Election-based Asset Allocation Optimizations

Minimizing Portfolio Volatility Amid U.S. Presidential Uncertainty

Duke University – The Fuqua School of Business

Master of Quantitative Management (MQM) Program

Capstone Project Presentation

TEAM 56

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Project Overview & Objectives

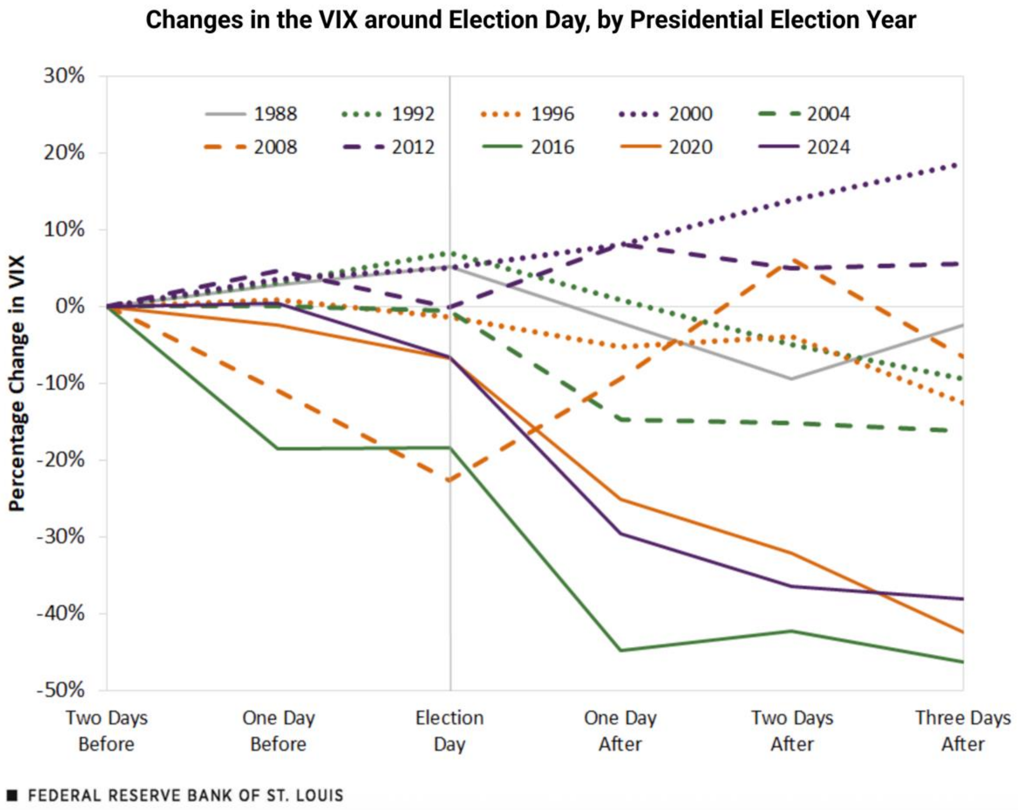
- We developed a **volatility-driven asset allocation tool** that recommends optimal investment weights under **U.S. presidential election scenarios**, with the goal of **minimizing post-election portfolio risk**.
- Our objective is to help investors **adapt to election-induced uncertainty** by reallocating across major asset classes: equity, bond, commodity, and emerging markets.
- Leveraging **ARIMA, GARCH, and Random Forest**, we modeled volatility responses across **six indexes** during each election cycle (2000–2024) and quantified both expected and abnormal risk.
- **Final output**: a Python-based decision tool that uses **user-defined election inputs** to generate personalized portfolio allocations designed to preserve wealth during periods of heightened political uncertainty.

Project Framework & Agenda

- **Challenge**: U.S. presidential elections introduce volatility across financial markets. Clients require a data-driven, adaptive strategy to **preserve wealth amid political uncertainty**.
- **Actions**:
  - **Analysis 1 –** Modeled long-term volatility patterns across 4-year election cycles using normalized variance weights.
  - **Analysis 2 –** Measured phase-specific volatility shifts during Pre-Election, Election Month, and Post-Election periods.
  - **Analysis 3 –** Identified abnormal volatility shocks using GARCH and ARIMA models with pre-election training windows.
  - **Analysis 4 –** Translated election characteristics into structured political features for scenario modeling.
  - **Analysis 5 –** Trained a Random Forest model to predict composite risk and generate optimal asset allocation recommendations.
- **Results**: A Python-based portfolio tool that recommends **risk-minimizing asset allocations** based on user-defined election scenarios.

Election Uncertainty in Financial Markets

- **Presidential elections trigger significant market uncertainty**, especially in the days immediately before the outcome is known.
- **Implied volatility (VIX) consistently declines after Election Day**, averaging a **15% drop** within 3 days across 10 elections (1988–2024).
- **Greater pre-election uncertainty leads to sharper volatility drops**—as seen in 2016, 2020, and 2024.
- **Volatility doesn't always decrease**: Elections in 2000, 2008, and 2012 saw increases in VIX due to contested outcomes or macroeconomic shocks.
- **Implication for asset managers**: Election outcomes influence volatility patterns across equities, bonds, commodities, and currencies—necessitating proactive allocation strategies.



Source: "[What Happens to Expected Stock Volatility around Election Day?]" (Federal Reserve Bank of St. Louis, 2024)

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Client's Need & Research Question

- **Client Goal:** Minimize portfolio volatility during U.S. presidential elections
- **Challenge:** Conventional asset allocation lacks election-specific guidance and ignores short-term uncertainty spikes
- **Our Focus:** Build a data-driven tool that adapts allocations based on political and market risk signals

- **Research Question:**
  How do U.S. presidential elections influence market uncertainty across major asset classes, and how can historical volatility patterns inform optimal asset allocation recommendations?

