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Analysis of the Impact of Federal Funds Rate Change on US Treasuries Returns using SAS

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ABSTRACT

This paper analyzes the impact of federal funds rate changes on government bond returns and return volatility and compares it with equities market reaction. The purpose of this work is to construct a model estimating an expected risk exposure at a hypothetical point of time in the future given a description of current market conditions and historically observed events, which can be helpful in explaining expected movements and predicting future bond prices and volatility to use by portfolio managers in choosing asset allocation. We identify to which extent there is an impact of rate changes and the length of its effects. For our analysis we use data on major government bond prices and major macroeconomic characteristics of the U.S. economy between February 1990 and June 2015, collected on a daily basis. We model and forecast expected returns using ARIMA modeling based on different scenarios. Vector Autoregression and Vector Error Correction modeling is applied to estimate the impact of rate changes on government bonds performance and volatility. Credit markets behavior is compared to the equities market reaction. Findings are consistent with the previously published papers. US treasuries positively react on Federal Funds rate change, while equities market demonstrates a negative reaction. Long-term relationship between US Treasuries markets and Federal Funds rate is identified. The fact that a change in US treasuries market may be Granger caused by a change in Federal Funds target rate is statistically proved. All estimations are performed using SAS software.[1]

INTRODUCTION

Financial markets are sensitive to many factors, including various macroeconomic parameters and policy changes (Ekanayake et al, 2008). Markets tend to react different on positive and negative events, as well as on difference between expectations and actual events. Investors are interested in predicting future market movements to optimize investment decisions under different scenarios. Professionals generate expectations based on their best guesses, technical and fundamental analysis, and multiple predictive models, creating a full overview based on different scenarios to make the best possible decisions.

Various policy changes are among the most influential factors impacting financial markets (Rigobon et al, 2002, Ekanayake et al, 2008). Federal Reserve regulates the US economy through monetary policy using Federal Funds target rate as a major influential instrument. Federal Open Market Committee (FOMC) is in charge of United States national monetary policy and oversees the nation's open market operations. FOMC makes decisions regarding changes in Federal Funds Target Rate (FDTR) during regular meetings based on current economic conditions and future economic expectations. Typically an increase or a decrease in FDTR pulls equities and credit markets in different directions depending on other economic factors (Rigobon et al, 2002, Ekanayake et al, 2008) and preceding expectations (Bernanke et al, 2005). These facts increase interest for predicting FDTR impact on financial markets, and constantly stimulate demand for better models with higher predictive power.

Monetary policy is affecting all financial entities and activities in different ways. Theoretical finance assumes a positive relation between credit market returns and negative correlation between federal funds target rate and equity market returns. This may be explained by the fact that newly issued bonds tend to have higher coupon rates when issued later on an increase FDTR rate regime. This makes previously issued bonds less attractive for investors and therefore reduces the price during the secondary markets trading. This leads to an increase in returns to investors, who can now buy the bonds at lower price and still have the same coupon payments. All these changes are reflected in bond yields, calculated as a ration of a coupon to a current market price of security. A change in bond yields can be considered an approximation of returns on investment. Stock markets returns are represented by change in stocks prices as well as dividends paid. An increase in FDTR means an increase in cost of financing for companies, which may cause a decrease in their profits, and therefore dividends paid to shareholders. Also expectations regarding a potential decrease in profits and dividends may lead to a decrease in equity market price. This is the way finance explains expectations of a negative impact of equities markets on an increase in FDTR.

The question of FDTR increase is on the FOMC agenda again after years of no change. Market participants expect a potential increase announcement later in 2015 or early 2016. The abovementioned fact makes this paper relevant

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[1] JEL classification codes: G11, G12, G17, C32, C87. Keywords: Bond Yields, Stock Returns, Risk Analysis, Forecasting, SAS, Time Series Modeling, ARIMA, VAR, VECM, Cointegrtion, Causality.

[2] For variables available on a quarterly basis we impute the latest available numbers for each day when no

and up to date with the current economic situation, since it estimates expected changes due to FDTR rise based on current economic conditions.

LITERATURE REVIEW

Two major ways for statistical analysis applied to financial markets include historical analysis and stochastic approach. Both are widely described in numerous papers. Both ways may be used together or preference may be given to any type of analysis. In this paper we focus on time series analysis for financial forecasting based on historically observed data.

Autoregressive integrated moving average (ARIMA), vector autoregressive models (VAR), general autoregressive conditional heteroskedasticity models (GARCH) and various others are the widely accepted time series analysis modeling technique. ARIMA models were described by Box and Jenkins in 1970 and still hold one of superior places in financial forecasting allowing to produce models with good fit and generate precise short-term forecasts. Advantages of VAR models include incorporation of dynamically changing regressors (Zellner, 1962). They are widely used as an analytical tool, which makes possible to describe the interdependence mechanism between variables. GARCH models, introduced by Engle (1982), allow estimating conditional volatility, which can represent expected investment risks. Multivariate GARCH models (MGARCH), which allow to estimate various shocks impact on volatility were proposed by Harvey et al in 1994. Other models like neural networks and state-space models allow for latent variables and processes and may include elements of simulation, which stands them in between two major analysis flows.

Abovementioned models can be utilized for both equities and credit markets (Ekanayake et al, 2008). The two markets may react different on various shocks, so different quantitative models may work better for analysis of stocks and bonds. Time series analysis is more often used for analysis of equities market, while credit markets are in general more quantitatively complex and less analyzed by the time-series approach. We use time-series analysis for predicting markets movements, which is less common for credit markets. By applying time-series models we demonstrate how to create and use another helpful analytical tool, which allows to better understand market movements.

Federal funds rate change impact on equities markets is comprehensively analyzed, while credit markets related literature has a few time series analysis application papers published so far. Many authors are focused on an event – study framework, identifying impact of a change in FDTR on different classes of assets. Most of them do not implement out of sample forecasts. They also try to identify expected and unexpected portions of FDTR change onto financial markets (Bernanke et al, 2005; Hakan et al, 2010, Yin et al, 2010; Hsing, 2007). Both Bernanke and Hakan prove that unanticipated portion of FDTR change is influential, once an expected change does not lead to a significant markets reaction, while Hsing proves a decline of such an impact with an increase in maturity. Bernanke et al (2005) find a hypothetical 25 basic point increase in FDTR leads to a 1% increase in broad stock indexes. Ekanayake et al (2008) prove federal funds rate increase on average causes a negative reaction of stock markets, and a decrease in federal funds target rate positively affects stock markets. Friedman (1982) brings, that an increased volatility of a target rate leads to a decrease in external funding of corporations, increases bond yield spreads, and potentially change portfolio choice strategies for bond markets. Nishiyama's findings support this idea with proving the causality relationship between long-term bond yields and the FDTR in 2007.

Federal funds target rate change is also justified to impact returns volatility (Bernanke et al, 1999; Bomfim, 2003, Bera et al, 1993). Chulia et al (2010) concludes the negative surprises trigger a bigger reaction in stock prices than positive ones. They also predict a 48 basis points increase in stock volatility during the first hour after the rate change announcement. Gospodinov et al (2012) validates the findings of other authors showing a bigger reaction of asset prices on unexpected changes while the expected component and general change is not causing a significant volatility transformation. Bollerslev et al (2000) findings verify the idea of a significant impact of macroeconomic announcements on credit markets volatility.

Many authors (Adebiyi et al, 2014, Mondal et al, 2014) find ARIMA modeling efficient in out-of-sample forecasting returns in the short-run. Others widely use VAR modeling to express an impact of FDTR change and its unexpected portion impact of financial markets (Bernanke et al, 2005; Hsing et al 2004; Kim et al, 2000). GARCH models are used to predict a change in volatility caused by total and unexpected FDTR changes (Chulia et al, 2009). In current world realities analytics complexity increases, requiring involvement of larger number of parameters and greater quantitative power. Big data analysis needs more efficient algorithms and relies on complex models, which also require powerful statistical software. There is a number of statistical software and packages that allow utilizing time series methodologies with ease. Numerous successful attempts to create a working forecasting system concentrated on particular tasks using SAS are made (Ratnaraj, 1995; Tangedal, 2003 Soriano et al, 2002; Gharibvand et al, 2010; Zlupko, 2009). In this paper we show how to build a useful forecasting system and analyze various factors impact using SAS.

DATA

Data from Bloomberg Financial are used for this paper. We are interested in absolute changes in bond yields. We add data on equities markets represented by S&P500 index to compare the behavior of stock and bond markets under the FDTR change shock. We also use data on major macroeconomic variables extracted from Bloomberg, including consumer expenditures (PCE), new privately housing unit starts, unemployment rate, and M2 money velocity. Consumer expenditures, new housing starts and unemployment rate are very important economy characteristics indicating an economic cycle stage and overall economic health and are taken into consideration by many authors (Bernanke et al, 2005; Ekanayake et al, Haiyan, 2010). They also impact FOMC decisions regarding changes in monetary policy (Tylor, 1993; Mandler, 2012; Malliaris et al, 2009). M2 money velocity is a result of macroeconomic conditions and monetary policy and is considered an informative measure of population and business investment activity. Investors have a choice of classes of assets to choose for their portfolios. They prefer some assets to other ones and create a quasi-competition among assets. Thus, returns on one class of assets impact demand and, therefore, price and returns on other classes of assets (Bernanke, 2003). To acount for such effects we include most competing asset classes as explanatory variables in our models. We are interested in each class of US Government bond returns, which are expected to be influenced by other US government bond classes as well as equities markets and macroeconomic factors. Thus we also use equities market characteristics (S&P500) and oil prices (for Brent) as additional indicators. We restrict a potential impact by the abovementioned parameters for our model purposes. We download data on major categories of US government bonds for a period from February 1990 to June 2015 on a daily basis. For these data available with smaller frequency (FDTR, PCE, Unemployement, Housing starts, and M2 money velocity) we impute the level figures equal to the last information available, since market participants use these levels as a description of current economic conditions. All US treasuries data and FDTR data are used in a basic points scale, and housing starts are transformed by taking a log to maintain the comparable scale. All other variables are used on their real levels.

Data covers a period of more than 25 years with many situational changes during this time frame. Initial data are non-stationary, so we use first differencing to reach stationarity. We also consider a potential structural break in our data, since the observed period covers the financial crisis of 2007. On the one hand, we speculate that this event may be treated as another “black swan”, creating outliers. On the other hand, crisis time covers relatively wide time period, which makes data behavior different from common outliers. To account for that and to estimate an impact of crisis we performed Chow test for a structural break for each of our models, and found no structural break which make implying further restrictions on a sample not necessary. The detailed results of the test are disclosed in the estimation results section.

Two different approaches are used for federal funds rate changes impact on financial markets. General approach (Kishor et al, 2013; Yin et al, 2010; Young et al, 2012) assumes that changes in level Federal Funds rate impact financial markets. We use pure federal funds rates to utilize this approach. Another theory assumes that only unexpected changes in FDTR impact financial markets, while expected changes do not cause any significant reaction (Bernanke et al, 2005; Berument et al, 2010, Hsing et al, 2004). Identifying unexpected changes is represented by two different methods in existing literature. The first one uses a change in federal funds rate futures rates to identify an expected portion of federal funds rate, and takes a difference between expected and real rate as unexpected part (Bernanke et al, 2005). The second one (Hsing et al, 2004) utilizes the difference between an effective federal funds rate (EFFR) changes and FDTR changes, as EFFR may be considered a measure of market expectations. For the purposes of this paper we use pure FDTR changes and unexpected changes based on EFFR approaches.

