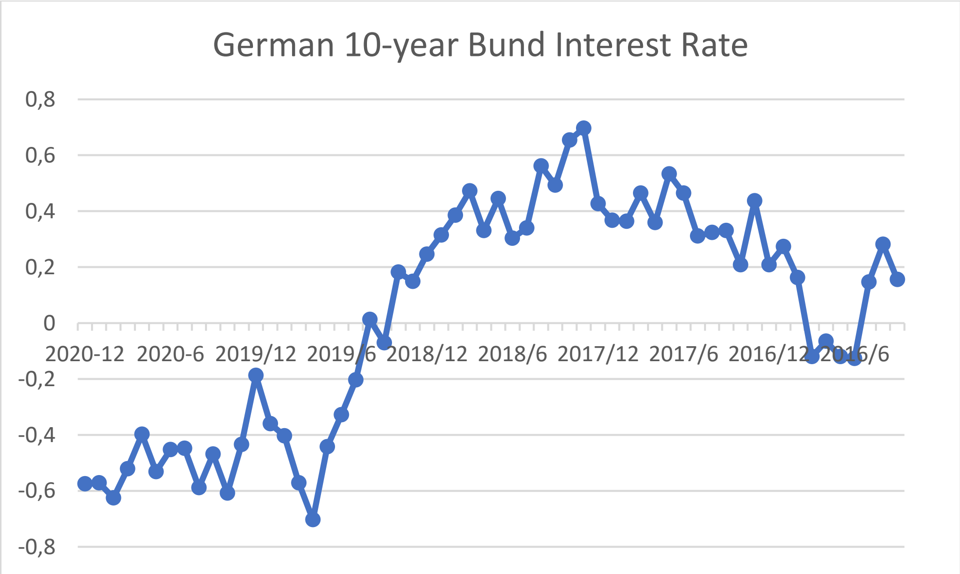
Graph 9: Ratio of Government Holdings in Overall Debt Security Stock Issued by the General German Government (Deustche Bundesbank Eurosystem Debt Securities Holdings Statistics, n.d)

Other holders are households and non-profit organizations; and their proportion is quite ignorable compared to others.

Date/ Ratio	Ratio of Non-residentials in overall Debt Security Stock Issued by the general government	Ratio of Monetary Financial Corporations in overall Debt Security Stock Issued by the general government	Ratio of Government in overall Debt Security Stock Issued by the general government
2016-02	70,2%	25,1%	3,8%
2020-12	51,3%	37,7%	10,7%

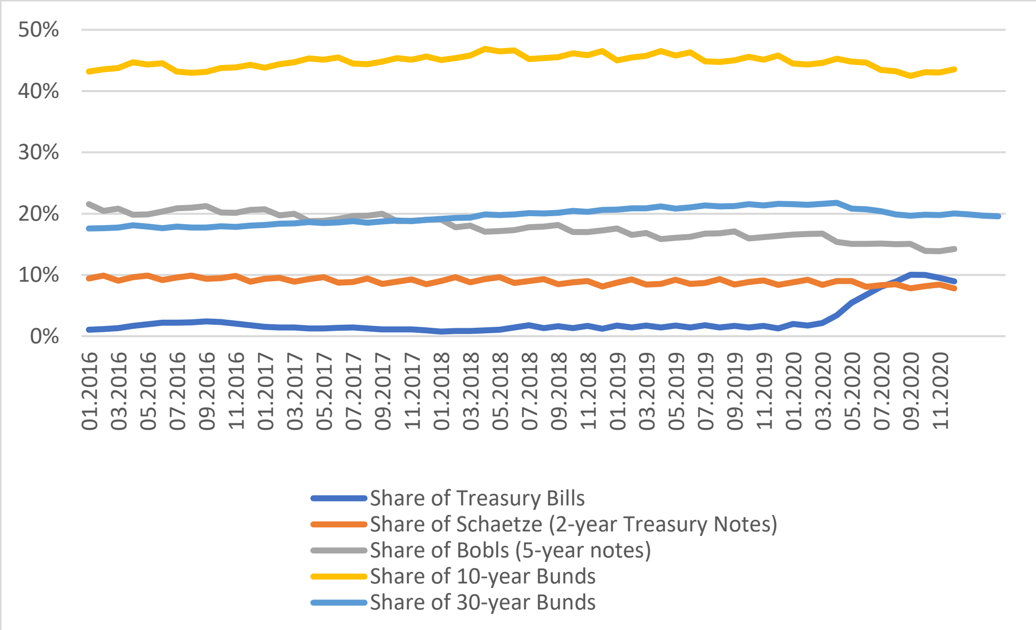
Table 2 Ratio Change of Different Types of Investors' Holdings in General German Government Debt Security Stock (Deustche Bundesbank Eurosystem Debt Securities Holdings Statistics, n.d)

Consequently, data suggest that while to overall debt issuance has increase, the composition of holders has changed. Although rankings have not changed, it can be said that selling of non-residentials and the newly issued debt has been absorbed by either the government itself or the monetary financial institutions.



Graph 10: German 10-Year Bund Generic Yield Graph

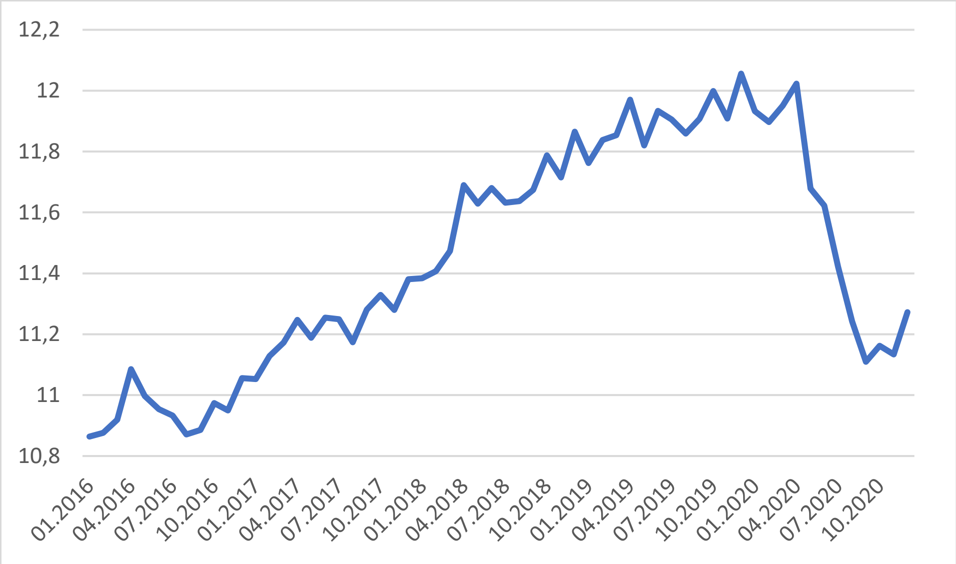
According to the monthly federal government debt bulletin (German Finance Agency Publications, n.d), published by the German Finance Agency, it can be argued that the overall duration composition remains stable. Although the 30-year bunds' amount surpasses the 5-year notes' amount over time, this effect is compensated by the sharp rise in treasury bills.