Our Theory of Change

Index Weights by Election Cycle

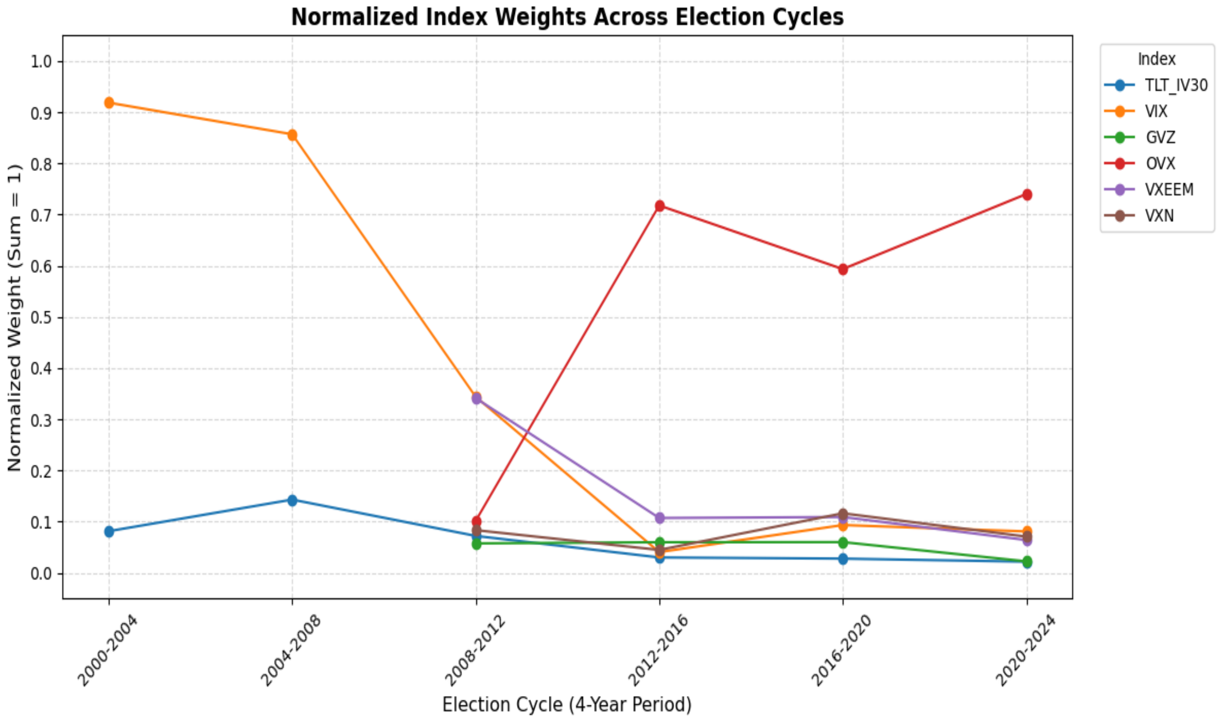
Analysis 1 — Long-Term Volatility Patterns Across U.S. Presidential Election Cycles (2000–2024)

- **Objective**: Assess how different volatility indexes contribute to market uncertainty during each 4-year U.S. presidential election cycle.
- **Methodology**:
  - Computed the **monthly variance** of six volatility indexes (GVZ, OVX, TLT_IV30, VIX, VXEEM, VXN) for each election cycle.
  - Converted variance into **normalized weights** to evaluate relative contributions to total market risk.
- **Normalization Formula**:

$$w_{i,c} = \frac{\sigma_{i,c}^2}{\sum_j \sigma_{j,c}^2}$$

where $\boldsymbol{\sigma^2_{i,c}}$ is the monthly variance of index *i* during cycle *c*.