THE LIST OF VARIABLES

- *GT2* – 2-year US government bond yields.
- *GT5* – 5-year US government bond yields.
- *GT10* – 10-year US government bond yields.
- *GT30* – 30-year US government bond yields.
- *SPX* – S&P500 Index.
- *FDTR* – federal funds target rate.
- *dFDTR* – First difference in *FDTR*
- EFFR – Effective federal funds rate.
- *dEFFR* – First difference in *EFFR*
- *unexpFR* – Unexpected part of the federal funds rate as difference between Effective tax rate and FDTR.
- *BRENT* – Oil price (Brent).

- *M2VEL* – M2 money velocity[2].
- *UNEMPL* – US Unemployment rate actual.
- *HOUS* – latest new housing starts.
- *PCE* - latest new housing starts.

The descriptive statistics for all variables is shown in Table 1.

METHODOLOGY

We are interested in analyzing reaction of *GT2*, *GT5*, *GT10*, and *GT30* on a change in *FDTR*. We also analyze *SPX* reaction on FDTR change to find out if equities and credit markets react differently. We apply ARIMA, VAR, and VECM modeling to estimate markets reaction. Each model specification and identification processes are presented below.

DATA PREPARATION AND TESTING

Level data for the given time series are not stationary in mean and variance, which can be identified by performing graphical analysis (see Figures 1 to 7 for details). First differencing is used to achieve data stationarity before running ARIMA and VAR models. A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. The first difference of a time series is the series of changes from one period to the next. If Y_t denotes the value of the time series Y at period t, then the first difference of Y at period t is equal to Y_t-Y_{t-1}. The autocorrelations decrease rapidly as reflected in the diagnostics plots (see Figures 1 to 7 for details), indicating a stationary time series.

We use the Augmented Dickey–Fuller test (ADF) to further test for a unit root in a time series sample (please, see Table 2 for sample output). It is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are used for testing a null hypothesis that an observable time series is stationary around a deterministic trend (see Table 3 for sample output). Based on the p-values of the ADF and KPSS tests we conclude that the time series is stationary (see Tables 4 for both tests result summary).

ARIMA

Autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. ARIMA models are generally denoted as ARIMA (p, d, q), where parameters *p*, *d*, and *q* are non-negative integers: p is the order of the autoregressive model, d is the degree of differencing, and q is the order of the moving-average model.

We run ARIMA to model the behavior for each of *GT2*, *GT5*, *GT10*, *GT30*, and *SPX*. Total 12 models for each outcome variable are performed and reviewed to identify a model that provides the best fit: 6 models to quantify the effect of FDTR and another 6 models to quantify the effect of unexpected rate change on each of the outcomes.

We run ARIMA model using (`proc arima`) for each of the outcome variables. Optimal lags are chosen by correlograms (plot of ACF and PACF versus Lag), goodness of fit criteria (Akaike Information Criteria (AIC), and standard errors estimate. All models correlogram and statistical results are consistent leading to a single true model choice. (Tables 5, 7, 10, 12, 15, 17, 20, 22, 24, and 27 represent the selection process for each asset consecutively).

For all GT2 bond yields ARIMA (1,1,2) model is chosen based on the abovementioned criteria with most for both methods (see Figure 1 for graphs). For GT5, GT10, GT30, and SPX ARIMA (2,1,3) provides best fit based on the abovementioned criteria for both methods (see Figures 2,3,4,7 for graphs). All Chow tests (Tables 9, 14, 19, 26, and 29) represent no structural break at the beginning (February 2007) and end (March 2009).

To estimate an impact of FDTR change on various classes of assets we create an out-of-sample set of observation, where all macroeconomic variables are given no change, financial market variables other than the output variable in each model are predicted by ARIMA, and FDTR and its unexpected portion are given a change of 25 basis points. Such an approach should help in estimating an impact of FDTR change since it allows isolating a change virtually to make it a virtually conducted experiment.

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[2] For variables available on a quarterly basis we impute the latest available numbers for each day when no announcements were made. Typically new data are issued at a particular date or at the last date of a calendar month, so the approach used allows us to catch up changes on a timely manner.

VAR AND VECM

We run VAR model using (**proc varmax**) for each of the outcome variables. We consider all asset types, and federal funds rate, since asset prices in general impact each other by participating in daily trades. All macroeconomic parameters and the oil price are considered as exogenous, since they impact financial markets and FDTR, but are not directly impacted by them. We assume that the latter parameters represent the US economy situation, creating conditions for financial markets movements, and so they should be included into the model. Optimal lag 2 is chosen based on the Hannan-Quinn (HQC) and Akaike Information Criteria (AIC) (see Table 30 for details) and subsequent models testing.

VAR model is primarily used for identification of *FDTR* and it unexpected portion impact on financial markets returns. Since we want to catch up the returns, monthly data are constructed by taking the latest available numbers for each calendar month for all variables. We use the first differences to obtain changes and returns and make data stationary.

VAR model is performed on differenced variables, since level variables are non-stationary. Strong VAR statistics witnesses a strong short run relationship between included variables. Our primary interest in the model is in estimating impulse response to a shock in *FDTR* identifying an impact of possible changes of one standard deviation. An uncorrelated time series can still be serially dependent due to a dynamic conditional variance process. A time series exhibiting conditional heteroscedasticity, or autocorrelation in the squared series, is said to have autoregressive conditional heteroscedastic (ARCH) effects (see Table 31 for details). We perform Engle's ARCH test ($p<0.0001$) to assess the significance of ARCH effects and conclude that no ARCH effects are present.

Having level variables non-stationary, we assume a possibility of long-term relationship between variables as well. Long-term relationships are tested by cointegration tests and estimated by Vector Error Correction Model (VECM). We perform Johansen test for testing cointegration of several time series (see Table 32 for details). Both restricted and unrestricted test results show an existence of 5 cointegrating vectors, which indicates an existence of strong long-term relationship between model variables. We estimate the relationship by VECM model of rank 5 (**proc varmax**) (please see Table 33 for details). Granger causality test is performed to identify causal relationship between the explanatory variable and regressors.

ESTIMATION RESULTS AND FORECASTING

In this section we represent the output for best modes fitted and explain the economic sense of estimates. This section also covers the analytical portion of results. We also show forecasts based on different modeling techniques.

FORECASTING RETURNS USING ARIMA MODELING

Table 34 represents the best model specifications for each case. Tables 6, 8,11,13, 16, 18, 21, 23, and 28 represents estimation results for each ARIMA model consecutively. We indicate that all asset classes returns, as well as unemployment, money velocity, oil prices, target rate, along with unexpected rate change are identified as significant predictors ($p<0.05$) of *GT2*. An effect of rate change is positive, which is consistent with theoretical assumptions and prior findings. There is no significant difference in impact between *FDTR* and *unexpFR* found. An impact of unexpected portion of rate change is smaller than an effect of level rate change, which is different from the majority of prior finding. We speculate that such a difference from prior papers published before the financial crisis can be caused by an impact of a long period with no change in rate and relatively small recent volatility in efficient rate.

Fitting ARIMA for *GT5 and GT10* indicates that unemployment, money velocity, oil, PCE along with bond yields and SPX are identified as significant predictors ($p<0.05$). We find an impact of *FDTR* and its unexpected portion change statistically insignificant, decreasing with exclusion of expected portion of change and partially negative. An impact of unexpected portion of rate change on *GT5* is smaller than the effect of level rate change, which is different from major prior finding. We assume that such a difference with prior papers published before the financial crisis can be caused by an impact of a long period with no changes in rate and relatively small recent volatility in efficient rate. An impact of unexpected portion of rate change on *GT10* is bigger than an effect of level rate change, which is consistent with prior publications.

We indicate that all asset classes returns, as well as unemployment, money velocity, oil prices, target rate, along with unexpected rate change are identified as significant predictors ($p<0.05$) of *GT30*. There is no significant difference in impact between *FDTR* and *unexpFR* found. An impact of unexpected portion of rate change is smaller than an effect of level rate change, which is different from major prior finding. The estimation results show that Federal funds rate is always statistically significant and the scale rises when an unexpected portion is used as a regressor. This supports findings of other authors.

Based on the best ARIMA model for each scenario we forecast expected changes in each asset class returns a few periods ahead. Since no macroeconomic data changes are present for the out-of-sample observations, only a modeled *FDTR* shock should be identified. Figures 9-17 represent forecasts of expected changes in outcome variables due to change in *FDTR* and its unexpected portion versus no shock simulated samples based on different

ARIMA models. All graphs show only a short-term impact of a shock in *FDTR*. *GT2*, *GT10*, and *GT 30* demonstrate a few basis point upward movement in yields change due to 25 basis points increase in *FDTR*, which approaches zero change over the following 2-3 days. Unexpected portion change itself brings less volatility in returns than the entire change. The same scale of change was artificially created and used. We use the latest available effective Federal Funds rate to estimate the unexpected portion.

VAR MODEL ESTIMATION RESULTS

VAR model is performed on differenced variables since level variables are non-stationary. This approach involves an economic concept of returns. We treat a change in variables as returns on investment on a daily and monthly basis consecutively. Strong model statistics supports the assumption of well-defined short-term integration of variables in the model. All roots found are close to zero, which indicates the model stability. We construct an impulse response function for each of the asset classes to identify a potential impact of FDTR shock on assets returns (see Figure 18 for details). Impulse response represents a change in a variable of interest caused by a one standard error change in explanatory variable. Based on VAR estimation results, 1 standard deviation change (4 basis points) causes an increase in US Treasuries volatility and leads to an increase in yield changes after 4-5 days after the shock. Equities market negatively reacts to an increase in FDTR change demonstrating about 5 basis points decrease in 5 days after the 4 basis points shock in *FDTR*. These findings, representing a short-term relationship, are consistent with prior findings.

Johansen cointegration test supports the idea of existence of long-term cointegration, which is consistent with prior publications. VECM model normalized for *GT2* is estimated based on 5 integration vectors. Long-run parameter (beta) and adjustment coefficients (alpha) estimates are give in Table 33. Granger causality test (see Table 34) indicates that US Treasuries returns changes are Granger caused by changes in model variables within 95% confidence interval. *SPX* changes are Granger caused by changes of model explanatory variables at 90%.

CONCLUSION

In this paper we analyze an impact of Federal Funds target rate change on US Treasuries markets returns. We apply various time series analysis methods to estimate potential changes in financial market returns in case FOMC makes a decision to increase FDTR on a few points. ARIMA, VAR, and VECM models are used to identify potential aftermath of such a rise. We apply different forecasting scenarios and prove a positive impact of an increase in FDTR on bonds markets and a negative impact on stock markets. Our findings are consistent with prior publications, but bring smaller scale changes predicted comparing to papers published before the financial crisis of 2007. We speculate that one of the reasons for such a change can be caused by the markets adaptation to a long period of historically low rates, and a gradual slow upward movement may be less influential than the same during more volatile time.

We represent a step-by-step methodology of creating and using time-series analytical tools for financial markets analysis. We further provide interpretation of the estimation results and user cases in current economic context. The code, output, and further details are provided in the Appendix.

