Original Research Article

Timing the Money: Temporal Dynamics of 2016 U.S. Presidential Campaign Disbursements from Transaction Totals

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ABSTRACT

This study investigates the temporal dynamics of campaign disbursements during the 2016 United States presidential election using daily expenditure data from the Federal Election Commission (FEC), compiled through Kaggle's public campaign finance dataset. Focusing on six major federal candidates, the research employs linear trend analysis, quadratic trend analysis, and seasonality (residual) analysis to examine how disbursement patterns evolve across the election cycle. Results reveal that overall spending trends are weakly linear, with low explanatory power ($R^2 \leq 0.08$), while quadratic models modestly improve fit ($R^2 \leq 0.12$), uncovering nonlinear behaviors such as mid-period surges and late-cycle accelerations. Seasonality analysis highlights substantial differences in volatility, with one candidate exhibiting pronounced episodic bursts and others maintaining steady expenditure pacing. Collectively, the findings suggest that campaign spending is event-driven rather than time-driven, responding to strategic milestones rather than following smooth temporal growth. Policy recommendations emphasize the need for real-time expenditure monitoring, proportional pacing regulations, and data-driven budgeting frameworks to enhance transparency and efficiency. Future research should incorporate stochastic and autoregressive models (e.g., random walk) and link financial trajectories to key political events to better capture the dynamic and strategic nature of modern campaign finance behavior.

Keywords: Temporal Dynamics; Campaign Disbursements; Trend Analysis; Seasonality; Event-Driven

INTRODUCTION

The United States presidential and general elections play a decisive role in shaping national strategies, policymaking, and the country's long-term direction (1). This is because presidential elections do more than decide who holds office. They shape the direction of major national policies, including the economy, education, healthcare, environmental protection, and defense (2). The results of these elections affect people's daily lives in real, tangible ways, such as job opportunities, taxes, and the quality of public services. Because of this, understanding what influences election outcomes has been a significant, long-standing focus for researchers in political science, economics, and sociology (3).

Even with their high stakes, presidential campaigns are often limited by strict financial realities. Candidates have to make tough choices about how to spend limited funds while trying to reach as many voters as possible (4). Every stage of the campaign, from early groundwork, the primaries and the general election, comes with decisions about where and when to spend. These choices reveal a

campaign's broader strategy (5). Spending often shifts around key moments like debates or state primaries, and how campaigns handle these shifts can say a lot about their planning and priorities (6).

Although campaign finance data is publicly available and frequently analyzed, most research focuses on total fundraising or how money is spent by category (7). Much less attention has been paid to how spending unfolds over time, whether it be week by week or month by month (8). Some work suggests longer campaign durations may affect outcomes, though the evidence is mixed (9). This study looks specifically at that timeline. Using 2016 Federal Election Commission (FEC) data, it tracks how seven major presidential candidates spent their money throughout the election season. However, this analysis includes only six of the candidates due to the limited data available on the seventh candidate. The analysis focuses on three main variables: the candidate's name, how much they spent, and the date each expense was recorded. By looking at spending patterns month by month and week by week, the study compares how different candidates paced and prioritized their spending.

The findings offer a clearer view of how campaigns manage their resources over time. Some candidates spend heavily early on, while others hold back and ramp up closer to Election Day. Others take a steadier, consistent approach (10). These patterns offer insight into the strategic thinking behind campaign decisions and may help explain some of the outcomes we see at the ballot box. Beyond just contributing to the academic conversation on campaign finance, this study also aims to make campaign spending more understandable to the public. By focusing on when the money is spent, not just how much, we can better understand how presidential campaigns are run, and what it takes to stay competitive in a high-stakes race (11).

METHODS AND MATERIALS

Data Description

The dataset for this study was taken from Kaggle (12), one of the most widely used open data platforms among researchers. The original data came from the Federal Election Commission (FEC), which serves as the official public source for campaign finance records in the United States. The FEC's database provides detailed and transparent information on campaign contributions and expenditures, making it a dependable resource for studying how money is spent during elections.