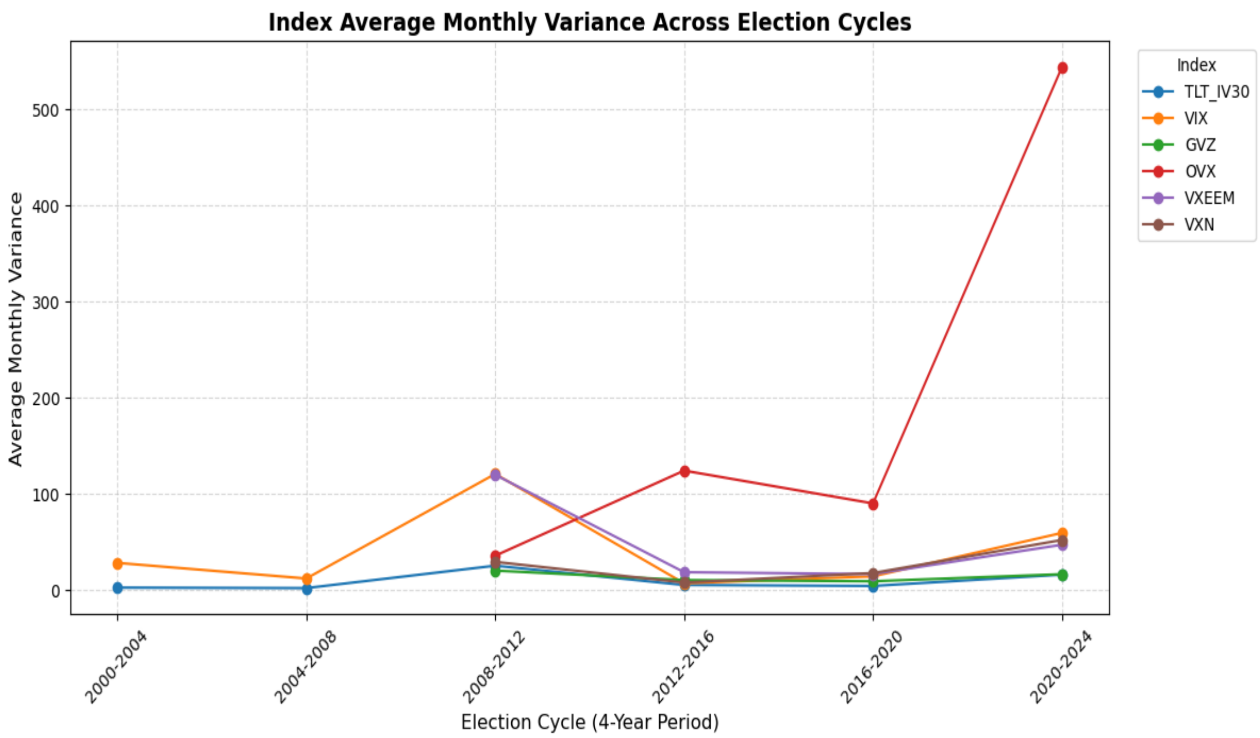
- **Interpretation**:
  Imagine each cycle as a "volatility bucket." The weight tells us what share of that bucket each index represents—revealing which asset classes drive long-term volatility trends during elections.



Variance Patterns by Election Cycle

Analysis 1 — Long-Term Volatility Patterns Across U.S. Presidential Election Cycles (2000–2024)

- **Objective**: Identify how different volatility indexes contribute to overall market uncertainty across 4-year election cycles (2000–2024).
- **Method**: Compute the average monthly variance of each index in every election cycle using finalized volatility data. Normalize these values to show the relative volatility weight per cycle.
- **Findings**: OVX (Oil Volatility Index) exhibited a sharp increase post-2016, becoming the dominant contributor to overall market variance in recent cycles.
- **Visual**: Line chart illustrates average monthly variance trajectory across all six volatility indexes, which highlights shifts in risk concentration over time.



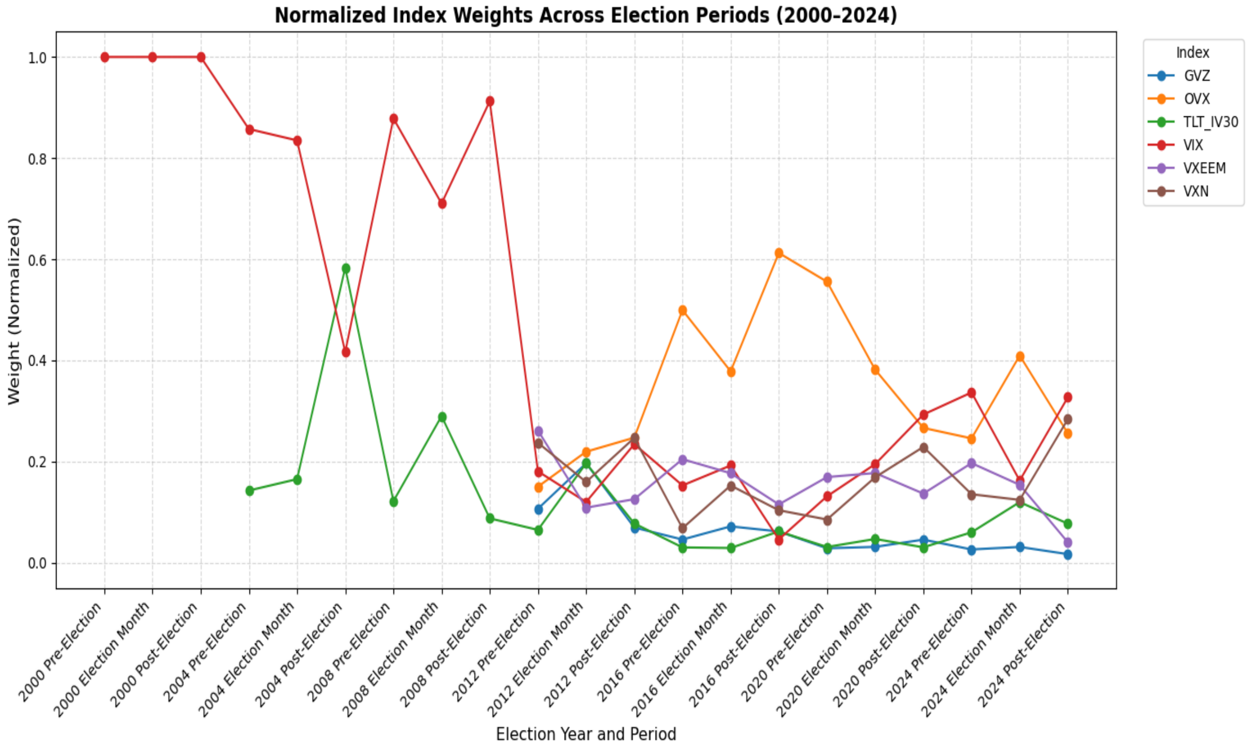
Index Weights by Election Phase

Analysis 2 – Election-Phase Volatility and Risk Weight Dynamics (2000-2024)

- We divided each election year into three phases: **Pre-Election** (3 months before), **Election Month**, and **Post-Election** (2 month after).
- For each phase, we calculated **average monthly variances** and **normalized them** so index weights sum to 1.
- **Normalization Method -** We use the same method as we did for 4-year cycles analysis:

$$w_{i,y,p} = \frac{\sigma^2_{i,y,p}}{\sum_j \sigma^2_{j,y,p}}$$

Where $w_{i,y,p}$ is the share of index i's variance in year y and phase p, relative to the total variance across all indexes.



