Do Budget Deficits Affect Real Interest Rates? A Test of Ricardian Equivalence Theorem

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Abstract: This study re-examines the Ricardian Equivalence theorem (RET) by using advanced time series econometric models to investigate updated data of the U.S. budget deficits and real interest rates. We employ a multi-model approach to thoroughly investigate the properties of two time series, namely the U.S. federal budget deficits (BDEF) and real interest rates (INTRATE) for the study period from 1798 to 2009. It is found that BDEF and INTRATE are I(0) processes. The AR (2) is the most appropriate model for the BDEF series, while the ARMA (3,2) is the proper model for the INTRATE series. The estimated VAR (2) model, comprising the two stationary series BDEF and INTRATE, implies that the BDEF series has no effect on the INTRATE series. The Granger-causality test also shows that there is no direction of causality from the BDEF series to the INTRATE series. Our findings are consistent with what the Ricardian Equivalence theorem predicts and, therefore, support the proposition that the budget deficits are neutral. This study significantly contributes to the extant literature of the relationship between the budget deficits and the real interest rates by applying the multi-model approach. Furthermore, our long time series dataset enables us to make reliable inferences.

Keywords: ARMA; VAR; Ricardian Equivalence Theorem; Budget Deficits; Interest Rates

JEL Classification: E40; C22

1. Introduction and Brief Literature Review

The Ricardian equivalence theorem (RET) implies that budget deficits are neutral. Given that the RET holds, real economic variables, such as real interest rates, will not be affected by the budget deficits (Rose & Hakes, 1995). However, the relationship between budget deficits and real interest rates, in fact, is one of the most controversial issues in macroeconomics (Aisen & Hauner, 2013; Laubach, 2009). Economics theory and empirical evidence provide inconclusive answers for this relationship (Laubach, 2009; Thomas & Danhua, 2009). For example, a recent study of Thomas and Danhua (2009), using the data of the United States (the U.S.) in the period from 1983 to 2005, shows that the relationship between budget

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deficits and real interest rates is statistically significant and economically relevant. Similarly, applying the system Generalized Method of Moments (GMM) to explore a large panel dataset from emerging economies, Aisen and Hauner (2013) conclude that budget deficits have a significantly positive impact on interest rates. Laopodis (2012, p. 547) employs vector auto-regression (VAR) and Granger causality analyses to investigate data of the United States from 1960 to 2006 and states that "budget deficits negatively affect the equity market through increases in interest rates". This implies that the Ricardian Equivalence theorem is violated. Whereas, using the Markov regime-switching model to examine data from the U.S. economy, Choi and Holmes (2011) point out that the relationship between budget deficits and real long-term interest rates switches between an insignificant relationship (Ricardian Equivalence regime) and a positive relationship (traditional viewpoint).

Following Choi and Holmes (2011); and Laopodis (2012), we investigate the relevance of the Ricardian Equivalence theorem for the nexus between the budget deficits and the real interest rates time series by using a multi-model approach. More specifically, we employ appropriate ARMA models and VAR models to investigate this relationship. We also use the Granger test to find out the nature of causality between BDEF and INTRATE. The null hypothesis in each case is that INTRATE does not 'Granger cause' BDEF and vice versa. We find that the real interest rates may not be affected by the U.S. federal budget deficits. Our finding, therefore, is consistent with what the Ricardian Equivalence theorem has predicted.

This study contributes to the extant literature of the relationship between budget deficits and the real interest rates by applying the multi-model approach. In our opinion, this approach allows us to thoroughly examine the link between the two time series. Furthermore, the technique of impulse response functions is adopted to trace out the response of the dependent variables in the VAR system to shocks in the error terms. We also apply variance decomposition technique to measure the contribution of each type of shock to the forecasted error variance of the variables in the VAR model. Finally, to the best of our knowledge, our time series data, covering a long period from 1798 to 2009, is the biggest dataset that has ever been used in the relevant literature. This facilitates using advanced econometric estimations to explore the dynamic nature of the budget deficits-real interest rates relation. A long time series dataset enables us to make reliable inferences as well.