Graph 14: German Debt Securities Composition According to Terms

An approximation for the overall duration of federal securities is made as follows:

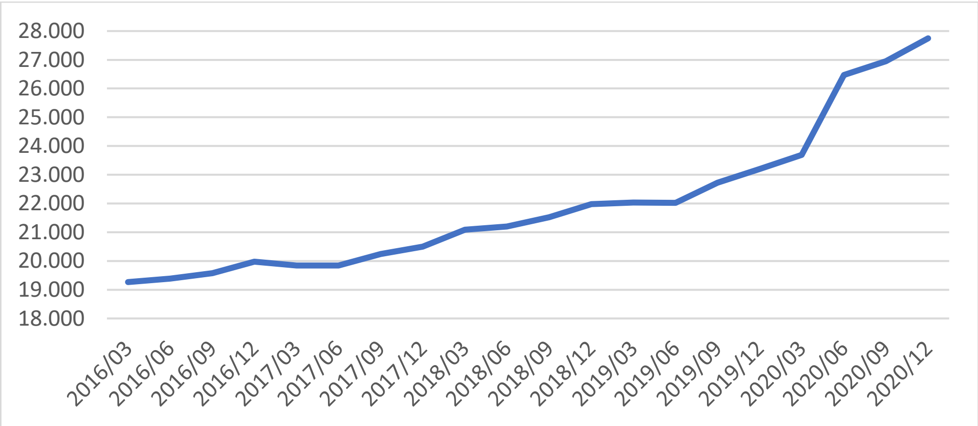
All treasury bills classified in "Bubills" are considered to have a maturity of 0.5 years; where all notes classified in Schaetze are considered to have a maturity an exact 2 years. Accordingly, all data shown in "Bobls" are considered to have a maturity of an exact 5 year, all bonds classified in 10-year Bunds are considered to have exactly 10 years to maturity and finally all bonds classified is 30-year bunds are considered to have exactly 30 years to maturity. It is evident that this does not hold true, as there are other "bunds" maturing in 7 and 15 years as well. However; it is considered to be an adequate approximation. With this approximation, it can be argued that the average duration had been increasing until the outbreak of Coronavirus pandemic. Thereafter, the duration has decreased to values unseen since early 2017.



Graph 11: Custom Approximation of Average Duration of Debt Securities in Years

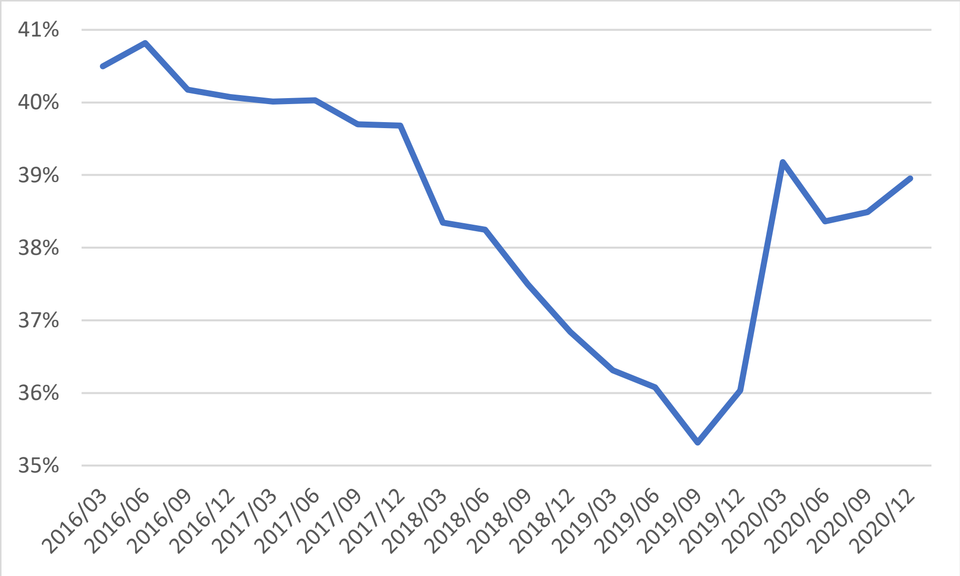
2.1.3. An Overview of the U.S Treasuries Market

According to the treasury bulletin provided by the United States Government (Bureau of the Fiscal Service, n.d), the total public debt has increased by 44.03% from March 2016 to December 2020, where the initial total public debt was 19.26 trillion dollars and reached to approximately 27.75 trillion dollars.



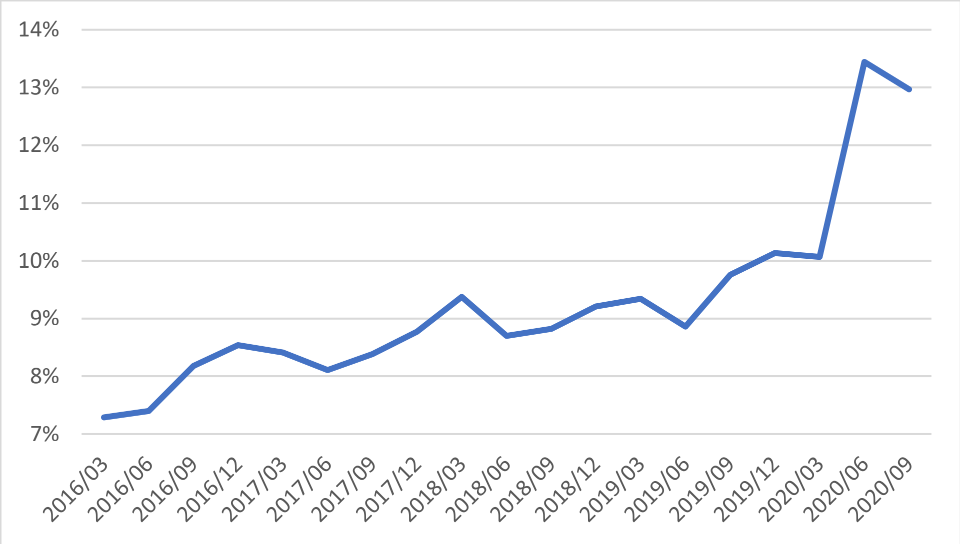
Graph 16: Total Public Debt in Billion Dollars (Bureau of the Fiscal Service, n.d)

This increase of 8.48 trillion dollars was primarily absorbed by FED and government accounts, with a total number of 3 trillion dollars. However, despite of being the leader in increase of nominal debt, their share has decreased to 38.96% in December 2020 from an initial value of 40.50% at March 2016. This is a differing attribute when compared to both Germany and Turkey.



