Trade Policy Sensitive Portfolio

MF 825 - Portfolio Construction

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Abstract

The following paper investigates how sector returns are affected by trade policy uncertainty, with a focus on recent tariff escalations under the Trump administration in April 2025. Using a multi-factor regression framework, we estimate each sector's sensitivity to trade and macroeconomic uncertainty. Then, based on these sensitivities, we construct a dynamic portfolio made especially for navigating through trade uncertainty. Our results show that the market itself is already able to absorb trade policy risks well as our optimized portfolio's performance can only manage to match the market's performance.

Introduction

The resurgence in trade policy uncertainty, driven by renewed tensions under the Trump administration in April 2025, has become a major source of financial market volatility. The world saw a similar situation only a couple of years ago during the 2018-2020 U.S.-China trade war. Sudden changes in tariffs and global trade relations now pose systemic risks that could extend beyond traditional economic cycles.

Indeed, while institutional investors are actively monitoring uncertainty risks, retail investors are equally, or even more exposed due to lack of information. Trade policies can directly impact corporate profitability by disrupting supply chains, which in turn raises costs and shifts global supply and demand patterns. As a result, sectors such as industrials, technology, and manufacturing may experience significant disturbance during uncertain periods. Moreover, beyond financial markets, increased trade uncertainty also affects day-to-day life through higher consumer prices and slower economic growth.

From a portfolio construction perspective, the recent development of global tensions highlights the limitations of passive diversification in managing geopolitical shocks. A factor-based approach may offer a more nuanced method for isolating and mitigating specific risks related to trade uncertainty. In this project, we build on these concepts by quantifying sensitivities to trade uncertainty by sector and designing a dynamically weighted portfolio that minimizes exposure to tariff-driven volatility. By integrating time-varying factor sensitivities with real-time economic indicators, we aim to enhance risk-adjusted returns and build a more resilient investment strategy for navigating periods of heightened trade tensions.

Data

Data Collection

Before we begin our analysis, we have identified key data sources that would be vital for our project's feasibility. We assembled a comprehensive set of financial and macroeconomic datasets from reputable academic and governmental sources, ensuring reliability and consistency. Monthly and daily returns for the 49 U.S. industry portfolios were obtained from the Ken French Data Library. These returns are already dividend-adjusted and widely used in empirical research in the field of finance, ensuring its credibility and ideal for our intended research.

Additionally, to measure market-wide risk factors, we collected the Fama-French market excess return (Mkt-Rf) and the corresponding risk-free rate from the same library. As for trade policy risks, we noticed three main valuables sources. The first is Matteo Iacoviello's Trade Policy Uncertainty (TPU) index. It quantifies uncertainty arising specifically from trade policy actions.

The second is from Economic Policy Uncertainty's eponymous index, the EPU index. It captures broader macro policy risk. The third is a series of macro and financial uncertainty indexes constructed by Sydney Ludvigson and collaborators, which provide structured estimates of latent macroeconomic risk factors. Finally, short-term inflation expectations were approximated using the 1-Year Treasury Constant Maturity Rate, sourced directly from the Federal Reserve Economic Data (FRED), further ensuring the quality of our datasets.

Data Manipulation

Despite the fact that the bulk of our datasets come from reputable sources, all datasets were still carefully cleaned and standardized. Monthly industry returns were converted from percentage to decimal format for consistency. Excess returns were computed by subtracting the risk-free rate from each sector's raw return. Macro uncertainty variables, such as the TPU and EPU indexes were merged with sector returns based on a common calendar month convention. Dates were also formatted consistently as Year-Month entities to ensure a seamless process.

Our sample period was set from January 1990 to December 2024, which was determined by the intersection of data availability across all data sources. This period was deemed sufficient for our analysis since it captures multiple trade and macroeconomic disruption events, including the 2018-2020 U.S.-China trade war.

Ultimately, we constructed a clean and comprehensible merged dataset that includes sector-level excess returns, trade and macroeconomic uncertainty variables, and short-term interest rates, providing a solid foundation for performing regression and building our dynamic portfolio.