The remainder of the paper is structured as follows. Section 2 will summarize the concept on stationarity of a time series and discuss how one can find out if a time series is stationary through its autocorrelation function. The formal tests of stationarity (augmented Dickey-Fuller test, and Phillips-Perron test) will be briefly presented. ARMA models, VAR model, and the relevant procedures of estimation will be then introduced to set the theoretical foundation of applications in the next section. The sources of data are also indicated in this section. The illustration of the above econometric procedures and their inferences, which employs annual data of the United States for the period from 1798 to 2009, will be presented in section 3. Finally, there will be some concluding remarks as well as the implications of the results for the Ricardian Equivalence theorem.

2. Data and Methods

2.1. Data

This study uses annual data on the U.S. federal budget deficits (measured as the percentage of GDP) and the U.S. real interest rates for the study period from 1798 to 2009. These series are respectively denoted as BDEF and INTRATE. The BDEF time series are obtained from http://www.usgovernmentDEBT.us/. The nominal interest rates and price data, which are used to compute a measure of INTRATE time series, are obtained from http://measuringworth.com/datasets.html. Table 1 presents descriptive statistics of BDEF and INTRATE series. The mean value of BDEF is 1.16% while the mean value of INTRATE is 7.16%. There are 211 observations for each series. Jarque-Bera statistics of the two series show that the two series are not normally distributed

Table 1 Descriptive Statistics

	BDEF	INTRATE
Mean	1.165687	7.163307
Median	0.020000	6.217515
Maximum	28.05000	28.06066
Minimum	-4.33000	-9.349151
Std. Dev.	3.823536	6.075390
Skewness	4.165189	0.754984
Kurtosis	24.74265	4.238390
Jarque-Bera	4766.299	33.52802
Probability	0.000000	0.000000
Sum	245.9600	1511.458
Sum Sq. Dev.	3070.079	7751.176
Observations	211	211

2.2. Methods

Stationary Stochastic Processes

The important requirement of time series analysis is that the underlying time series is stationary, which implies that the distribution of the variable does not depend upon time (strictly stationary). However, in most practical situations, a weak stationary process often suffices. In short, a weak stationary time series (hereinafter referred to as the term “stationary process” or “stationary time series”) $\{Y_t\}$ is characterized by:

$$E\{Y_t\} = \mu < \infty \quad (1)$$

$$V\{Y_t\} = E\{(Y_t - \mu)^2\} = \gamma_0 < \infty \quad (2)$$

$$Cov\{Y_t, Y_{t-k}\} = E\{(Y_t - \mu)(Y_{t-k} - \mu)\} = \gamma_k$$
$$k = 1, 2, 3... \quad (3)$$

If a time series does not simultaneously satisfy the above-mentioned characteristics of (1), (2), and (3), it is called a non-stationary time series. In other words, a non-stationary time series will have a time-varying mean or a time-varying variance, or both.

Tests of Stationarity

At the informal level, the correlogram of a time series, which is a graph of autocorrelation at various lags, can be employed to check whether it is stationary or not. For stationary time series, the correlogram tapers off quickly. For non-stationary time series, it dies off gradually. For a purely random series, the autocorrelations at all lags 1 and greater are zero. At the formal level, stationarity can be identified by finding out if the time series contains a unit root. The ADF tests and Phillips-Perron test can be used for this purpose. If the time series is not stationary, difference it one or more times to obtain stationarity.

General ARMA Processes

First, we define a moving average process of order q, denoted as an MA (q) process, as the equation (4):

$$y_t = \varepsilon_t + \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + ... + \alpha_q \varepsilon_{t-q} \quad (4)$$

An autoregressive process of order p, denoted as an AR (p), is written as the following equation (5):

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + ... + \theta_p y_{t-p} + \varepsilon_t \quad (5)$$

Where: ε_t is a white noise process which has zero mean, constant variance, and is serially uncorrelated; $y_t = Y_t - \mu$ is the demeaned series, with Y_t is the original series.

Many stochastic processes cannot be modeled as purely autoregressive or as purely moving average, since they have the qualities of both types of processes. The logical extension of the models is autoregressive moving average process of order (p,q), denoted as ARMA(p, q), and its equation is written as equation (6):

$$y_t = \theta_1 y_{t-1} + ... + \theta_p y_{t-p} + \varepsilon_t + \alpha_1 \varepsilon_{t-1} + ... + \alpha_q \varepsilon_{t-q} \quad (6)$$

The Box-Jenkins (BJ) Methodology

Having tested the stationarity of a time series, we can apply the BJ strategy to build its appropriate ARMA models. This strategy consists of three main steps as follows.