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TABLES

Table 1. Summary statistics, daily data.

Variable	Minimum	Maximum	Mean	Median	Std Dev
GT2	0.1550000	9.0320000	3.6268187	4.0585000	2.3640912
GT5	0.5430000	9.0660000	4.2945584	4.5435000	2.1147716
GT10	1.3880000	9.0620000	4.8784491	4.7765000	1.8160034
GT30	2.2230000	9.1720000	5.4230635	5.2085000	1.5680181
SPX_Index	295.4600000	2130.82	1052.91	1121.21	442.4557284
FDTR	0.2500000	8.2500000	3.2182689	3.2500000	2.3577057
dFDTR	-75.0000000	75.0000000	-0.1207547	0	4.0031954
unexpFR	-75.0000000	96.0000000	0.0015094	0	5.4219315
Brent	9.6400000	146.0800000	48.0748144	29.0300000	35.2869411
M2VEL	1.5025000	2.2026000	1.9299783	1.9691000	0.1976096
Unempl	3.8000000	10.0000000	6.1176728	5.7000000	1.5658844
Housing	6.1696107	7.7288558	7.1170005	7.2384968	0.3792109
PCE	-3.4000000	9.0000000	4.9062028	5.1000000	1.9777966

Table 2. Sample output results of the ADF test (SAS generated table)

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-6757.30	0.0001	-83.04	<.0001		
	1	-7125.85	0.0001	-59.69	<.0001		
	2	-7260.84	0.0001	-48.42	<.0001		
Single Mean	0	-6759.97	0.0001	-83.06	<.0001	3449.89	0.0010
	1	-7134.78	0.0001	-59.72	<.0001	1783.36	0.0010
	2	-7280.09	0.0001	-48.46	<.0001	1174.02	0.0010
Trend	0	-6760.36	0.0001	-83.06	<.0001	3449.78	0.0010
	1	-7136.13	0.0001	-59.72	<.0001	1783.45	0.0010
	2	-7283.00	0.0001	-48.46	<.0001	1174.17	0.0010

Based on the p-values of the ADF tesrt we conclude that the time series is stationary.

Table 3. Sample output results of the KPSS test (SAS generated table)

KPSS Stationarity Test			
Type	Lags	Eta	Pr > Eta
Single Mean	34	0.0917	0.6277
Trend	34	0.0759	0.2982

Unlike the null hypothesis of the Dickey-Fuller, the null hypothesis of the KPSS states that the time series is stationary

Table 4. Summary of the p-values for ADF and KPSS tests for 2-year US government bond yields based on a full sample.

VARIABLE (SAS) (First Difference)	**ADF test p-value**	**KPSS test p-value**
GT2	<0.0001	>0.05
GT5	<0.0001	>0.05
GT10	<0.0001	>0.05
GT30	<0.0001	>0.05
S&P500	<0.0001	>0.05
FDTR	<0.0001	>0.05
unexpFR	<0.0001	>0.05
BRENT	<0.0001	>0.05
M2VEL	<0.0001	>0.05
UNEMPL	<0.0001	>0.05
HOUS	<0.0001	>0.05

Table 5. Selection of the best ARIMA model based on the federal funds target rate for 2-year US government bond yields.

ARIMA	**AIC**	**Std Error Estimate**
(1,1,1)	-43864.7	0.022724
(1,1,0)	-43443.9	0.023247
(0,1,0)	-42151.3	0.024926
(0,1,1)	-43866.7	0.022723
(1,1,2)*	-43870.6	0.022716
(2,1,0)	-43859.1	0.022731

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 6. Maximum likelihood estimation details for ARIMA (1,1,2) fitting 2-year US government bond yields series based on the federal funds target rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	-0.0001473	0.0003202	-0.46	0.6456	0	dGT2	0
MA1,1	0.24327	0.18067	1.35	0.1781	1	dGT2	0
MA1,2	0.33055	0.07776	4.25	<.0001	2	dGT2	0
AR1,1	0.68548	0.18293	3.75	0.0002	1	dGT2	0
NUM1	1.14601	0.01235	92.80	<.0001	0	dGT5	0
NUM2	-0.23582	0.01997	-11.81	<.0001	0	dGT10	0
NUM3	-0.15205	0.01365	-11.14	<.0001	0	dGT30	0
NUM4	0.00003810	0.00001960	1.94	0.0519	0	dSPX_Index	0
NUM5	0.0004619	0.00006024	7.67	<.0001	0	dFDTR	0
NUM6	-0.0010511	0.0002147	-4.90	<.0001	0	dBrent	0
NUM7	-0.58581	0.08844	-6.62	<.0001	0	dM2Vel	0
NUM8	0.58855	0	Infty	<.0001	0	dUnempl	0
NUM9	-0.0086458	0.01466	-0.59	0.5554	0	dHousing	0
NUM10	-0.0017346	0.0017878	-0.97	0.3319	0	dPCE	0

Table 7. Selection of the best ARIMA model based on the unexpected part of the federal funds rate for 2-year US government bond yields.

ARIMA	AIC	Std Error Estimate
(1,1,1)	-43820.5	0.022778
(1,1,0)	-43405.1	0.023296
(0,1,0)	-42105.2	0.024988
(0,1,1)	-43822.4	0.022777
(1,1,2)*	-43824.1	0.022773
(2,1,0)	-43810.7	0.02279

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 8. Maximum likelihood estimation details for ARIMA (1,1,2) fitting 2-year US government bond yields series based on the unexpected part of the federal funds rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	-0.0002114	0.0003256	-0.65	0.5160	0	dGT2	0
MA1,1	0.20435	0.23491	0.87	0.3844	1	dGT2	0
MA1,2	0.31106	0.10213	3.05	0.0023	2	dGT2	0
AR1,1	0.64757	0.23718	2.73	0.0063	1	dGT2	0
NUM1	1.15024	0.01236	93.03	<.0001	0	dGT5	0
NUM2	-0.23866	0.02001	-11.93	<.0001	0	dGT10	0
NUM3	-0.15267	0.01369	-11.15	<.0001	0	dGT30	0
NUM4	0.00003456	0.00001964	1.76	0.0785	0	dSPX_Index	0
NUM5	0.0001495	0.00004285	3.49	0.0005	0	unexpFR	0
NUM6	-0.0010554	0.0002157	-4.89	<.0001	0	dBrent	0
NUM7	-0.57834	0.08891	-6.50	<.0001	0	dM2Vel	0
NUM8	0.58855	0	Infty	<.0001	0	dUnempl	0
NUM9	-0.01044	0.01470	-0.71	0.4777	0	dHousing	0
NUM10	-0.0017330	0.0017935	-0.97	0.3339	0	dPCE	0

Table 9. Structural change (Chow) test results for 2-year US government bond yields series (SAS generated table)

Structural Change Test					
Test	Break Point	Num DF	Den DF	F Value	Pr > F
Chow	205	8	295	0.71	0.6838
Chow	230	8	295	0.40	0.9210

Table 10. Selection of the best ARIMA model based on the target federal funds rate for 5-year US government bond yields.

ARIMA	AIC	Std Error Estimate
(1,1,1)	-53104.5	0.013809
(1,1,0)	-52691.7	0.014121
(0,1,0)	-51587.3	0.014988
(0,1,1)	-53103.1	0.013811
(1,1,2)	-53124.3	0.013794
(2,1,3)*	-53192.1	0.013742

Table 11. Maximum likelihood estimation details for ARIMA (2,1,3) fitting 5-year US government bond yields series based on the federal funds target rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	-0.0001976	0.0001871	-1.06	0.2909	0	dGT5	0
MA1,1	-0.86334	0.10201	-8.46	<.0001	1	dGT5	0
MA1,2	-0.08398	0.13779	-0.61	0.5422	2	dGT5	0
MA1,3	0.11763	0.04745	2.48	0.0132	3	dGT5	0
AR1,1	-0.43771	0.10271	-4.26	<.0001	1	dGT5	0
AR1,2	0.03982	0.10560	0.38	0.7061	2	dGT5	0
NUM1	0.42352	0.0045205	93.69	<.0001	0	dGT2	0
NUM2	0.78603	0.0090302	87.04	<.0001	0	dGT10	0
NUM3	-0.14180	0.0081944	-17.30	<.0001	0	dGT30	0
NUM4	0.00002690	0.00001187	2.27	0.0235	0	dSPX_Index	0
NUM5	-0.0000487	0.00003681	-1.32	0.1862	0	dFDTR	0
NUM6	0.0002790	0.0001303	2.14	0.0323	0	dBrent	0
NUM7	-0.53384	0.05340	-10.00	<.0001	0	dM2Vel	0
NUM8	0.69888	0	Infty	<.0001	0	dUnempl	0
NUM9	0.01672	0.0088433	1.89	0.0586	0	dHousing	0
NUM10	-0.0008528	0.0010782	-0.79	0.4290	0	dPCE	0

Table 12. Selection of the best ARIMA model based on the unexpected part of the federal funds rate for 5-year US government bond yields.

ARIMA	AIC	Std Error Estimate
(1,1,1)	-53103.5	0.01381
(1,1,0)	-52691.5	0.014121
(0,1,0)	-51586.4	0.014989
(0,1,1)	-53102.1	0.013812
(1,1,2)	-53123	0.013795
(2,1,3)*	-53190.9	0.013743

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 13. Maximum likelihood estimation details for ARIMA (2,1,3) fitting 5-year US government bond yields series based on the unexpected part of the federal funds rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	-0.0001911	0.0001871	-1.02	0.3070	0	dGT5	0
MA1,1	-0.86536	0.10227	-8.46	<.0001	1	dGT5	0
MA1,2	-0.08428	0.13827	-0.61	0.5422	2	dGT5	0
MA1,3	0.11779	0.04756	2.48	0.0133	3	dGT5	0
AR1,1	-0.43963	0.10298	-4.27	<.0001	1	dGT5	0
AR1,2	0.04064	0.10582	0.38	0.7009	2	dGT5	0
NUM1	0.42308	0.0045035	93.94	<.0001	0	dGT2	0
NUM2	0.78637	0.0090275	87.11	<.0001	0	dGT10	0
NUM3	-0.14192	0.0081979	-17.31	<.0001	0	dGT30	0
NUM4	0.00002727	0.00001187	2.30	0.0216	0	dSPX_Index	0
NUM5	-0.0000198	0.00002600	-0.76	0.4455	0	unexpFR	0
NUM6	0.0002770	0.0001306	2.12	0.0339	0	dBrent	0
NUM7	-0.53549	0.05356	-10.00	<.0001	0	dM2Vel	0
NUM8	0.69888	0	Infty	<.0001	0	dUnempl	0
NUM9	0.01689	0.0088430	1.91	0.0562	0	dHousing	0
NUM10	-0.0008618	0.0010786	-0.80	0.4243	0	dPCE	0

Table 14. Structural change (Chow) test results for 5-year US government bond yields series (SAS generated table)

Structural Change Test					
Test	Break Point	Num DF	Den DF	F Value	Pr > F
Chow	205	8	295	0.83	0.5788
Chow	230	8	295	0.90	0.5137

Table 15. Selection of the best ARIMA model based on the federal funds target rate for 10-year US government bond yields.

