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Behind the Volatility Index Levels: The Paradox of 2016

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Abstract

The low 2016 volatility index levels present a paradox in light of previous research suggesting periods of uncertainty and negative news events should reflect higher VIX levels. This study uses daily data for the VIX, VIX futures and the VVIX, to examine the information content of variations in the natural logarithmic changes in the index levels relative to 12 other parallel time periods encompassing 2004-2016. Straight-forward *variation* and *predictive* tests are constructed to determine signs of unusual market volatility behavior. The results reveal strong evidence of unusual volatility behavior during the 2016 election period, pocked by frequent periods of abnormal returns. The 2016 VIX levels alone are shown to be insufficient to draw conclusions regarding investor sentiment.

Keywords: VIX, VIX futures, VVIX, market volatility, investor sentiment, 2016 US presidential election, Volatility of Volatility, uncertainty

The low implied 30-day forward volatility levels during 2016, present a puzzle in light of previous research showing that periods of uncertainty should reflect higher *Chicago Board Option's Exchange* (CBOE) S&P 500 *Volatility Index* (VIX) levels. The time-period investigated is striking due to the frequency of negative news reports combined with historically low VIX levels and unperturbed financial markets. During the same time period, unprecedented levels of public uncertainty and fear were regularly reported.

The 2016 election period EP_{16} paradox: a strong economy, strong stock market, low inflation, low unemployment and low VIX levels combined with high levels of anxiety, uncertainty and fear of the future.

The purpose of this paper is to apply a straight-forward examination of the natural logarithmic changes and variability in stock market volatility indexes to explain the seemingly byzantine behavior of the VIX during the period June 1, 2016 through November 30, 2016.

This study examines daily data over the period 2004-2016 for the ***VIX***, *VIX Futures* (***VX***) and the *Volatility of Volatility* index (***VVIX***). The 2016 results are compared to 12 parallel time periods, representing four actual election years, 2004, 2008, 2012 and 2016, and nine parallel periods in non-election years. The findings indicate that VIX levels alone are insufficient to explain the underlying uncertainty.

1. Background

The impact of negative news is expected to have a negative impact on stock returns and a positive impact on VIX levels as shown by Tetlock (2007), Mamaysky and Glasserman (2017). Their findings demonstrate that increases in VIX are large following the release of negative news events. The more unusual the negative news event, the larger the increase in VIX is. Positive news events are shown to have the reverse effect on VIX levels.

In a perfect world, with no negative news, election periods are expected to have higher volatility levels due to the uncertainty of the outcome. Godell and Vahamaa (2013) study the effects of political uncertainty on implied stock market volatility during five US presidential election cycles. They document increases in VIX with changes in the probability of success of the eventual winner. The association between implied volatility and the probability of electing the eventual winner is positive even after the authors control for changes in overall election uncertainty. The findings indicate that the presidential election process engenders market anxiety as investors form and revise their expectations regarding future macroeconomic policies. VIX decreases as the winner of the US presidential election becomes more certain.

Academic research on VIX and investor sentiment largely confirms the expected relationship between uncertainty and the stock market. Researchers, including Whaley (2000), Traub, Ferreira, McArdle and Antogelli (2000) and Smales (2014), provide evidence in support of high VIX levels during periods of uncertainty, when investors require additional compensation in the form of above-average excess returns for riskier assets. Two studies suggest that VIX levels alone are insufficient to determine the variance premium for stock returns. The first, is a unique study by Dhaene, Dony, Forys, Linders and Shoutens (2012), that proposes a new fear index, with the moniker *FIX*. The quantification of the *FIX* takes into account: market risk (VIX), liquidity risk, systemic risk and herd behavior via the concept of comonotonicity. This approach allows the authors to measure an overall level of market uncertainty as well as to identify precisely the individual importance of the distinct risk components.