Identification: Choose the most appropriate values for p, q of tentative model. The sample autocorrelation function (SAC) and the sample partial autocorrelation function (SPAC) of the stationary process are computed to find out if the series is purely autoregressive, or purely of the moving average type, or the mixture of the two. Model AR (p) is chosen if SPAC correlogram has significant spikes through lags p and cuts off after p; and SAC correlogram dies down. Model MA (q) is chosen if SAC correlogram has significant spikes through lags q and cuts off after p; and SPAC correlogram dies down. In the absence of any of these two situations, a combined ARMA model may provide an appropriate representation of the data.

Estimation: Choose the most appropriate values for the tentative model parameters. Ordinary least square method (OLS method) is often used to estimate these parameters.

Diagnostic checking: Examine the residuals from the tentative model just estimated to find out if they are a white noise process. If they are, the tentative model is probably a good approximation to the process. If they are not, the BJ procedure will be started all over again.

Vector Autoregressive Models (VAR)

The VAR models consider several time series at a time. Here, all variables are treated as endogenous in a simultaneous system. If we have two variables, Y_t and X_t, the VAR includes two equations. The first order VAR would be given by equations (7) and (8):

$$Y_t = \delta_1 + \theta_{11} Y_{t-1} + \theta_{12} X_{t-1} + \varepsilon_{1t} \quad (7)$$

$$X_t = \delta_2 + \theta_{21} Y_{t-1} + \theta_{22} X_{t-1} + \varepsilon_{2t} \quad (8)$$

If each equation contains the same number of lagged variables in the system, OLS method can be used to estimate their parameters. However, determining the lag length is one of the practical challenges in VAR modeling. A reasonable strategy is to estimate VAR models for various lag lengths and then choose the most appropriate model on the basic of Akaike or Schwarz information criteria.

3. Results and Discussion

3.1. Tests of Stationarity of BDEF and INTRATE

Graphical Analysis

Before we conduct formal tests of stationarity, it is very helpful to get some initial impression about the likely nature of the two time series by plotting them. Figure 1 and Figure 2 show that BDEF and INTRATE series fluctuate around their means over the period of study and tend to return to their means in the long run (called mean reversion). These give an intuitive clue about the stationarity of the two series.

Correlogram and Statistical Significance of Autocorrelation Coefficients

The correlogram up to 20 lags of the BDEF series (Figure 3) shows that its autocorrelations decline rapidly as the lags increase (we are 95% confident that the true autocorrelation coefficients (ACs) from lag 4 onward are zero, except the ACs at lags 1, 2 and 3). This, once again, reinforces our feel from previous subsection that the BDEF series may be stationary.

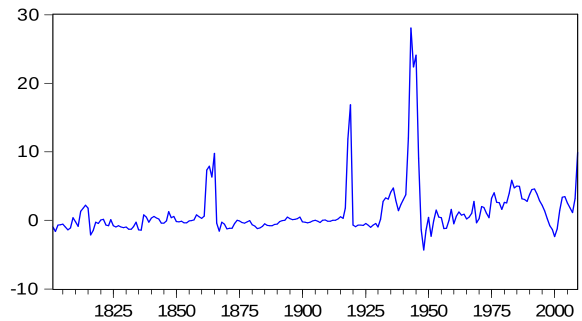

Figure 1. The Time Series BDEF (1798-2009)

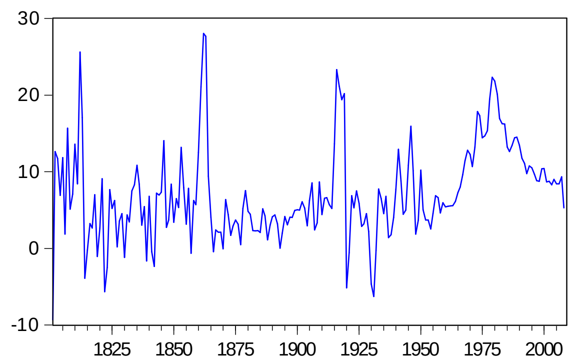

Figure 2. The Time Series INTRATE (1798-2009)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.746	0.746	119.55	0.000
		2	0.459	-0.219	165.01	0.000
		3	0.230	-0.057	176.47	0.000
		4	0.067	-0.048	177.44	0.000
		5	0.009	0.076	177.46	0.000
		6	0.016	0.039	177.52	0.000
		7	0.042	0.014	177.90	0.000
		8	0.047	-0.031	178.38	0.000
		9	0.067	0.072	179.40	0.000
		10	0.065	-0.023	180.35	0.000
		11	0.014	-0.085	180.39	0.000
		12	-0.026	0.007	180.54	0.000
		13	-0.034	0.037	180.81	0.000
		14	-0.036	-0.019	181.11	0.000
		15	-0.041	-0.039	181.50	0.000
		16	-0.022	0.035	181.61	0.000
		17	-0.010	-0.005	181.64	0.000
		18	-0.008	-0.004	181.65	0.000
		19	-0.023	-0.055	181.78	0.000
		20	-0.030	0.025	181.99	0.000

