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Empirical Project: How did the Government Shutdown Affect Trump's Popularity?

I. Introduction

Trump's presidency has proven to be highly controversial since he was elected. From building the Mexican Wall to raging about Democrats in court, Trump has made many polarizing comments and decisions. Recently, he forced our country into the longest government shutdown in its history that lasted from December 22, 2018 to January 25, 2019. Therefore, in this empirical project, we seek to explore and analyze how his popularity has fluctuated in the aftermath of his executive decision.

II. Executive Summary

This report summarizes the regression model and statistical results of the effects of the government shutdown on Trump's popularity. In this report, we use the multiple regression model along with the four Least Squares Assumptions to analyze aggregate approval ratings collected from multiple polls surveying Trump's popularity. In Section 3, we discuss how the poll data was processed and supplemented, as well as all the other control variables we included in the regression. In Section 4, we explain the key assumptions of the model of how they were held or not. Section 5 details the results of our analysis and reasoning for why the outcomes make sense. Lastly, Section 6 summarizes the results and provides the conclusion that the government shutdown actually did not have a significant impact on Trump's popularity.

III. Data Description

We downloaded the data from FiveThirtyEight, a website that compiled poll data of Donald Trump's approval ratings. From there, we processed the data to place more focus on the government shutdown and how it affected his ratings. Trump's ratings have skyrocketed and plummeted multiple times in his career, but we hoped to find a time period where the ratings were relatively stable. Looking at the poll data, there seems to be little fluctuation in his approval ratings from October to November. We also wanted to pay more attention to the time nearer to the government shutdown. Therefore, we only kept data from November 2018 until the present. Next, we deleted the data from the "voters" and "adults" subgroups and only kept the results from the "all polls" subgroup. We believe that only the "all polls" subgroup is representative of both voters and adults.

The dependent variable is Trump's popularity, which we measured based on the approval ratings given in the poll data. In the data, the variable is defined as *approve*=Yi. The independent variables include: *shutdownbinary*=X1i (the variable of interest), *shutdownmagnitude*=X2i, *postshutdownbinary*=X3i, *postshutdownmagnitude*=X4i, *unemployment*=X5i, *tweets*=X6i, *taxation*=X7i, *stocks*=X8i, and *legislation*=X9i. We defined *shutdownbinary* as 1 if the survey's start date is during the shutdown (from December 22, 2018 to January 25, 2019) and 0 if the survey's start date is not during the shutdown. We only looked at the start dates of the surveys for consistency. We defined *shutdownmagnitude* as the number of days since the shutdown began and 0 for the dates that are not during the shutdown. We defined *postshutdownbinary* as 1 for the dates that are after the shutdown (starting from January 26th, 2019) and 0 for the dates before and during the shutdown. We defined *postshutdownmagnitude* as the number of days after the shutdown is over and 0 for the dates that are before and during the shutdown. We did not include a *preshutdown* variable (defined as 1 before the shutdown and 0 during and after the shutdown) in the regression, because this is a dummy variable trap and would violate the perfect multicollinearity assumption. If we included the *preshutdown* variable, *preshutdown* + *postshutdownbinary* + *shutdownbinary* would always be 1.

We used unemployment data from November 2018 (3.7), December 2018 (3.9), and January 2019 (4.0) for *unemployment*. Since February's unemployment rates have still not been released, we just assumed it to be the same as January's (4.0). We defined *tweets* as 1 for the dates when Trump posted a tweet receiving more than 200,000 likes that included content on Democrats, the Mexican Wall, Cohen, and other controversial topics; we defined *tweets* as 0 for all other dates. We defined *taxation* as 1 for 2018 and 0 for 2019, because the taxation rate became less beneficial to those with a lower income bracket in 2019. From demographics of Trump supporters, we know that people with lower incomes tend to support him more than those of higher incomes. For *stocks*, we used the market adjusted closing price data from the Dow Jones Industrial Average. The adjusted closing price provides a better analysis of the market, because it takes into account more factors such as dividends and stock splits. For Saturdays and holidays, we used the previous day's adjusted closing price data. For Sundays, we used the next day's opening price data. We believe this best represents what the stock prices would be even though the market is closed on weekends and holidays. Lastly, we defined *legislation* as 1 for the dates where bills predominantly supported by Republicans were passed and 0 for all other dates. Because many Republicans support Trump, we believe that if legislation in line with their beliefs are passed, then Trump's approval ratings will increase. Below are the summary statistics of all the variables:

summarize approve

Variable	Obs	Mean	Std. Dev.	Min	Max
approve	522	43.09291	3.284157	34	52

summarize shutdownbinary

Variable	Obs	Mean	Std. Dev.	Min	Max
shutdownbi~y	522	.3199234	.466894	0	1

summarize shutdownmagnitude

Variable	Obs	Mean	Std. Dev.	Min	Max
shutdownma~e	522	6.421456	10.81118	0	35

summarize postshutdownbinary

Variable	Obs	Mean	Std. Dev.	Min	Max
postshutdo~y	522	.243295	.4294833	0	1

summarize postshutdownmagnitude

Variable	Obs	Mean	Std. Dev.	Min	Max
postshutdo~e	522	3.465517	7.192163	0	30

summarize unemployment

Variable	Obs	Mean	Std. Dev.	Min	Max
unemployment	522	3.11954	1.542887	0	4

summarize tweets

Variable	Obs	Mean	Std. Dev.	Min	Max
tweets	522	.1130268	.3169293	0	1

summarize taxation

Variable	Obs	Mean	Std. Dev.	Min	Max
taxation	522	.4942529	.5004466	0	1

summarize stocks

Variable	Obs	Mean	Std. Dev.	Min	Max
stocks	522	24669.46	953.8633	21792.2	26191.22

summarize legislation

Variable	Obs	Mean	Std. Dev.	Min	Max
legislation	522	.2183908	.4135504	0	1

IV. Discussion of the Key Assumptions

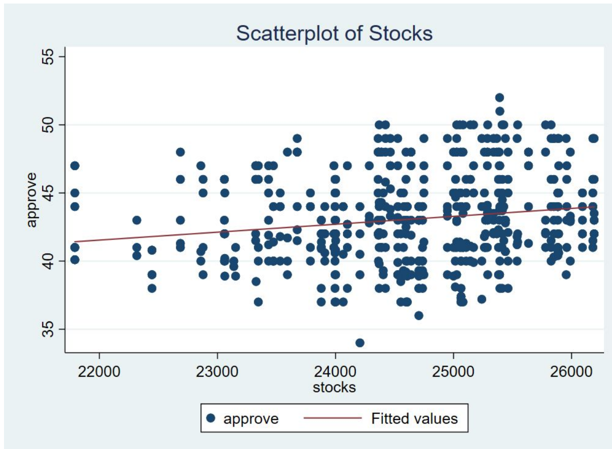
There are four main assumptions that we considered.

1. The conditional mean of the error given the independent variables is zero; $E(u||X1i, X2i, \ldots, X9i)=0$. The conditional expected value of the error term, u, given all the X's is zero when there are control variables in the regression so that the error term is uncorrelated with the variables of interest. In this case, our variable of interest is *shutdownbinary* and we defined nine other control variables. Although this assumption may not be complete satisfied because we do not know if we have included all necessary control variables so that *u* is uncorrelated with *shutdownbinary*, we believe that the control variables we included account for much of the effects. Therefore, for the sake of the regression, we will assume the conditional mean independence assumption holds. This means that the coefficient for the *shutdownbinary* variable is unbiased and has a causal effect on approval ratings but the coefficients for the control variables are in general biased and not interpretable (cannot prove causal effect).

2. (X1i ,…,X9i ,Yi), i =1,…,524, are i.i.d. The data uses a time series to analyze the effects of the government shutdown on approval ratings. Obviously, Trump's popularity on Day 1 of the shutdown would be highly correlated with his popularity on the Day 2 and all other days of the shutdown. However, for the sake of the regression analysis, we will consider this assumption as held.

3. Large outliers are rare (finite fourth moments). The variables that are binary (*shutdownbinary*, *postshutdownbinary*, *tweets*, *taxation,* and *legislation* which are bounded and only take values of 0 and 1) do not have any large outliers. As for the variables that are not binary (*stocks*, *unemployment*, *shutdownmagnitude*, and *postshutdownmagnitude*), *shutdownmagnitude* and *postshutdownmagnitude* are also bounded and only take values from 0 to 35. From this data, we can tell there are obviously no large outliers. *Unemployment* takes on

3.7 for all the November dates, 3.9 for all the December dates, and 4.0 for all the January and February dates. Again, there are no large outliers. Below is a graph of *approve* against *stocks.* There is one slightly low point, but we do not consider it to be a large outlier.



4. There is no perfect multicollinearity. This condition is satisfied, because there is no perfect linear combination of variables. None of the variables are linear combinations of each other.