ARIMA	AIC	Std Error Estimate
(1,1,1)	-56061.6	0.011774
(1,1,0)	-55543.3	0.012109
(0,1,0)	-54112.9	0.01308
(0,1,1)	-56061.9	0.011775
(1,1,2)	-56069.4	0.011769
(2,1,3)*	-56162.8	0.011708

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 16. Maximum likelihood estimation details for ARIMA (2,1,3) fitting 10-year US government bond yields series based on the federal funds target rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	0.0005818	0.0001685	3.45	0.0006	0	dGT10	0
MA1,1	-0.75457	0.11147	-6.77	<.0001	1	dGT10	0
MA1,2	-0.04395	0.14898	-0.30	0.7680	2	dGT10	0
MA1,3	0.12435	0.05507	2.26	0.0239	3	dGT10	0
AR1,1	-0.26191	0.11220	-2.33	0.0196	1	dGT10	0
AR1,2	0.05244	0.10780	0.49	0.6266	2	dGT10	0
NUM1	-0.06073	0.0053418	-11.37	<.0001	0	dGT2	0
NUM2	0.56779	0.0065778	86.32	<.0001	0	dGT5	0
NUM3	0.52730	0.0045697	115.39	<.0001	0	dGT30	0
NUM4	0.00003383	0.00001015	3.33	0.0009	0	dSPX_Index	0
NUM5	-0.0000361	0.00003106	-1.16	0.2446	0	dFDTR	0
NUM6	-0.0002407	0.0001114	-2.16	0.0307	0	dBrent	0
NUM7	-0.65532	0.04580	-14.31	<.0001	0	dM2Vel	0
NUM8	0.46531	0	Infty	<.0001	0	dUnempl	0
NUM9	-0.01028	0.0076602	-1.34	0.1795	0	dHousing	0
NUM10	0.0023090	0.0009324	2.48	0.0133	0	dPCE	0

Table 17. Selection of the best ARIMA model based on the unexpected part of the federal funds rate for 10-year US government bond yields.

ARIMA	AIC	Std Error Estimate
(1,1,1)	-56061.2	0.011774
(1,1,0)	-55543.7	0.012108
(0,1,0)	-54115.2	0.013078
(0,1,1)	-56061.6	0.011775
(1,1,2)	-56069.2	0.011769
(2,1,3)*	-56161.8	0.011709

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 18. Maximum likelihood estimation details for ARIMA (2,1,3) fitting 10-year US government bond yields series based on the unexpected part of the federal funds rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	0.0005873	0.0001684	3.49	0.0005	0	dGT10	0
MA1,1	-0.75440	0.11150	-6.77	<.0001	1	dGT10	0
MA1,2	-0.05140	0.14881	-0.35	0.7298	2	dGT10	0
MA1,3	0.12066	0.05507	2.19	0.0285	3	dGT10	0
AR1,1	-0.26208	0.11219	-2.34	0.0195	1	dGT10	0
AR1,2	0.04495	0.10778	0.42	0.6767	2	dGT10	0
NUM1	-0.06136	0.0053276	-11.52	<.0001	0	dGT2	0
NUM2	0.56803	0.0065757	86.38	<.0001	0	dGT5	0
NUM3	0.52754	0.0045714	115.40	<.0001	0	dGT30	0
NUM4	0.00003422	0.00001015	3.37	0.0007	0	dSPX_Index	0
NUM5	0.00001376	0.00002210	0.62	0.5336	0	unexpFR	0
NUM6	-0.0002325	0.0001116	-2.08	0.0372	0	dBrent	0
NUM7	-0.65195	0.04593	-14.20	<.0001	0	dM2Vel	0
NUM8	0.46531	0	Infty	<.0001	0	dUnempl	0
NUM9	-0.01006	0.0076591	-1.31	0.1889	0	dHousing	0
NUM10	0.0023314	0.0009326	2.50	0.0124	0	dPCE	0

Table 19. Structural change (Chow) test results for 10-year US government bond yields series (SAS generated table)

Structural Change Test					
Test	Break Point	Num DF	Den DF	F Value	Pr > F
Chow	205	8	295	1.33	0.2261
Chow	230	8	295	1.84	0.0693

Table 20. Selection of the best ARIMA model based on the federal funds target rate for 30-year US government bond yields.

ARIMA	AIC	Std Error Estimate
(1,1,1)	-49140.2	0.017099
(1,1,0)	-48547.5	0.017655
(0,1,0)	-46672.9	0.019534
(0,1,1)	-49112.6	0.017126
(1,1,2)	-49108.8	0.017127
(2,1,3)*	-49230.8	0.017013

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 21. Maximum likelihood estimation details for ARIMA (2,1,3) fitting 30-year US government bond yields series based on the federal funds target rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	-0.0010294	0.0002626	-3.92	<.0001	0	dGT30	0
MA1,1	-0.61026	0.14445	-4.22	<.0001	1	dGT30	0
MA1,2	0.02197	0.18333	0.12	0.9046	2	dGT30	0
MA1,3	0.12911	0.06984	1.85	0.0645	3	dGT30	0
AR1,1	-0.05043	0.14514	-0.35	0.7282	1	dGT30	0
AR1,2	0.06840	0.11815	0.58	0.5627	2	dGT30	0
NUM1	-0.08882	0.0077228	-11.50	<.0001	0	dGT2	0
NUM2	-0.20788	0.01257	-16.54	<.0001	0	dGT5	0
NUM3	1.11326	0.0096522	115.34	<.0001	0	dGT10	0
NUM4	-0.0000277	0.00001475	-1.88	0.0604	0	dSPX_Index	0
NUM5	-0.0000381	0.00004449	-0.86	0.3916	0	dFDTR	0
NUM6	0.0010378	0.0001613	6.43	<.0001	0	dBrent	0
NUM7	-0.32702	0.06686	-4.89	<.0001	0	dM2Vel	0
NUM8	0.49864	0	Infty	<.0001	0	dUnempl	0
NUM9	0.0086169	0.01127	0.76	0.4447	0	dHousing	0
NUM10	-0.0037947	0.0013709	-2.77	0.0056	0	dPCE	0

Table 22. Selection of the best ARIMA model based on the unexpected part of the federal funds rate for 30-year US government bond yields.

ARIMA	AIC	Std Error Estimate
(1,1,1)	-49238.2	0.017006
(1,1,0)	-48555.9	0.017647
(0,1,0)	-46679.5	0.019527
(0,1,1)	-49120.4	0.017118
(1,1,2)	-49116.6	0.01712
(2,1,3)*	-49238.2	0.017006

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 23. Maximum likelihood estimation details for ARIMA (2,1,0) fitting 30-year US government bond yields series based on the unexpected part of the federal funds rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**	**Lag**	**Variable**	**Shift**
MU	-0.0010252	0.0002624	-3.91	<.0001	0	dGT30	0
MA1,1	-0.60528	0.14399	-4.20	<.0001	1	dGT30	0
MA1,2	0.02348	0.18250	0.13	0.8976	2	dGT30	0
MA1,3	0.12878	0.06959	1.85	0.0642	3	dGT30	0
AR1,1	-0.04535	0.14468	-0.31	0.7539	1	dGT30	0
AR1,2	0.06739	0.11777	0.57	0.5672	2	dGT30	0
NUM1	-0.08849	0.0076999	-11.49	<.0001	0	dGT2	0
NUM2	-0.20773	0.01256	-16.54	<.0001	0	dGT5	0
NUM3	1.11274	0.0096473	115.34	<.0001	0	dGT10	0
NUM4	-0.0000277	0.00001474	-1.88	0.0606	0	dSPX_Index	0
NUM5	-0.0000912	0.00003187	-2.86	0.0042	0	unexpFR	0
NUM6	0.0010091	0.0001615	6.25	<.0001	0	dBrent	0
NUM7	-0.33941	0.06699	-5.07	<.0001	0	dM2Vel	0
NUM8	0.49864	0	Infty	<.0001	0	dUnempl	0
NUM9	0.0085211	0.01127	0.76	0.4495	0	dHousing	0
NUM10	-0.0038530	0.0013705	-2.81	0.0049	0	dPCE	0

Table 24. Selection of the best ARIMA model based on the federal funds target rate for S&P500.

ARIMA	**AIC**	**Std Error Estimate**
(1,1,1)	72462.46	12.02127
(1,1,0)	72969.31	12.355
(0,1,0)	74639.56	13.51993
(0,1,1)	72473.33	12.02897
(1,1,2)	72405.31	11.98363
(2,1,3)*	72385.6	11.96961

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 25. Maximum likelihood estimation details for ARIMA (1,0,1) fitting S&P500 series based on the federal funds target rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	0.13139	0.16849	0.78	0.4355	0	dSPX_Index	0
MA1,1	-0.40966	0.09149	-4.48	<.0001	1	dSPX_Index	0
MA1,2	0.48365	0.11060	4.37	<.0001	2	dSPX_Index	0
MA1,3	0.30059	0.04483	6.71	<.0001	3	dSPX_Index	0
AR1,1	0.11015	0.09368	1.18	0.2397	1	dSPX_Index	0
AR1,2	0.42770	0.09339	4.58	<.0001	2	dSPX_Index	0
NUM1	10.94876	5.48800	2.00	0.0460	0	dGT2	0
NUM2	21.18973	9.00513	2.35	0.0186	0	dGT5	0
NUM3	35.06409	10.61850	3.30	0.0010	0	dGT10	0
NUM4	-12.84328	7.30554	-1.76	0.0787	0	dGT30	0
NUM5	-0.08279	0.03155	-2.62	0.0087	0	dFDTR	0
NUM6	1.62019	0.11271	14.38	<.0001	0	dBrent	0
NUM7	-8.40649	46.97912	-0.18	0.8580	0	dM2Vel	0
NUM8	9.98113	0	Infty	<.0001	0	dUnempl	0
NUM9	-8.08593	7.87355	-1.03	0.3044	0	dHousing	0
NUM10	1.12781	0.95856	1.18	0.2394	0	dPCE	0

Table 26. Structural change (Chow) test results for 10-year US government bond yields series (SAS generated table)

Structural Change Test					
Test	Break Point	Num DF	Den DF	F Value	Pr > F
Chow	205	8	295	1.57	0.1344
Chow	230	8	295	2.51	0.0119

Table 27. Selection of the best ARIMA model based on the unexpected part of the federal funds rate for S&P500.