Figure 3. Correlogram of the Time Series: BDEF

Figure 4 depicts the correlogram up to 20 lags of INTRATE time series that gives us an unclear impression of the stationarity. The SACs decay to zero quite slowly and have significant peaks up to lag 10 (at the 5% level).

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.611	0.611	79.885	0.000
		2	0.403	0.047	114.73	0.000
		3	0.330	0.107	138.23	0.000
		4	0.198	-0.084	146.73	0.000
		5	0.275	0.250	163.25	0.000
		6	0.205	-0.111	172.46	0.000
		7	0.225	0.176	183.62	0.000
		8	0.264	0.019	199.11	0.000
		9	0.225	0.075	210.35	0.000
		10	0.202	-0.069	219.50	0.000
		11	0.110	-0.038	222.23	0.000
		12	0.053	-0.068	222.87	0.000
		13	0.089	0.092	224.65	0.000
		14	0.048	-0.097	225.18	0.000
		15	0.015	-0.025	225.23	0.000
		16	0.092	0.118	227.18	0.000
		17	0.113	0.042	230.16	0.000
		18	0.092	-0.059	232.11	0.000
		19	0.031	-0.063	232.33	0.000
		20	-0.053	-0.056	233.00	0.000

Figure 4. Correlogram of the Time Series: INTRATE

The Augmented Dickey-Fuller Test (ADF Test)

In this subsection, we test the presence of unit root in BDEF and INTRATE time series by the ADF procedure. On the basis of the above graphical analysis, the "trend" term will be excluded from the ADF test equations of BDEF and INTRATE series. The test results are respectively given in Table 2 and Table 3.

Table 2. ADF Unit Root Test on BDEF

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.265051	0.0000
Test critical values:	1% level	-3.461478	
	5% level	-2.875128	
	10% level	-2.57409	

Note: *MacKinnon (1996) one-sided p-values.
Null Hypothesis: BDEF has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

Table 2 presents ADF unit root test on BDEF series. The *t* value of $BDEF_{t-1}$ coefficient is -6.265 which (in absolute terms) is much larger than even the 1% critical *t* value of -3.461. Hence, the null hypothesis that the time series has a unit root is rejected at 1% significant level. This means the BDEF series is stationary. ADF unit root test on INTRATE series is given in Table 3. The ADF test statistic -7.08 is so large in absolute terms that the null hypothesis cannot be accepted at any conventional levels of significant (Table 3). The conclusion is that the INTRATE series is stationary.

Table 3. ADF Unit Root Test on INTRATE

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.084427	0.0000
Test critical values:	1% level	-3.461478	
	5% level	-2.875128	
	10% level	-2.57409	

Note: *MacKinnon (1996) one-sided p-values.
Null Hypothesis: BDEF has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

The Phillips-Perron Test

The Phillips-Perron unit root tests presented in Table 4 give us similar awareness about the stationarity of BDEF and INTRAT time series to the results from the ADF tests. The null hypothesis that the BDEF time series has a unit root is rejected at 1% level (Phillips-Perron test statistic = -4.748, *p*-value = 0.0001). Similarly, the null hypothesis that the INTRATE time series has a unit root is also rejected at 1% level (Phillips-Perron test statistic = -7.106, *p*-value = 0.0000). Then both BDEF and INTRATE are said to be I(0) processes.

The results from the Augmented Dickey-Fuller test and the Phillips-Perron test imply that BDEF and INTRATE series have limited memories of their past behavior. The impacts of a particular random shock, which may be due to policy interventions, on such time series are temporary. It must be mentioned, however, that although INTRATE time series is stationary and its correlogram (Figure 4) provides us with an ambiguous impression of the stationarity. We can see that even with stationarity, it takes a quite long period for INTRATE series to return to its long run average.