Variance Patterns by Election Phase

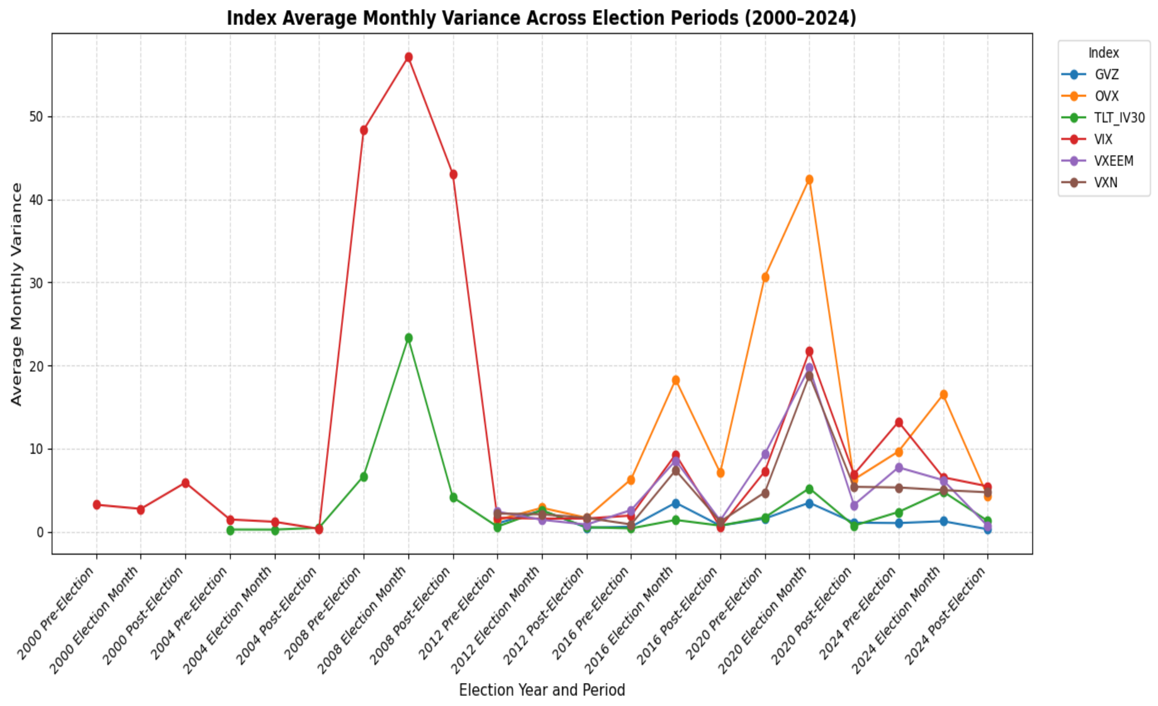
Analysis 2 – Election-Phase Volatility and Risk Weight Dynamics (2000-2024)

- We then calculated and visualized **average monthly variance** of each index across the **Pre-Election**, **Election Month**, and **Post-Election** periods (2000–2024).

- **Volatility spikes** were common during elections and sometimes extended post-election.

- Several indexes showed volatility spikes during election windows, though some may reflect broader macro events (e.g., **VIX spike in 2008**, **OVX surge in 2020**).

- **Election sensitivity varies** across asset classes, highlighting the need for scenario-specific analysis.



Event Study – Objective & Framework

Analysis 3 – Event Study on U.S. Presidential Elections Using GARCH and ARIMA Forecasting

- **Objective**: We aim to measure how volatility indexes react to U.S. presidential elections by isolating post-election movements that deviate from expectations formed **before** the outcome is known.
- **Approach:**
  - We define a **pre-election training window** from **August 1 to October 31**.
  - We use that data to forecast index behavior during the **post-election window** (December–January).
  - Two models are applied:
    - → **ARIMA(1,0,0)** to forecast index levels
    - → **GARCH(1,1)** to forecast conditional volatility

- **Measuring Abnormality**:

$$\text{ARIMA Abnormal}_t = Y_t^{\text{actual}} - Y_t^{\text{forecast}}$$

$$\text{GARCH Abnormal Std} = \sigma_{\text{post}}^{\text{actual}} - \hat{\sigma}_{\text{post}}^{\text{forecast}}$$

- **Statistical Test**:
  We run **one-sample t-tests** to assess whether these differences are significant—indicating a shock potentially tied to political uncertainty.

Why It Matters:
We believe this setup can help us detect **mean shifts** and **volatility shocks** that occur around elections—while avoiding lookahead bias—so we can build more reliable inputs for our final allocation model.

GARCH Results – Key Findings & Comparison

Analysis 3 – Event Study on U.S. Presidential Elections Using GARCH and ARIMA Forecasting

- **GARCH(1,1) models** were fitted on pre-election return volatility to forecast post-election conditional volatility.
- We detected **statistically significant abnormal volatility** in multiple indexes post-election (e.g., VIX, OVX, TLT).
- Some assets showed **elevated volatility** (e.g., VIX in 2008, VXN in 2024), while others experienced a sharp **decline** (e.g., OVX in 2020–2024).
- We believe these results help us flag which asset classes are more prone to volatility shocks during election transitions—inputs we use in our portfolio tool.

