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The "Donald" and the market: is there a cointegration?

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Abstract
This paper analyses the relationship between post-election main sentiment on Donald Trump and financial markets. The sample period, spans from 8 November (the election Day) and 28 February. Our study intends to verify if there exist a co-implication between Trump's Favorable (TF), namely the percentage of favorable opinions on Trump, and some financial variables (i.e. stock and Treasury returns, currency and commodities). The results of cointegration analysis show that Trump's Favorable has explanatory power for stock market returns, 10 long term Treasury bond and decrease of gold. Furthermore, we found no evidence of the opposite relation.

Keywords: Trump's Favorable, financial cointegration, poll sentiment, markets

JEL codes: G10, G14, G11

1. Introduction

The United States went to polls to elect a president on November 8, 2016. The election of Donald J. Trump as the 45th President surprised (positively and negatively) most observers, as well as financial markets. In fact, after Trump's victory, the capitalization of world stock markets has been consistently positive exceeding the threshold of 70 trillion dollars. "America first" and "make America great again" slogans, pushed up financial markets: for instance, Standard and Poor's increased by 11%, Treasury bond yield (30%)[1].

Generally speaking, since the expectations of financial markets are strongly influenced by politics, the impact of political elections and administrations on markets has been object of study for an extensive strand of economic literature (see Wisniewski, 2016). Several studies have made investigations on presidential political cycles showing a peak of stock returns during presidential election (Herbst and Slinkman, 1984), higher yields for the last half of a political term (Huang, 1985), or excess in stock returns under Democratic administrations over a period of almost eighty years (Santa-Clara and Valkanov, 2003). Moreover, researchers have demonstrated the influence of political uncertainty in terms of higher risk premia (Pastor and Veronesi, 2013) and increased stock market volatility (Goodell and Vahamaa, 2013), especially near the elections. Political sentiment is also determinant on investing decisions. Empirical evidence shows that as political climate changes, there’s a portfolio rearrangement that generates predictable stock returns (Addoum and Kumar, 2016). Specifically, political sentiment could be considered as a partial mediator between political cycles and stock market returns, since the latter are predicted by investors’ sentiment, after controlling for political cycles (Adjei and Adjei, 2017); moreover, in the U.S., a stronger correlation between investors’ sentiment and returns, is verified during Democratic Presidencies (Liston and Chong, 2014).

Our work is related to literature which attempts to answer the question of how election polls affect stock markets (Levy and Yagil, 2015, 2012; Döpke and Pierdzioch, 2006; Gwilym and Buckle, 1994; Gemmill, 1992). Regarding the 1987 election in London, Gemmill (1992) finds a relationship between opinion polls and the share prices of the FTSE 100 Index. Furthermore, Gwilym and Buckle (1994), extending Gemmill's study to the 1992 election, find the same relationship between the opinion polls and the FTSE 100 Index. Döpke and Pierdzioch (2006) for Germany, find that the government's popularity seems to be driven by excess stock returns. Recently, Levi and Tagili

1 Source: Bloomberg and Datastream.

(2012, 2015) investigate the relationship between daily US presidential election poll results and stock returns for 2008 and 2012 election. Their results imply that "stock returns are positively related to the poll results that support the favorite Democratic candidate" and they occur in the time period closest to Election Day.

Although the impact of political elections on markets is well known and studied, the relationship between the presidential political sentiment post-elect (incumbent's popularity) and its impact on financial markets have not been investigated in depth. This paper will fill in this gap.

The aim of this paper is answering to three main research questions: i) How does political sentiment post-election influence financial market?; ii) Is there a relationship between TF growth during the term of a presidential administration and the change in financial markets after the presidential election?; iii) What is its "direction"?