ARIMA	AIC	Std Error Estimate
(1,1,1)	72469.26	12.02568
(1,1,0)	72976.9	12.36006
(0,1,0)	74644.98	13.52388
(0,1,1)	72479.98	12.03328
(1,1,2)	72412.02	11.98796
(2,1,3)*	72392.08	11.97379

Lower values of AIC and standard error indicate better model fit. The asterisks above indicates the best (that is, minimized) values of the Akaike Information Criterion and Standard Error Estimate

Table 28. Maximum likelihood estimation details for ARIMA (1,0,1) fitting S&P500 series based on the unexpected part of the federal funds rate (SAS generated table)

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	0.14302	0.16850	0.85	0.3960	0	dSPX_Index	0
MA1,1	-0.41222	0.09160	-4.50	<.0001	1	dSPX_Index	0
MA1,2	0.48114	0.11093	4.34	<.0001	2	dSPX_Index	0
MA1,3	0.29996	0.04490	6.68	<.0001	3	dSPX_Index	0
AR1,1	0.10747	0.09378	1.15	0.2518	1	dSPX_Index	0
AR1,2	0.42620	0.09349	4.56	<.0001	2	dSPX_Index	0
NUM1	9.92010	5.47590	1.81	0.0700	0	dGT2	0
NUM2	21.45898	9.00795	2.38	0.0172	0	dGT5	0
NUM3	35.48828	10.62147	3.34	0.0008	0	dGT10	0
NUM4	-12.83585	7.31101	-1.76	0.0791	0	dGT30	0
NUM5	-0.01442	0.02257	-0.64	0.5229	0	unexpFR	0
NUM6	1.62503	0.11297	14.38	<.0001	0	dBrent	0
NUM7	-7.74995	47.10634	-0.16	0.8693	0	dM2Vel	0
NUM8	9.98113	0	Infty	<.0001	0	dUnempl	0
NUM9	-7.72131	7.87483	-0.98	0.3268	0	dHousing	0
NUM10	1.13935	0.95899	1.19	0.2348	0	dPCE	0

Table 29. Structural change (Chow) test results for 10-year US government bond yields series (SAS generated table)

Structural Change Test					
Test	Break Point	Num DF	Den DF	F Value	Pr > F
Chow	205	7	297	1.74	0.0999
Chow	230	7	297	1.53	0.1576

Table 30. Identification of optimal lag based on AIC, BIC, and HQC:

```
lags          loglik     p(LR)        AIC           BIC           HQC

   1     -458.07204               3.681056      4.596796*     4.048029
   2     -388.42536   0.00000     3.447398      4.821009      3.997858*
   3     -333.82298   0.00000     3.318215*     5.149695      4.052162
   4     -309.62592   0.08122     3.400180      5.689530      4.317614
```

```
5    -279.68907  0.00749    3.442285     6.189506     4.543205
6    -260.72278  0.38128    3.560575     6.765665     4.844982
7    -224.96794  0.00039    3.562277     7.225238     5.030171
```

The asterisks above indicates the best (that is, minimized) values of the respective information criteria, AIC = Akaike Information Criterion, BIC = Schwarz (Bayesian) Information Criterion, and HQC = Hannan-Quinn Criterion.

Table 31. Tests for ARCH effects

Univariate Model White Noise Diagnostics					
	Durbin	Normality		ARCH	
Variable	Watson	Chi-Square	Pr > ChiSq	F Value	Pr > F
GT2	1.90336	9999.99	<.0001	303.52	<.0001
GT5	1.90430	4082.46	<.0001	408.28	<.0001
GT10	1.90912	3575.55	<.0001	408.92	<.0001
GT30	1.90560	3698.35	<.0001	655.07	<.0001
FDTR	1.88419	9999.99	<.0001	451.42	<.0001
Brent	1.93369	9999.99	<.0001	498.35	<.0001
M2VEL	1.90708	9999.99	<.0001	122.58	<.0001
Unempl	1.87633	9999.99	<.0001	125.90	<.0001
Housing	1.90373	9999.99	<.0001	108.94	<.0001
PCE	1.90869	9999.99	<.0001	58.68	<.0001

Table 32. Results of the Johansen test

Cointegration Rank Test Using Trace						
H0: Rank=r	H1: Rank>r	Eigenvalue	Trace	5% Critical Value	Drift in ECM	Drift in Process
0	0	0.0157	322.6952	68.68	Constant	Linear
1	1	0.0109	176.2532	47.21		
2	2	0.0051	74.7723	29.38		
3	3	0.0017	27.5527	15.34		
4	4	0.0012	11.5043	3.84		

Cointegration Rank Test Using Trace Under Restriction						
H0: Rank=r	H1: Rank>r	Eigenvalue	Trace	5% Critical Value	Drift in ECM	Drift in Process
0	0	0.0158	324.3055	75.74	Constant	Constant
1	1	0.0109	176.8949	53.42		
2	2	0.0051	75.2981	34.80		
3	3	0.0017	27.7620	19.99		
4	4	0.0013	11.6954	9.13		

Table 33. VECM Coefficients and parameter estimates

Long-Run Parameter Beta Estimates					
Variable	1	2	3	4	5
GT2	1.00000	1.00000	1.00000	1.00000	1.00000
GT5	-0.27019	-3.32939	-1.13280	-1.22868	-0.73623
GT10	-0.24449	4.05890	-0.96345	0.31061	1.54187
GT30	0.03184	-1.62630	1.48736	-1.00104	-1.18029
FDTR	-0.60528	-0.13594	-0.19838	0.42849	1.00327

Adjustment Coefficient Alpha Estimates					
Variable	1	2	3	4	5
GT2	-0.00143	-0.00071	0.00243	0.00154	-0.00051
GT5	-0.00244	-0.00019	0.00662	0.00240	-0.00037
GT10	-0.00238	-0.00584	0.00431	0.00259	-0.00024
GT30	-0.00194	-0.00233	-0.00002	0.00260	-0.00012
FDTR	0.01537	0.00016	0.00067	0.00016	-0.00006

Table 34. Granger causality test results

Granger-Causality Wald Test			
Test	DF	Chi-Square	Pr > ChiSq
1	10	26.33	0.0033
2	10	58.75	<.0001
3	10	50.16	<.0001
4	10	43.53	<.0001
5	10	18.16	0.0523

GRAPHS

Figure 1. 2-year US government bond yields and its first difference, which converts non-stationary data to stationary:

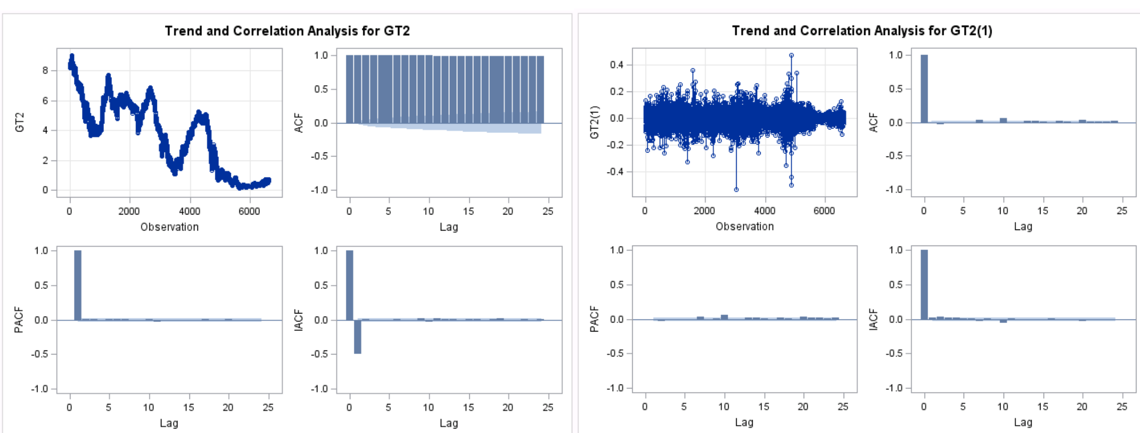


Figure 2. 5-year US government bond yields and its first difference, which converts non-stationary data to stationary:

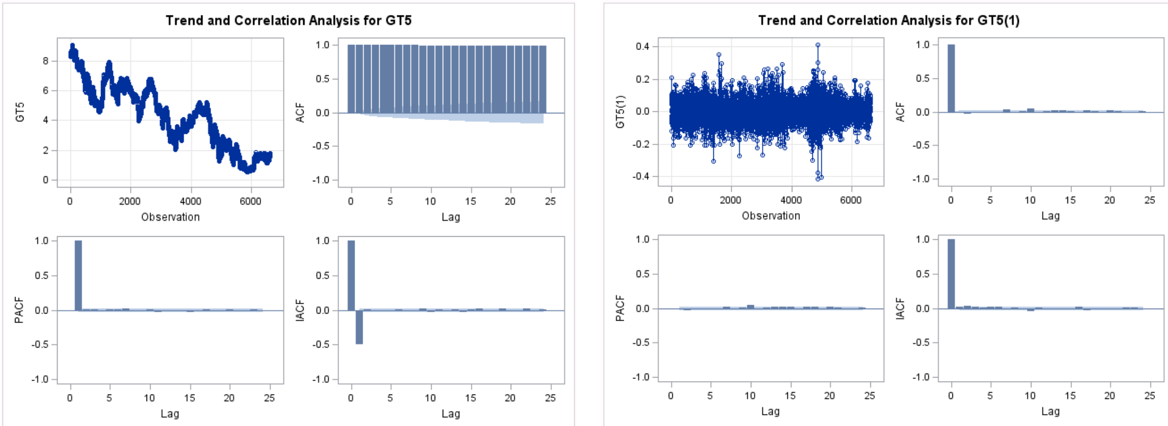


Figure 3. 10-year US government bond yields and its first difference, which converts non-stationary data to stationary:

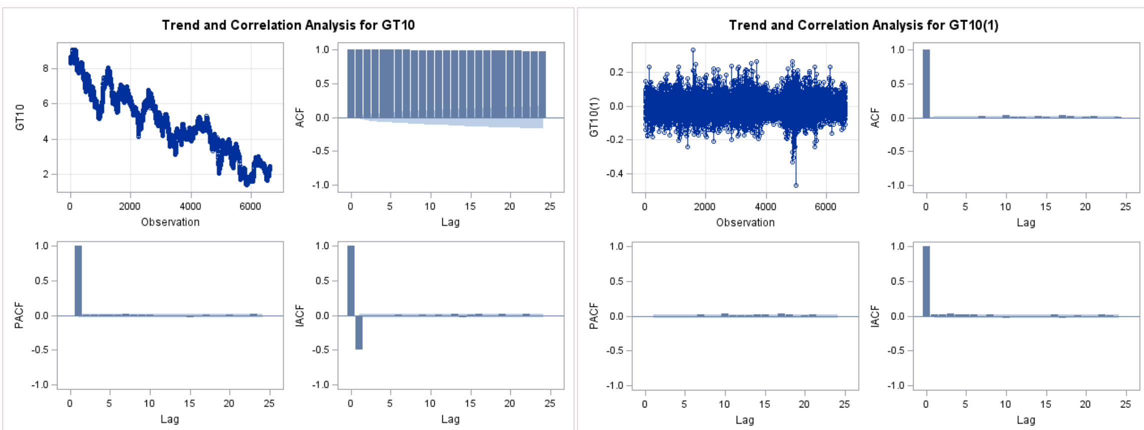


Figure 4. 30-year US government bond yields and its first difference, which converts non-stationary data to stationary:

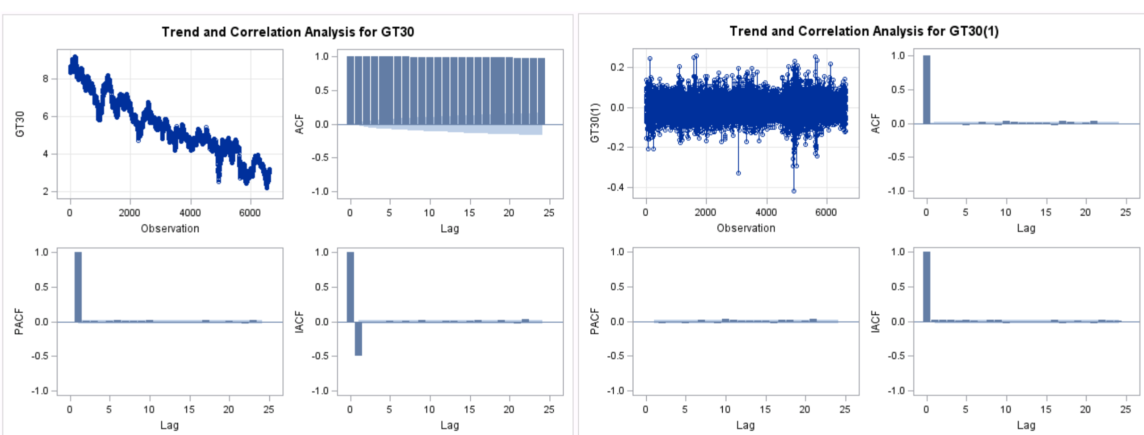


Figure 5. Federal funds target rate and its first difference, which converts non-stationary data to stationary:

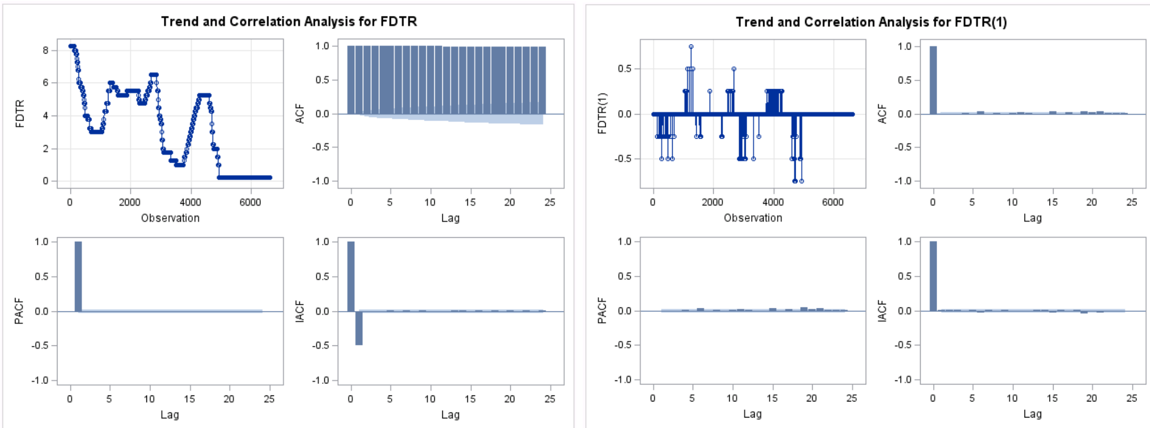


Figure 6. Effective federal funds rate and its first difference, which converts non-stationary data to stationary:

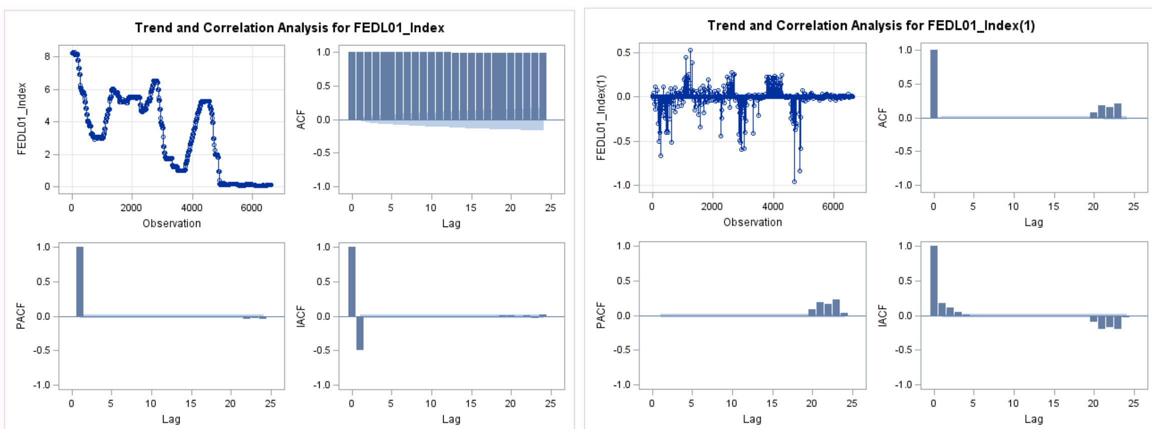


Figure 7. SPX Index and its first difference, which converts non-stationary data to stationary:

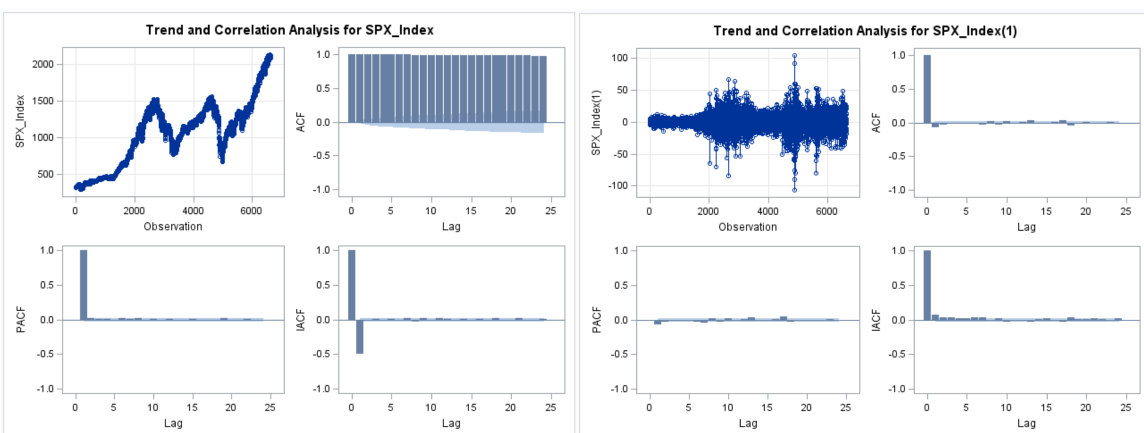


Figure 8. Sample ARIMA diagnostics output and maximum likelihood estimators.

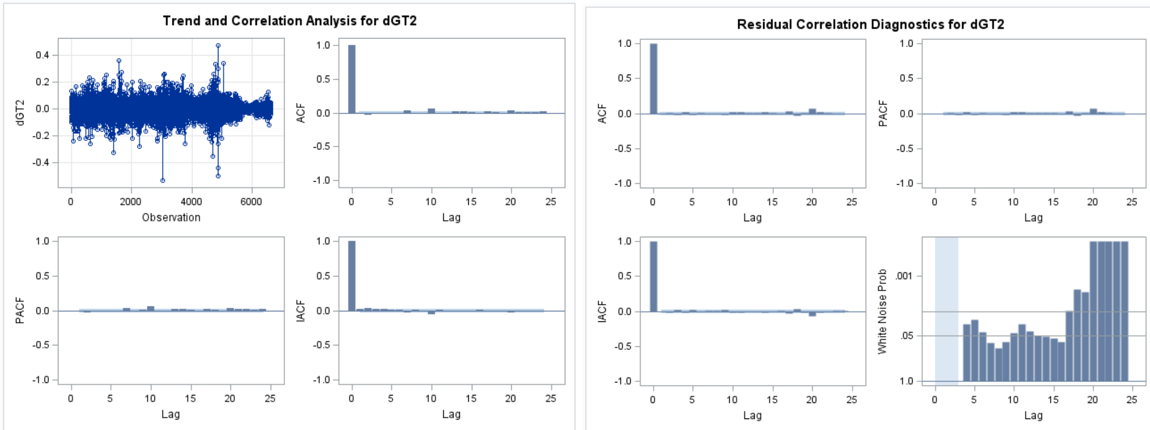


Figure 9. Prediction of S&P 500 without a shock in fed rate

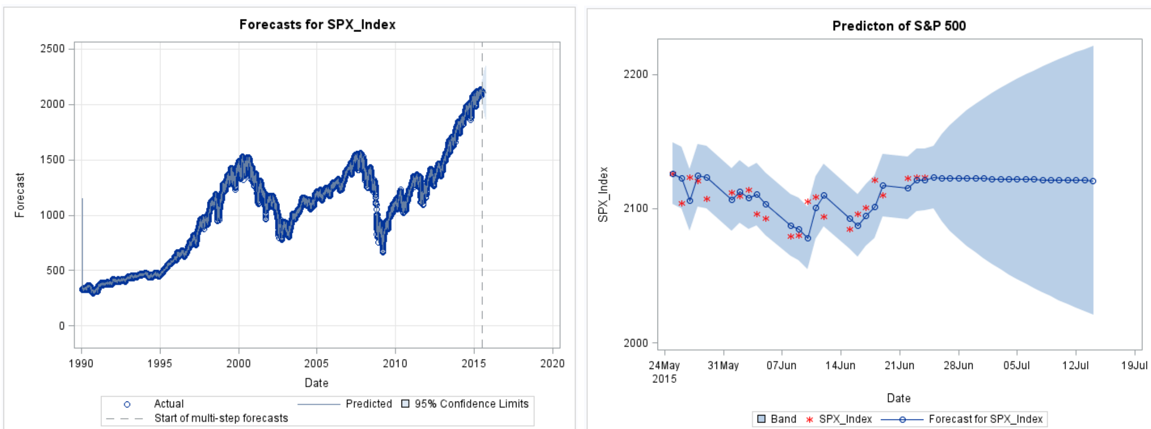


Figure 10. Prediction of first difference in 2-year US government bond yields with and without a shock in federal funds target rate

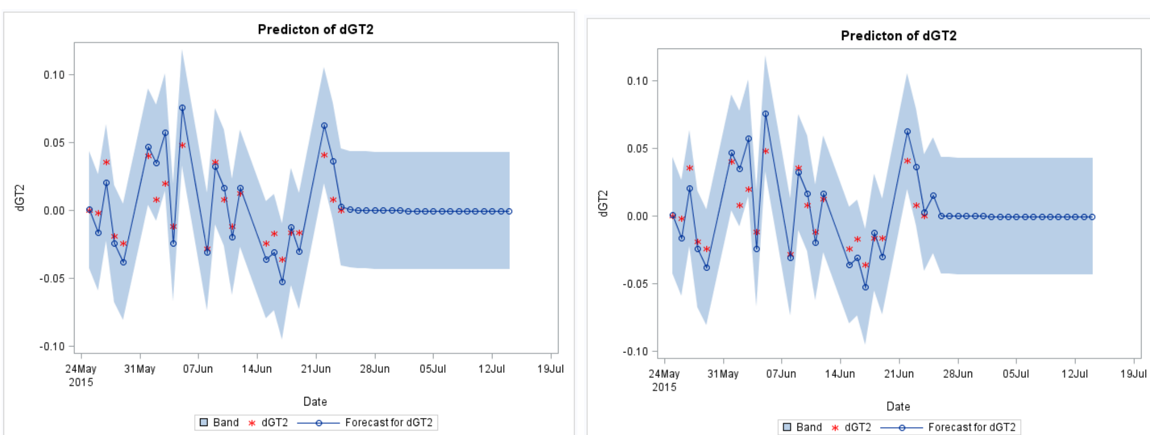


Figure 11. Prediction of first difference in 2-year US government bond yields with and without a shock in the unexpected part of the federal funds rate