Table 4. Phillips-Perron Unit Root Test on BDEF and INTRATE

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic for BDEF		-4.748796	0.0001
Phillips-Perron test statistic for INTRATE		-7.105677	0.0000
Test critical values:	1% level	-3.461327	
	5% level	-2.875062	
	10% level	-2.574054	

Note: *MacKinnon (1996) one-sided p-values.

3.2. Estimate Appropriate ARMA Models for BDEF and INTRATE

We have noted that the BDEF and INTRATE processes (in level form) are stationary. We can now apply the ARMA (p, q) model to them.

ARMA Model for BDEF

From Figure 3, two facts stand out: (1) the SACs decline up to lag 3, then the rest of them is statistically not different from zero; and (2) SPACs drop dramatically and all SPACs after the second lag are statistically insignificant. This suggests that MA (3); or AR (2); or ARMA (2, 3) may be tentative models. These three models were estimated by OLS method (the detail results are not reported). For AR (2) model, we obtain the equation (9) as follows:

$$bdef_t = 1.309 + 0.96 bdef_{t-1} - 0.258 bdef_{t-2} + \hat{\varepsilon}_t$$

(2.286) (14.012) (-3.772)

R^2 =0.59 d=1.98

AIC=4.66 F = 153.77 (9)

The equation (9) shows that all of model’s parameters are statistically significant. The *F*-value =153.77 is so high that we can reject the null hypothesis that collectively all the lagged terms are statistically insignificant. We also see AR (2) model provides a slightly better fit than the others, which is confirmed by the smallest value of the Akaike information criterion (AIC = 4.66). The adjusted R-squared of the regression is 0.59, implying that equation (9) can explain about 59%

of the movement of BDEF series while the remaining 41% is explained by other factors.

The estimated SACs and SPACs of residuals from equation (9) are given in Figure 5. This figure shows that none of the auto-correlations and partial auto-correlations is individually statistically significant. Moreover, as we can see from the last column of Figure 5, the *p*-value of the LB statistic up to lag 36 is larger than 5%. Thus, the null hypothesis that the sum of 36-squared ACs is zero cannot be rejected. This suggests that the series of residuals estimated from equation (9) is a white noise process. Hence, the above AR (2) may be the most appropriate model for BDEF series.

ARMA Model for INTRATE

A similar procedure of estimation (with the technical assistance of add-ins 'Automatic ARIMA selection' on EVIEWS 7.1) is applied for the INTRATE time series. The ARMA (3, 2) model for INTRATE series is shown in Table 5. Based on the AIC =5.80, this model is preferred to others (the detail results of the other models are not reported). The correlogram of the residuals obtained from ARMA (3,2) for INTRATE (unreported to save space) gives the impression that the residuals correspond to a white noise process. If the ARMA (3, 2) is accepted as the most appropriate estimation, it will be able to explain about 49% the behavior of the INTRATE series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.012	-0.012	0.0318	
		2	0.024	0.024	0.1601	
		3	0.036	0.036	0.4335	0.510
		4	-0.084	-0.084	1.9470	0.378
		5	-0.030	-0.034	2.1484	0.542
		6	0.002	0.004	2.1493	0.708
		7	0.073	0.082	3.3229	0.650
		8	-0.037	-0.040	3.6216	0.728
		9	0.031	0.021	3.8410	0.798
		10	0.079	0.077	5.2444	0.731
		11	-0.029	-0.013	5.4363	0.795
		12	-0.055	-0.066	6.1135	0.806
		13	-0.004	-0.009	6.1176	0.865
		14	0.017	0.034	6.1825	0.907
		15	-0.055	-0.045	6.8830	0.908
		16	0.016	-0.005	6.9450	0.937
		17	-0.000	-0.012	6.9450	0.959
		18	0.031	0.050	7.1652	0.970
		19	-0.017	-0.022	7.2313	0.980
		20	-0.014	-0.030	7.2792	0.988
		21	0.024	0.026	7.4109	0.992
		22	-0.035	-0.006	7.7052	0.994
		23	-0.111	-0.128	10.664	0.969
		24	0.170	0.167	17.619	0.728
		25	0.043	0.066	18.055	0.754
		26	0.119	0.125	21.509	0.609
		27	0.078	0.036	22.993	0.578
		28	-0.023	-0.020	23.120	0.626
		29	-0.105	-0.093	25.824	0.528
		30	-0.019	0.013	25.909	0.578
		31	0.064	0.051	26.930	0.576
		32	-0.024	-0.001	27.074	0.619
		33	0.001	-0.020	27.074	0.668
		34	0.027	-0.022	27.252	0.706
		35	-0.003	-0.006	27.255	0.748
		36	-0.022	-0.011	27.384	0.782