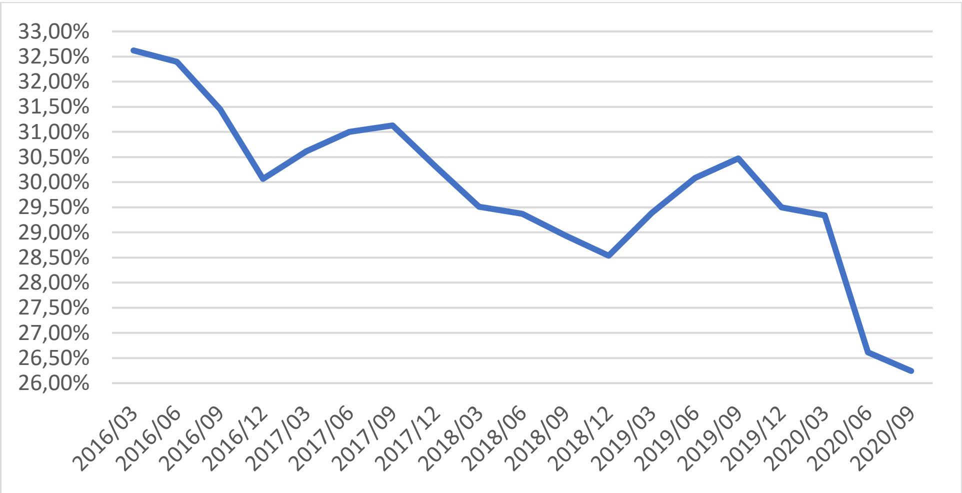
Graph 12: Share of Federal Reserve and Government Accounts in Total Public Debt (Bureau of the Fiscal Service, n.d)

The biggest increase has occurred in mutual funds: While nominal increase of debt stock held by mutual funds is approximately 2.1 trillion dollars, the ratio of holding in total public debt accounted for 12.97% in September 2020, suggesting a 5.70% increase from March 2016. Thus, it is obvious that the other big absorber of newly issued debt is mutual funds.



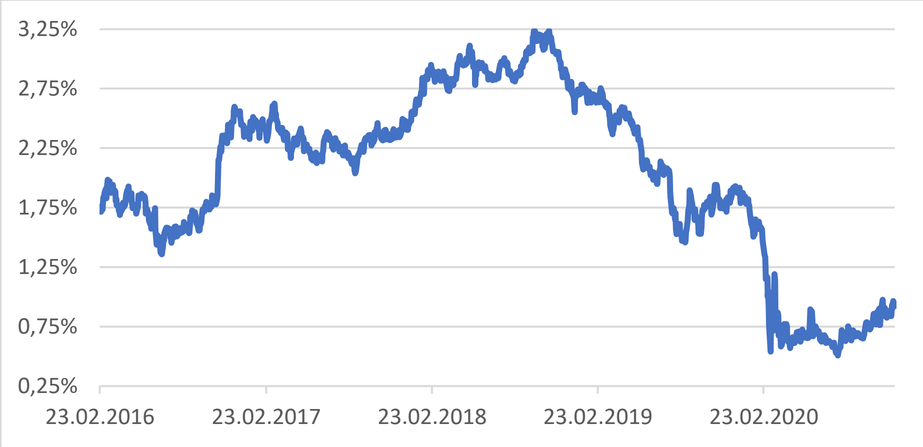
Graph 18: Share of Mutual Funds in Total Public Debt (Bureau of the Fiscal Service, n.d)

As for the foreign and international investors, while their nominal debt holdings has increased by 786.6 billion dollars, their share in the total has decreased by more than 6% from March 2016 to a value of 26.24% in September 2020. Thus, it can be stated the United States has also seen the trend of falling foreigner shares apply for them.



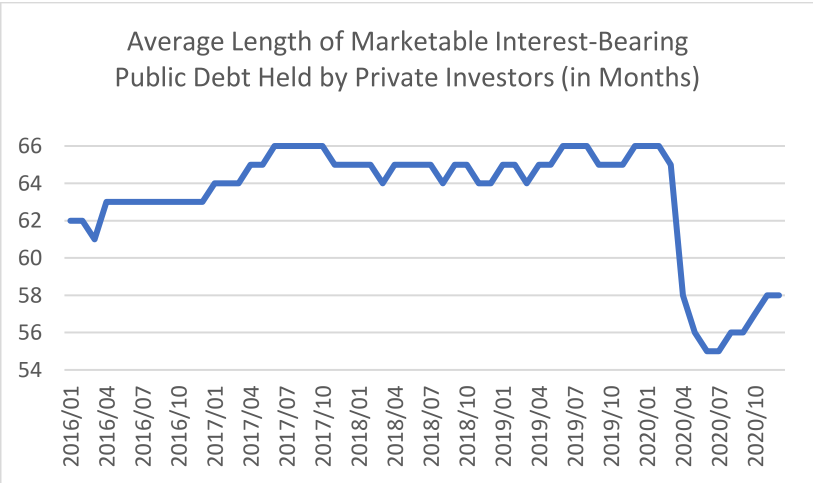
Graph 139: Share of Foreign and International Investors in Total Public Debt (Bureau of the Fiscal Service, n.d)

Finally, it can be stated that the generic 10-year U.S Government bond yield has had a fluctuating period for the date range of this study: It initially shows a modest decrease, where after it is followed by a more significant increase and finally, a decrease occurs in the yields which is then followed by an even sharper decrease.



Graph 14: Generic 10-year US Government Bond Yield

The average length of the borrowing program of the U.S treasury seems to be very consistent over time, though it encounters a decrease after the outbreak of the Coronavirus pandemic. However, regarding the chart below, it can be argued that the U.S treasury is not trading duration.



Graph 15: Average Length of Marketable Interest-Bearing Public Debt Held by Private Investors (In Months) (BUREAU OF THE FISCAL SERVICE, N.D)

3. VARIABLE SELECTION

3.1. Dependent Variable Selection

In this study, the use of machine learning models to predict the price returns of aforementioned governments' debt issuances with a maturity of ten year is being examined. The securities that have been used in the price return calculation for the German and U.S debt has been selected such that the security is the then-current 10-year bund or note, respectively. Accordingly, securities used in the price return prediction processes for these two countries has altered in a sliding manner so that the price return prediction is made with the newly issued 10-year debt security. However, the application of price return prediction for the Turkish Government bond has been handled in a different way. Within the date range of this study's data set, the longest-term fixed coupon Turkish Government Bonds were those maturing on 08 March 2028, 11 August 2027, and 11 February 2026. Although the primary aim of this study is to predict the price return on the long end of the curve, several factors other than duration only should be included to properly reflect the market dynamics for the Turkish Government Bond. More specifically, it can be argued that liquidity and transaction frequency should be taken into consideration whilst the selection process of the Turkish lira denominated bond to be examined. Therefore, for the long end of the curve for Turkish bonds, the bond maturing on 11 February 2026 has been picked. Further evidence about the selection rationale of this one specific bond is provided in the "Turkish Bond Market Overview" section.

A full list of bonds subject to predictions is provided in table 3. Price returns of the bonds, the dependent variables, are derived from these bonds.