=== GARCH Event Study Results ===

	Model	Index	Election_Year	Pre_Start	Post_End	Predicted	Actual	Abnormal	t_stat	p_value	Significant_@5%
14	GARCH	VIX	2000	2000-08-07	2001-01-07	6.0798	5.2682	-0.8116	-8.787520e+01	0.0	True
8	GARCH	TLT_IV30	2004	2004-08-02	2005-01-02	10.9103	4.7873	-6.1230	-1.959522e+02	0.0	True
15	GARCH	VIX	2004	2004-08-02	2005-01-02	5.5723	5.2534	-0.3189	-1.831694e+02	0.0	True
9	GARCH	TLT_IV30	2008	2008-08-04	2009-01-04	11.3773	7.7256	-3.6518	-8.532052e+02	0.0	True
16	GARCH	VIX	2008	2008-08-04	2009-01-04	9.9819	5.9806	-4.0013	-2.661015e+02	0.0	True
0	GARCH	GVZ	2012	2012-08-06	2013-01-06	3.7691	5.9699	2.2008	5.271000e+02	0.0	True
4	GARCH	OVX	2012	2012-08-06	2013-01-06	3.3080	2.3918	-0.9162	-1.852380e+03	0.0	True
10	GARCH	TLT_IV30	2012	2012-08-06	2013-01-06	3.6383	3.1631	-0.4752	-1.905150e+02	0.0	True
17	GARCH	VIX	2012	2012-08-06	2013-01-06	5.2788	5.8143	0.5355	9.927240e+01	0.0	True
21	GARCH	VXEEM	2012	2012-08-06	2013-01-06	4.2528	3.4925	-0.7604	-3.238401e+02	0.0	True
25	GARCH	VXN	2012	2012-08-06	2013-01-06	4.2069	4.6234	0.4165	6.043033e+03	0.0	True
1	GARCH	GVZ	2016	2016-08-08	2017-01-08	4.3925	8.6509	4.2584	3.315760e+06	0.0	True
5	GARCH	OVX	2016	2016-08-08	2017-01-08	4.2541	6.5866	2.3326	7.526000e+02	0.0	True
11	GARCH	TLT_IV30	2016	2016-08-08	2017-01-08	3.8929	5.1381	1.2452	1.564757e+03	0.0	True
18	GARCH	VIX	2016	2016-08-08	2017-01-08	6.2012	4.6372	-1.5640	-3.815921e+02	0.0	True
22	GARCH	VXEEM	2016	2016-08-08	2017-01-08	4.8023	4.7080	-0.0943	-2.261110e+01	0.0	True
26	GARCH	VXN	2016	2016-08-08	2017-01-08	5.0229	4.0944	-0.9285	-5.686294e+03	0.0	True
2	GARCH	GVZ	2020	2020-08-03	2021-01-03	3.2477	3.6836	0.4359	1.490875e+02	0.0	True
6	GARCH	OVX	2020	2020-08-03	2021-01-03	7.9928	3.9906	-4.0022	-1.628321e+03	0.0	True
12	GARCH	TLT_IV30	2020	2020-08-03	2021-01-03	6.1097	4.1056	-2.0041	-3.804546e+02	0.0	True
19	GARCH	VIX	2020	2020-08-03	2021-01-03	5.7471	5.2295	-0.5177	-1.149583e+02	0.0	True
23	GARCH	VXEEM	2020	2020-08-03	2021-01-03	10.0583	8.5602	-1.4980	-1.443560e+02	0.0	True
27	GARCH	VXN	2020	2020-08-03	2021-01-03	3.4606	3.1340	-0.3266	-3.682509e+02	0.0	True
3	GARCH	GVZ	2024	2024-08-05	2025-01-05	1.6861	3.5648	1.8786	6.955066e+02	0.0	True
7	GARCH	OVX	2024	2024-08-05	2025-01-05	7.0177	6.3438	-0.6739	-6.751250e+01	0.0	True
13	GARCH	TLT_IV30	2024	2024-08-05	2025-01-05	4.0176	4.3515	0.3339	2.493779e+09	0.0	True
20	GARCH	VIX	2024	2024-08-05	2025-01-05	5.5671	8.3620	2.7949	1.267121e+03	0.0	True
24	GARCH	VXEEM	2024	2024-08-05	2025-01-05	4.8290	4.2919	-0.5371	-1.495650e+01	0.0	True
28	GARCH	VXN	2024	2024-08-05	2025-01-05	4.1956	6.3064	2.1109	4.515990e+02	0.0	True

ARIMA Results – Key Findings & Comparison

Analysis 3 – Event Study on U.S. Presidential Elections Using GARCH and ARIMA Forecasting

- **ARIMA(1,0,0) models** capture autocorrelation and better reflect short-term time series trends in volatility levels.
- Found **statistically significant post-election deviations** in major indexes (e.g., VIX, VXN, OVX), particularly in 2020 and 2024.
- **Magnitude of surprise** was highest in 2020 (e.g., VXN, OVX), suggesting responses to broader crises like the pandemic.
- **Cross-model validation** with GARCH results supports robustness of election-related volatility signals.