The second article, by Drechsler (2013), demonstrates that uncertainty is strongly reflected in option prices but the *fluctuations* in the VIX and implied volatility curve contain an important uncertainty component. The author uses a calibration of the equilibrium model to simultaneously match salient moments of consumption and dividends, the equity premium, risk-free rate, the variance premium and implied volatility skew to document the predictive power of the variance premium for stock returns. Drechsler's results imply that uncertainty and its variation are important for jointly explaining the equity premium, risk-free rate, and the large variance premium embedded in the "high" price of options. The Dhaene, et al. (2012) and the Drechsler (2013) articles indicate the need to look beyond VIX levels to determine underlying uncertainty.

2. Data

The VIX and VX data series begin on 3/26/2004 with the trade of the first VIX futures contract. The later introduction of the VVIX on 1/3/2007, results in 696 fewer observations for this index than VIX and VX. The last trading day for all data series is 12/30/2016, resulting in a population of 3,214 observations for the VIX, VX indexes and 2,518 for VVIX.

The daily VX data set is constructed by rolling the *nearest* available contract into the next, one day prior to the delivery of the current contract. Specifically, on the first VX trading day, 3/26/2004, a position is established in the nearest available contract, the *May 04*. One day prior to the May 04 delivery, 5/19/04, the position is rolled into the *Jun 04* contract. On 6/16/04, one day prior to the Jun 04 delivery, the contract is rolled into the *Jul 04*, and so on. With the exception of the missing *Apr 04* contract, there are no further interruptions to the pattern of rolling one-month near futures throughout the 2004-2016 time-period.

Table 1 displays the average levels of VIX_i, VX_i and $VVIX_i$, where *i* is equal to each election, and parallel non-election, period (EP_i). The bold values in each column represent the highest values in each election period. The 2016 VIX and VX averages are the *lowest* since 2006 while VVIX is at its *highest level* since introduction. The high volatility of VIX relative to its average value in 2016 suggests a large amount of uncertainty surrounding the 30-day forward volatility estimate of the S&P 500 index. Column $E(VVIX_i)/E(VIX_i)$ shows that the 2016 VVIX multiple of 6.7315, is the *highest* since the index was introduced in 2007. Similarly, column VX_i Premium indicates the 7.56% is also at its *highest* level since trading began in 2004.

Table 1. Average Volatility

EP_i	$E(VIX_i)$	$E(VX_i)$	$E(VVIX_i)$	$E(VVIX_i)/E(VIX_i)$	VX_i Premium
2004	15.04	15.80	na	na	5.05%
2005	12.61	13.38	na	na	6.11%
2006	13.32	13.74	na	na	3.15%
2007	20.72	20.65	91.24	4.4035	-0.34%
2008	**36.88**	**33.81**	88.72	2.4056	-8.32%
2009	25.64	26.71	77.58	3.0257	4.17%
2010	23.92	25.16	89.24	3.7308	5.18%
2011	29.21	28.74	97.64	3.3427	-1.61%
2012	17.11	18.40	92.98	5.4342	7.54%
2013	15.74	15.98	80.48	5.1131	1.52%
2014	15.87	16.01	85.18	5.3674	0.88%

Table 1 (continued). Average Volatility

EP_i	$E(VIX_i)$	$E(VX_i)$	$E(VVIX_i)$	$E(VVIX_i)/E(VIX_i)$	VX_i Premium
2015	17.54	17.63	94.46	5.3854	0.51%
2016	14.56	15.66	**98.01**	**6.7315**	**7.56%**
2004-2016	**19.15**	**19.54**	**87.62**	**4.5755**	**2.61%**

The data is parsed, as shown in Table 2, into four actual *election periods* and nine *parallel non-election periods* with the corresponding number of observations, n_i, shown in the last column. Each election period (EP_i) is defined as the first trading day in June to the last trading day of November. The four years in bold indicate an actual US Presidential election period and the remaining nine years indicate a parallel time period in a non-election year. Both the actual and the parallel non-election periods are referred to as EP_i for simplicity.