We based on the assumption that stock market movements reflect people's expectations, specially people's voting behavior is influenced by past economic (Fair, 1996) and financial performance (Döpke and Pierdzioch, 2006; Prechter et al., 2012). When people express confidence in incumbent's popularity, financial markets reflect this sentiment. Generally speaking, a market drop after the election suggests that the investors not support the presidential capability of making the economy grow; if the market moves up it suggests that the markets are optimistic. (Chien et al., 2014). In our case appears to have this relationship but the direction of causality is not exactly clear on this one. Therefore, we want to explore this causality.

This study examines the impact of changing in Trump's sentiment on the return of financial markets. Using Trump Favorable post-election, we identify a short-long relationship between political sentiment and financial markets (such as S&P500, 10 US year yields, USD/EUR exchange rate, WTI crude oil, gold and silver), by cointegration analysis. Overall, our results establish a strong link between Trump Favorable (political sentiment) and financial markets. As shown in our results for the Engle and Granger (1987), through VECM, cointegration tests and the Johansen cointegration tests, we robustly find that TF, S&P500, LTIR and GOLD are cointegrated. Further, Granger causality testing finds that movement of this financial markets is caused by TF; this imply that there are shifts in portfolio compositions of investors when political climate changes. This result has very important implications in terms of investment decisions both for firms and traders.

2. Empirical model: integration, cointegration and causality

In order to quantify the effects of Trump's victory and to analyze the pathway of Trump Favorable on financial markets, we conduct a cointegration analysis. This econometric technique is helpful to understand the relationship between TF and financial variables and to establish the direction of causality (if TF leads market growth/decrease or contrary). The variables chosen are: Trump's Favorability (TF), Standard & Poor's 500 (S&P500), US 10-year yields (LTIR), exchange rate dollar to euro (USD/EUR), WTI crude oil (WTI), gold (GOLD) and silver (SILVER).

To this purpose, we adopt the following econometric tools: i) Johansen and Juselius (1990) cointegration approach to explore the existence of a cointegration relationship; ii) Vector Error Correction model (VECM) to examine the long and short run dynamic relationship; iii) Granger-causality (1987) through VECM, in order to point out the direction of causality.

2.1 Johansen cointegration

Johansen test is used to verify the null hypothesis of no cointegration among TF and markets financial variables, against the alternative hypothesis of cointegration. Johansen produces two statistics: the likelihood ratio test, based on maximal eigenvalue of the stochastic matrix and the test based on the trace of the stochastic matrix. The two statistics are:

$$\lambda_{\text{trace}}(r) = -T\sum_{\text{i=r+1}}^{n} \ln(1-\lambda_i) \qquad (1)$$

$$\lambda_{\max}(\text{r,r+1}) = -\text{T}\ln(1-\lambda_{\text{r+1}}) \qquad (2)$$

where λ_i is the $n-r$ least squared canonical correlations and T is the sample size. The trace tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors. The maximum eigenvalue tests the null hypothesis of $r$cointegrating vectors against the alternative hypothesis of r+1cointegrating vectors.

2.2 Vector Error Correction model

Below we show a Vector Error Correction model (VECM). Let $Y_{t,i} \equiv (X_i, M_j)$, where X_i is TF and M_j is the vector of financial market variables (M_j= S&P500, LTIR, USD/EUR, WTI, GOLD, SILVER). If $Y_{t,i}$ is cointegrated, a VEC model is:

$$\Delta Y_{t,i} = \alpha_i + \gamma_i \beta_i Y_{t-1} + \sum_{j=1}^{k} \Gamma_{j,i} \Delta Y_{t-j,i} + \varepsilon_{t,i} \qquad (3)$$

where α is a constant vector while the matrix Γ reflects the short-run aspects of the relationship among the elements of $Y_{t,i}$. β_i represents the cointegrating vector, and γ is the error correction coefficient. The latter provides information about the speed of adjustment to the long-run equilibrium. The error correction coefficient is expected to have negative sign with range $-1 < \gamma < 0$.