=== ARIMA Event Study Results ===

	Model	Index	Election_Year	Pre_Start	Post_End	Predicted	Actual	Abnormal	t_stat	p_value	Significant_@5%
43	ARIMA	VIX	2000	2000-08-07	2001-01-07	22.7470	26.9439	4.1969	13.1696	0.0000	True
37	ARIMA	TLT_IV30	2004	2004-08-02	2005-01-02	10.0484	9.9530	-0.0954	-0.9951	0.3257	False
44	ARIMA	VIX	2004	2004-08-02	2005-01-02	15.6225	12.8202	-2.8023	-26.3463	0.0000	True
38	ARIMA	TLT_IV30	2008	2008-08-04	2009-01-04	16.0971	28.9260	12.8289	12.8549	0.0000	True
45	ARIMA	VIX	2008	2008-08-04	2009-01-04	51.0291	57.1728	6.1437	4.8088	0.0000	True
29	ARIMA	GVZ	2012	2012-08-06	2013-01-06	16.7683	14.0327	-2.7356	-18.5849	0.0000	True
33	ARIMA	OVX	2012	2012-08-06	2013-01-06	32.6897	29.3850	-3.3047	-12.5113	0.0000	True
39	ARIMA	TLT_IV30	2012	2012-08-06	2013-01-06	15.6383	13.0765	-2.5618	-28.4751	0.0000	True
46	ARIMA	VIX	2012	2012-08-06	2013-01-06	16.3832	16.8142	0.4310	1.6972	0.0976	False
50	ARIMA	VXEEM	2012	2012-08-06	2013-01-06	23.1433	21.8201	-1.3232	-6.3008	0.0000	True
54	ARIMA	VXN	2012	2012-08-06	2013-01-06	18.0875	18.6562	0.5688	2.0200	0.0503	False
30	ARIMA	GVZ	2016	2016-08-08	2017-01-08	16.3578	17.1210	0.7632	3.2489	0.0024	True
34	ARIMA	OVX	2016	2016-08-08	2017-01-08	40.3968	38.1480	-2.2488	-1.8640	0.0699	False
40	ARIMA	TLT_IV30	2016	2016-08-08	2017-01-08	12.6184	14.9049	2.2865	13.0703	0.0000	True
47	ARIMA	VIX	2016	2016-08-08	2017-01-08	16.3161	12.9066	-3.4095	-25.4829	0.0000	True
51	ARIMA	VXEEM	2016	2016-08-08	2017-01-08	23.3632	21.5582	-1.8050	-6.7696	0.0000	True
55	ARIMA	VXN	2016	2016-08-08	2017-01-08	18.7750	15.4308	-3.3442	-18.0235	0.0000	True
31	ARIMA	GVZ	2020	2020-08-03	2021-01-03	23.1880	19.5240	-3.6640	-24.0209	0.0000	True
35	ARIMA	OVX	2020	2020-08-03	2021-01-03	54.7819	43.5305	-11.2514	-34.5412	0.0000	True
41	ARIMA	TLT_IV30	2020	2020-08-03	2021-01-03	16.9026	12.5830	-4.3196	-18.2916	0.0000	True
48	ARIMA	VIX	2020	2020-08-03	2021-01-03	33.7130	23.2011	-10.5119	-34.2448	0.0000	True
52	ARIMA	VXEEM	2020	2020-08-03	2021-01-03	27.3776	24.1156	-3.2619	-9.0352	0.0000	True
56	ARIMA	VXN	2020	2020-08-03	2021-01-03	38.1088	28.3373	-9.7715	-39.3328	0.0000	True
32	ARIMA	GVZ	2024	2024-08-05	2025-01-05	18.5994	16.2165	-2.3829	-16.5169	0.0000	True
36	ARIMA	OVX	2024	2024-08-05	2025-01-05	42.3807	33.7698	-8.6109	-17.7506	0.0000	True
42	ARIMA	TLT_IV30	2024	2024-08-05	2025-01-05	18.5889	13.9388	-4.6501	-23.1312	0.0000	True
49	ARIMA	VIX	2024	2024-08-05	2025-01-05	23.4160	15.6641	-7.7520	-23.2793	0.0000	True
53	ARIMA	VXEEM	2024	2024-08-05	2025-01-05	23.1091	18.5036	-4.6055	-26.5101	0.0000	True
57	ARIMA	VXN	2024	2024-08-05	2025-01-05	24.6812	18.5264	-6.1547	-17.6449	0.0000	True

Election Rating System — Framework Overview

Analysis 4 – Quantifying U.S. Presidential Election Characteristics with a Rating System

- We developed a **quantitative rating system** to encode political risk across U.S. presidential elections (2000–2024).

- The framework translates key political characteristics into numerical values:
    - **Winning Party** (Republican = 0, Democrat = 1)
    - **Incumbent Re-elected** (Yes = 1, No = 0)
    - **Contested or Delayed Outcome** (Yes = 1, No = 0)
    - **Party Switch** (Yes = 1, No = 0)
    - **First-Term President** (Yes = 1, No = 0)
    - **Crisis Year** (Yes = 1, No = 0)
    - **Electoral Mandate Strength** (1–5, based on Electoral College margin)

- We believe this rating system helps translate qualitative political shifts into **structured, model-ready inputs**.

- These features feed directly into our **scenario-based portfolio model** to account for **transition risks** and **volatility triggers**.

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Objective Function: Election-Aware Risk Minimization

Analysis 5 – Machine Learning-Based Asset Allocation under Political Uncertainty

- We aim to **minimize a custom risk metric** that captures both expected volatility and unexpected shocks following U.S. presidential elections.