Table 2. Election Periods

EP_i	First Trade Day	Last Trade Day	n_i
2004	**1-Jun**	**30-Nov**	**127**
2005	1-Jun	30-Nov	127
2006	1-Jun	30-Nov	128
2007	1-Jun	30-Nov	128
2008	**2-Jun**	**28-Nov**	**126**
2009	1-Jun	30-Nov	128
2010	1-Jun	30-Nov	128
2011	1-Jun	30-Nov	128
2012	**1-Jun**	**30-Nov**	**126**
2013	3-Jun	29-Nov	127
2014	2-Jun	28-Nov	127
2015	1-Jun	30-Nov	127
2016	**1-Jun**	**30-Nov**	**128**

Testing comparisons of EP_{16} are made to all other parallel time periods as well as to the *populations*. The populations are defined as:

1) **Data Period Y (DP_Y)**. The annual populations begin on the first trading day, through the last in each year *Y*, resulting in n_Y observations.

2) **Data Period N (DP_N)**. The global population *N* begins on 3/26/04 and ends on 12/30/16, resulting in *N* observations.

The DP_Y represent a greater barrier to overcome than DP_N because annual values are more closely related to disturbances caused by an election period. Table 3 below clarifies the population data periods for DP_N and DP_Y.

Table 3. Population N and Y

Year	DP_N	DP_Y	n_Y
2004	**26-Mar**	**3/26 - 12/31**	**193***
2005		1/03 - 12/30	252
2006		1/03 - 12/29	251
2007		1/03 - 12/31	251
2008		**1/02 - 12/31**	**253**

Table 3 (continued). Population N and Y

Year	DP_N	DP_Y	n_Y
2009		1/02 - 12/31	252
2010		1/04 - 12/31	252
2011		1/03 - 12/30	252
2012	**N = 3214**	**1/03 - 12/31**	**250**
2013		1/02 - 12/31	252
2014		1/02 - 12/31	252
2015		1/02 - 12/31	252
2016	**30-Dec**	**1/04 - 12/30**	**252**

* VX trading began on 3/26/2004. VVIX trading began on 1/3/2007.

3. Methodology

This section presents a common application of *Variation Test* (VT) and *Predictive Test* (PT) methodologies applied to each *X*, where $X = \ln(VIX_{i,t}/VIX_{i,t-1})$, $\ln(VX_{i,t}/VX_{i,t-1})$ and $\ln(VVIX_{i,t}/VVIX_{i,t-1})$.

3.1 Variation Tests (VT)

The variation tests (VT) are straight-forward *F-tests* comparing the sample variation $S(X_{16})$, to each other sample election period $S(X_i)$ and to population $d = DP_Y$ and DP_N.

$$VT\#1 = S(X_{2016})/S(X_i) \tag{1}$$

$$VT\#2 = S(X_i)/\sigma(X_d) \tag{2}$$

S(Xi) is the sample variation of Xt during EPi:

$$\left[1/(n_i - 1) \sum_{t_i = \text{Jun } 1}^{n_i = \text{Nov } 30} (X_{t_i} - E(X_i))^2 \right]^{1/2}$$

t_i = any day t during EP_i and i = 6/1 through 11/30 for each year, y = 2004, 2005, … 2016. X_{ti} = the natural logarithmic function of changes in X_i: $\ln(X_{i,t}/X_{i,t-1})$. $\sigma(X_d)$ is the population standard deviation: $[1/d \sum_{t=1}^{d = n_y \text{ or } N} (X_t - E(X_d))^2]^{1/2}$ for each $d = DP_Y$ and DP_N.

VT#3 tests the significance of the intraday volatility EP_{16}, $S(IV_{2016})$, relative to the same in other parallel time periods $S(IV_i)$. VT#4 tests the robustness of the results by evaluating each $S(X_i)$ relative to the populations intraday volatility $\sigma(IV_d)$.

$$VT\#3 = S(IV_{2016})/S(IV_i) \tag{3}$$

$$VT\#4 = S(IV_i)/\sigma(IV_d) \tag{4}$$

Where: $S(IV_i)$ is the sample volatility of intraday trading values during EPi, or $[1/(n-1) \sum_{t_i = \text{Jun } 1}^{n_i = \text{Nov } 30} (IV_{t_i} - E(IV_i))^2]^{1/2}$, and the inputs are defined as $IV_{t_i} = (VX_{H,t_i} - VX_{L,t_i})/VX_{O,t_i}$. IV_{t_i} = the Intraday Volatility of VX on day t during EPi, VX_{H,t_i} = the Highest value of VX on day t during EPi, VX_{L,t_i} = the Lowest value of VX on day t during EPi, VX_{O,t_i} = the Opening value of VX on day t during EPi.