2.3 Granger-causality

Through Granger-causality we test if financial variables spread to TF, or *vice versa*, or even if two variables have a bi-directional relation. Granger test is explained as follows:

$$X_t = \sum_{i=1}^{n} \alpha_i \Delta Y_{t-1} + \sum_{j=1}^{n} \beta_j \Delta X_{t-j} + \sum_{r=1}^{n} \theta_r \mathrm{ECT}_{t-r} + \mu_{1t} \qquad (4)$$

$$Y_t = \sum_{i=1}^{m} \lambda_i \Delta X_{t-1} + \sum_{j=1}^{m} \delta_j \Delta Y_{t-j} + \sum_{r=1}^{m} \vartheta_r \mathrm{ECT}_{t-r} + \mu_{2t} \qquad (5)$$

where X_t, is the Trump Favorable, $Y_t$are the six financial variables, $\alpha_i, \beta_i, \lambda_i, \delta_i$ are the coefficients, ECT_{t-r} refers to the error-correction term derived from long-run cointegrations, $\mu_{1;2t}$are the error terms assumed uncorrelated, and *m* and *n* indicate the maximum number of lags. Failing to reject the null hypothesis of "X does not Granger-cause Y" and reject the null hypothesis of "Y does not Granger-cause X" means that X changes are Granger-caused by a change in Y, namely that lagged Y influences X significantly in equation (4) and that lagged X influences Y significantly in equation (5). To verify the existence of a long-run relationship between each two of our variables, VEC

Granger causality test with the MWald test is implemented. The study uses chi-square statistic and probability to measure causality between the Trump Favorable and financial markets.

3. Data

In our analysis, we use daily time series data (five working days per week) of stock market index Standard and Poor's 500 (S&P500), US 10-year yields (LTIR), dollar to euro exchange rate (USD/EUR), WTI crude oil (WTI), gold (GOLD) and silver (SILVER)[2]. All financial data have been taken from Datastream. For a measure of Trump Favorable (TF), we extract data from Real Clear Politics, that provides selected political news stories and editorials from several news publications. To this purpose, we select an aggregation of polling data for a period that spans from 8 November 2016 (Trump's election) until 28 February 2017 (for detail see http://www.realclearpolitics.com). Table I gives an overview of descriptive statistics.

All series have non-symmetric distributions. Negative skewness of almost all variables implies a thicker lower tail (skewed to the left), while silver is skewed to the right. The kurtosis statistics indicates that all series are more peaked than in the case of a normal distribution. In a normal distribution, the kurtosis is equal to 3, while distributions with kurtosis greater than 3 are defined leptokurtic (such as LTIR).

3.2 Graphical Evidence

First of all, we graphically demonstrate the influence of Trump's consensus on financial markets. Figure 1 shows the financial variables, series compared with Trump Favorable (TF) during the sample period. For each comparison between TF series (point line) and financial variables series (black line), we record both co-movements and reverse trends. From the graphs, is clear that each market's performance is equally exposed to the US sentiment post-election.

We can deduce the sentiment on Trump has a very similar shape such as S&P500, LTIR, USD/EUR, WTI, while a reverse movement with GOLD and SILVER.

2 The WTI crude oil has been widely used in the literature as the benchmark price for global oil markets. Gold and silver, have been perceived as a hedge against sudden shocks and also a safe haven over stock market turbulence (Hood and Mallik 2013).

Plots comparing Trump Favorable with Gold and Silver, are particularly interesting. The pattern is cyclical, when TF growth there is a decrease on gold and silver. These levels of volatility affect these commodities in contrast with the hypothesis that Gold is an accepted standard of value (Gilmore et al., 2009). In general, during periods characterized by economic uncertainty, equity prices fall and gold price rises, as investors' attention focuses on gold considered safe haven (Baur and McDermott, 2010; Arfaoui and Rejeb, 2016); this trend is verified in our analysis.