Figure 5. Correlogram of the Residuals Obtained from AR(2) Model for BDEF

Table 5. ARMA (3,2) Model for INTRATE

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.186804	0.976407	7.360462	0
AR(1)	-0.667808	0.099515	-6.710632	0
AR(2)	0.184886	0.079036	2.339266	0.0203
AR(3)	0.532881	0.061353	8.685557	0
MA(1)	1.395079	0.105177	13.26406	0
MA(2)	0.685288	0.094367	7.261936	0
R-squared	0.506713	Mean dependent var		7.12311
Adj. R-squared	0.494503	S.D. dependent var		6.10916
F-statistic	41.49961	Durbin-Watson stat		1.93599
Prob(F-statistic)	0			

3.3. VAR Model for BDEF and INTRATE Time Series

The Empirical VAR Model

In this section, we will consider a bivariate VAR model comprising two stationary series BDEF and INTRATE. This model explains current BDEF in terms of lagged INTRATE and lagged BDEF, and current INTRATE in terms of lagged INTRATE and lagged BDEF. We assume that each equation contains p lag values of BDEF and INTRATE, which will be selected on the basis of the smallest value of the FPE, AIC, SC or HQ criteria. As presented in Table 6, we find that p = 2 is the appropriate lag order determined by the SC and HQ criteria.

Table 6. Selections of the VAR Lag Length

Lag	FPE	AIC	SC	HQ
0	501.0583	11.89248	11.92512	11.90568
1	132.2747	10.56063	10.65856	10.60025
2	122.7958	10.48626	10.64947*	10.55229*
3	122.9690	10.48763	10.71613	10.58007
4	124.7741	10.50214	10.79592	10.62100
5	118.5174	10.45060	10.80967	10.59587
6	117.5714	10.44245	10.86680	10.61412
7	114.6191*	10.41683*	10.90647	10.61492
8	117.9504	10.44523	11.00015	10.66973

Note: * indicates lag order selected by the criterion

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

We obtain the estimated parameters of the two equations given in Table 7. First, consider the BDEF regression. Most coefficients are statistically significant except INTRATE at lag 1 and intercept coefficient. However, the *F*-value = 84.58 is large enough to reject the null hypothesis that the various lagged coefficients simultaneously equal to zero. Second, for the INTRATE regression, we can see that the coefficients of BDEF at lag 1 and 2, and INTRATE at lag 2 are not statistically significant, but collectively, they are significant on the basis of the standard *F* test. (*F*-statistic = 30.63). However, the adjusted R-squared of this regression is low (~ 36.29%). Both these imply that BDEF may have no effect on INTRATE.

We conducted autocorrelation LM test for the residuals obtained from the above-mentioned VAR (2) model to test whether or not there is serial correlation. The null hypothesis that there is no serial correlation is accepted at almost lag orders suggesting that there is no serial correlation in the residual series (presented in Table 8).

Table 7. A Standard VAR (2) Model Comprising BDEF and INTRATE

	BDEF	INTRATE
BDEF(-1)	0.924840	0.048694
	[13.5620]	[0.34901]
BDEF(-2)	-0.278194	-0.054921
	[-4.13805]	[-0.39929]
INTRATE(-1)	-0.009237	0.576817
	[-0.26400]	[8.05768]
INTRATE(-2)	0.101921	0.050860
	[2.89415]	[0.70589]
C	-0.241804	2.646330
	[-0.88659]	[4.74247]
R-squared	0.623842	0.375215
Adj. R-squared	0.616466	0.362965
Sum sq. resides	1154.066	4830.929
S.E. equation	2.378484	4.866315
F-statistic	84.58137	30.62812

Note: t-statistics are presented in [ ]

Table 8 Autocorrelation LM Test for the Residuals Obtained from the VAR(2)

Lags	LM-Stat	Prob
1	3.513770	0.4758
2	6.806446	0.1465
3	3.575570	0.4665
4	9.398860	0.0519
5	18.89568	0.0008
6	0.376483	0.9844
7	1.229621	0.8732
8	7.861581	0.0968
9	2.508513	0.6431
10	5.431874	0.2458
11	1.518727	0.8233
12	1.580891	0.8122

Note: Probes from chi-square with 4 degree of freedom.