3.2 Predictive Tests (PT)

The predictive tests are based on the *abnormal* (AR) and *cumulative abnormal returns* (CAR) generated from equation 5:

$$\ln(VX_{d,t}/VX_{d,t-1}) = \theta_{d,o} + \theta_{d,1} * \ln(VIX_{d,t}/VIX_{d,t-1}) + AR_{d,t} \tag{5}$$

where: $\ln(VX_{d,t}/VX_{d,t-1})$ = the lognormal of the near VIX futures contract on day *t*, for population $d = DP_Y$ and DP_N, $\ln(VIX_{d,t}/VIX_{d,t-1})$ = the lognormal of the VIX spot index on day *t* for population *d*. $\theta_{d,o}$ and $\theta_{d,1}$ =

regression coefficients for population *d.* $AR_{d,t}$ = the *abnormal return* prediction of $\ln(VX_{d,t}/VX_{d,t-1})$ for parameters based on *d,* i.e., $AR_{d,t} = \ln(VX_{d,t}/VX_{d,t-1}) - (\theta_{d,o} + \theta_{d,1} * \ln(VIX_{d,t}/VIX_{d,t-1})$.

PT#1 and PT#2 apply *t-tests* to determine if AR_{d,t_i} and CAR_{d,t_i} are insignificantly different from zero at each point in time based on population *d*:

$$\text{Ho: } AR_{d,t_i} = 0 \qquad \text{Ha: } AR_{d,t_i} \neq 0$$

$$\text{Ho: } CAR_{d,t_i} = 0 \qquad \text{Ha: } CAR_{d,t_i} \neq 0$$

Each day during EP_i, AR_{d,t_i} and CAR_{d,t_i} are tested for significance relative to the volatility of the population, $\sigma(AR_d)$ and $\sigma(CAR_d)$ respectively.

$$PT\#1 = AR_{d,t_i}/\sigma(AR_d) \tag{6}$$

$$PT\#2 = CAR_{d,t_i}/\sigma(CAR_d) \tag{7}$$

PT#3 and PT#4 apply *F-tests* to determine the significance of $S(AR_{d,16})$ and $S(CAR_{d,16})$ relative to each $S(AR_{d,i})$ and $S(CAR_{d,i})$ respectively, to test the hypotheses:

$$\text{Ho: } S(AR_{d,16})/S(AR_{d,i}) = 1 \qquad \text{Ha: } S(AR_{d,16})/S(AR_{d,i}) \neq 1$$

$$\text{Ho: } S(CAR_{d,16})/S(CAR_{d,i}) = 1 \qquad \text{Ha: } S(CAR_{d,16})/S(CAR_{d,i}) \neq 1$$

$$PT\#3 = S(AR_{d,16})/S(AR_{d,i}) \tag{8}$$

$$PT\#4 = S(CAR_{d,16})/S(CAR_{d,i}) \tag{9}$$

where: $\sigma(AR_d) = ((\frac{1}{d}) * \sum_{t=1}^{d = N \text{ or } n_y} ((AR_{d,t} - E(AR_d))^2)^{1/2}$, $\sigma(CAR_d) = ((\frac{1}{d}) * \sum_{t=1}^{d = N \text{ or } n_y} ((AR_{d,t} - E(AR_d))^2)^{1/2}$,

$S(AR_{d,i}) = ((\frac{1}{n_i}) * \sum_{t_i = \text{Jun } 1}^{n_i = \text{Nov } 30} ((AR_{d,t_i} - E(AR_{d,i}))^2)^{1/2}$, $S(CAR_{d,i}) = ((\frac{1}{n_i}) * \sum_{t_i = \text{Jun } 1}^{n_i = \text{Nov } 30} ((CAR_{d,t_i} - E(CAR_{d,i}))^2)^{1/2}$.