V. Econometric Analysis

Our null hypothesis for this project is that the shutdown did not affect approval ratings (popularity) at all, or the shutdown's effect on approval ratings is zero. Our alternative hypothesis is that the shutdown did affect approval ratings, or the shutdown's effect on approval ratings is not zero. When we used the multiple regression model to analyze the values, we obtained the following results:

Linear regression Number of obs = 522

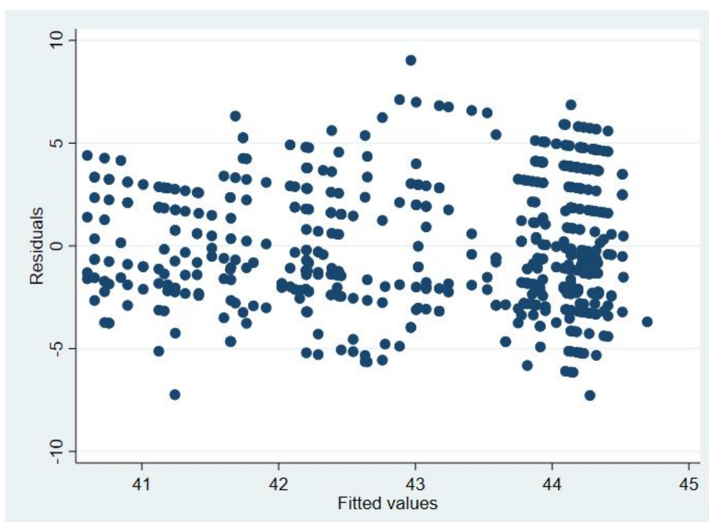
F(9, 512) = 11.01

Prob > F = 0.0000

R-squared = 0.1376

Root MSE = 3.0765

approve	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
shutdownbinary	-.7666709	1.016527	-0.75	0.451	-2.763747	1.230406
shutdownmagnitude	-.1140992	.0372558	-3.06	0.002	-.1872922	-.0409061
postshutdownbinary	-3.99138	1.08039	-3.69	0.000	-6.113922	-1.868838
postshutdownmagnitude	.0874235	.0551101	1.59	0.113	-.0208462	.1956933
stocks	.0002214	.0002674	0.83	0.408	-.000304	.0007468
tweets	.3218057	.4002966	0.80	0.422	-.4646202	1.108232
unemployment	-.1680904	.255634	-0.66	0.511	-.670311	.3341301
taxation	-1.14947	.8589554	-1.34	0.181	-2.836981	.5380404
legislation	.2074466	.4480818	0.46	0.644	-.6728586	1.087752
_cons	40.28795	6.956279	5.79	0.000	26.62159	53.95432



The R-squared value calculated from the regression model is .1376. Although this is not that close to 1, the residual graph does not seem to show an obvious pattern but is randomly scattered around 0. Therefore, we are not too worried on the fit of this regression model to the data.

We used eight control variables, *postshutdownbinary*, *tweets*, *taxation, legislation, stocks*, *unemployment*, *shutdownmagnitude*, and *postshutdownmagnitude*. In general, the coefficients of the control variables are biased. This is because the expected value of the error term given the control variables is not zero. However, even though we cannot gather much information from the biased coefficients of the control variables, we can get a more accurate result for the coefficient of the variable of interest, *shutdownbinary*. To see the results more clearly, we will analyze the effect of the shutdown in periods of time.

To find the effects of the shutdown evaluated at date *d*, we used the formula (coefficient of *shutdownbinary*) + (*d*)(coefficient of *shutdownmagnitude*).

Day 1 of the shutdown:

(-.76667)+1(-.11410) = -.88077

Day 10 of the shutdown:

(-.76667)+10(-.11410) = -1.90767

Day 20 of the shutdown:

(-.76667)+20(-.11410) = -3.04867

Day 35 of the shutdown:

(-.76667)+35(-.11410) = -4.76017

To find the effects of the shutdown evaluated at postshutdown date *p*, we used the formula (coefficient of *postshutdownbinary*) + (*p*)(coefficient of *postshutdownmagnitude*).

Day 1 after the shutdown:

(-3.99138)+1(.08742) = -3.90396

Day 10 after the shutdown:

(-3.99138)+10(.08742) = -3.11718

Day 20 after the shutdown:

(-3.99138)+20(.08742) = -2.24298

Day 30 after the shutdown:

(-3.99138)+30(.08742) = -1.36878

These results make sense. During the shutdown, the effects of the government shutdown on Trump's approval rating kept getting increasingly negative. Starting from the first day after the end of the shutdown, Trump's approval ratings continued to be negative but increasingly less so. At day 30, the rating continues to rise even closer to approval ratings from before the government shutdown. This makes sense in real life, because from the poll graphs, we can see that Trump's approval ratings have risen to pretty much to the same level as before the shutdown.

Looking at the regression data of *shutdownbinary*, the above results also make sense. The p-value of *shutdownbinary* is 0.451. This is not statistically significant for any significant level. This means that we fail to reject the null hypothesis. We cannot confidently say that the government shutdown affected Trump's approval ratings/popularity. The previous calculations support this outcome, as we can see a general trend of rising ratings as post-shutdown days continue.

VI. Conclusion

We can conclude that there is no statistical evidence that the government shutdown affected Trump's popularity. Although ratings drastically decreased during the shutdown, they rebounded quickly after the shutdown ended. As of the end of February 2019, Trump's approval ratings seem to have completely recovered. This is concerning, as it suggests that our president's powerful yet questionable actions have little impact on his overall popularity.