4. Findings

The first step of cointegration analysis is the Augmented Dickey-Fuller Unit Root Test (1979) (ADF) to identify the non-stationary condition of variables, i.e. the presence of a stochastic trend in those individual series. To standardize the variables, we transform them in their natural logarithm. For the study, the ADF test is conducted for all variables taking into account all possible deterministic components and lag lengths. The test was first conducted in levels (after in first difference) on all the series, and the number of the lagged level terms was chosen based on the SBC information criteria. ADF estimation results (Table II) show the presence of unit roots at the level, but not in first difference (except for LTIR that is stationary at level), namely there is a possible long-run linear combination. As Engle and Granger (1987) demonstrate, if two variables are individually integrated of order one, there is possibility of a causal relationship in at least one direction, can share common stochastic trends.

The idea behind cointegration is that there are common forces that comove the variables over time. The presence of cointegration between variables implies that at least one of them can be utilized to help forecast other variables because a valid causal relationship based on the error-correction model exists. The main cointegration test employed in this investigation is the multivariate test based on the autoregressive representation of Johansen and Juselius (Table IV). In order to get optimal lag length for cointegration analysis, we have used four criteria: Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ). According to them, the appropriate number of lags should be 1 (Table III)

The results obtained suggest that it is possible to accept the hypothesis that a double cointegrating vector is present in the model, both for trace and maximum eigenvalue, since the null hypothesis of no cointegration is rejected at two levels of confidence (*r* denotes the maximum number of cointegrating vectors). This implies that there exists a significant two cointegrating relationship; consequently, there should be a long-run relationship between TF and it determinants.

4.1 Dynamic Cointegration

Once verified that variables follow unit-root processes and they are cointegrated, we estimate the vector error correction (VECM) model and impulse response function analysis, to examine the effects of changes in Trump's sentiment on financial variables, in order to verify their adjustment mechanisms. Table V reports the final estimated findings.

First of all, we note that the all error corrections are statistically significant at 1% and have the correct (negative) sign. The size is between 0.085 and 0.46, and this suggests that the 0.085% (0.46%) of disequilibrium during the period $t - 1$ is corrected in day t. The time required for a halfway adjustment is obtained using $\ln(1-0.5)/\ln(1-\alpha)$, where α is the error correction coefficient in the VEC model. It takes approximately 8 days to complete a halfway adjustment towards the long-run equilibrium. The goodness of fit of statistical model is well performed, in fact the explanatory variables explain about 30% of the variations in Trump's Favorability.

Now we proceed to the short-run Granger causality test (Table VI), to indicate the direction of causality between variables, based on estimating VECM. The significance of the F-statistics for the lag values of the independent specifies that there is a three-directional short-run causal effect running from TF to S&P500, LTIR and GOLD; instead there's a unidirectional effect from SILVER to WTI crude oil. By contrast, the results do not yield the same conclusions in the opposite direction. Furthermore, we found that the change of Trump's favourable opinions leads to a positive change on stock market and Treasury bond returns and negative one on GOLD. We deem that Trump Favorable explains the change in the financial markets but there's no evidence of the opposite. We could suppose that a decrease in TF should induce investors to sell in stock and Treasury markets and buy gold.

Finally, the impulse response functions (IRFs) have been computed, in order to examine the dynamic post-sample effects on each series from a one-standard deviation shocks to the variables.

The impulse response functions (Figure 2) allow us to observe the response paths of financial variables to shocks in the Trump’s consensus and it helps to provide additional insights over the time of adjustment (in our case 8 days, according to VEC model results). For each chart, the vertical axis indicates the approximate percentage point change in the index, due to a one-standard deviation shock and the horizontal axis shows the responses up to 20 days. The response of stock returns and of LTIR to TF sentiment is greater after 2 days. The responses of Gold and Silver to the TF are very similar, showing that stock return and these commodities are negatively correlated. TF does not have an immediate effect on WTI crude oil. Finally, after 8 days, all shocks gradually disappear. Summarizing the results are in accordance with our a priori expectations depending on our assumption. We see a positive response to S&P500, LTIR, USD/EUR, WTI Crude oil, and a negative response to GOLD and SILVER.