4. Results

4.1 Variation Test Results

Table 4 displays the level values for $S(VIX_i)$, $S(VX_i)$ and $S(VVIX_i)$ with the corresponding F-test results for VT#1 in columns $S(VIX_{16})/S(VIX_i)$, $S(VX_{16})/S(VX_i)$ and $S(VVIX_{16})/S(VVIX_i)$. The findings show that $S(VIX_{16})$ and $S(VX_{16})$ are significantly higher than $S(VIX_i)$ and $S(VX_i)$ in seven of thirteen EP_is. Further, the level values of $S(VIX_{16})$ and $S(VX_{16})$ are exceeded by only one other year, 2011. The VVIX results indicating that the variation in the VVIX index during EP_{16}, $S(VVIX_{16})$, is higher than all other $S(VVIX_i)$ since introduction, and significantly so in seven of nine EP_is.

Table 4. Election Period Variation based on VT#1

EP_i	$S(VIX_i)$	$S(VIX_{16})/S(VIX_i)$	$S(VX_i)$	$S(VX_{16})/S(VX_i)$	$S(VVIX_i)$	$S(VVIX_{16})/S(VVIX_i)$
2004	4.56%	**2.2319**	4.61%	**1.5412**	na	na
2005	5.01%	**2.0300**	3.30%	**2.1526**	na	na
2006	6.03%	**1.6890**	4.65%	**1.5267**	na	na
2007	9.02%	1.1285	5.75%	1.2341	5.31%	**1.4207**
2008	9.51%	1.0705	6.47%	1.0980	5.20%	**1.4492**
2009	5.34%	**1.9069**	4.05%	**1.7511**	3.98%	**1.8955**
2010	6.05%	**1.6816**	5.20%	**1.3650**	4.21%	**1.7904**
2011	**10.48%**	0.9714	**7.42%**	0.9571	6.20%	1.2158
2012	6.34%	**1.6068**	5.92%	1.1983	4.14%	**1.8216**
2013	6.03%	**1.6885**	4.14%	**1.7163**	5.15%	**1.4633**
2014	7.76%	1.3116	5.17%	**1.3743**	5.32%	**1.4171**
2015	9.17%	1.1105	6.39%	1.1105	5.75%	1.3121
2016	**10.18%**	1.0000	**7.10%**	1.0000	**7.54%**	1.0000

Table 5 displays level values for $\sigma(VIX_Y)$, $\sigma(VX_Y)$ and $\sigma(VVIX_Y)$ respectively. The results of the F-tests are revealed in columns $S(VIX_i)/\sigma(VIX_N)$- $S(VVIX_i)/\sigma(VVIX_Y)$ using volatility results from both DPY and DPN. Columns $S(VIX_i)/\sigma(VIX_N)$ and $S(VX_i)/\sigma(VX_N)$ show that $S(VIX_i)$ and $S(VX_i)$ are significantly greater than $\sigma(VIX_N)$ and $\sigma(VX_N)$ only for the 2011 and 2016 election periods. When the sample variances are compared to $\sigma(VIX_Y)$ and $\sigma(VX_Y)$ in columns $S(VIX_i)/\sigma(VIX_Y)$ and $S(VX_i)/\sigma(VX_Y)$, respectively, the single significant variable relative to $\sigma(VIX_Y)$ is the volatility of VIX during EP_{16}, $S(VIX_{16})$.The volatility of VVIX, columns $S(VVIX_i)/\sigma(VVIX_N)$ and $S(VVIX_i)/\sigma(VVIX_Y)$, identifies the 2016 election period as the only one significantly greater than both $\sigma(VVIX_N)$ and $\sigma(VVIX_Y)$. Tables 4 and 5 show that EP_{16} is a period of unprecedented uncertainty as indicated by consistently significant variations across all comparisons. Surprisingly, the results for EP_{16} overshadow even those for 2008, a year of significant economic disruption and bank failures.