Granger-Causality Tests

Damodar (2004, p. 22) notes that "[…] although regression analysis deals with the dependence of one variable on other variables, it does not necessarily imply causation. In other words, the existence of a relationship between variables does not prove causality or the direction of influence". Thus, in this subsection, we will use the Granger test to find out the nature of causality between BDEF and INTRATE. The null hypothesis in each case is that INTRATE does not 'Granger cause' BDEF and vice versa. It is important to note that the term 'causes' in 'Granger causes' does not mean contemporaneous causality between the two variables. Granger causality implies a relationship between the current value of one variable and the lagged values of other ones.

Table 9. Granger Causality Test

Dependent variable: BDEF			
Excluded	Chi-sq	df	Prob.
INTRATE	11.43328	2	0.0033
All	11.43328	2	0.0033
Dependent variable: INTRATE			
Excluded	Chi-sq	df	Prob.
BDEF	0.165668	2	0.9205
All	0.165668	2	0.9205

The results given in Table 9 show that the direction of causality is from INTRATE to BDEF (INTRATE 'Granger causes' BDEF). Meanwhile, there is insufficient information in the data to reject the null hypothesis that BDEF does not "Granger cause" INTRATE. This is another way to say that there is no direction of causality from BDEF to INTRATE.

Analyzing the Impulse Responses and Variance Decompositions

The impulse response functions (IRFs) trace out the response of the dependent variables in the VAR system to shocks in the error terms, while the variance decompositions measure the contribution of each type of shock to the forecast error variance of the variables in the VAR model (Damodar, 2004; Verbeek, 2004). The results of IRFs appear in four figures form Figure 6 to Figure 9.

Figure 6 and Figure 7 depict the response in BDEF series and INTRATE series to a shock in them, respectively. We can see shocks are not persistent and their effects eventually die out because these series are stationary.

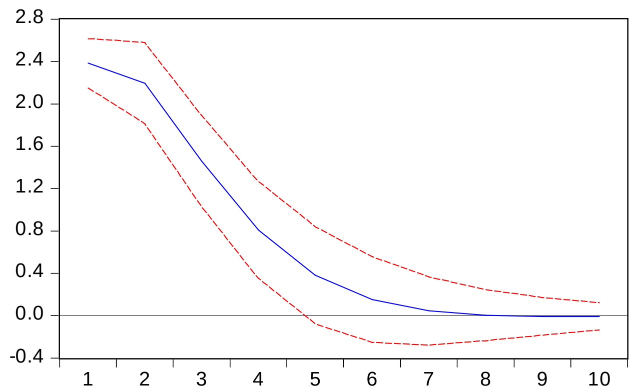

Figure 6. Impulse-Response Analysis: Response of BDEF to BDEF

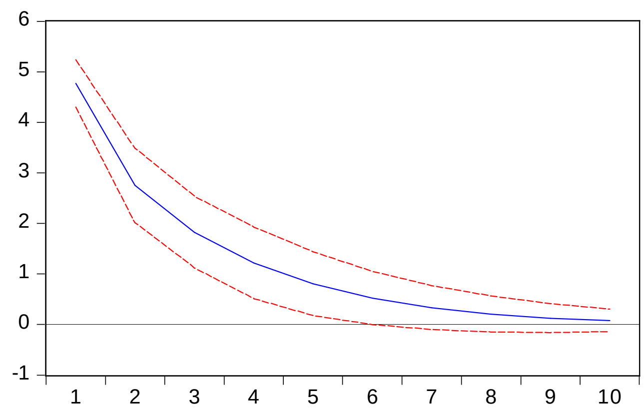

Figure 7. Impulse-Response Analysis: Response of INTRATE to INTRATE

Figure 8 shows that BDEF is generally higher after the INTRATE increases, reaching a maximum of nearly 0.7% points higher in year 5. Then the response in BDEF series gradually converges to zero.