Turkish Bonds' ISIN Codes	**U.S 10-year Notes' ISIN Codes**	**German 10-year Bunds' ISIN Codes**
TRT110226T13	US912828M565	DE0001102390
	US912828P46	DE0001102408
	US912828R366	DE0001102416
	US9128282A70	DE0001102424
	US912828U246	DE0001102440
	US912828V988	DE0001102457
	US912828X885	DE0001102465
	US9128282R06	DE0001102473
	US9128283F58	DE0001102499
	US9128283W81	DE0001102507
	US9128284N73	
	US9128284V99	
	US9128285M81	
	US9128286B18	
	US9128286T26	
	US912828YB05	
	US912828YS30	
	US912828Z948	
	US912828ZQ64	
	US91282CAE12	
	US91282CAV37	

Table 3: Used Bonds’ ISIN codes to derive price returns as dependent variables

3.2.Independent Variable Selection

Independent variables are selected from prior available observations than that of the to be modelled dependent variables; that means as the dependent variables are close prices of Turkish Government Bond's price return in percentage, the German 10-year Bunds' price returns in percentages and the U.S 10-year Notes' price returns in percentages, independent variables' observations are selected to be either one of the opening prices, previous closes or an earlier fixings. Independent variables are primarily selected intuitively such that the market prices of selected independent variables are subjectively relevant to the dependent variable. More specifically, based on empirical observations, assets that seem to have a relation (of correlation, causality and even one step ahead of causality; cointegration) with the time series formed by the dependent variables have been examined. Therefore, while the independent variable selection is discussed below, both intuitive reasoning will be argued, and some quantitative evidence will be provided to support the arguments.

The independent variable selection process is consciously limited to either prices or interest rate yields of securities that are tradeable. This has an important implication, being that it therefore excludes both macroeconomic indicators (such as the gross domestic product and its change or the inflation rate) and any information on monetary size of the economy. Exemplarily, when price returns of U.S 10-year notes have been modelled, the FED's balance sheet size has been considered not to be in the scope of useable items, albeit the possibility of a strong relationship between asset prices and FED's balance sheet size in recent years. This fact creates a challenge: Important material that might have potentially served to capture the relationship with the dependent variable might have been barred out because of this limitation. However, it is vital to note that this study does not intend to capture mathematical perfection, both because it is merely impossible, and it refrains the work from a possible pure professional orientation.

3.2.1. Turkish Government Bond's Independent Variables

Turkey has been considered as an emerging market for a long time. Generally, when the market sentiment is uncanny or even bad, all types of emerging markets' asset classes, which can be further specified as bonds, stocks and the local currencies against a hard currency (and generally the U.S Dollars), are being sold for the sake of safe heaven seeking as they are considered to be risky. Therefore, U.S Dollars / Turkish Lira (USDTRY) currency could be used as one simplified indication whether assets whose country of risk is Turkey are demanded or offered in the market. In addition, as Turkey is a net importer country, it is reasonably fair to say that noteworthy shifts in the USDTRY currency are expected to impact prices of imported goods. The exchange rate pass-through to the consumer price index has been an investigated topic in literature; although the pass-through rate has dependances on income groups and main spending groups, Turkey's overall exchange rate pass-through rate has been calculated around %16,5 - %17,5 for the 2003-2016 period (Kaya & Soybilgen, 2019). Moreover, the exchange rate's direction directly effects inflation expectations. However, it is vital to note that by "inflation expectations", a non-measurable subjective matter is in subject rather than any concrete measure such as the likes of the inflation expectations survey, which is being conducted by the Central Bank of Turkey by collecting bank economists' forward inflation expectations, as these survey's results are quite disappointing and are outperformed by naïve statistical models (Soybilgen & Yazgan, An evaluation of inflation expectations in Turkey, 2016). Hence, the Istanbul time 09:00 AM Bloomberg fixing of the USD/TRY currency rate is selected to be an explanatory variable. Inflation and bond yields are believed to be in a strong relationship (albeit awkward disagreements about the direction of their causality), it can be argued that alterations in the inflation outlook could cause respective alterations in interest rates.

The Istanbul Stock Exchange Index is also used as an additional indication whether risk sentiment of the market is good or bad and if TRY denominated assets are being demanded in the market. The prevailing proposition is that stock are risky assets, and this applies for the Turkish Lira denominated stocks as well, and with Turkey being considered as an emerging market, the runaway effect tends to scale up, that is it can be argued that in a risk-off environment in the financial markets, the stock market of Turkey might be hit more than its peers of the developed markets, and more specifically the ones that are being modelled in this study, the German stock index (DAX) and the American stock index (S&P500). Else, it can be argued that unlike developed markets, bonds and stocks might not steadily move in opposite directions; because emerging market bonds, at least Turkish Government Bonds, might not be considered as safe as German Bunds and U.S Treasury Notes. In general, it can be said that Turkish financial assets are synchronically bought together or sold together. Thus, the Istanbul Stock Exchange's open price's daily change in percentage is selected to be another variable. The reason why daily change in percentage is derived with the open price, instead of the close price of the current day, is because current day's close price does not get determined until the market closes and therefore it is not applicable to predict the current day's close change in percentage of the Turkish Bond.

By the same token, U.S 10-year notes' yield is considered to be a very important indicator for the financial markets, both because it is an important interest rate benchmark of the reserve currency of world, and it is also one of the best indicators of the market sentiment. It is also considered to be an indicator of the current state of the economic cycle. To specify, as the United States Treasury cannot default on its own currency (and the reserve currency), U.S bonds are considered as safe "heavens". When the market is distressed, U.S bonds are widely demanded as a result of "flight to quality". This has a remarkable implication: When markets are stressful, the borrowing costs of the U.S treasury diminishes. On the other hand, the rise of yields of U.S bonds can potentially put pressure on emerging markets' assets, as higher returns on assets of better quality attract investors. Based on these grounds, the U.S 10-year yield is one of the most prominent indicators for not only the emerging markets but also financial markets across the globe, hence the daily change in basis points of the first lag is selected to be one variable. The reason why the yield difference is derived by the first lag, instead of the original series, is to avoid data-snooping, that is the close price of the U.S 10-year bond yield of the current day occurs after the close of the predicted dependent variable.

Gold price is also added to independent variables, mainly because it is an important indicator of the overall risk sentiment, it has a historical weight as a mean of value storage and although there might be times where its relationship with inflation weakens, it is still widely considered to be linked to be a protector against inflation. In addition, gold is considered to be a common variable for all three bonds. Therefore, the daily percentage change in gold's ounce price's 09:00 AM Istanbul time Bloomberg fixing has been selected to be the final explanatory variable.

The relationship between inflation and USDTRY could be supported with objective measures: Inflation data in Turkey is being announced in the first Mondays of each month. The measured correlation between the prices of the USDTRY series used in this study on inflation announcement dates and the inflation index is as significant as 0,9775. As they both exhibit trending characteristics, this could be evaluated as expected. Furthermore, the month-on-month USDTRY change, and the month-on-month inflation percentage have a correlation of 0,6762. It is somewhat evident that the USDTRY currency and inflation are correlated.

It is also important to demonstrate the relationship between inflation and interest rates because one of the grounds of USDTRY being related to bond prices is its tie with inflation. As mentioned above, USDTRY currency impacts interest rates not only by worsening inflation expectation (and ultimately its outlook) but also by causing inflation. In a more quantitative way, this argument can be supported with the Granger causality test. Within the date range of the data set of this study; on the inflation announcement dates, sum of squared residuals-based F-test's p-value for a lag number of one of the Granger Causality test, applied on the monthly difference of inflation index and yields' monthly is 0,0123 (Table 4). Therefore, we reject the null hypothesis of no causality. Thus, based on this practical test, it can be argued that yield changes of this bond could be modelled by Turkey's monthly inflation.

