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ELECTION ARBITRAGE DURING THE 2024 U.S. PRESIDENTIAL ELECTION

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Abstract

In this study, we examine the arbitrage opportunities presented by the 2024 U.S. Presidential Election through the construction of a pair of systematic asymmetric portfolios designed to outperform market benchmarks (e.g., the S&P 500) in the event of either candidate's victory. The systematic approach to constructing the asymmetric portfolios involves three key steps: (1) conducting qualitative analysis of election policies to create thematic baskets, (2) identifying key event windows in the election cycle based on betting odds volatility, and (3) implementing dynamic floor and cap filters to select assets based on their average returns during these event windows. The asymmetric nature of the portfolios arises from the dynamic filtering mechanism, which requires assets to exceed a performance threshold during positive events while ensuring returns remain above a specified floor during negative events. Two asymmetric portfolios were constructed—one for each presidential candidate. Post-election results demonstrate that the combined performance of the asymmetric portfolios significantly outperformed the benchmark, indicating the presence of election-driven arbitrage opportunities.

1 Introduction

Arbitrage opportunities during U.S. presidential election cycles have historically been explored through various channels, ranging from direct wagers in betting markets to indirect strategies in U.S. stock and options markets. Election outcomes often produce distinct winners and losers across the financial asset spectrum, largely influenced by the policy leanings of the winning candidate or party toward specific industries, subsectors, or companies, as highlighted by Hanke et al. (2020). Drawing inspiration from structured notes issued by Julius Baer (JB) Group Ltd. tied to the 2020 U.S. presidential election, this study constructs a pair of asymmetric portfolios designed to capitalize on election-dependent outcomes, with each portfolio corresponding to a specific presidential candidate.

Mirroring the JB structured notes, which comprised two baskets of 15 stocks corresponding to each election candidates, the long-only asymmetric portfolios in this study are constructed using policy-driven thematic baskets, analysis of key election events through betting odds volatility, and dynamic threshold and floor filtering mechanisms. The assets included in each portfolio were selected based on two criteria: their potential to be the biggest beneficiaries of the proposed policies of a given candidate or their role as significant political contributors to the respective campaigns.

The asymmetric nature of these portfolios is embedded in the dynamic threshold and floor filtering. This approach requires selected assets to exceed a specified return threshold during positive election event windows and to maintain performance above a defined floor during negative event windows. The overarching objective of this study is to construct a pair of asymmetric portfolios such that, regardless of which candidate wins, the combined performance of the two portfolios significantly outperforms market benchmarks (e.g., the S&P 500).

2 Literature Review

A substantial number of empirical study have digged into the possible connection between political candidates and the return of stock markets around elections and in general (Hanke et al., 2020). Jayachandran (2006) have investigated variables linking sectors and single stock to political parties via campaign contribution data. On the other hand, Addoum and Kumar (2016) showcased a long-term analysis on the stock market depend on which political party was in power. Knight (2006) combined firm specific daily returns of a sample of 70 firms and the daily probability of a Bush Victory from the Iowa Electronic Market 6-months leading up to the 2000 U.S. Presidential Election (Bush vs. Gore). In his regressions, Knight (2006) utilized indicator variables for stocks being positively associated with a potenital Bush or Gore victory. Combining there indicator variables, Knight (2006) found that Bush-favored firms are worth 3% more benchmark and Gore-favored firms are worth 6% less, implying a statistically significant differential return of 9%.

3 Presidential Prediction Markets

3.1 Overview of Prediction Markets

Prediction markets, also known as event markets, provide platforms where participants can purchase shares based on the outcomes of future events, such as political elections. By aggregating individual expectations, these markets frequently yield real-time, crowd-sourced probabilities that reflect public sentiment and forecast trends. In recent years, several online platforms, including **Polymarket**, **PredictIt**, and **Kalshi**, have emerged as major venues for predicting the outcomes of events like the 2024 U.S. presidential election. Each platform has its own distinctive characteristics, shaped by differences in financial structure, regulatory compliance, and user demographics.

3.2 Platform-Specific Structures and Operations

Polymarket: Polymarket is a decentralized, cryptocurrency-based prediction market. Here, participants trade contracts that reflect the probability of specific events, including election results. Shares are bought and sold at variable prices driven by demand, with each contract paying out $1 if the event occurs or becoming worthless otherwise. As of October 2024, Polymarket reported nearly $2.5 billion in trading volume for the 2024 presidential election, with market odds indicating a 66% probability of a win for Donald Trump, according to share prices. The platform's decentralized structure and cryptocurrency basis appeal to users familiar with blockchain technologies.

PredictIt: PredictIt differs from Polymarket in that it is a fiat-currency platform operating under a "no-action" letter from the Commodity Futures Trading Commission (CFTC). This framework allows PredictIt to operate with a cap on individual investment per question, usually set at $850, to meet regulatory requirements. Share prices range between $0.01 and $0.99, with each share's price representing the market's perceived likelihood of an event. A successful prediction pays out at $1. Currently, PredictIt's data shows a leading probability for Donald Trump as the favored candidate based on recent share values.