For this project, the dataset was narrowed down to include only information from the 2016 U.S. Presidential and General Election. This focus made it possible to look more closely at how major candidates managed their spending during that specific election cycle. After filtering, the dataset included about 65,500 transaction records, with each record representing a single disbursement made by one of the seven major presidential candidates. Since one candidate has very few disbursements, the candidate was removed from the analysis due to a small sample size and associated unreliable results. Hence, there are 6 candidates included for research purposes. Each entry in the dataset contains several key variables: the candidate's name, the amount spent, the date of the disbursement, and a brief description of the expense. Although the description variable could be used to explore specific types of spending, such as media, travel, or consulting, this study focuses on the first three variables. By concentrating on who spent money, how much they spent, and when they spent it, the analysis highlights patterns in timing and overall spending behavior across the campaign period.

To keep the data consistent, all transactions made on the same day by the same candidate were combined into a single daily total. This process has created a continuous time series of daily spending, which helps reveal spikes in spending activity and patterns over time. It also allows for a clear comparison of how different candidates allocated their resources throughout the campaign season. A detailed summary of variable definitions and descriptive statistics is presented in Table 1, which provides the foundation for the subsequent trend and comparative analyses.

It is noteworthy that Table 1 includes a small number of negative disbursement values, which typically reflect reimbursements, refunds, or administrative corrections within the FEC reporting system. These entries were retained to preserve the completeness and integrity of the dataset. However, their impact on the analysis is considered minimal for two reasons. First, negative disbursements constitute a very small proportion of the total transaction records and therefore exert negligible influence on the overall spending patterns. Second, such entries appear across all candidates rather than concentrated in a particular campaign. Because the occurrence is relatively uniform, any distortion introduced by these negative values is likely to be cancelled in comparative analyses.

To meet the main research objective of analyzing how federal campaign disbursements change over time,

Table 1. Descriptive Statistics for Disbursement Amount of Different Candidates

candidate ID	total	count	mean	std	min	max	median
Individual Disbursement-Oriented							
1	61443126.19	10199	6024.43	35976.06	-42392.00	1207996.79	271.88
2	421265115.60	23181	18172.86	356355.86	-16805.50	24783344.54	277.80
3	86962787.47	11857	7334.30	67768.11	-66648.16	5116968.21	334.89
4	11862667.26	4070	2914.66	11816.12	-2500.00	387369.26	500.00
5	2017068.43	986	2045.71	11333.58	-6316.70	215000.00	289.00
6	45980545.90	15200	3025.04	42033.63	-12528.92	2001396.10	158.00
Daily Disbursement-Oriented							
1	61443126.19	353	174059.80	305519.30	-1500.00	2187445.56	29270.24
2	421265115.60	591	712800.50	2453805.00	-19932.30	26033548.20	19966.79
3	86962787.47	325	267577.80	541950.40	-4823.55	5305773.70	70251.27
4	11862667.26	356	33322.10	92109.22	-217.29	1088631.24	3005.17
5	2017068.43	123	16398.93	41734.29	-1205.10	276937.72	3313.34
6	45980545.9	338	136037.10	336319.8	-4948.80	2594071.62	26044.76

Note: Very large numeric values (e.g., 421265115.60) hereinafter represent U.S. dollars.
Legend for Candidate IDs: 1 - Ted Cruz, 2 - Hillary Clinton, 3 - Donald Trump, 4 - Bernie Sanders, 5 - John Kasich, 6 - Marco Rubio (all candidates are hereinafter referred to using their ID numbers).

this study uses both trend analysis and seasonality analysis through time-series modeling. The goal is to capture the overall direction of spending as well as the short-term fluctuations that occur during the campaign cycle. By combining linear and quadratic trend models, the analysis accounts for general increases or decreases in spending as well as possible nonlinear changes, such as acceleration, slowing, or turning points that may appear around key election events. Including a seasonality component connected to the quadratic trend offers a more complete view of how campaign disbursements evolve.

Linear Trend Model

The linear trend model assumes a steady rate of change in daily disbursements over time. It can be expressed as (13):

$$D_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{1}$$

Where
D_t = daily disbursement amount on day t,
β_0 = intercept, representing the baseline disbursement level,

β_1 = slope, representing the average daily change in disbursement, and
ε_t = random error term capturing unobserved influences.

This model tests whether expenditures follow a simple increasing or decreasing pattern across the election period, assuming linear growth or decline without curvature (14).