- Our **objective function (aka Custom_Risk)** is defined as:

$$\min_{\mathbf{w}} \quad \sum_{i=1}^{n} w_i^2 \cdot \left(\hat{\sigma}_{i,\text{post}}^2 + \lambda \cdot \text{Abnormal}_i^2\right)$$

- This function integrates two components for each asset:
  - **Expected Volatility** ($\hat{\sigma}_{i,\text{post}}^2$): predicted by GARCH models from pre-election data.
  - **Unexpected Shocks** (Abnormal_i): measured as the squared difference between actual and predicted post-election volatility.

- **λ** is a penalty term that balances the trade-off between baseline risk andelection-driven uncertainty.

- We optimize asset weights ***wi*** to minimize this combined volatility exposure across all six asset classes.

Model Results

Analysis 5 – Machine Learning-Based Asset Allocation under Political Uncertainty

- We then want to identify the most reliable model for predicting election-driven risk (**Custom_Risk**) across asset classes.

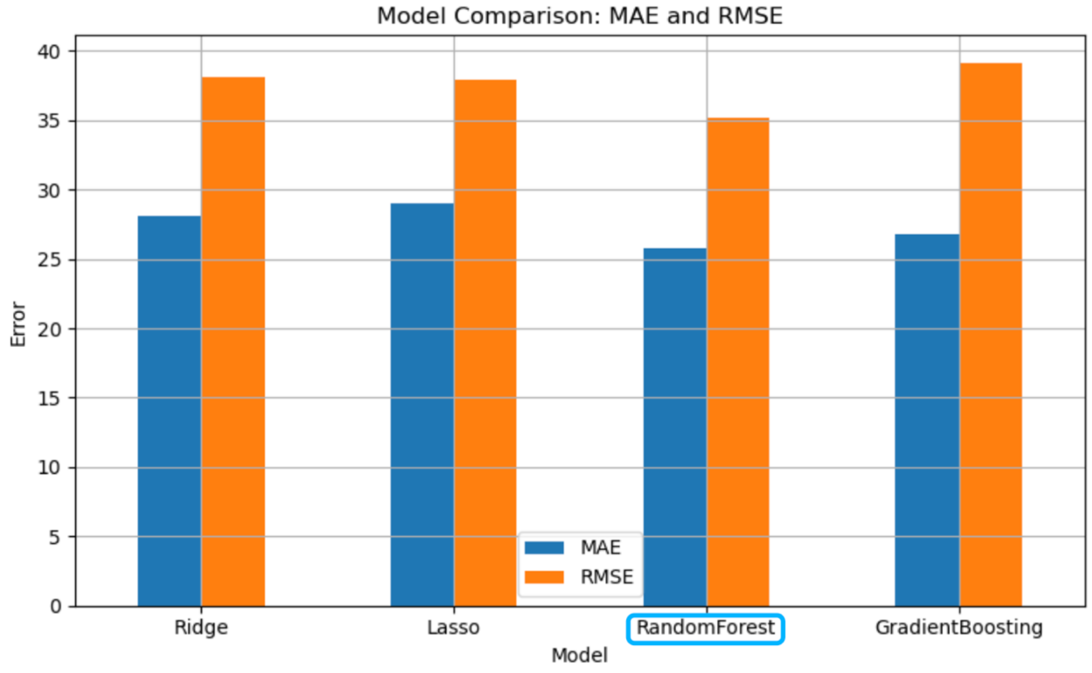
- **Evaluation Metrics**:
  - We compared models using **MAE** and **RMSE** to reflect prediction accuracy.
  - Results show **Random Forest** achieved the **lowest error across both metrics**.

- **Decision**:
  - We **select Random Forest** as the final model powering our client-facing tool.
  - It balances **predictive power**, **flexibility**, and handles **nonlinear interactions** across asset and political features effectively.

- **Why it matters**:
  We believe this can ensure our portfolio allocation engine is built on the most robust and interpretable forecast of post-election volatility.

=== Model Comparison ===

	Model	MAE	RMSE
0	Ridge	28.103377	38.141156
1	Lasso	29.022365	37.946007
2	RandomForest	25.756800	35.217927
3	GradientBoosting	26.770568	39.164242