Kalshi: Kalshi operates as a regulated exchange and recently obtained CFTC approval to offer election-based contracts. It shares similarities with traditional financial exchanges, offering event contracts priced between $0.01 and $0.99, with each successful prediction paying out $1. Kalshi launched its 2024 presidential election market in October, and early trading volumes indicate nearly equal support for candidates Kamala Harris and Donald Trump, highlighting its new role in political prediction markets.

3.3 Comparative Analysis of Platform Mechanics

The structure and operation of each platform vary considerably in terms of regulatory status, financial mechanics, and user demographics, which directly shape participant behaviors:

Regulatory Compliance: Kalshi stands out as a fully regulated exchange, having received CFTC approval to offer contracts based on U.S. election outcomes. PredictIt operates under specific regulatory allowances with investment caps, whereas Polymarket leverages a decentralized model, operating in a more ambiguous regulatory environment.

Financial Mechanics: Each platform has a unique approach to investment limitations and payout structures. PredictIt enforces an $850 cap per question, while Polymarket and Kalshi have fewer restrictions on investments, especially Polymarket, which functions within a decentralized framework. Share prices on each platform serve to quantify market sentiment, translating user expectations into probabilities.

User Demographics and Accessibility: Polymarket's cryptocurrency reliance draws a tech-oriented audience, while PredictIt and Kalshi's use of fiat currency broadens accessibility. Kalshi's regulated status may attract participants preferring greater compliance assurance.

In summary, platforms like Polymarket, PredictIt, and Kalshi provide distinct avenues for forecasting political outcomes such as the U.S. presidential election. Variations in their operational models reflect broader trends in the evolution of prediction markets, offering diverse insights into public expectations and sentiment.

4 Thematic Baskets Based on Trump/Harris 2024 Campaign Promises

4.1 Thematic Baskets Reasoning

As the first step in establishing a universe of stocks, we performed an in-depth analysis of each candidate's potential policy impact and market perceptions of campaign promises. Our primary objective is not to predict what happens over the four years of a president's term; rather, we aim to anticipate the market's immediate reaction to their electoral vote. Our analysis is deliberately kept simplistic and straightforward, focusing not on individual stocks but rather on sub-sectors likely to be most affected by each candidate's campaign promises. We view this qualitative analysis as a "regularization" step in our methodology, intended to minimize the risk of identifying spurious correlations that align well with the data but lack predictive power.

We have identified the following **Trump's 2024 Key Campaign Promises** around which thematic baskets are constructed:

- **Trade Policy**: Plans to impose a 10% tariff on all imported goods, prioritize domestic production, and introduce a 60% tariff specifically on goods from China.
- **Law Enforcement and Crime**: Suggests deploying the military to address crime and dismantling structures referred to as the "Deep State".

- **Energy Policy**:Promotes increased oil drilling on pubic lands, providing tax incentives for fossil fuel producers, and reducing initiatives supporting the adoption of electric vehicles.
- **Education Policy**:Advocates for dismantling the Department of Education and the Department of Commerce.
- **Immigration**: Proposes terminating policies perceived as promoting open borders, reinstating and expanding travel bans targeting specific Muslim-majority countries, and completing the U.S.-Mexico border wall.

On the other hand, **Harris-Biden's 2024 key campaign** promises revolve around the following themes:

- **Tax & Economy**: Plans to increase corporate tax rates and allocate funding toward renewable energy and social welfare initiatives.
- **Climate Change**: Committed to reducing greenhouse gas emissions, supporting the adoption of electric vehicles, and investing $375 in climate change initiatives.
- **Foreign Policy**: Advocates for military support for Ukraine and Israel, alongside broader support for allies and international cooperation.

4.2 Election 2024 Thematic Baskets

1. **For Profit Education / Elderly Care (L/S)**
    - Trump's policies tend to favor market-driven solutions to regulate for-profit education while potentially scaling back federal oversight.
    - Republic administration poses risks for federal healthcare spending, particularly for adult and healthcare facilities reliant on Medicaid and Medicare.
2. **NATO Defense / U.S. Defense (L/S)**

- Trump criticized NATO members that fail to meet 2% of their GDP defense spending guidelines, threatening to pull U.S. security guarantees. European NATO members may have to increase defense budgets, benefiting European defense contractors.
- Trump's criticism of U.S. interventions and potential federal spending shifts could create uncertainty for U.S. defense companies.

3. **Trump Supporters & Donors (Long)**
   - The basket includes companies led by CEOs who have supported, endorsed, or been associated with Trump, reflecting key endorsements during the 2024 campaign.
4. **Trump Beta (Long)**
   - A collection of stocks closely tied to Trump's Republican ideology, either with a narrative or direct involvement.
5. **Onshoring / Nearshoring (L/S)**
   - Trump favors America First policy that prioritizes onshoring, focusing on industrial and agricultural automation and increased production of steel.
   - Biden oversaw significant expansin of nearshoring, hence focus on Mexican industrials and materials.

4.3 Overview of Sectors in Financial Markets

In financial markets, sectors represent distinct areas of the economy, each responding uniquely to political shifts, especially during presidential election cycles. Historically, certain sectors have aligned with Republican or Democratic policies, influencing their performance based on electoral outcomes.