Quadratic Trend Model with Seasonality

The quadratic trend model introduces curvature and integrates a seasonal component to account for periodic fluctuations in spending behavior. The general form is (15):

$$D_t = \beta_0 + \beta_1 t + \beta_2 t^2 + S + \varepsilon_t \tag{2}$$

Where
β_2 captures the acceleration or deceleration (curvature) of spending over time,
S represent the seasonality, modeling recurring oscillations in disbursement intensity,
Other symbols are as previously defined.
This formulation enables the analysis to separate

systematic long-term trends (linear and quadratic terms) from short-term cyclical fluctuations (sine and cosine components) (16). Together, these equations provide a rigorous framework to examine both the directional and periodic characteristics of campaign finance dynamics throughout the election timeline.

RESULTS

In alignment with the stated research objectives, the results are organized into three subsections. The first subsection presents the Linear Trend Analysis, followed by the Quadratic Trend Analysis, which introduces nonlinear curvature effects. The final subsection provides the Detrended (Seasonality and Residual) Analysis, focusing on the underlying fluctuations and irregularities in disbursement behavior after removing trend components. Together, these sections offer a comprehensive examination of both long-term trends and short-term dynamics in campaign spending patterns. It is important to note that the primary objective is to compare the long-term trends and seasonal patterns across models, rather than to evaluate or optimize the underlying autoregressive structures. While diagnostic checks such as residual analysis, autocorrelation inspection, and stationarity tests (e.g., ADF or KPSS) are certainly valuable, they are not central to the paper's research focus. For ease of analysis, all calculations are done via Python programming.

LINEAR TREND ANALYSIS

For the Linear Trend Analysis, both the estimated model results for each candidate and the corresponding visual representations are provided. The findings are illustrated through plotted trend lines, allowing for a clear comparison of the direction, magnitude, and variability of daily disbursement patterns across candidates.

Table 2 shows clear differences in the magnitude and direction of linear disbursement trends across the six candidates. Candidate 2 exhibits the strongest positive slope ($b_1 = 4049.04$), indicating a steady and pronounced growth in daily disbursement over time, nearly an order of magnitude higher than the others. In contrast, Candidates 1, 3, 4, and 5 all show small negative slopes (ranging from −111.88 to −172.09), suggesting gradual declines in their spending patterns. Candidate 6 has a modest positive slope (105.11), implying slight growth but at a much lower rate than Candidate 2. However, the overall goodness of fit ($R^2 = 0.00$–0.08) is low for

all six, which means that the linear model explains only a small portion of the variance; daily disbursements fluctuate far more than a simple linear trend can capture. Among all, Candidate 2 stands out as the only one with a meaningful upward trajectory, whereas the others remain relatively flat or slightly downward.

Figure 1 visually reinforces these numerical findings, highlighting both similarities and contrasts among the six linear trend lines. Candidate 2's orange line rises sharply across the entire 2015–2016 period, dominating the upper half of the graph and visually confirming its strong positive slope. Candidates 1 and 3 display gentle upward inclines with relatively stable levels, indicating mild increases over time. By contrast, Candidates 4 and 5 present subtle downward lines, suggesting gradual reductions in disbursement. Candidate 6's brown line is nearly flat, signifying minimal temporal change. Overall, while all candidates share relatively small variations in slope (indicating general stability of expenditure), Candidate 2's line diverges sharply upward, making it the primary outlier in terms of growth momentum, whereas the others cluster together with moderate, near-horizontal trajectories.

QUADRATIC TREND ANALYSIS

Likewise, a similar presentation format is adopted for the Quadratic Trend Analysis, where both the model estimation results and graphical illustrations are provided. This parallel structure allows for direct comparison between linear and nonlinear patterns, highlighting how curvature effects influence each candidate's disbursement trajectory over time.