5. Conclusion

This paper intends to highlight the link between post-election Trump's Favorable and financial markets. Using poll data of post-election Trump’s sentiment, we examine the relationship among stock, currency, and commodities market, from the Election Day to 28 February. To this purpose we performed a cointegration analysis, that evidences how Trump sentiment index has a short (VECM) and long-run (Johansen and Juselius) impact on S&P 500, 10y Treasury and Gold. Furthermore, as shown by the results of Engle and Granger test, we robustly find that the change of Trump’s favourable opinions leads to a positive change on stock market and Treasury bond returns and a negative one on GOLD. We deem that Trump's Favorable explains the change in the financial markets but there’s no evidence of the opposite. We think that our results could be explained by the announcement effects due by proposals of fiscal rates reduction, expenses in infrastructures and a lesser financial regulation, even though the effectiveness of these programs have not been tested yet during the sample period. These findings are also arguable as the perspectives of protectionist policies could affect, otherwise, financial markets in the contest of a global economy.

Our results should be interesting for investors: if markets incorporate efficiently the main sentiment, their trend is predictable and investors can use this information to optimize their portfolio choices. More specifically, a decrease in the TF should induce investors to sell their stocks and substitute them with gold and *vice versa*. At the same time, this process is also questionable: it's known that financial quotations often are inflated by irrational investing decisions, pushed by social and political sentiment and detached from economic variables.

Our tests support the assumption that stock market movements reflect people's expectations. When people express confidence in Trump, financial markets reflect this sentiment, namely market returns are led by TF.

Our study could be prosecuted making a deeper analysis for specific sectors and adding the majority party of the Congress as variable. These elements should be useful in order to evaluate the strength of a president's popularity and its correlation with financial markets.