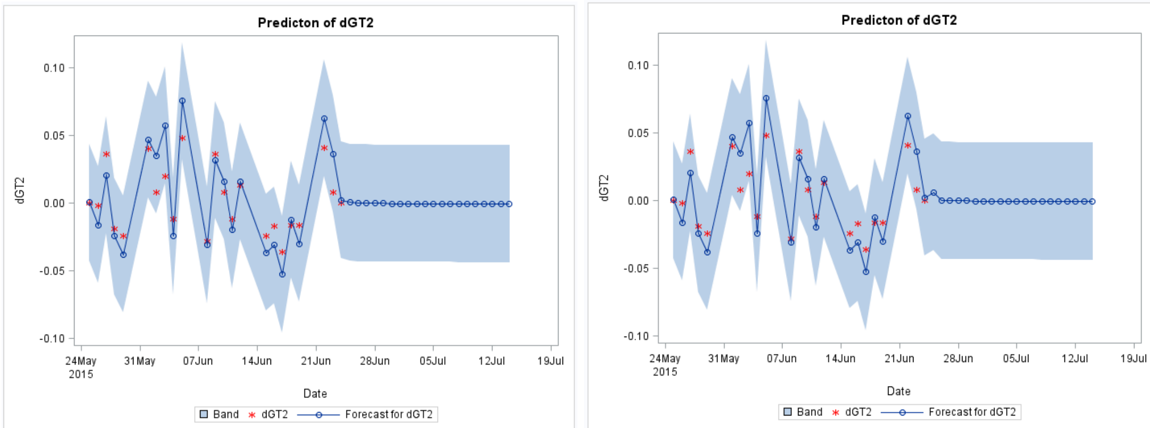


Figure 12. Prediction of first difference in 5-year US government bond yields with and without a shock in federal funds target rate

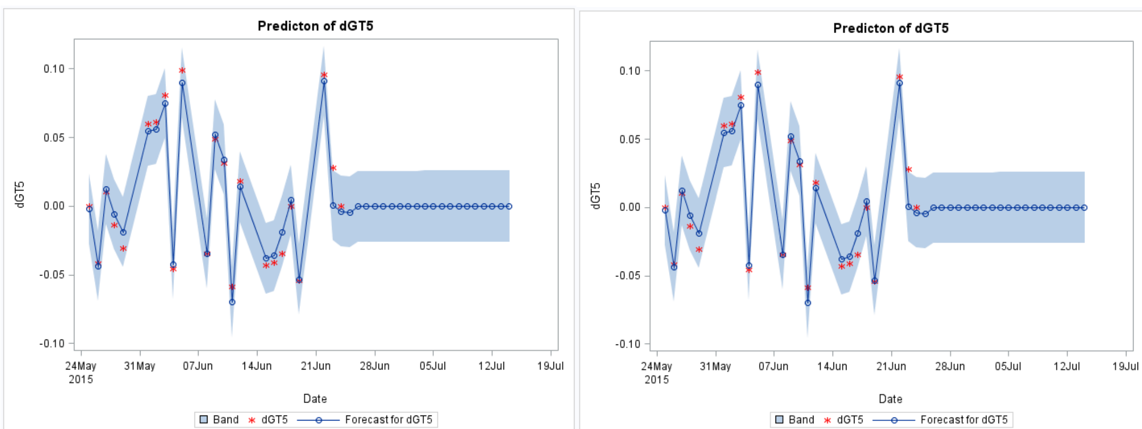


Figure 13. Prediction of first difference in 5-year US government bond yields with and without a shock in the unexpected part of the federal funds rate

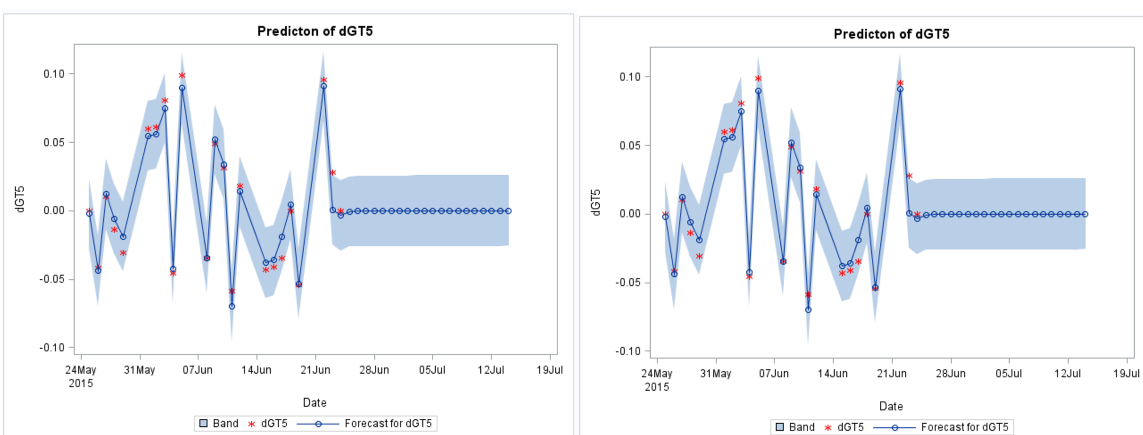


Figure 14. Prediction of first difference in 10-year US government bond yields with and without a shock in federal funds target rate

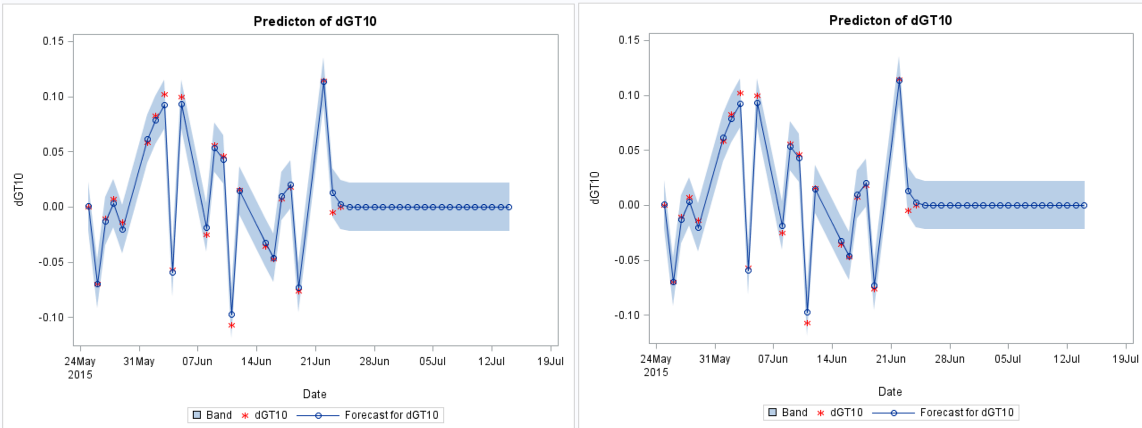


Figure 15. Prediction of first difference in 10-year US government bond yields with and without a shock in the unexpected part of the federal funds rate

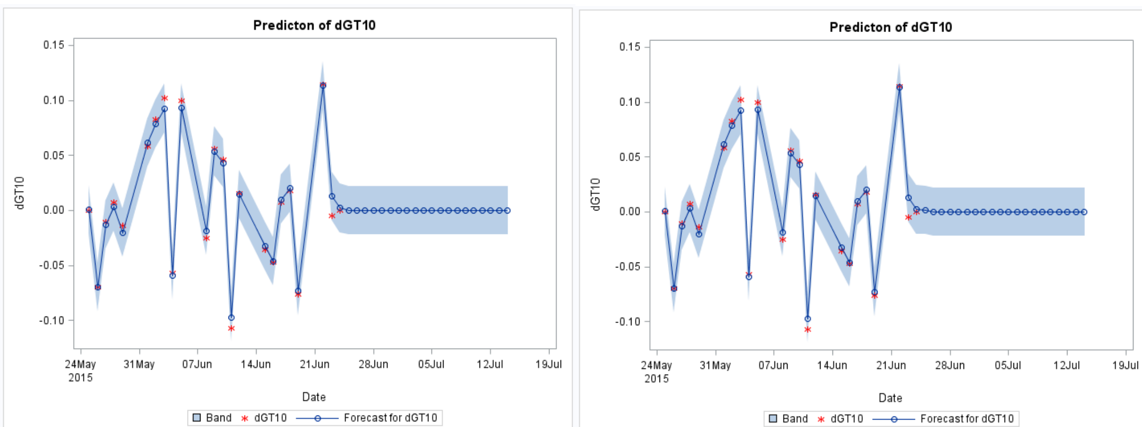


Figure 16. Prediction of first difference in 30-year US government bond yields with and without a shock in federal funds target rate

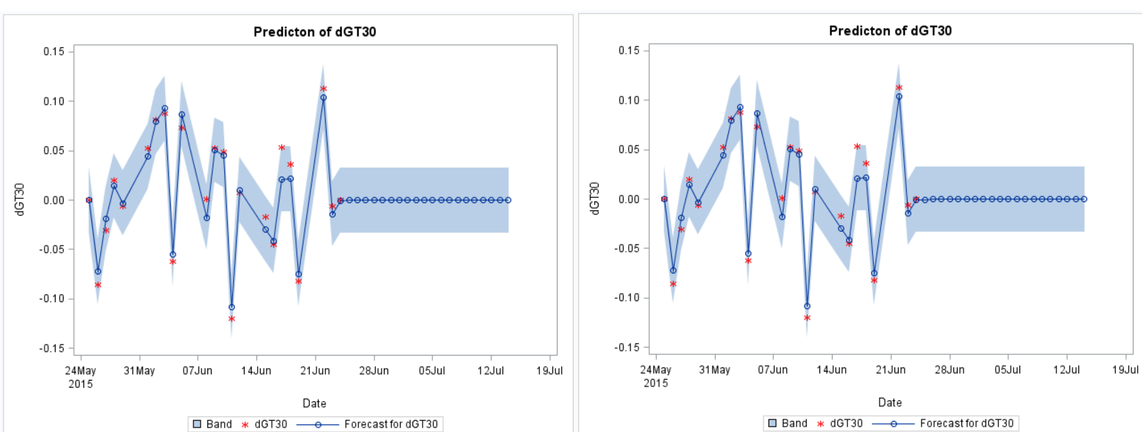


Figure 17. Prediction of first difference in 30-year US government bond yields with and without a shock in the unexpected part of the federal funds rate