Table 5. Election Period Variation based on VT#2

EP	$\sigma(VIX_Y)$	$\sigma(VX_Y)$	$\sigma(VVIX_Y)$	$S(VIX_i)/\sigma(VIX_N)$	$S(VX_i)/\sigma(VX_N)$	$S(VIX_i)/\sigma(VIX_Y)$	$S(VX_i)/\sigma(VX_Y)$	$S(VVIX_i)/\sigma(VVIX_N)$	$S(VVIX_i)/\sigma(VVIX_Y)$
2004	4.59%	3.81%	na	0.64761	0.8959	0.9931	1.2107	na	na
2005	5.24%	3.03%	na	0.71201	0.6414	0.9563	1.0882	na	na
2006	5.92%	4.16%	na	0.8558	0.9045	1.0188	1.119	na	na
2007	8.27%	5.22%	5.45%	1.28083	1.1189	1.0907	1.103	1.0536	0.9742
2008	7.82%	5.50%	4.57%	1.35023	1.2575	1.2164	1.175	1.0329	1.1393
2009	5.57%	4.38%	3.64%	0.75799	0.7885	0.9579	0.9257	0.7897	1.0916
2010	7.30%	5.46%	4.59%	0.85956	1.0116	0.8296	0.953	0.8361	0.9185
2011	8.32%	5.93%	5.27%	**1.48803**	**1.4426**	1.2598	1.2509	1.2312	1.1759
2012	5.94%	5.75%	4.10%	0.89957	1.1523	1.0659	1.0297	0.8217	1.0097
2013	6.93%	5.06%	5.38%	0.85603	0.8045	0.8699	0.8177	1.0229	0.9573
2014	7.26%	5.06%	5.63%	1.102	1.0047	1.0692	1.0212	1.0563	0.9454
2015	8.71%	5.75%	6.28%	1.30155	1.2434	1.0529	1.1113	1.1408	0.9155
2016	7.69%	6.37%	4.85%	**1.44553**	**1.3802**	**1.3248**	1.1138	**1.4978**	**1.5569**
2004-16	**7.04%**	**5.14%**	**5.04%**	**na**	**na**	**na**	**na**	**na**	**na**

The final volatility measures used to evaluate the volatility during the 2016 election period are based on VIX futures *intraday volatility* (IV_i). Table 6 shows the level values for $S(IV_i)$ and $S(IV_Y)$ respectively. The results for VT#3 are displayed in column $S(IV_{16})/S(IV_i)$ and show that the intraday volatility during EP16 is significantly greater than all other election periods examined. VT#4, columns $S(IV_i)/\sigma(IV_N)$ and $S(IV_i)/\sigma(IV_Y)$, confirms the unusually high intraday volatility by showing $S(IV_{16})$ is the only election period with significantly greater volatility compared to both $\sigma(IV_N)$ and $\sigma(IV_Y)$.

Overall, the four variation tests provide a strong case for significant investor uncertainty during the 2016 election period relative to twelve other parallel time periods.

Table 6. Intraday Volatility of VXi

EP_i	$S(IV_i)$	$S(IV_Y)$	$S(IV_{16})/S(IV_i)$	$S(IV_i)/\sigma(IV_N)$	$S(IV_i)/\sigma(IV_Y)$
2004	0.014944	0.015969	**5.3729**	0.3467	0.9358
2005	0.014302	0.017193	**5.614**	0.3318	0.8319
2006	0.029695	0.026590	**2.7039**	0.6889	1.1168
2007	0.041698	0.040416	**1.9256**	0.9674	1.0317
2008	0.041912	0.064621	**1.9157**	0.9723	0.6486
2009	0.018529	0.022432	**4.3333**	0.4299	0.8260

Table 6 (continued). Intraday Volatility of VXi

EP_i	$S(IV_i)$	$S(IV_Y)$	$S(IV_{16})/S(IV_i)$	$S(IV_i)/\sigma(IV_N)$	$S(IV_i)/\sigma(IV_Y)$
2010	0.020925	0.048890	**3.8371**	0.4854	0.4280
2011	0.037961	0.033788	**2.1151**	0.8807	1.1235
2012	0.025697	0.027607	**3.1246**	0.5961	0.9308
2013	0.025283	0.031683	**3.1757**	0.5865	0.7980
2014	0.042718	0.041438	**1.8796**	0.9910	1.0309
2015	0.047469	0.042814	**1.6915**	1.1012	1.1087
2016	**0.080292**	**0.062552**	**1.0000**	**1.8627**	**1.2836**
2004-16	**$\sigma(IV_N)$ =**	**0.043105**	**VT#3**	**VT#4**	**VT#4**