4.4 Platform-Specific Sector Alignments

Republican-Leaning Sectors: Sectors like energy, defense, and financials have generally shown stronger performance under Republican administrations. Policies favoring deregulation and tax cuts typically benefit the energy and financial sectors, while increased defense spending supports growth in the defense and aerospace industries.

Democratic-Leaning Sectors: In contrast, green energy, healthcare, and technology sectors often align with Democratic initiatives. Democratic administrations tend to advocate for renewable energy incentives, expanded healthcare access, and technological innovation, leading to favorable conditions for these industries.

4.5 Historical Sector Performance

Republican victories have typically spurred gains in energy, defense, and financials, driven by expectations of deregulation and increased defense budgets. Democratic wins, conversely, have supported sectors like green energy, healthcare, and technology, in anticipation of policies favoring clean energy, healthcare reform, and innovation.

4.6 Unique Dynamics of the 2024 Election

The 2024 presidential race may see different responses due to evolving priorities. A bipartisan interest in energy transition could blur traditional alignments in the energy sector. Post-pandemic healthcare concerns may foster broader support for public health measures, impacting the usual Democratic advantage in healthcare. Additionally, heightened focus on data privacy and AI regulation may yield mixed results for the technology sector, with both parties advocating stricter oversight. Meanwhile, the current global environment suggests a bipartisan approach to defense, possibly reducing the traditional Republican advantage in defense-related industries.

In summary, while historical data reveal trends in sector alignment with political parties, the 2024 election may prompt unique shifts in performance as both parties address evolving economic and regulatory challenges.

5 Data exploration

5.1 Data Collection

To conduct our analysis, we collected a diverse range of data from several sources to capture both financial market dynamics and election sentiment as reflected in prediction markets.

Equity Market Data: We downloaded historical adjusted closing prices for sectors within the S&P 500 index. These data were sourced directly from S&P500 databases, providing sector-specific insights on price movements. Additionally, we obtained sector Exchange-Traded Fund (ETF) data and representative stocks through Yahoo Finance. This data allows us to analyze how different sectors respond to shifts in election sentiment.

Cryptocurrency and Foreign Exchange Data: To account for alternative assets and currency market movements, we included cryptocurrency data such as Bitcoin (BTC) as well as exchange rate data for the Mexican Peso (MXN) and Chinese Yuan (CNY). These data series were sourced from Yahoo finance Python API, offering a view of asset classes that might exhibit unique responses to political events.

Prediction Market Data: For election outcome probabilities, we relied on odds data from the Bloomberg Terminal and prediction platforms such as Kalshi, Polymarket, and PredictIt. These sources provided daily odds for each candidate, which we used to compute a probability spread reflecting market sentiment shifts.

By consolidating these diverse datasets, we have established a comprehensive foundation for examining the correlation between market reactions and election-related expectations.

5.2 Data Cleaning

After collecting the necessary data, we performed a series of data cleaning steps to ensure consistency across datasets and to prepare the data for analysis.

Frequency Alignment: Since prediction market data was available on a daily basis, we adjusted the financial data, which had varying frequencies, to match this daily timeline. For financial data sources with missing days (e.g., weekends and holidays for stock market data), we employed linear interpolation to fill in the gaps. This method allowed us to maintain a consistent time series and ensure smooth transitions between observed values without introducing significant biases from missing data points.

Standardization and Rescaling: To ensure comparability, we standardized the various datasets by rescaling each time series to have a similar range. This normalization process helped prevent any single dataset from disproportionately affecting the correlation analysis in later stages.

By implementing these data cleaning steps, we created a coherent dataset with uniform daily frequency and minimal missing values, ready for the subsequent stages of analysis.

6 Methodology

Asset Mapping & Ranking

1. Calculate Daily Percentage Change in Odds: For each candidate (Trump and Harris), calculate the daily percentage change in their odds of winning. Define an extreme event as any daily percentage change that exceeds 4%.

2. Classify Extreme Events: - If the change in odds for a candidate exceeds the threshold and is positive, classify it as a positive event - If the change in odds for a candidate exceeds the threshold and is negative, classify it as a negative events 3. Assess Market Reaction: After categorizing each extreme event as positive or negative, evaluate the cumulative return of the stock over the following 5-day window. - If the cumulative return is positive, take a long position on the stock - If the cumulative return is negative,

take a short position on the thematic basket. For each basket, calculate the avg returns of each asset over all the events

Long in descending order mean returns and for the short in descending order absolute mean returns.

7 Modeling

7.1 Asset Selection Methodology

Starting with a comprehensive universe of over 1,000 assets—encompassing stocks, currencies, and digital assets—we developed a systematic funneling process consisting of multiple layers of filtering. First, we applied a thematic basket approach tailored to the policy agendas of the presidential candidates (e.g., EU defense vs. U.S. defense companies). This allowed us to identify key industries and assets closely associated with each candidate, reducing the asset pool from approximately 1,000 to 300.