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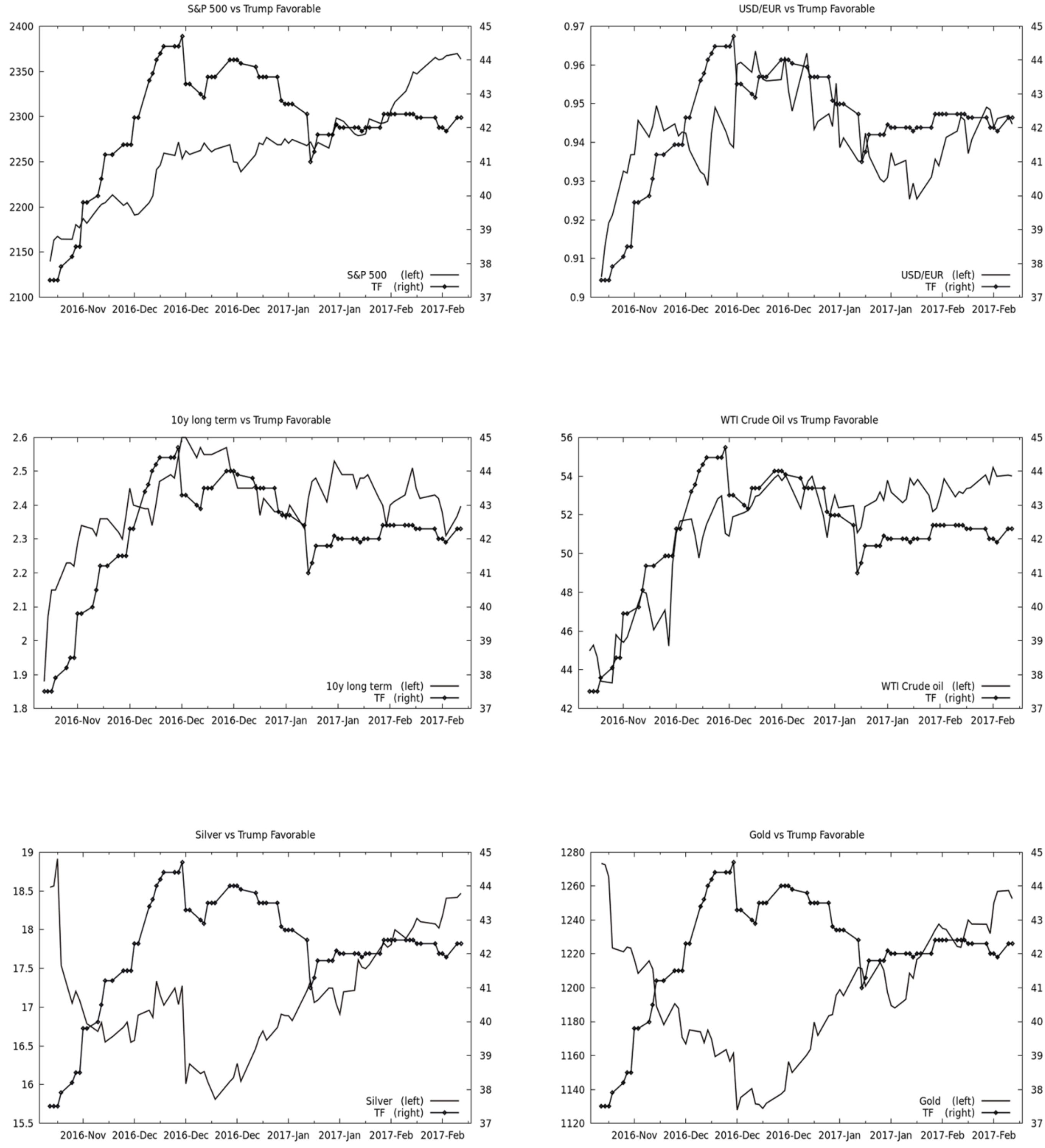
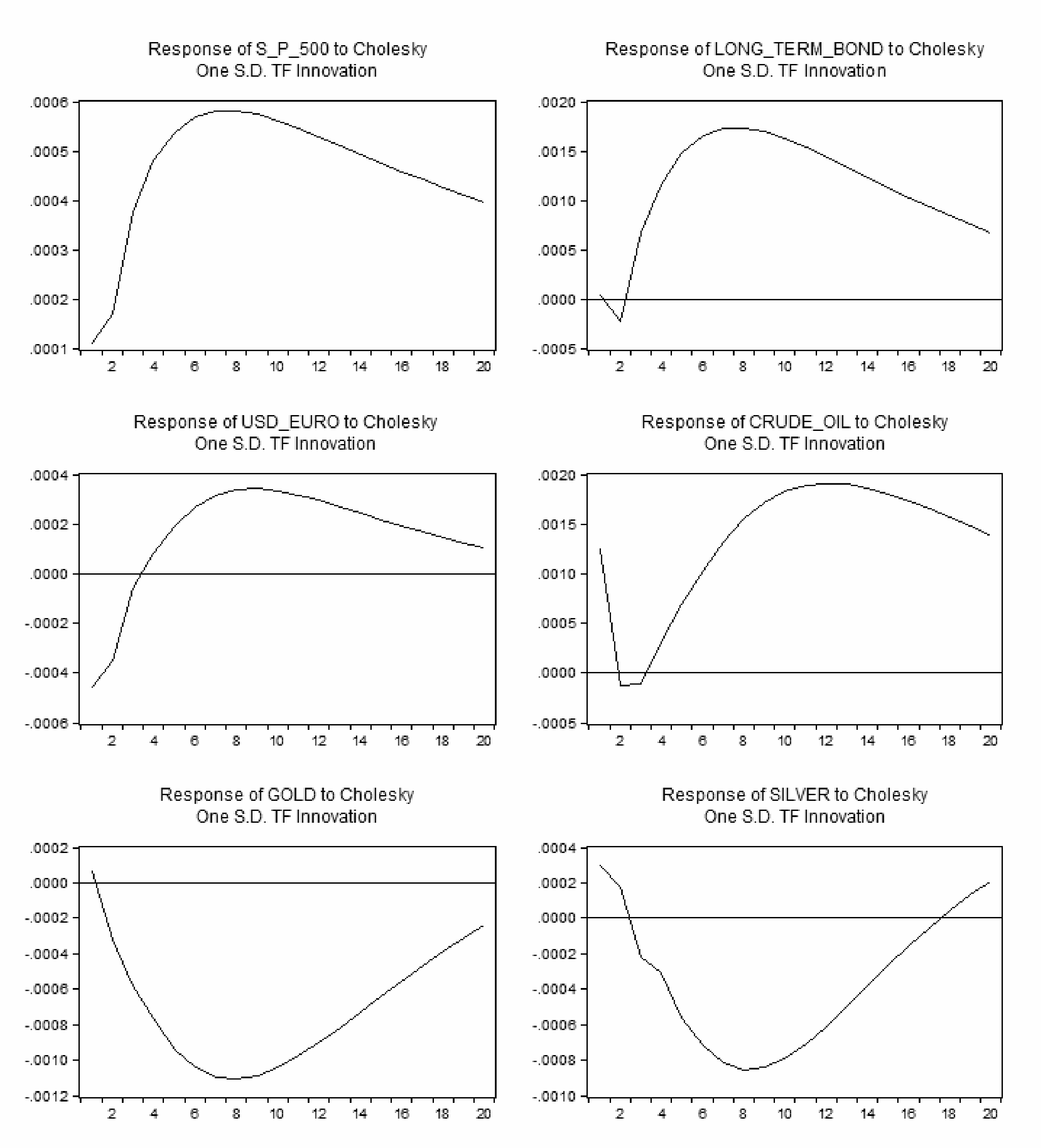
Figure 1. Trump Favorable versus Financial Markets