Test	F-Score	P-Value
Sum of Squared Residual Based F-Test	6,7234	0,0123
Test	**Chi-Square**	**P-Value**
Sum of Squared Residual Based Chi-Square Test	7,1039	0,0077
Likelihood Ratio Test	6,6882	0,0097
Parameter F-Test	6,7234	0,0123

Table 16: Granger Causality Test – USDTRY causing Inflation Increase

In addition, the correlation between the USDTRY's 09:00 AM fixing and the bond's close price is -0.2694, suggesting that when TRY is being sold, the bond is being sold as well. With this correlation, it can also be deducted that the argument above, suggesting that Turkish assets are being bought/sold together, has a certain amount of validity.

The correlation between the Istanbul Stock Market Index's open price's daily percentage change and the bond price's daily percentage change is 0.2916. This value suggests that the bond price and the stock market generally move in the same direction, validating the argument that Turkish financial assets are synchronically bought together or sold together, and that this argument may be applied to the bond and the stock market.

The correlation between gold's daily percentage change and the modelled bond's daily percentage change is .0945. This figure suggests there is a low correlation between the two. This might be due to the changing perception of gold for what it is being traded for, that is its shifty perception of being demanded for "safe heaven" at times and for "inflation protector" at other times. However, it is important to note that the approval of this possibility is beyond the scope of this study. Additionally, it should be noted gold's price variation as an independent variable aims to both capture the risk appetite of the market and act as a common explanatory variable for all three dependent variables; therefore its causality is not being sought.

The correlation between the U.S Government 10-year note's generic yield's first lag's daily difference in basis points and the dependent variable is a disappointing value of -0.0768. However, when a Granger-causality test is applied, the sum of squared residual-based F-test's p-value stands at 0.0293 for a lag number of one, implying that the price return of the dependent variable could be explained by the first difference in basis points of the generic yields' first lags. Therefore, the variable is used as an explanatory variable, despite of a low correlation value.

Test	F-Score	P-Value
Sum of Squared Residual Based F-Test	4,7607	0,0293
Test	**Chi-Square**	**P-Value**
Sum of Squared Residual Based Chi-Square Test	4,7722	0,0289
Likelihood Ratio Test	4,7631	0,0291
Parameter F-Test	4,7607	0,0293

Table 5: Granger Causality Test – U.S Yield Increase causing price move in TRT110226T13

Correlation					
	Bond Daily Close Price % Change	USDTRY Fixing Daily % Change	ISE Open Price % Change	XAU/USD Fixing Daily % Change	US 10-year yield's first lags' daily difference in bps
Bond Daily Close Price % Change	1	-0.2694	0.2916	0.0945	-0.0768

Table 6: Correlation Table of Turkish Dependent Variable and its Explanatory Variables

3.2.2. U.S Note's Independent Variables

The U.S 10-year note's selected explanatory variables are the VIX Index's daily change in percentage, the S&P500's daily change in percentage and the gold's price change in percentage.

The U.S Government bonds are considered to be "safe heavens" in the financial markets; therefore, they are demanded heavily in times when uncertainty prevails the markets. As one important determinant for the demand of the assets is risk appetite, VIX Index could be used to measure the risk appetite and the tendency of avoiding risk in the markets. VIX Index is an implied volatility of a hypothetical option on S&P 500, and it is also commonly known as the "Fear and Greed Index", which may be used as analytical indicator of risk. Thus, the open price's daily percentage change is selected to be one variable. The reason why the open price is selected instead of the close price, is in parallel with explanations above, that is its availability and suitability to model the close price percentage change of the U.S 10-year Treasury note.

Similarly, the S&P 500 Index's daily return can also used to explain the daily return of the U.S 10-year note's price change, both because generally when the market has a specific intraday direction, the asset classes; stock and government bonds, tend to move in the opposite directions and it may be and indicator of the risk appetite of the market. However, it is important to note that had the data been in months or quarters, in modern times where central banks' primary crisis response is to increase the monetary size of the economies, this opposition would possibly fade, as stock markets tend to exceed and renew their all-time highs and yields have had a steady direction to the south in the past years. As the stocks are considered to be riskier than government bonds ("safe heavens"), they are expected to have negative correlation with a certain amount of meaning.

At last, the gold's ounce price, XAUUSD, is general enough to be included as one common variable, that is the gold price is more comprehensive than just being a country-specific attribute. Furthermore, in different times, it reflects different market phenomenon: It is said to be a protector against inflation in times, and a "safe heaven" in other times. Therefore, it can be used sometimes to explain inflation (and thus nominal yields) and in other times the risk appetite of the market with its differing nature depending on market conditions.

Within the date range of the data set of this study, correlation values for the U.S 10-year treasury notes' price returns and daily percentage change of the VIX Index, the S&P 500 and the gold's ounce price has been measured with VIX Index's S&P 500' prices close prices, and the ounce gold's 09:00 AM Eastern Daylight Time Bloomberg fixing prices. Any missing data of any asset type on any given data has ben filled with linear interpolation.

The correlation of the U.S 10-year treasury note with the VIX Index, the S&P 500 and the gold's ounce price are respectively 0.2585, -0.3415 and 0.0337.

These correlation figures suggest our intuitive reasoning arguments to hold true to a certain extent. The VIX Index's price and the U.S 10-year treasury notes' prices tend to move in the same direction, suggesting that when volatility (and thus the perceived risk rises), the alleged safe heaven demand increases. On the other hand, the S&P500's daily change and the notes' price returns move in opposite directions, suggesting that when one is being demanded, the other is being offered and this validates the argument that the stock market index is considered to be risky, and the notes are considered to be safe heavens and their directions depend somewhat on the risk appetite. Finally, it can be said that there is no significant correlation between gold's ounce price and the treasury notes' price returns, validating the changing nature of the gold's perception depending on market conditions.

The selected independent variables are not argued to have a causality on the U.S 10-year bond's price or yield, therefore a Granger causality test is not needed.

Correlation				
	Bond Daily Close Price % Change	VIX Open Price % Change	S&P500 Open Price% Change	XAU/USD Fixing Daily % Change
Bond Daily Close Price % Change	1	0.2585	-0.3415	0.0337

Table 7: Correlation Table of the U.S Dependent Variable and its Explanatory Variables

3.2.3. German Bund's Independent Variables

One of the selected independent variables to explain the German 10-year Bunds' price returns is the EUR/USD currency rate's daily percentage change, as Bunds are Euro denominated assets and it is needed to purchase these assets. Moreover, it the price of this currency pair contains information about the relative politic, economic content of the two sovereign countries, Germany and the United States.

DAX is the German Stock Index, and its daily percentage change can also be used to explain the daily return of the German 10-year Bunds' price percentage change, as they are expected to move in opposite directions in daily timeframe.

Moreover, as both gold and bonds of developed markets are considered to be "safe heavens" in the financial markets at times, they might be having similar demands periodically. In addition, as the bond yields are affected by inflation and inflation expectations and gold has been perceived to be a protector against inflation, the two of the Bund and gold might have a relation in that sense.