Next, to pinpoint the most relevant assets for each candidate, we implemented dynamic thresholds and floors during event windows where betting odds for either candidate exhibited daily changes exceeding 4%. These thresholds required the cumulative returns of selected assets to surpass a specified level during positive events while ensuring they did not drop below a set floor during negative events. This process further refined the selection to approximately 40 assets for each candidate's portfolio. Finally, we selected the top 15 best-performing assets within each candidate's portfolio, resulting in two distinct election portfolios—one for Harris and one for Trump.

7.2 Data Collection and Preparation

Our analysis utilized daily stock returns across selected sectors and betting odds for the 2024 U.S. presidential candidates, Donald Trump and Kamala Harris. The data sources included adjusted closing prices for stocks and daily betting odds changes. Stock returns were calculated as:

$$r_{t,i} = \frac{P_{t,i} - P_{t-1,i}}{P_{t-1,i}} \times 100$$

where $r_{t,i}$ is the return of stock i on day t, and $P_{t,i}$ represents its adjusted closing price.

Daily percentage changes in betting odds were computed for each candidate as:

$$\Delta O_t^c = \frac{O_t^c - O_{t-1}^c}{O_{t-1}^c} \times 100$$

where O_t^c is the betting odds for candidate c (Trump or Harris) on day t. These percentage changes formed the basis for identifying critical events.

7.3 Exponentially Weighted Events

In this study, we apply an exponentially weighted methodology to election-related events to emphasize the importance of events that occur closer to the election date. This approach reflects the increasing impact of late-breaking developments on market behavior and public sentiment as the election date approaches. Unlike simple weighting, exponential weights ensure a gradual decay in importance for earlier events, preserving the relevance of key milestones while attenuating the influence of older events.

The weight assigned to each event is defined as:

$$w = e^{-c \cdot d_{to\_election}},$$

where $d_{to\_election}$ represents the number of days from the event to the election date. The decay constant c is calibrated to ensure that the weight of an event occurring halfway through the year (January 1, 2024, to election day) is halved compared to an event occurring on the election date:

$$c = \frac{\ln(0.5)}{D_{total}},$$

where D_{total} is the total number of days from January 1, 2024, to the election date. This ensures consistency in the decay rate, aligning event significance with temporal proximity to the election.

The weighted change in odds for each event i is then computed as:

$$\Delta O_i^{weighted} = w_i \cdot \Delta O_i,$$

where ΔO_i represents the original change in odds for event i, and w_i is the corresponding weight.

The use of exponential weights is particularly justified in the context of financial markets, where late events often introduce greater uncertainty and market volatility. By prioritizing these events, we can better capture their disproportionately large influence on asset returns and market dynamics.

7.4 Dynamic Thresholds and Floors for Asset Returns

To evaluate the impact of election events on asset performance, we implement a dynamic approach to thresholds and floors, which are tailored to the observed performance of assets. Unlike fixed thresholds, the dynamic thresholds leverage the Year-to-Date (YTD) performance of individual assets, providing a more tailored filtering mechanism. This adjustment accounts for varying volatility and performance characteristics across assets.

7.4.1 Dynamic Positive Threshold (θ_+)

The positive threshold is calculated as the average of all positive daily returns for a given asset from the start of the year (t_0) to the day before the event ($t-1$):

$$\theta_+ = \frac{\sum_{i=t_0}^{t-1} r_i \cdot \mathbb{I}(r_i > 0)}{\sum_{i=t_0}^{t-1} \mathbb{I}(r_i > 0)},$$

where: - r_i is the daily return of the asset on day i, - $\mathbb{I}(r_i > 0)$ is an indicator function that equals 1 if $r_i > 0$ (positive return) and 0 otherwise.

For positive events, the average cumulative return of an asset during all positive event windows must exceed this dynamically determined threshold:

$$R_{[t_1,t_2]} = \frac{\sum_{j=1}^{n} R_{j,[t_1,t_2]}}{n} > \theta_+,$$

where $R_{j,[t_1,t_2]}$ is the cumulative return of the asset during the event window $[t_1, t_2]$ of the j-th positive event.

7.4.2 Dynamic Negative Floor (θ_-)

The negative floor is calculated as the average of all negative daily returns for a given asset from the start of the year (t_0) to the day before the event ($t-1$):

$$\theta_- = \frac{\sum_{i=t_0}^{t-1} r_i \cdot \mathbb{I}(r_i < 0)}{\sum_{i=t_0}^{t-1} \mathbb{I}(r_i < 0)},$$

where: - $\mathbb{I}(r_i < 0)$ is an indicator function that equals 1 if $r_i < 0$ (negative return) and 0 otherwise.

For negative events, the average cumulative return of an asset during all negative event windows must remain above this dynamically determined floor:

$$R_{[t_3,t_4]} = \frac{\sum_{k=1}^{m} R_{k,[t_3,t_4]}}{m} > \theta_-,$$

where $R_{k,[t_3,t_4]}$ is the cumulative return of the asset during the event window $[t_3, t_4]$ of the k-th negative event.