4.2 Predictive Test Results

The *Predictive Tests* (PTs) are based on the results from 14 regressions; 13 apply DP_Y and 1 applies DP_N. The regressions establish predictive values for $\ln(VX_{d,t}/VX_{d,t-1})$, given contemporaneous values for $\ln(VIX_{d,t}/VIX_{d,t-1})$. The focus of each PT is the significance of the *abnormal returns* (AR_{d,t_i}) and *cumulative abnormal returns* (CAR_{d,t_i}) during each election period. The $CARs_{d,t_i}$ are cumulated from the first trading day in June to the last trading day in November for each EP_i, but the parameters are estimated using DP_Y and DP_N. The regression statistics are displayed in Table 1, for the interested reader.

Table 7 displays the results for PT#1 and PT#2 as the *number* of significant AR_{Y,t_i} and CAR_{Y,t_i} days, $n^*_{Y_i}$, as a proportion of the total number of days in the election period, n_i, $\boldsymbol{n^*_{Y_i}/n_i}$, using parameters generated from approximately 252 observations per year. Columns $AR_{Y,ti}/S(AR_Y)$ indicate EP_{16} has the largest number of significant days at the 90% confidence level and the second the largest at the 95% level. The number of significant CAR_{Y,t_i}, displayed in columns $CAR_{Y,ti}/S(CAR_Y)$, reveal no interesting results for 2016. This finding suggests that the 2016 election period has a relatively large number of shocks that did not persist over time.

Table 7. Proportion of significant $AR_{Y,ti}$ and $CAR_{Y,ti}$ Days

EPi	$AR_{Y,ti}/S(AR_Y)$		$CAR_{Y,ti}/S(CAR_Y)$	
	90%	95%	90%	95%
2004	3.94%	3.15%	13.39%	7.87%
2005	2.34%	2.34%	26.56%	10.94%
2006	7.03%	5.47%	21.09%	17.19%
2007	7.81%	6.25%	41.41%	29.69%
2008	6.30%	5.51%	21.26%	15.75%
2009	5.47%	3.91%	12.50%	3.91%
2010	6.25%	3.91%	12.50%	6.25%
2011	7.81%	5.47%	**50.78%**	**35.16%**
2012	5.56%	3.17%	42.86%	26.98%
2013	6.30%	4.72%	21.26%	15.75%
2014	8.66%	**7.87%**	40.94%	30.71%
2015	7.03%	3.13%	11.72%	9.38%
2016	**9.38%**	7.03%	13.28%	8.59%
	PT#1	**PT#2**		

Description: Parameters Estimated for Population (N = 3,213). Parameters Estimated for each year separately, n » 252.

Table 8 displays the results from repeating the first two PTs using DPN, rather than DPY. The results indicate the election period of 2008 has the highest number of significant $AR_{N,ti}$ days at the 90% significance level and 2016 has the highest at the 95% level. The significance of the number of $CAR_{N,ti}$ days remains unremarkable in 2016, providing further support for frequent shocks that do not persist.

Table 8. Proportion of significant $AR_{N,ti}$ and $CAR_{N,ti}$ Days

EPi	$AR_{N,ti}/(AR_N)$		$CAR_{N,ti}/(CAR_N)$	
	90%	95%	90%	95%
2004	4.76%	3.97%	25.40%	15.87%
2005	4.69%	3.91%	23.44%	14.84%
2006	7.03%	5.47%	17.19%	13.28%
2007	7.81%	4.69%	49.22%	42.97%
2008	**11.11%**	6.35%	26.19%	23.02%
2009	3.91%	3.91%	32.81%	11.72%
2010	6.25%	5.47%	11.72%	7.03%
2011	4.69%	1.56%	58.59%	51.56%
2012	7.94%	5.56%	**74.60%**	**65.87%**
2013	1.57%	1.57%	11.02%	6.30%
2014	8.66%	7.03%	33.86%	18.90%
2015	9.45%	6.30%	13.39%	10.24%
2016	10.94%	**7.09%**	18.75%	12.50%
	PT#1		**PT#2**	

Description: Parameters Estimated for Population (N = 3,213).