Within the date range of the data set of this study, correlation values for the German 10-year Bunds' price returns and daily percentage change of the EUR/USD currency rate, the DAX Index's daily change, the gold's ounce price's percentage change, U.S Government 10-year bond's generic yield has been measured with the 09:00 AM Berlin Time EUR/USD Bloomberg fixing, DAX's daily open prices, gold's 09:00 AM Berlin time Bloomberg fixing and the previous close of the generic U.S 10-year yield. Any missing data of any asset type on any given data has been filled with linear interpolation.

The correlation of the German 10-year Bund's daily price return in percentage with the EUR/USD currency rate's daily percentage change, the DAX's daily percentage change, the generic 10-year U.S Bond yield change in basis points and gold's ounce price's daily percentage change are respectively 0.0037, -0.1255, -0.1432 and 0.1065. These numbers suggest that there is almost no correlation between the currency with which the Bund is bought and the Bund itself. However, as the EUR/USD currency rate has an indirect relation with the Bund, as discussed in the intuitive reasoning section, this variable is still retained. Furthermore, the negative correlation between the Bund and the DAX validates previous arguments, that they tend to move in opposite directions depending on the overall risk appetite of the market. In addition, the correlation between gold's price return and the Bund's price return The correlation between the generic 10-year yield of the U.S and the Bunds' price returns suggest that they tend to move in the same way, as bond prices and yields move inversely to each other, that is their prices returns might be moving in the same directions. It is worth investigating the cointegrating relation between the price return of U.S 10-year Note and the German 10-year Bund.

Correlation

	Bond Daily Close Price % Change	EURUSD Fixing Daily % Change	DAX Open Price% Change	US 10-year yield's first lags' daily difference in bps	XAU/USD Fixing Daily % Change
Bond Daily Close Price % Change	1	0.0037	-0.1255	-0.1432	0.1065

Table 17: Correlation Table of the German Dependent Variable and its Explanatory Variables

Dependent Variable	**Independent Variable 1**	**Independent Variable 2**	**Independent Variable 3**	**Independent Variable 4**
Turkish Government Bond's Daily Percentage Change	Daily percentage change in Istanbul time 09:00 AM Bloomberg fixing of the USD/TRY currency rate	Daily percentage change in Istanbul Stock Exchange's open price	Daily change in generic yield's first lags of the 10-year US bond in basis points	Daily percentage change in gold's ounce price's 09:00 AM Istanbul time Bloomberg fixing
German 10-year Bunds' Daily Percentage Change	Daily percentage change in Berlin time 09:00 AM Bloomberg fixing of the EUR/USD currency rate	Daily percentage change in DAX's Open Price	Daily percentage change in gold's ounce price's 09:00 AM Berlin time Bloomberg fixing	Daily change in generic yield's first lags of the 10-year US bond in basis points
U.S 10-year Notes' Daily Percentage Change	Daily percentage change in VIX Index's Open Price	Daily percentage change in S&P500's Open Price	Daily percentage change in gold's ounce price's 09:00 AM Eastern Daylight time Bloomberg fixing	

Table 9: Dependent Variables and Their Explanatory Variables

4. DATA SET AND THE METHODOLOGY

All data is retrieved from the Bloomberg Professional terminal, and data set ranges from 23 February 2016, which is the very first settlement date of the selected Turkish Bond, to 7 December 2020, which was when the study on the data set has originated.

While the selected baseline to compare model performances is the random walk model, trained machine learning models include “linear regression”, “random forest”, “gradient boosted forest”, and “support vector machine”. Selected performance metrics to evaluate the results of these models are “Root Mean Square Error”, “Mean Absolute Percentage Error” and directional accuracy. All data has been processed with Python.

4.1. Random Walk

The random walk model is selected as the benchmark model to compare all other models.

According to the Random Walk model (without a drift), the best prediction for the next step is the previous step, as the estimated autocorrelations for price return series are not statistically significantly different than 0. As past data does not give any information about the future, the estimation process is as follows:

$$Y^*{}_t = Y_{t-1}$$

where $Y^*{}_t$ denotes the predicted value for time t and Y_{t-1} denotes the actual value for time t - 1.

4.2. Ordinary Least Squares Regression

According to Moutinho and Hutcheson (2011), Ordinary Least-Squares is a linear model which serves to model a single dependent variable whose interval data is available. In other words, "it models the relationship between a dependent variable and a collection of independent variables" (Pohlmann & Leitner, 2003). "The "least-squares" part of ordinary least squares reflects the fact that the OLS estimate of the parameters is the one that yields the least (or minimum) sum of squared residuals." (Chumney & Simpson, 2006)

Following Lakshmi, Mahaboob, Rajaiah and Narayana,

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i , i = 1,2, \dots , n$$

Where β_0 is the intercept and β_1 is the slope for regressor variable, is a simple linear regression model, with a single independent variable, or a regressor. When the regression model is built with multiple explanatory variables, it can be said that the response variable Y may be related to k regressors. Then, the model is as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i , i = 1,2, \dots , n$$

Which is a Multiple Linear Regression Model.

In this study, the multiple linear regression model is built upon "Ordinary Least Squares" method, which is simply seeking the minimization of error terms of predictions.

Let $\widehat{Y}_i$ denote the observed value for the predicted Y_i value.

$$\varepsilon_i = \widehat{Y}_i - Y_i$$

Epsilon is the error term for i. For a multiple regression model with k variables, the optimization problem that solves the coefficients of the regressors is as follows:

$$min \sum_{i=1}^{k} \varepsilon_i$$

4.3.Random Forests

“Random Forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and within the same distribution for all trees in the forest” (Brieman , 2001). Random forests can be built either for classification or regression problems. A random forest regressor consists of a collection of tree-structured regressors where trees are independent identically distributed random vectors and each one casts a value to be averaged arithmetically at input given inputs (Brieman , 2001).

Random forests are based on bagging of decision trees in which bootstrapped training sets from the original data set are obtained in a way such that only one sample of variables are considered in each split (so that the algorithm ensures trees are not too strongly correlated).

Let b = 1; . . .; B denote the number of bootstrap iterations. The random forest algorithm can then be summarized as follows:

1. Obtain the bootstrapped data from the original data covering the time span up to $T_{i,}\, t_i \; = 1, \dots , T_i$.

2. Using the bootstrapped data obtained in step 1, estimate a regression tree $\hat{g}_{RF}^{(b)}(f)$ by just considering p factors at random from all vectors when determining the best variable/split point for each terminal node of tree until the minimum node size n_{min} is reached.

3. Repeats steps 1 and 2 B times.

After obtaining B decision trees by following these steps, h_i - steps-ahead predictions of explained variables are calculated as the average value of B trees as follows:

$$\hat{Y}_{t_i} + h_i \mid t_i = \frac{1}{B}\sum_{b=1}^{B} \hat{g}_{RF}^{(b)}(\,\hat{f}_{t_i} + h_i \mid t_m\,)\,.$$

4.4.Gradient Boosted Forests

Gradient boosting models are additive regression models where base learners are sequentially fitted to pseudo-residuals by least squares at each iteration.