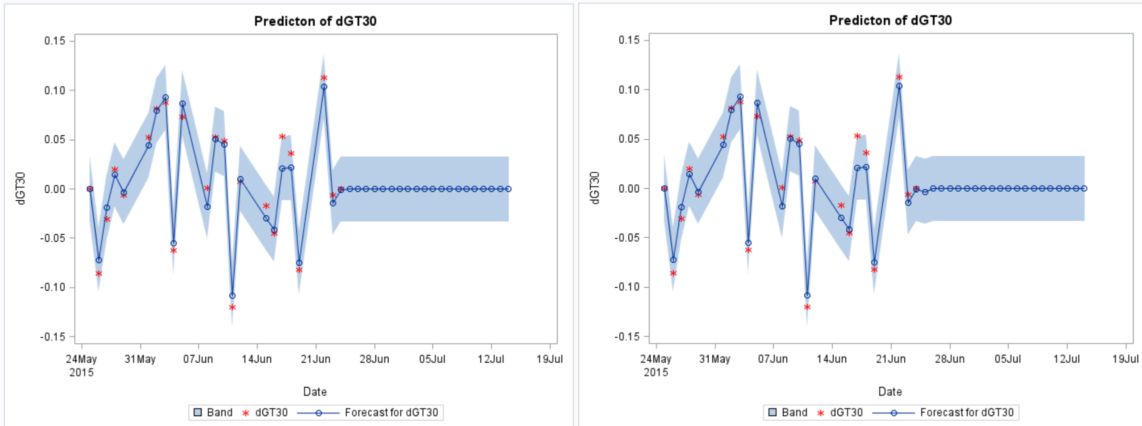
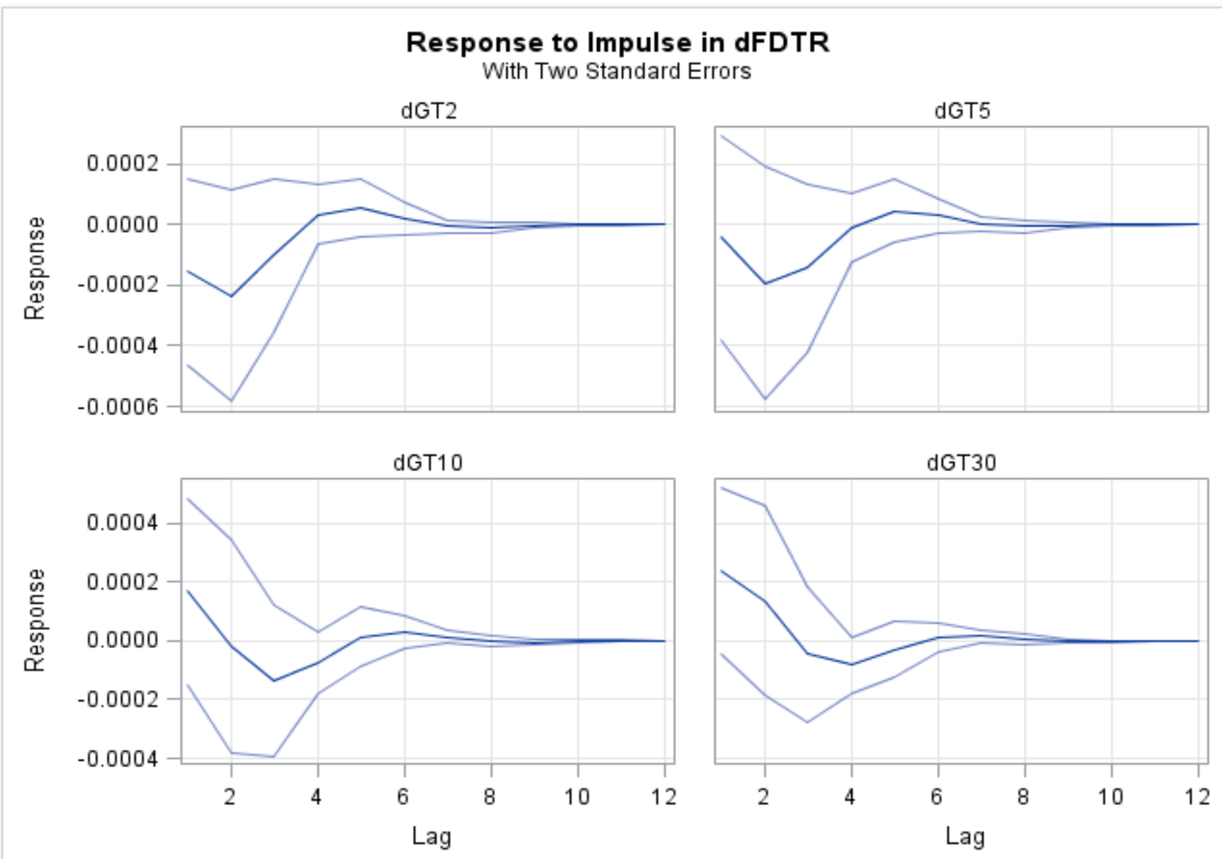
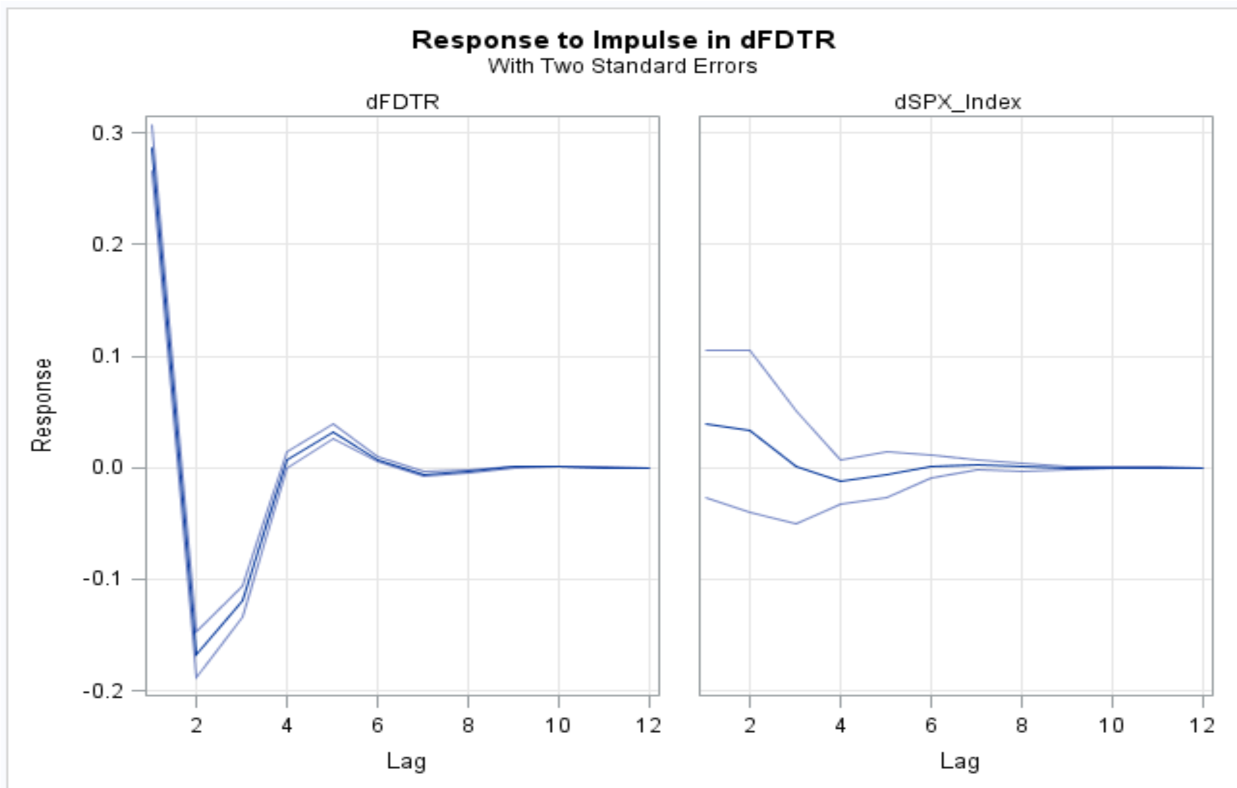


Figure 18. Response to impulse in FDTR in different bond yields and SPX





CODES APPENDIX

We create summary statistics using the following code:

```
proc means data = DataFullDayDif min max mean median std;
var GT2 GT5 GT10 GT30 SPX FDTR EFFR unexpFR Brent M2Vel Unempl Housing
PCE;
run;
```

The autocorrelations decrease rapidly in this plot, indicating that the change in abovementioned variable is a stationary time series.

```
proc arima data=DataFullDayDif;
    identify var=GT2;
run;
proc arima data=DataFullDayDif;
    identify var=GT2(1);
run;
```

Augmented-Dickey Fuller (ADF) and KPSS tests are used to test for stationarity:

```
proc arima data = DataFullDayDif;
    identify var=GT2(1) stationarity=(adf);
run;
```

Unlike the null hypothesis of the Dickey-Fuller, the null hypothesis of the KPSS states that the time series is stationary:

```
   proc autoreg data = DataFullDayDif;
      model dGT2 = / stationarity=(KPSS);
   run;
```

The code for ARIMA modeling is represented below:

```
/* p=number of autoregressive terms */
/* d=dependent var is integrated */
/* q=number of moving avg terms */

proc arima data = DataFullDayDif;
      identify var=GT2 crosscorr=(GT5 GT10 GT30 FDTR FDTR Brent M2Vel Unempl
      Housing PCE);
      estimate input=(GT5 GT10 GT30 FDTR Brent M2Vel Unempl Housing PCE)
      p=1 q=2 method=ml;
      run;
  quit;
```

The code for VAR modeling is represented below:

```
   proc expand data=DataFullDayDif  out=DataFullDayDif_interpolate;
         id date;
      run;
   proc varmax data= DataFullDayDif_interpolate plot=impulse;
      id date interval=day;
      model GT2 GT5 GT10 GT30 FDTR SPX = Brent M2Vel Unempl Housing PCE / p=2
   lagmax=12 dftest
                    print=(iarr(3) estimates diagnose)
                    cointtest=(johansen=(iorder=2))
                    ecm=(rank=1 normalize=GT2);
      cointeg rank=5 normalize=GT2 exogeneity;
   run;
```

Code used for GARCH models is represented below:

```
proc autoreg data=DataFullMonthDif_interpolate;
      /* AR(2)-EGARCH(1,1) model */
      model dGT2 = date / nlag=2 garch=(p=1,q=1,type=exp);
      /*    pgarch_1_1   */
      model dGT2 = date / garch=(p=1,q=1,type=pgarch);
      /* other garch models:
      ar_1 :            model r = / noint nlag=1 method=ml;
      arch_2 :          model r = / noint garch=(q=2);
      garch_1_1 :       model r = / noint garch=(p=1,q=1);
      st_garch_1_1 :    model r = / noint garch=(p=1,q=1,type=stationary);
      ar_1_garch_1_1 : model r = / noint nlag=1 garch=(p=1,q=1);
      igarch_1_1 :      model r = / noint garch=(p=1,q=1,type=integ,noint);
      egarch_1_1 :      model r = / noint garch=(p=1,q=1,type=egarch);
      garchm_1_1 :      model r = / noint garch=(p=1,q=1,mean=log);
      qgarch_1_1 :      model r = / noint garch=(p=1,q=1,type=qgarch);
      tgarch_1_1 :      model r = / noint garch=(p=1,q=1,type=tgarch);
      pgarch_1_1 :      model r = / noint garch=(p=1,q=1,type=pgarch);
      */
run;

proc varmax data=DataFullMonthDif_interpolate;
      model GT2 GT5 GT10 GT30 FDTR Brent M2Vel Unempl Housing PCE / p=1
      print=(roots estimates diagnose);
```

```
      garch p=1 q=2;
      nloptions tech=qn  maxiter=500;
   run;
```

CONTACT INFORMATION

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