7.4.3 Justification for Dynamic Thresholds and Floors

The dynamic thresholds and floors offer several advantages over fixed counterparts: 1. Adaptability to Market Sensitivities: By adjusting thresholds based on YTD performance, the methodology captures real-time changes in market behavior and asset-specific characteristics. 2. Asset-Specific Thresholds: Dynamic filters transform universal benchmarks into asset-specific thresholds, allowing stable assets (e.g., government bonds) and highly volatile assets (e.g., Bitcoin) to be evaluated on their respective merits. This differentiation ensures that stable assets are not penalized by stringent thresholds, while volatile assets are not disproportionately favored. 3. Robustness Across Market Conditions: Dynamic thresholds account for differences in performance trends across assets, enhancing the robustness of the filtering mechanism.

7.5 Asset Filtering and Backtesting

After constructing the dynamic thresholds and floors, assets are filtered based on the following criteria: 1. For positive events: $R_{[t_1,t_2]} > \theta_+$. 2. For negative events: $R_{[t_3,t_4]} > \theta_-$.

Filtered assets are then included in a portfolio for backtesting. Portfolio performance is evaluated using cumulative returns:

$$P(t) = \sum_{i=1}^{k} w_i \cdot R_i(t),$$

where w_i is the weight assigned to asset i, $R_i(t)$ is its return at time t, and k is the total number of filtered assets.

7.6 Implications of Methodology

This methodology emphasizes the growing importance of recent events through exponential weighting and introduces dynamic thresholds based on YTD performance. By tailoring thresholds to individual assets, the approach balances responsiveness to near-election developments with robust filtering mechanisms. The differentiation between stable and volatile assets improves precision, ensuring a realistic reflection of their risk-return profiles. Ultimately, this methodology enhances decision-making under uncertainty by providing actionable insights that align with both historical trends and real-time market dynamics.

7.7 Weighted Backtesting and Performance Evaluation

To evaluate portfolio performance, a weighted backtesting approach was implemented. Each stock i in the portfolio was assigned a weight proportional to its weighted return:

$$w_i = \frac{\bar{R}_i^{\text{weighted}}}{\sum_{k \in \text{portfolio}} \bar{R}_k^{\text{weighted}}}$$

The portfolio's cumulative return over the test period was then computed as:

$$R^{\text{Portfolio}} = \sum_{i \in \text{portfolio}} w_i \cdot R_i$$

Performance metrics included:

- Excess returns relative to the benchmark.
- Stability of portfolio composition under different thresholds.

8 Robustness Analysis

To ensure the robustness of our model, we conducted an additional analysis by adjusting the threshold used for defining critical events. Originally, we identified events based on a 3.5% daily change in betting odds for each candidate. To test the model's stability, we lowered this threshold to 3%, thereby capturing a broader range of sentiment shifts with smaller fluctuations in odds.

8.1 Effect of Adjusting the Threshold

Lowering the threshold allowed us to observe if the model's portfolio selections and performance remained consistent when incorporating more frequent but less extreme events. Specifically, by using a 3% threshold, we reclassified events and recalculated cumulative returns for each stock within the adjusted event windows:

$$\Delta O_t^c = \frac{O_t^c - O_{t-1}^c}{O_{t-1}^c} \times 100$$

where events were now defined as $\Delta O_t^c > 3\%$ or $\Delta O_t^c < -3\%$.

8.2 Comparison of Portfolio Stability

We then applied the same methodology to construct long and short portfolios using the 3% threshold and compared these portfolios to those derived with the original 3.5% threshold. By analyzing the cumulative returns and composition of each portfolio under both thresholds, we assessed the consistency of asset selection and the robustness of our strategy. This allowed us to evaluate if the portfolios maintained their performance characteristics despite changes in the sensitivity to betting odds shifts.

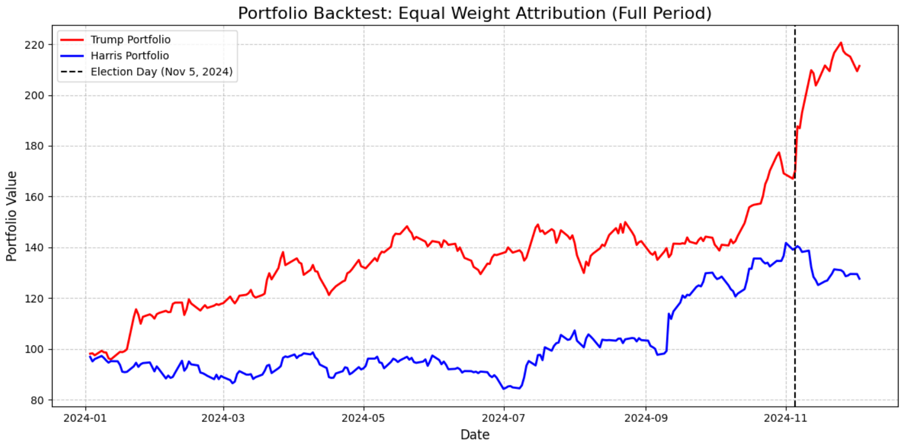
8.3 Robustness Evaluation

The robustness of the model was confirmed if the portfolios constructed under the 3% threshold retained similar asset composition and achieved comparable performance metrics relative to the original 3.5% threshold. This analysis provided a valuable test of the model's stability, ensuring that our portfolio construction strategy is not overly sensitive to minor parameter adjustments, thus validating its robustness.