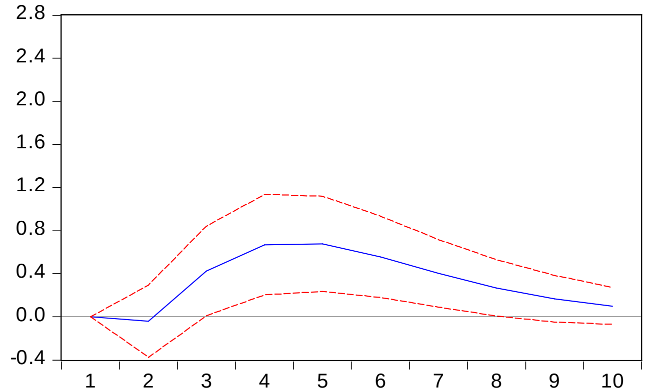

Figure 8. Impulse-Response Analysis: Response of BDEF to INTRATE

Figure 9 shows that a one-standard deviation increase in the BDEF creates a small response in INTRATE. After a small brief change, the response in the INTRATE falls to zero quickly (implying that INTRATE will return to its initial level). The results of variance decompositions are represented in Table 10, which shows three key characteristics as follows:

- Most of the variance of BDEF and INTRATE series is explained by their own shocks;
- The proportion of the movement in BDEF series, which is due to shocks in INTRATE series, is generally higher than that in INTRATE series, which is due to shocks in BDEF series;
- At the year 10-time horizon, approximately 10.92% of the forecast error variance of BDEF series in the VAR can be explained by exogenous shocks to the INTRATE series. Conversely, this number is only approximately 4.63% in the case of INTRATE series.

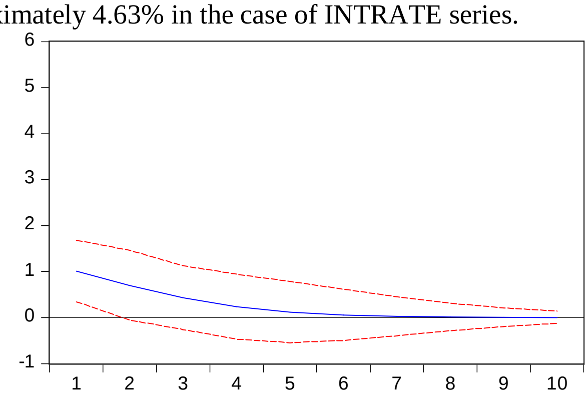

Figure 9. Impulse-Response Analysis: Response of INTRATE to BDEF

Table 10. Variance Decompositions

Variance Decomposition of BDEF:			
Period	S.E.	BDEF	INTRATE
1	2.378484	100.0000	0.000000
2	3.233737	99.98151	0.018495
3	3.572845	98.60817	1.391829
4	3.722628	95.54609	4.453905
5	3.801976	92.61318	7.386817
6	3.844946	90.71086	9.289145
7	3.866112	89.73407	10.26593
8	3.875362	89.30637	10.69363
9	3.878991	89.13961	10.86039
10	3.880297	89.07982	10.92018
Variance Decomposition of INTRATE:			
Period	S.E.	BDEF	INTRATE
1	4.866315	4.280202	95.71980
2	5.630991	4.726771	95.27323
3	5.934594	4.778104	95.22190
4	6.062131	4.727782	95.27222
5	6.116136	4.680489	95.31951
6	6.138519	4.653850	95.34615
7	6.147501	4.641634	95.35837
8	6.150988	4.636621	95.36338
9	6.152304	4.634692	95.36531
10	6.152791	4.633976	95.36602

Note: Cholesky Ordering: BDEF-INTRATE

From an economic point of view, Rose and Hakes (1995, p. 57) document that “an implication of Ricardian equivalence is that deficits are neutral. That is, deficits fail to affect real variables such as real interest rates”. Our previous analyses provide evidence that is consistent with what the RET predicts. This means the U.S. federal budget deficits (BDEF) will have no impact on real interest rates (INTRATE).

4. Conclusion

This study investigates the relationship between the U.S. federal budget deficits and the real interest rates time series. We estimated appropriate ARMA models and VAR models for the BDEF and INTRATE, as well as discussed the implications of the results for the RET. It is found that the real interest rates will not be affected by the U.S. federal budget deficits. This conclusion is in agreement with what the RET predicts. However, it is noteworthy that although our empirical evidence does not support the significant influences of the deficits on the real interest rates, such an evidence “should not make us confident that larger future deficits will also fail to increase interest rates”, as what Rose and Hakes (1995, p. 64) have warned.

5. Acknowledgements

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6. References

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