The gradient tree boosting algorithm can be summarized as follows:

Let m = 1, … , M denote the number of iterations, $\{y_{t_i},\ f_{t_i}\}_1^{T_i}$ be the original data set and $\{y_{\pi(t_i)},\ f_{\pi(t_i)}\}_1^{\bar{T}_i}$ denote the fraction of the original training set randomly selected without replacement, and λ the learning parameter. The steps are as follows:

1. Initialize $h_0(f) = argmin_{\Upsilon} \sum_{t_q=1}^{T_q} L(Y_{i_t}, \Upsilon)$.

2. Use a subsample of the training set, $\{y_{\pi(t_i)},\ f_{\pi(t_i)}\}_1^{\bar{T}_i}$.

3. For $\pi_{(t_i)} = 1, 2, \dots, \bar{T}_i$ compute r$r_{n(t_i),m} = \left[\frac{\partial L\left(y_{\pi(t_i)}, h\left(f_{\pi(t_i)}\right)\right)}{\partial h\left(f_{\pi(t_i)}\right)}\right]_{h=h_m-1}$

4. Fit a regression tree to the targets $r_{\pi(t_i),m}$, giving terminal regions $R_{j,m}, j = 1, 2, \dots, J_m$.

5. For $j = 1, 2, \dots, J_m$, compute $\Upsilon_{j,m} = argmin_{\Upsilon} \sum_{f_{n(t_i)} \in R_{j,m}} L\left(y_{\pi(i)}, h_{m-1}(f_{\pi(t_i)}) + \Upsilon\right)$

6. Update $h_m(f) = h_{m-1}(f) + \lambda \sum_{j=1}^{j_m} \Upsilon_{j,m} I(f \in R_m)$.

7. Repeat steps 2, …, 6 M times.

8. Derive the final model $\hat{h}(f) = h_m(f)$.

In this study, after the final model has been obtained, h_q step ahead predictions of explained variables are calculated as $\hat{y}_{t_i + h_i | t_i} = \hat{h}(\hat{f}_{t_i + h_i | t_m})$.

4.5.Support Vector Regressors

Following the studies of McDonald et al. (2014), Smola & Schölkopf (2004) and Alpaydın (2010),

Let χ denote the space of input patterns, given that

$\{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\} \subset \chi \times \mathbb{R}$,

bringing the feature space to a higher dimension.

We define a linear function f, taking the form:

$$f(x) = (w, x) + b \text{ with } w \in \chi, b \in \mathbb{R}$$

where $(.,.)$ denotes the dot product operator in χ.

In ε-SV, the goal is to find a function $f(x)$ that maximum deviation is ε from the actually obtained targets y_i for all the training data that is at the same time as flat as possible.

To flatten means a minimization of w. This optimization is processed as follows:

$$minimise\ \frac{1}{2}\ \|w\|^2 + C\ \sum_{i=1}^{m}(\mathcal{E}_i + \mathcal{E}_i^*)$$

$$subject\ to \begin{cases} y_i - (w, x_i) - b \le \varepsilon + \mathcal{E}_i \\ (w, x_i) + b - y_i \le \varepsilon + \mathcal{E}_i^* \\ \mathcal{E}_i, \mathcal{E}_i^* \ge 0 \end{cases}$$

Where C is a trade-off between the flatness of the function f and the amount up to which deviations larger than ε are tolerated.

$$With\ w = \sum_{i=1}^{m}(a_i - a_i^*)\, x_i\ \ and$$

$$f(x) = \sum_{i=1}^{m}(a_i - a_i^*)\, K(x_i, x) + b,$$

where $K(x_i, x)$ is known as the kernel function, and a_i, a_i^* are the dual variables.

The kernel function used in this study is a radial basis function, following McDonald et al. (McDonald, Coleman, McGinnity, Li, & Belatreche, 2014). Thus the kernel function is as follows:

$$k(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right)$$

5. RESULTS AND DISCUSSION

For regression performance metrics, mean absolute percentage error and residual mean squared error all three of the Turkish government bond, 10-year U.S note and 10-year Bund's return forecasts outperform the baseline model, the random walk for all six k-step ahead forecasts, for k = 1, 5, 10, 30, 60, 90. In that sense, it can be argued that the selected machine learning algorithms are better predictors than the random walk model.

If we go into the details of the Turkish analysis, model results suggest that, according to RMSE, the best model is that created with the linear model, with a value of 0.0117, followed by the gradient boosted tree model with an RMSE value of 0.0122. However, although the support vector regressor model is the worst model according to the directional accuracy metric, it is the model with the lowest RMSE for 5-day, 10-day, 30-day, 60-day and 90-day ahead forecasts. Additionally, the support vector regressor has the lowest MAPE values for all 6 different step ahead forecasts, suggesting that it might be a good predictor. The distribution of actual returns indicate a mean of %0,01 and a skewness figure of 0.4706; suggesting that the distribution is positively skewed and therefore more of the data points are less than the mean. However, support vector regressor's predicted values do not predict a single negative return for the whole series, which is why the directional accuracy is low compared to all other models and even to random. As the predicted values are components of a return series, which is expected to have a mean very close to 0, predictions can statistically outperform another one, while being harshly inaccurate; as the support vector regressor suggests for the selected models.

Descriptive Statistics -TRT110226T13 Price Return Series	
Mean	0,000119
Standard Deviation	0,014912
Kurtosis	5,752012
Skewness	0,470659
Count	677

Table 10: Descriptive Statistics for the Turkish Bond

The lowest MAPE figure for all different step ahead forecasts for different types of models is 1.0169; for the 1-step ahead forecast with the support vector machine. However, for reasons mentioned above, it is also important to see a model with less volatile prediction metrics as well as with robust results. Therefore, for one step ahead predictions, the gradient boosted trees may be a better predicting model, as it seems to be less volatile in ranking and it has less controversial results. Moreover, with the selected explanatory variables, results suggest that the linear model may also be used; as it has a notable directional accuracy with 63.71%, and the smallest RMSE value.

TRT110226T13 Price Return Models' Prediction Performance						
	RMSE					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
Random Walk	0,0162	0,0185	0,0177	0,0189	0,0181	0,0175
Linear Regression	**0,0117**	0,0132	0,0131	0,0137	0,0135	0,0125
Random Forest	0,0124	0,0134	0,0135	0,0143	0,0138	0,0146
Gradient Boosted Tree	0,0122	0,0128	0,0127	0,0131	0,0130	0,0134
Support Vector Machine	0,0125	0,0126	0,0128	0,0128	0,0129	0,0121
	MAPE					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
Random Walk	2,7761	2,8799	2,6959	2,9695	2,9644	3,1303
Linear Regression	1,1959	1,2711	1,3495	1,4664	1,3857	1,4699
Random Forest	1,4624	1,5528	1,6685	1,7538	1,7417	1,9940
Gradient Boosted Tree	1,0339	1,0656	1,1310	1,1351	1,1128	1,3873
Support Vector Machine	**1,0169**	1,0173	1,0177	1,0195	1,0174	1,0187

	Directional Accuracy					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
Random Walk	0,5666	0,4979	0,5097	0,4786	0,5133	0,5065
Linear Regression	**0,6371**	0,4840	0,4871	0,4647	0,4855	0,5677
Random Forest	0,6055	0,4904	0,4914	0,4820	0,4855	0,5495
Gradient Boosted Tree	0,6181	0,4840	0,5065	0,5248	0,5000	0,5703
Support Vector Machine	0,4763	0,4776	0,4763	0,4685	0,4830	0,4923

Table 11: Performance metrics of Turkish Bond's price return forecasts made with used machine learning models

Another interesting point is, for the directional accuracies, both for the gradient boosted tree model and the linear model, the runner-up forecasts are made for 90-step ahead forecasts.