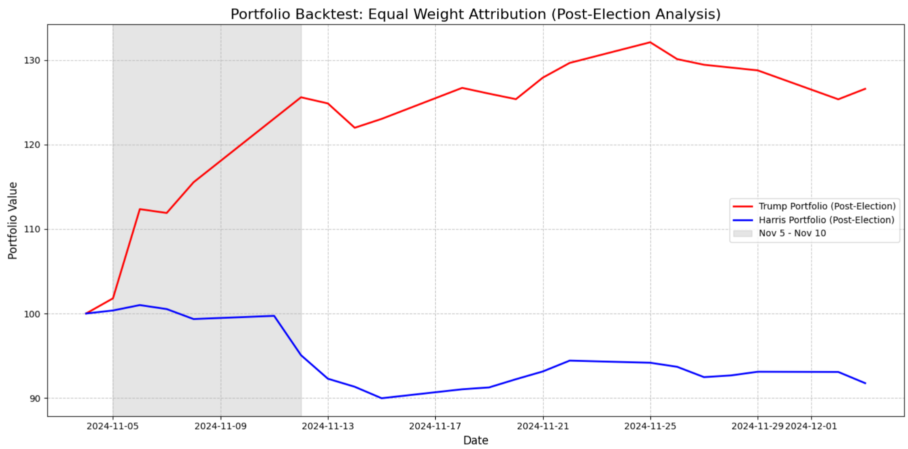
9 Result & Analysis

9.1 Backtesting

The backtesting analysis evaluated the performance of the Trump and Harris portfolios, each starting with an initial value of 100. The analysis covered the period from July 1, 2024, to December 4, 2024, focusing on cumulative returns, sector diversification, and market dynamics.



(a) Backtest Trump vs Harris



(b) Post-Election Asymmetric Portfolio Return

Figure 1: Backtest Asymetric Portfolio Pre and Post Election

As shown in Figure 1a, the two portfolios exhibited a 0.22 positive correlation leading up to the election, reflecting the tight 50/50 betting odds between the candidates. This alignment suggests that market participants priced in similar probabilities for either candidate's victory, resulting in converging portfolio behavior. The close competition likely influenced investor sentiment, with both portfolios moving in tandem as uncertainty dominated pre-election trading.

However, post-election, the correlation between the two portfolios turned negative -0.18 as visualized in Figure 2. The Trump portfolio experienced a significant rally, driven by market anticipation of policy shifts favoring traditional energy, onshoring, and

Portfolio	Annualized Return (%)	Annualized Volatility (%)	Sharpe Ratio
New Trump	97.32	44.88	2.17
New Harris	35.70	31.77	1.12
S&P 500	26.15	13.10	1.65

Table 1: Portfolio Performance Metrics 2024

deregulation. In contrast, the Harris portfolio saw a slight decline, though not as volatile or pronounced as the Trump rally. This divergence highlights the asymmetric nature of the portfolios, where one outperformed substantially during policy-driven optimism while the other demonstrated relative resilience. Such an asymmetric structure makes the combined portfolio particularly valuable for hedging or capitalizing on binary political outcomes, showcasing its strategic significance.

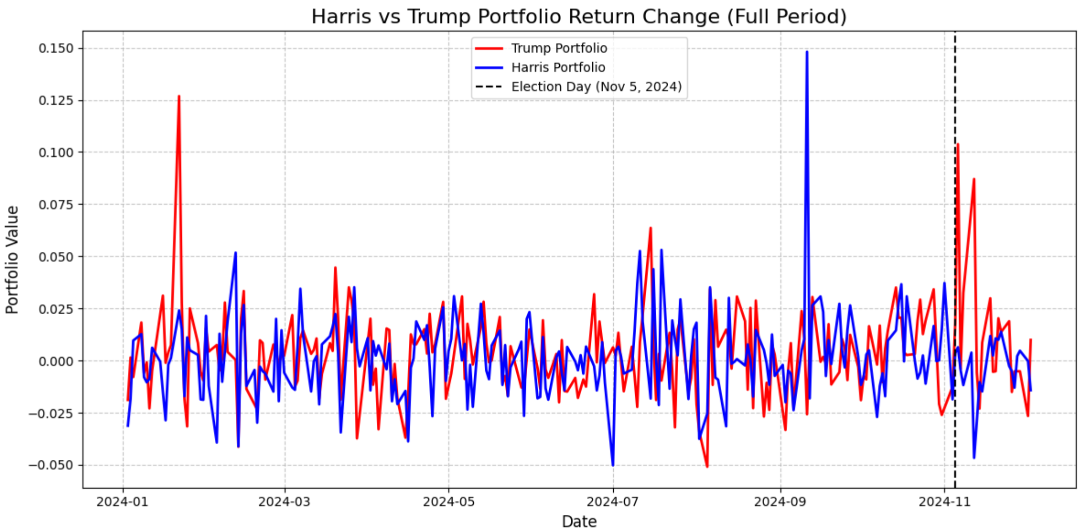
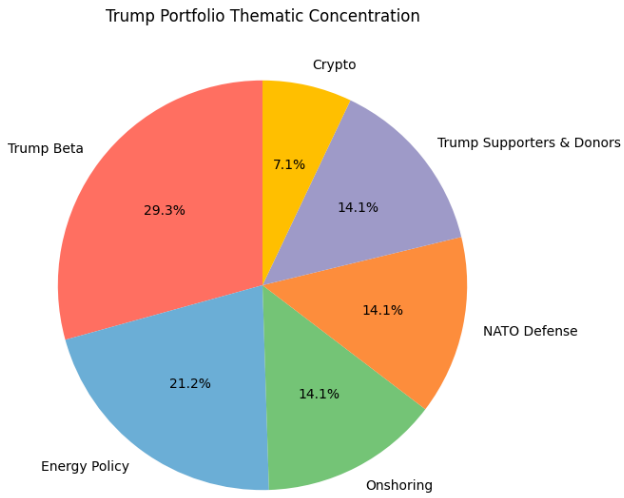