Notes: The black line (left side) is financial variable; Point line (right side) is Trump's Favorability. Source: RealClear Politics, Datastream. Authors' elaborations.

Figure 2. Impulse Response



Notes: The figures plot the impulse response functions with respect to a one standard deviation shock on TF.

Table I. Summary Statistics

	TF	S&P 500	LTIR	USD/EUR	WTI	GOLD	SILVER
Mean	42.108	2261.8	2.4065	0.94117	51.305	1197.0	17.115
Median	42.300	2268.4	2.4200	0.94202	52.450	1198.1	17.005
Maximum	44.700	2369.7	2.6000	0.96358	54.450	1273.4	18.916
Minimum	37.500	2139.6	1.8800	0.90526	43.320	1127.8	15.810
Std. Dev.	1.7008	55.753	0.11942	0.011293	3.0246	37.566	0.72122
Skewness	-1.1822	-0.0019	-1.5340	-0.31963	-1.2931	-0.062018	0.30116
Kurtosis	1.1684	-0.42595	4.2632	0.59281	0.37827	-0.77210	-0.51705

Notes: This table reports summary statistics of the sample. Data include daily observations during the period from 8 November to 28 February 2017 on Trump Favorable and six financial variables.

Table II. ADF test

Variables	Log level	Log differences
TF	-2.10 [0]	-8.75*** [0]
S&P 500	-2.80 [0]	-9.15*** [0]
LTIR	-4.83 [0]***	
USD/EUR	-3.25 [0]	-10.29***[0]
WTI	-2.48 [0]	-7.11***[0]
GOLD	-2.48[0]	-9.37***[0]
SILVER	-2.70[1]	-10.46***[0]

Notes: This table reports the ADF test. The reported numbers are the t-statistics. Critical values of ADF with trend and intercept are -3.13, -3.42, and -3.98 at the 10%, 5% and 1% level (*, **, and *** respectively). The appropriate lag length [ ] for ADF test is selected using Schwarz Bayesian criterion (SC)

Table III. Lag Structure Criteria

Lag	FPE	AIC	SC	HQ
1	1.15e-34*	-58.28688	-56.71293*	-57.66169*
2	2.12e-34	-57.71079	-54.56289	-56.46041
3	2.64e-34	-57.58597	-52.86413	-55.71040
4	2.89e-34	-57.69350	-51.39771	-55.19274
5	3.74e-34	-57.79431	-49.92457	-54.66835
6	2.68e-34	-58.73974	-49.29606	-54.98860
7	1.60e-34	-60.29466*	-49.27703	-55.91832

Notes: The tests of the lag length of TF variable on financial variables use four different criteria: FPE (Final prediction error), AIC (Akaike information criterion), SC (Schwarz information criterion), and HQ (Hannan-Quinn information criterion). * indicates the lag order selected by each criterion (at the 5% significance level).