Table 3 indicates that introducing a quadratic term provides a modest improvement in explaining daily disbursement patterns compared with the linear model (R^2 rising slightly to 0.06–0.12). Candidate 2 displays

Table 2. Linear Trend Analysis Results

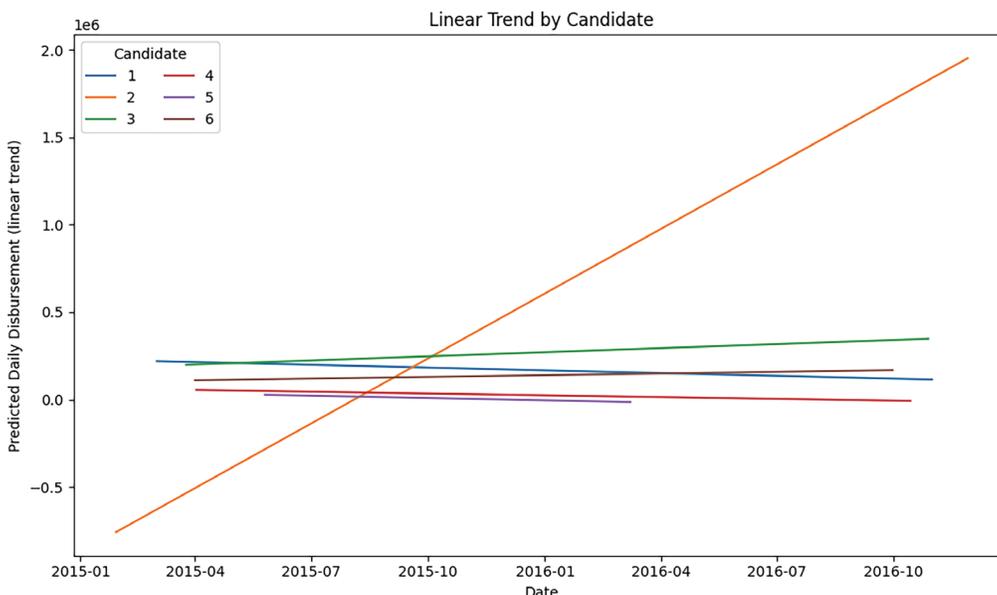| Candidate ID	intercept_b0	slope_b1	R-Square	n_obs
1	219308.71	-172.09	0.01	353.00
2	-757522.91	4049.04	0.08	591.00
3	198385.05	255.65	0.00	325.00
4	54787.85	-111.88	0.02	356.00
5	27255.03	-146.61	0.04	123.00
6	110252.27	105.11	0.00	338.00

Figure 1. Linear Trend Plot of Daily Disbursement for Each Candidate.

Table 3. Quadratic Trend Analysis Results

Candidate ID	intercept_b0	beta1_t	beta2_t2	R-Square	n_obs
1	-5285.34	2091.47	-3.97	0.12	353.00
2	603476.67	-5769.90	13.57	0.11	591.00
3	-105029.82	3388.27	-5.70	0.06	325.00
4	53746.96	-98.24	-0.03	0.02	356.00
5	32430.09	-295.12	0.68	0.04	123.00
6	-84042.09	2288.64	-4.33	0.07	338.00

the most pronounced curvature with a positive β_2 (13.57), suggesting an accelerating upward trend after an initial decline, implying that its spending dipped early but rose sharply later. Candidate 3 also exhibits strong curvature ($\beta_2 = -5.70$) and a large positive β_1 (3388.27), consistent with an initial increase followed by a leveling or downturn. Candidates 1 and 6 show similar concave-down patterns (negative β_2) but on a smaller scale, reflecting moderate growth that peaks mid-period. Candidates 4 and 5, on the other hand, have nearly flat β_1 and β_2 coefficients, indicating almost linear or slightly convex behavior with little change over time. Overall, the quadratic fits reveal greater heterogeneity: while Candidates 1 and 2 demonstrate significant curvature and stronger temporal dynamics, Candidates 3 to 5 exhibit far more stable disbursement

levels, and Candidate 6 shows moderate but distinct parabolic movement.