Figure 2: Correlation Harris vs Trump Portfolio Daily Return

The Trump portfolio demonstrates a concentrated focus on themes closely aligned with Trump's political and economic agenda. As shown in 3, key thematic baskets include Trump Beta (29%), comprising businesses directly associated with Trump, such as Rumble (RUM) and Trump Media & Tech Group (DJT), and Energy Policy (21%), featuring oil and gas companies like Comstock Resources (CRK). Other themes, such as Onshoring and NATO Defense (14% each), highlight investments in domestic manufacturing and European defense. While this alignment offers potential for high returns, it also introduces significant exposure to political and sector-specific risks.

The Harris portfolio, in contrast, reflects a diversified allocation aligned with progressive policies. The largest baskets are Clean Electricity and EV (33%) and Fiscal Stimulus Beneficiaries (33%), with investments in companies like Clearway Energy (CWEN-A) and CS Wind (112610.KQ). Additionally, Adult/Elderly Care (22%) features companies such as Enhabit (EHAB), reflecting Harris' focus on healthcare expansion. This portfolio prioritizes sustainability and healthcare while balancing risk through diversified exposure to policy-driven sectors.



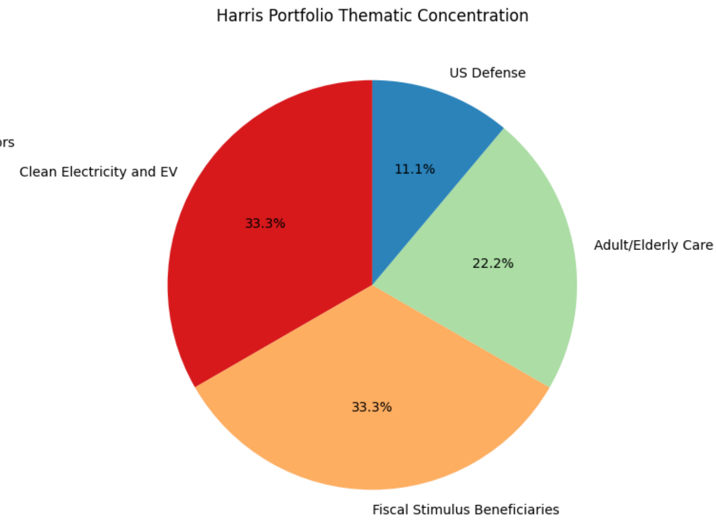


Figure 3: Correlation Harris vs Trump Portfolio Daily Return

9.2 Discussion

The performance and thematic allocation of the Trump and Harris portfolios highlight distinct investment strategies tied to their respective political agendas. The Trump portfolio demonstrated strong returns, driven by high-conviction bets in sectors such as technology, energy, and consumer discretionary. Key contributors included Tesla (TSLA) and Blackstone (BX), which benefited from momentum-driven market sentiment and alignment with Trump's policy focus on deregulation and domestic energy production. However, the portfolio's concentration in cyclical industries exposed it to significant volatility, particularly during periods of macroeconomic uncertainty. This concentration underscores the potential for outsized gains but also highlights the risks of limited diversification, making the portfolio highly sensitive to both policy and market fluctuations.

In contrast, the Harris portfolio provided a more stable risk-return profile, reflecting a diversified allocation aligned with progressive policy initiatives. Renewable energy and industrials, such as Clearway Energy (CWEN-A) and FTC Solar (FTCI), drove consistent gains, while defensive sectors like healthcare offered stability amid market fluctuations. The inclusion of fiscal stimulus beneficiaries further reinforced the portfolio's alignment with government spending priorities. However, challenges in stock selection, particularly in healthcare with underperformers like Pediatrix Medical Group (MD), demonstrated the need for refined allocation strategies even within defensive themes. Overall, the Harris portfolio achieved lower volatility while balancing growth opportunities and risk mitigation.