Table IV. Johansen Cointegration

Hypothesized	Trace	Max-Eigen	Critical Value (5%)	
No. of CE(s)	Statistic	Statistic	Trace	Max
r=0	160.7295***	59.05293***	125.6154	46.23142
$r \leq 1$	101.6766**	42.19277**	95.75366	40.07757
$r \leq 2$	59.48385	28.19369	69.81889	33.87687
$r \leq 3$	31.29016	15.59977	47.85613	27.58434
$r \leq 4$	15.69039	9.465989	29.79707	21.13162
$r \leq 5$	6.224401	6.211529	15.49471	14.26460
$r \leq 6$	0.012872	0.012872	3.841466	3.841466

Note: This table reports the result of Johansen cointegration. Trace test and Max eigenvalue test indicate 2 cointegrating equations at the 5% level; (*) denotes rejection of the null hypothesis at 10%, (**) denotes rejection of the null hypothesis at 5%, (***) denotes rejection of the null hypothesis at 1% The number of lags (in first differences) is 1.

Table V. Summary results from VECM

	1	2
ECT1(-1)	-0.085***	-0.14***
ECT2(-1)	-0.46***	-0.47***
R squared	0.29	0.45
Durbin-Watson	2.14	2.07

Notes: This table reports the estimate of VEC model. 1 shows that the VEC using 1-1 lags; 2 shows that VEC model using 1-2 lags; (*) denotes statistical significance at 10%, (**) denotes statistical significance at 5%, (***) denotes statistical significance at 1%. We perform diagnostic tests for residuals using the Ljung-Box portmanteau and Lagrange Multiplier tests. Results indicate the absence of serial correlation and heteroskedasticity.

Table VI. Dynamic Multivariate Causality Analysis through Vector Error Correction model

Independent Variables							
Dependent Variable	χ^2-statistics of lagged 1st differenced term, [p-value]						
	ΔTF	ΔS&P 500	ΔLTIR	ΔUSD/ EUR	ΔWTI	ΔGOLD	ΔSILVER
ΔTF		0.12 [0.73]	0.00 [0.98]	0.12 [0.73]	0.33 [0.56]	1.26 [0.26]	0.10 [0.74]
ΔS&P 500	4.87** [0.02]		0.47 [0.49]	0.01 [0.91]	0.09 [0.75]	0.02 [0.88]	0.91 [0.34]
ΔLTIR	6.99*** [0.00]	0.63 [0.43]		0.79 [0.37]	1.57 [0.20]	0.25 [0.61]	0.07 [0.78]
ΔUSD/EUR	0.25 [0.62]	0.60 [0.44]	0.41 [0.52]		0.00 [0.97]	0.48 [0.48]	2.28 [0.13]
ΔWTI	1.09 [0.29]	0.83 [0.36]	0.30 [0.58]	2.20 [0.13]		2.18 [0.13]	6.68*** [0.00]
ΔGOLD	3.40* [0.06]	1.12 [0.29]	0.92 [0.33]	1.06 [0.30]	0.19 [0.65]		1.99 [0.15]
ΔSILVER	0.37 [0.54]	1.23 [0.27]	0.00 [0.94]	0.05 [0.81]	0.08 [0.77]	0.62 [0.43]	

Notes: This table reports the results of Granger causality. (*) denotes statistical significance at 10%, (**) denotes statistical significance at 5%, (***) denotes statistical significance at 1%