Figure 2 highlights distinct curvature patterns among the six candidates. Candidate 2's orange curve dominates the plot, rising sharply after an early dip and reaching the highest predicted disbursement levels, indicating strong nonlinear acceleration. Candidate 1's blue curve forms a broad inverted U-shape, increasing steadily before tapering off, consistent with a mid-period spending peak. Candidate 3's green curve shows a similar but flatter pattern, peaking near the middle of the time range with lower amplitude. Candidates 4 and 5 display nearly flat or gently concave curves, reflecting stable, low-variance spending throughout the year. Candidate 6's brown curve lies between these extremes, with a smooth parabolic rise and fall.
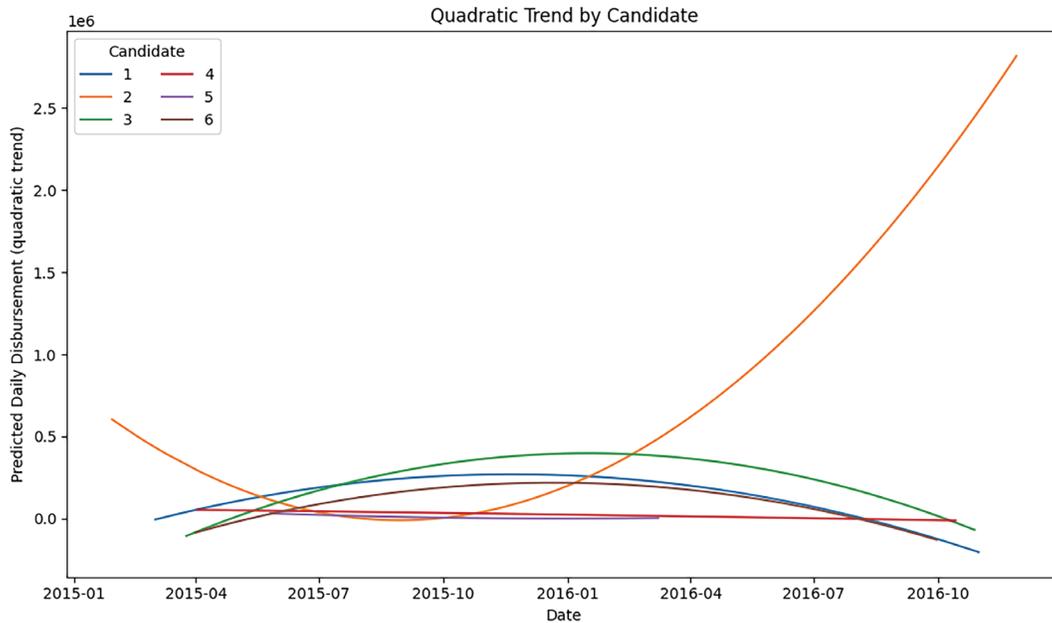
Figure 2. Quadratic Trend Plot of Daily Disbursement for Each Candidate.

Overall, while the linear trends primarily differed in slope, the quadratic trends reveal more dynamic timing of spending changes, most notably Candidate 1's late-period acceleration and Candidate 2's pronounced nonlinear surge, compared with the relatively steady behavior of the other four candidates.

Seasonality Analysis

In addition to examining overall trends, the Seasonality Analysis plays a crucial role in identifying whether disbursement behaviors follow consistent temporal patterns or are instead driven by irregular, event-specific fluctuations. This analysis helps determine whether candidates' spending reflects structured, periodic cycles or spontaneous, data-driven responses to campaign events and strategic opportunities.

As shown in Figure 3, after removing the quadratic trend component, the residual analysis reveals clear differences in the scale and volatility of daily disbursement fluctuations among the six candidates. Candidate 2 shows the largest residual amplitude, with spikes above 2×10^7, indicating sharp short-term bursts of spending rather than a steady rhythm.

In contrast, Candidates 1, 3, 4, 5, and 6 maintain residuals close to zero, suggesting more stable disbursement patterns after accounting for trend effects.

Candidate 3 shows mild mid-period oscillations, while Candidates 4 and 5 display the smallest seasonal ratios, indicating minimal deviation from predicted values. Overall, the hierarchy of volatility follows the order: Candidate 2 $\gg$ Candidates 3 $\approx$ 6 > Candidates 1 $\approx$ 4 $\approx$ 5.

When examining the timing and shape of residual clusters, most candidates show weak or inconsistent seasonality. Candidate 2 again stands out with increasing high-frequency peaks in the later months, likely reflecting end-of-cycle spending waves not captured by the quadratic model. Candidate 3 shows moderate mid-year clustering, whereas Candidates 1, 4, 5, and 6 display relatively flat residuals, suggesting evenly distributed or effectively smoothed disbursements.