For the 10-year U.S notes' price return forecasts, the majority of the results suggest that the gradient boosted trees model is outperforming the other models. Again, the support vector regressor model seems to be the second-best performing model for the one step ahead predictions, according to the RMSE and MAPE. However, for the very same reasons, the results of support vector regressors should be considered with caution.

Descriptive Statistics -U.S 10-year Note Price Return Series	
Mean	0,0000
Standard Deviation	0,005462495
Kurtosis	51,61331252
Skewness	-2,765869573
Count	1249

Table 12: Descriptive statistics for the 10-year U.S Notes

As the Turkish Bond's results, for RMSE and MAPE performance metrics of the U.S 10-year note, all models for all different step ahead forecasts outperform the selected baseline model, the random walk model. For the one step ahead predictions, the gradient boosted trees model has the lowest MAPE and RMSE figures, while the directional accuracy is at its most for the linear model. While the lowest MAPE value is 1.0340 for the one-step ahead forecast with the gradient boosted tree, its maximum value stands at 3.7511for the ten-step ahead forecast with the random walk model. The highest directional accuracy is achieved by the linear model for the one-step ahead forecast with a rate of 56.73%, which is then followed by the gradient boosted tree for the one-step ahead forecast with a rate of 53.20%. RMSE figures suggest that both gradient boosted trees and support vector machines outperform other models on average. For the one-step ahead forecasts, both gradient boosted trees model and the support vector regressor have an RMSE value of 0.0070 which stands at 0.0071 for the linear model and 0.0072 for the random forest model.

10-year U.S Note Price Return Models' Prediction Performance						
	RMSE					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
RW	0,0101	0,0099	0,0101	0,0097	0,0101	0,0106
Linear Regression	0,0071	0,0072	0,0072	0,0070	0,0072	0,0074
Random Forest	0,0072	0,0072	0,0073	0,0071	0,0075	0,0076
Gradient Boosted Tree	**0,0070**	0,0071	0,0071	0,0070	0,0072	0,0074
Support Vector Machine	**0,0070**	0,0070	0,0071	0,0070	0,0072	0,0073
	MAPE					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
RW	3,3645	3,0505	3,7511	3,4021	3,0682	3,7442
Linear Regression	1,0909	1,1318	1,1362	1,1763	1,2506	1,2094
Random Forest	1,6220	1,5314	1,5031	1,5980	1,7090	1,6094
Gradient Boosted Tree	**1,0340**	1,0723	1,0375	1,0495	1,0996	1,0871
Support Vector Machine	1,0510	1,0513	1,0477	1,0479	1,0467	1,0486
	Directional Accuracy					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
RW	0,4730	0,4895	0,5073	0,5452	0,4917	0,4656
Linear Regression	**0,5673**	0,5126	0,5031	0,5474	0,4965	0,4325
Random Forest	0,5176	0,5104	0,4968	0,4878	0,5342	0,4758
Gradient Boosted Tree	0,5320	0,4958	0,4841	0,5562	0,5082	0,4885
Support Vector Machine	0,5093	0,5104	0,5116	0,5143	0,5104	0,5190

Table 13: Performance metrics of 10-year U.S Notes' Price Return forecasts made with used machine learning models

Finally, the results for the 10-year Bunds' forecasts suggest that both for RMSE (0.0036) and MAPE (1.1803), the gradient boosted tree is the best model for one-step ahead forecasting (The cross-sectional averages for RMSE and MAPE are 0.0041 and 2.4016, respectively). As a matter of fact, gradient boosted tree outperforms all different step ahead forecasts in terms of MAPE performance metric. Moreover, it should be noted that all models once again outperform the random walk model in all three metrics.

For the one-step ahead forecast's directional accuracy; the linear model has an accuracy rate of 54.60% while the doubted support vector regressor model has a rate of 55.10%. However, once again, as a possible result of standardized variables, the predictions suggest that returns are always bigger than zero. Therefore, with such an obvious misconception, its directional accuracy power should be considered with caution. It can be summarized that for bunds as well, the gradient boosted trees and the linear models are more promising when compared to the random walk, random forests and the support vector machines.

10-year Bund Note Price Return Models' Prediction Performance						
	RMSE					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
Random Walk	0,0050	0,0053	0,0051	0,0051	0,0054	0,0055
Linear Regression	0,0038	0,0039	0,0038	0,0039	0,0040	0,0041
Random Forest	0,0039	0,0039	0,0040	0,0041	0,0040	0,0044
Gradient Boosted Tree	0,0036	0,0037	0,0037	0,0038	0,0038	0,0039
Support Vector Machine	0,0037	0,0037	0,0037	0,0037	0,0038	0,0039
	MAPE					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
Random Walk	4,4924	3,6778	4,3581	3,8737	4,9613	3,9758
Linear Regression	1,7351	1,5996	1,8686	2,1184	2,1192	1,9279
Random Forest	2,3083	1,9449	2,5173	2,308	2,1364	2,5139
Gradient Boosted Tree	1,1803	1,1519	1,2235	1,2076	1,2535	1,1851
Support Vector Machine	1,2877	1,2899	1,293	1,3093	1,2616	1,254

	Directional Accuracy					
	1-Day Ahead	5-Day Ahead	10-Day Ahead	30-Day Ahead	60-Day Ahead	90-Day Ahead
Random Walk	0,4878	0,501	0,5625	0,537	0,5046	0,535
Linear Regression	0,546	0,5269	0,5407	0,525	0,4779	0,4687
Random Forest	0,5163	0,5443	0,5125	0,5	0,5255	0,5025
Gradient Boosted Tree	0,5286	0,5113	0,5312	0,5087	0,4977	0,47
Support Vector Machine	0,551	0,5526	0,5521	0,55	0,5511	0,56

Table 14: Performance metrics of German Bund's price return forecasts made with used machine learning models

6. CONCLUSION

It can be suggested that, in this study, with the selected independent variables, all machine learning models used in this study outperform their baseline, the random walk model. With the selected independent variables, generally more robust results are attained with gradient boosted trees in terms of MAPE and RMSE; and directional accuracy is achieved more with linear regression, especially in terms of one-step ahead forecasting. Albeit good numerical results, support vector machines have their unique and obvious problem.

While these findings are coherent with the literature's findings, suggesting that machine learning methods may be beneficial for financial markets' forecasting, it should also be mentioned that better models with better explanatory variables in the infinite universe of possible variables should be further explored. However, although this study does not implement any trading strategies with possible risk management and trading rules, in terms of bond predicting, the findings of this study suggest that machine learning models for bond trading may be effective for practical use.

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