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Scenario-Based Allocations

Analysis 5 – Machine Learning-Based Asset Allocation under Political Uncertainty

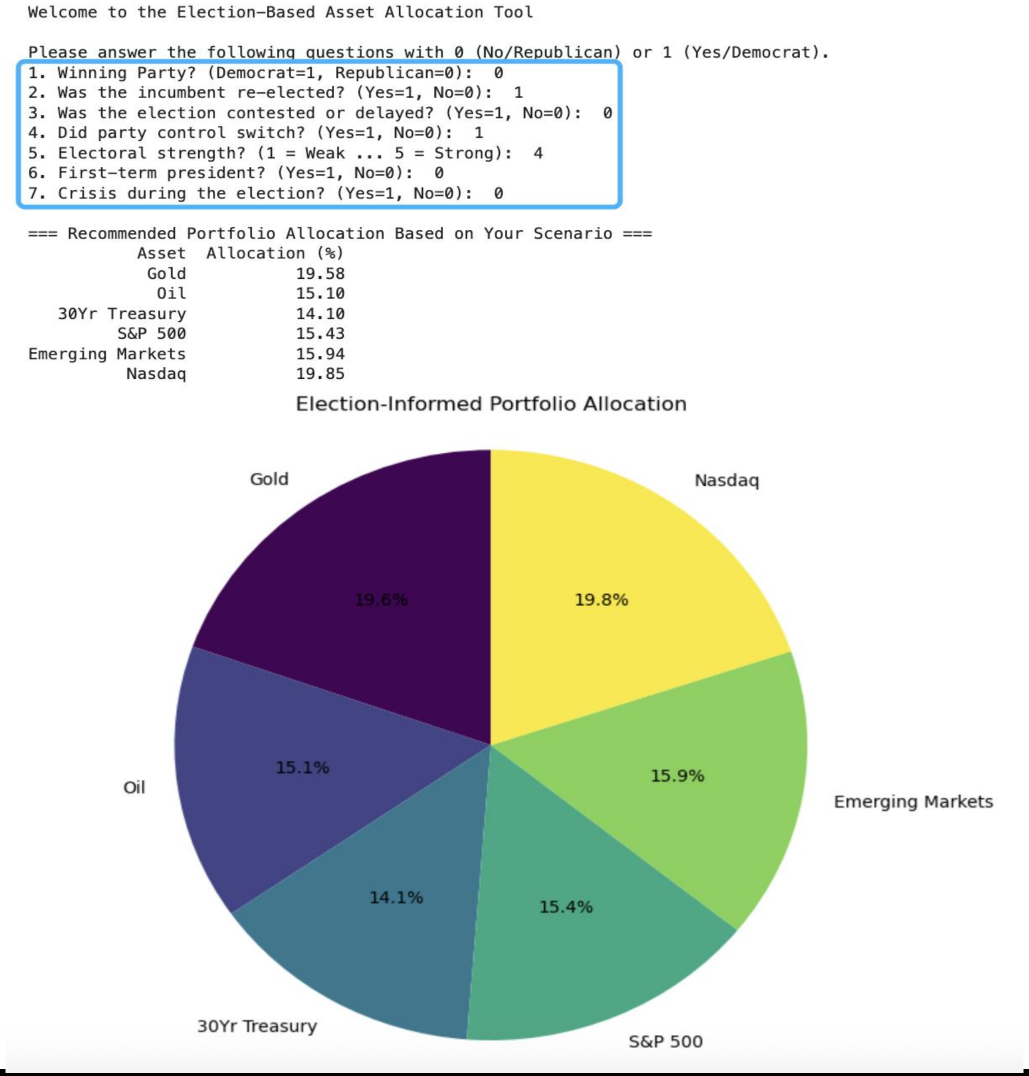
Scenario Summary: A Republican re-election with no crisis or delay, a party switch, and strong electoral strength (Score = 4).

Model-Driven Recommendation:

- Allocate more to **Nasdaq (19.8%)**, **Gold (19.6%)**, and **Emerging Markets (15.9%)**.
- Maintain balanced exposure to **S&P 500 (15.4%)**, **Oil (15.1%)**, and **30Yr Treasury (14.1%)**.

- **Key Insight**:
  - Our tool converts political features into customized portfolio weights that reduce exposure to post-election volatility.
  - This scenario favors risk diversification with modest preference for tech and precious metals.

⚠ *Please note: many other factors can influence market uncertainty. This model only reflects risks tied to U.S. presidential elections.*



Key Findings

- **Volatility Trends**: VIX and OVX showed the highest average variance, but some spikes (e.g., 2008, 2020) were driven by macro crises, not elections alone.
- **Election Phase Insights**: Pre-election and post-election windows often showed elevated variance, confirming phase-specific risk behavior.
- **Event Study (ARIMA/GARCH)**: Detected statistically significant abnormal movements in several elections, with large deviations in VIX, DXY, and OVX.
- **Political Feature Encoding**: Binary and ordinal variables (e.g., Party Switch, Crisis, Electoral Score) helped capture differences in political environments.
- **Model Evaluation**: Random Forest achieved the lowest MAE and RMSE, outperforming Ridge, Lasso, and Gradient Boosting. Selected as final model.
- **Final Tool Impact**: Enables real-time portfolio allocation recommendations based on custom election inputs, minimizing exposure to volatility shocks.

Deliverables, Use Cases & Applications

- **Project Deliverable:**
  - A zipped file containing all cleaned datasets and Python notebooks (.ipynb) for Analyses 1–5. Includes full modeling pipeline, forecasting scripts, and input-ready tools.
  - Click Here to Download
- **What's Inside:**
  - Cleaned & merged datasets (variance, event study, ratings)
  - Two modular Python code files (Analysis1-4, Analysis5, in .ipynb files)
  - Final allocation optimizer + scenario-based input tool (Analysis5.ipynb)
  - README with methodology, column definitions, and usage guidance
- **Client Use Cases:**
  - Clients can simulate asset allocations under various election scenarios and adjust for political risk.
  - Portfolio managers may use the tool to reduce volatility exposure in anticipation of election outcomes.
  - Analysts and policymakers can assess how different political conditions historically impacted financial markets.

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Limitations, Reflections, and Future Improvements

Key Limitations & Assumptions

- Focused only on U.S. presidential elections (2000–2024); excludes other political or macro events
- Model assumes average index behavior holds across similar future scenarios
- Data sourced from historical public datasets; real-time feeds not included

Lessons Learned

- Modeling volatility requires balancing statistical rigor with economic intuition
- Pre/post-election time windows must be carefully defined to avoid bias
- Working with noisy financial data demanded iterative feature selection and model tuning

Future Enhancements

- Integrate real-time macro and sentiment data feeds for forward-looking updates
- Expand to cover non-U.S. elections and midterms
- Build a user-friendly interface (UI) for portfolio managers to test multiple scenarios faster

That's All!

Thank You!

We appreciate your time and welcome any questions or feedback.