Overall, while minor shared fluctuations may stem from common external factors such as reporting cycles, the differences in magnitude and timing indicate largely distinct spending behaviors. Candidate 2 exhibits the most irregular and volatile disbursement pattern, whereas the others remain comparatively stable. To further contextualize these irregular bursts, future extensions of this analysis could link major residual spikes to specific political events, such as debates, primary election dates, or concentrated advertising pushes, which would help clarify whether these fluctuations correspond to identifiable campaign activities.
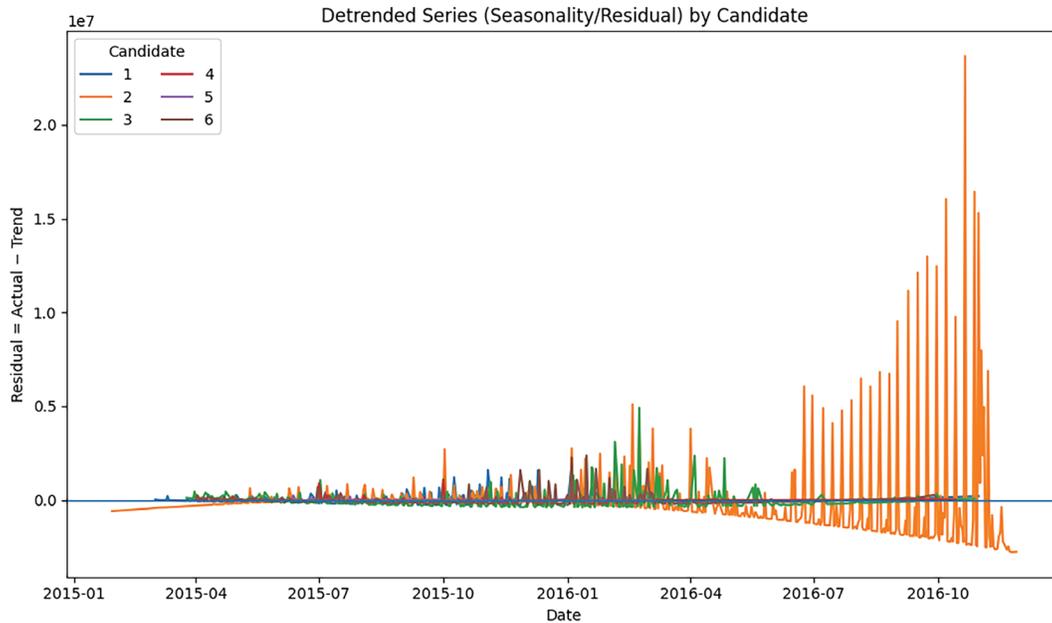
Figure 3. Seasonality Plot of Daily Disbursement for Each Candidate.

DISCUSSION

Across both the linear and quadratic trend analyses, several broad patterns emerge that point to shared characteristics in the six candidates' spending behaviors. Most notably, all candidates show relatively low R^2 values (ranging from 0.00 to 0.12), suggesting that neither linear nor quadratic time-based models fully capture the variation in their expenditures. This indicates that campaign spending is largely driven by short-term decisions, event timing, and strategic shifts rather than by consistent or gradually evolving patterns over time.

Although each candidate differs somewhat in slope and curvature, most maintain moderate to low volatility outside of major campaign surges. This reflects generally stable day-to-day spending once large events or strategic shifts are accounted for. The limited seasonality observed across candidates further suggests that, aside from occasional bursts of spending (particularly for Candidate 2), disbursement schedules are not anchored to strong cyclical or predictable temporal patterns. Instead, expenditures appear primarily responsive to campaign needs as they arise.

Taken together, these findings suggest that campaign expenditures tend to be tightly managed overall, with temporary increases tied to moments of heightened campaign activity rather than to ongoing financial drift or predictable cycles. The evidence therefore highlights campaigns' tendency to adjust spending reactively, often sharply, rather than following smooth, time-driven trajectories.