Table 9 depicts the results of PT#3 and PT#4, constructed to show the volatility of *abnormal* and *cumulative abnormal* returns during EP_{16} relative to the variabilities of each other election period based on annual parameters. Columns $S(AR_{Y,i})$ and $S(AR_{Y,16})/S(AR_{Y,i})$ reveal the $S(AR_{Y,16})$ is exceeded only by $S(AR_{Y,08})$, however, significance is established in only five time periods. Columns $S(CAR_{Y,i})$ and $S(CAR_{Y,16})/S(CAR_{Y,i})$, confirm the lack of a significant or notable cumulative effect for EP_{16} based on annual parameters. The tests are repeated using DP_N parameters with similar results.

Table 9. Residual Risk based on DPY

Year	$S(AR_{Y,i})$	$S(AR_{Y,16})/S(AR_{Y,i})$	$S(CAR_{Y,i})$	$S(CAR_{Y,16})/S(CAR_{Y,i})$
2004	3.69%	1.1003	6.44%	0.8199
2005	2.90%	**1.4**	5.58%	0.9462
2006	3.51%	1.1567	7.49%	0.7049
2007	2.82%	**1.4397**	7.41%	0.7126
2008	4.22%	0.9621	13.54%	0.39
2009	2.78%	**1.4604**	3.64%	**1.4505**
2010	3.18%	1.2767	6.53%	0.8086
2011	2.64%	**1.5379**	8.91%	0.5926
2012	3.82%	1.0628	4.23%	1.2482
2013	2.00%	**2.03**	3.54%	**1.4915**
2014	3.05%	1.3311	4.36%	1.211

Table 9 (continued). Residual Risk based on DPY

Year	$S(AR_{Y,i})$	$S(AR_{Y,16})/S(AR_{Y,i})$	$S(CAR_{Y,i})$	$S(CAR_{Y,16})/S(CAR_{Y,i})$
2015	3.19%	1.2727	7.09%	0.7447
2016	4.06%	1	5.28%	1
		PT#3		**PT#4**

The PT results point to a 2016 election period as one pocked by frequent unusual days, more so than other parallel time periods studied, but the shocks are not long-lasting.

5. Conclusions

The 2016 Paradox: a strong economy, strong stock market, low inflation, low unemployment and low VIX levels combined with high levels of anxiety, uncertainty and fear of the future. Incorrect conclusions regarding the state of investor sentiment were made because the focus was on a single parameter of risk-VIX *levels*. Using *volatility tests* and *predictive test*, this study demonstrates that VIX levels alone are insufficient, and at times misleading, in determining investor sentiment. The *volatility tests* showEP_{16} as a period of unusually high variations in VIX compared to other parallel non-election time periods. Similarly, intraday trading variations for VIX futures are exceptionally high during the 2016 election period. The *predictive tests* signal EP_{16} as a period with frequent abnormal shocks, without persistent echo. Together, the tests show that investor sentiment is better described by the distribution of VIX than the level.

This study provides evidence for significant investor disruption during the 2016 election period. The findings imply that in periods of economic calm, the *levels* of volatility indexes alone are insufficient and misleading in determining investor sentiment. The byzantine behavior of VIX during the 2016US Presidential election period, provides a unique opportunity to study VIX when economic concerns are not a dominate reason for investor anxiety. Under this scenario, VIX levels can remain low even while investor anxiety is high leading to incorrect conclusions regarding systematic risk levels.

The *volatility tests* indicate EP_{16} as a period of unusually high variations in the volatility indexes compared to other parallel non-election time periods. Similarly, intraday trading values for VIX futures, provides additional evidence in the form of exceptionally high intraday and volume variations.

The *predictive tests* consider the deviations of actual from predicted values for VIX futures. The results signal EP_{16} as a period with a relatively large number of significantly high abnormal return days but a low number of significant cumulative abnormal return days, indicating frequent shocks in EP_{16} that do not produce long-lasting results.

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