These findings emphasize the trade-offs inherent in portfolio management strategies. The Trump portfolio illustrates the potential for high returns through thematic concentration but at the cost of increased exposure to sector-specific risks. Meanwhile, the Harris portfolio exemplifies the benefits of diversification and alignment with long-term policy trends, achieving steady returns with reduced volatility. Future research could explore optimization techniques that balance thematic concentration and diversification to maximize risk-adjusted returns. Additionally, further analysis could focus on the impact of macroeconomic events, such as elections and policy shifts, on portfolio performance to better predict and manage risk under different market conditions.

10 Conclusion

The 2024 U.S. Presidential Election provided a unique opportunity to explore arbitrage strategies through the construction of asymmetric portfolios. By leveraging thematic baskets aligned with the policy agendas of Donald Trump and Kamala Harris, this study demonstrated the potential to outperform market benchmarks under election-driven volatility. The Trump portfolio capitalized on sectors such as energy, technology, and onshoring, while the Harris portfolio focused on renewable energy, healthcare, and fiscal stimulus beneficiaries. These contrasting allocations highlighted the distinct policy-driven impacts on asset performance.

Post-election analysis revealed that the Trump portfolio experienced significant gains driven by momentum in cyclical sectors, whereas the Harris portfolio provided stability with lower volatility, underscoring the benefits of diversification. The asymmetric design of the portfolios, combined with the dynamic thresholding methodology, proved effective in capturing upside potential while mitigating downside risks. Future research could refine these strategies by incorporating machine learning techniques for asset selection and optimizing risk-adjusted returns. This project underscores the strategic value of policy-aligned investment frameworks in navigating binary political outcomes.

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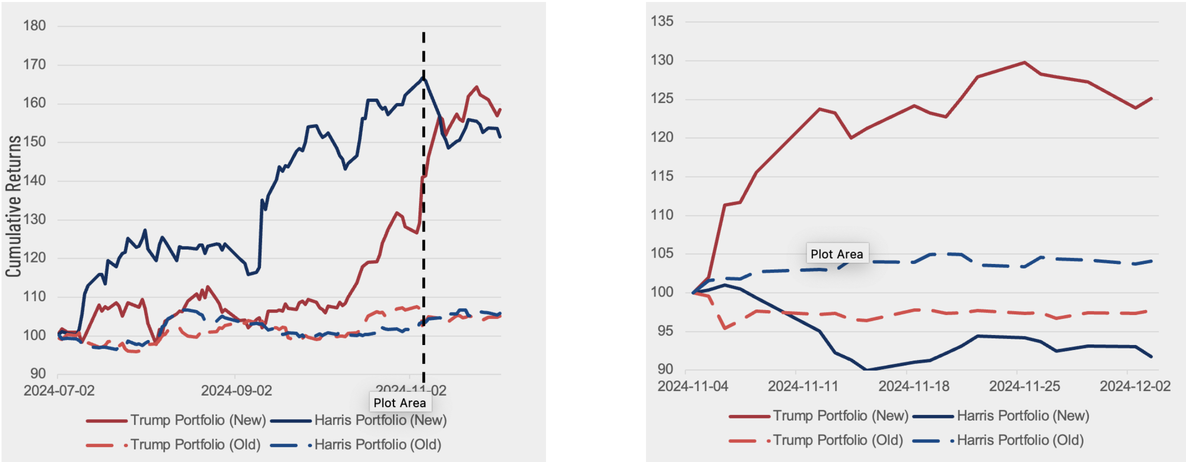
11 Appendix



(a) Backtest Trump vs Harris

(b) Post-Election Asymmetric Portfolio Return

Figure 4: New vs Old Portfolio Methodology Backtest

Portfolio	**Annualized Return (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**
New Trump	97.32	44.88	2.17
New Harris	35.70	31.77	1.12
Old Trump	13.02	13.34	0.97
Old Harris	14.26	10.08	1.41

Table 2: Portfolio Performance Metrics

11.1 Initial Weighted Portfolio Construction Method

The latest methodology introduced a weighted combination of assets responding to both positive and negative events. For each stock i, the weighted average return was calculated as:

$$\bar{R}_i^{\text{weighted}} = w^{\text{pos}} \times \bar{R}_i^{\text{pos}} + w^{\text{neg}} \times \bar{R}_i^{\text{neg}}$$

where:

- $\bar{R}_i^{\text{pos}}$: Average cumulative return of stock i during positive events.
- $\bar{R}_i^{\text{neg}}$: Average cumulative return during negative events.
- $w^{\text{pos}} = 0.8$, $w^{\text{neg}} = 0.2$: Predefined weights reflecting the relative importance of positive and negative events.

11.2 Initial Portfolio Selection and Optimization Method

Stocks were ranked based on their weighted average returns $\bar{R}_i^{\text{weighted}}$. The top n stocks with the highest weighted returns were selected for both long and short portfolios:

$$\text{Long Portfolio:} \quad \{i \mid \bar{R}_i^{\text{weighted}} > \text{threshold}\}$$

$$\text{Short Portfolio:} \quad \{i \mid \bar{R}_i^{\text{weighted}} < \text{threshold}\}$$

To optimize portfolio size:

- Different values of n were tested to maximize excess cumulative returns over a benchmark (e.g., S&P 500).
- The objective was to balance diversification (larger n) with performance (higher weighted returns).