From a policy and governance perspective, these empirical patterns support a more modest set of implications. The irregular and event-driven nature of spending suggests that monitoring systems may benefit from closer attention to short-term surges rather than relying solely on long-horizon trend expectations. Likewise, the variation in volatility across candidates underscores the importance of transparent reporting practices that help clarify whether sudden increases reflect legitimate strategic activities or potential misallocation. Rather than prescribing specific pacing regulations or fairness mechanisms, the results point more broadly to the value of timely disclosure, improved visibility into expenditure timing, and clearer documentation of event-related spending spikes.

Overall, the findings contribute to a more evidence-based understanding of how campaign disbursements unfold over time. By emphasizing empirically grounded observations, such as limited seasonality, low trend predictability, and candidate-specific volatility, the results offer a clearer picture of the temporal dynamics that shape financial decisions during an election cycle,

while avoiding policy recommendations that extend beyond the scope of the data.

CONCLUSION

This study analyzed daily federal campaign spending data from the Federal Election Commission (FEC), using a Kaggle dataset that compiles candidate expenditure records from the 2015-2016 election cycle. To better understand how spending patterns evolved over time, we applied three complementary approaches: linear trend analysis, quadratic trend analysis, and a seasonality (residual) assessment. Together, these methods helped us explore temporal trends, volatility, and irregularities in spending behavior across six federal candidates.

The linear trend analysis showed only weak directional patterns, with low explanatory power ($R^2 \leq 0.08$), suggesting that disbursement patterns were not easily predictable over time. The quadratic model offered a slight improvement (R^2 up to 0.12), revealing nonlinear dynamics such as mid-cycle surges or end-of-period accelerations, particularly notable for Candidates 1 and 2. The seasonality analysis added another layer of insight, exposing sharp contrasts in volatility. Candidate 2, for instance, displayed pronounced short-term fluctuations, while others maintained relatively stable spending. Overall, these results indicate that campaign disbursements tend to occur in bursts, driven by events or strategy shifts, rather than following steady or cyclical growth.

Several takeaways emerge from these findings, both for policy and for future research. The evident volatility underscores the value of improved real-time expenditure tracking and more adaptive budgeting tools. These could help ensure that both donor and taxpayer funds are allocated efficiently and in alignment with campaign goals. Introducing proportional pacing or expenditure-smoothing mechanisms could also help limit end-of-cycle spending spikes and promote greater financial fairness among candidates.

Additionally, future studies should move beyond basic trend models and explore stochastic and autoregressive approaches, such as random walk, AR(1), or ARIMA models, that can better capture temporal dependencies and reactions to external shocks. Linking disbursement data with specific political or media events (like debates, primaries, or ad releases) could also deepen causal understanding and strengthen model accuracy.

By incorporating both temporal and contextual factors, future research can improve the predictive power of campaign finance models and provide more actionable insights into how political funds are spent. Ultimately, these efforts can help advance efficiency, transparency, and accountability in both public and private campaign financing.

Limitations

While this study provides useful insights into temporal spending patterns during the 2015–2016 federal election cycle, several limitations should be acknowledged. First, the analysis focuses on a single election year, which restricts the generalizability of the findings. Spending dynamics can vary substantially across election cycles due to differences in political climate, candidate competitiveness, fundraising capacity, and media environments. Extending the analysis to multiple election years would help determine whether the observed patterns are consistent or context-specific.

Second, the dataset includes only six major candidates after filtering out those with insufficient observations. Although this improves data reliability, it limits the breadth of comparative analysis and may overlook spending behaviors from smaller campaigns or third-party candidates. Including a broader range of candidates in future datasets would provide a more complete picture of campaign finance dynamics.

Third, FEC data may contain reporting lags, corrections, or administrative delays that influence the apparent timing of disbursements. These reporting artifacts can obscure the true temporal sequence of spending decisions and potentially affect the detection of trend changes or spending spikes. Approaches that incorporate reporting delay adjustments or validation through auxiliary data sources could help address this issue.

Finally, the study focuses on aggregate daily spending totals and does not incorporate the specific categories of expenditures (e.g., media buys, staffing, travel, consulting). Different types of spending follow different temporal rhythms; for example, advertising expenditures often spike around debates or primary dates, whereas staffing costs remain relatively stable. Disaggregating expenditures by category would allow for a more nuanced understanding of what drives short-term fluctuations and candidate-specific volatility.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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