Methodology

Rolling Factor Regression

To measure dynamic sector sensitivities to uncertainty factors, we perform rolling regressions across the 49 industry portfolios. Each industry's excess return is regressed on a set of macroeconomic and policy factors:

1. Market excess returns (Mkt-Rf) – representing broad equity market exposure
2. Macro uncertainty (MacroU) – measuring latent macroeconomic risk
3. Financial uncertainty (FinU) – capturing financial market volatility
4. Trade policy uncertainty (TPU) – capturing trade-related risk
5. Short-term interest rates (ShortRate) – serving as proxy for inflation expectations

A 24-month rolling window is used to capture the time-varying nature of factor exposures. To enhance stability, we apply 20% shrinkage adjustment toward theoretical priors:

- The market beta is shrunk toward 1
- Other factor betas are shrunk toward 0

Mathematically, the regression can be written as:

$$R_{i,t} - R_{f,t} = \beta_{i,Mkt} \times (R_{m,t} - R_{m,t}) + \beta_{i,MacroU} \times MacroU_t + \beta_{i,FinU} \times FinU_t + \beta_{i,TPU} \times TPU_t + \beta_{i,EPU} \times EPU_t + \beta_{i,ShortRate} \times ShortRate_t + \epsilon_{i,t}$$

Portfolio Optimization

Using dynamically estimated factor betas, we construct an optimized portfolio that explicitly targets minimal exposure to uncertainty factors.

At each rebalance date (every six months), we solve the following quadratic programming problem:

Objective:

- Minimize the portfolio's total return variance

Constraints:

- Full investments : The sum of portfolio weights equal to 1
- Target market beta : target the beta at 0.5, 1 and 1.5
- Soft control over factor exposures: we apply soft penalty to minimize exposures to the set of macroeconomic and policy factors.

We introduce a penalty matrix that increases the objective function's value proportionally to the portfolio's total exposure to the selected uncertainty factors. This penalty is weighted by a tunable parameter γ, which controls how strongly we penalize unwanted exposures. A small regularization term is added to the covariance matrix to improve numerical stability.

Mathematically, the objective minimized is:

$$w'(\Sigma + \gamma PP')\, w$$

S.T

$$w'\, i = 1$$

$$w'\beta_{mkt} = \beta^*$$

Where:

- Σ is the rolling covariance matrix of industry returns (estimated over the past 24 months).
- P Contains the industry betas to uncertainty factors.
- γ is the penalty strength parameter (set to 10 in baseline tests),
- w is the portfolio weight vector
- β* is the target portfolio beta, which can be set to 0.5, 1 and 1.5.
- i is a vector of ones.

Performance evaluation

After constructing the dynamically optimized portfolios, we evaluate their performance along three key dimensions:

- Annualized Return: The average monthly return of each portfolio is annualized by multiplying by 12.
- Annualized Volatility: The standard deviation of monthly returns is scaled by $\sqrt{12}$ to obtain annualized volatility.
- Sharpe Ratio:
  Sharpe ratio is computed as the ratio of the portfolio's average excess return (portfolio return minus risk-free rate) to its volatility, both annualized.

Additionally, we track:

- Realized Market Beta & Uncertainty Factor Betas
  Using rolling 24-month regressions, we compute the realized market beta and the factor betas of each portfolio over time to verify alignment with the targeted beta levels (0.5, 1.0, and 1.5) and the minimization of factor betas. We compare the realized betas time series against the target values, highlighting any deviations.
- Cumulative Return Profiles:
  We plot the cumulative returns of each optimized portfolio alongside the cumulative return of the market, providing a visual assessment of performance differences over time. It can be mathematically define as:

$$\prod_{s=1}^{t} (1 + r_s)$$

R Shiny Application

To enhance the accessibility and interactivity of our optimized portfolio, we developed a custom R Shiny application. The app allows users to dynamically adjust model parameters and observe real-time changes in the portfolio's behavior, reflecting the full mechanics of our optimization engine in an intuitive format. In this section, we describe the data processing, backend calculations, and output generation embedded within the app. In short, we wanted to bring our model alive to the audience.

At its core, the Shiny application implements the same rolling-window framework as our main optimization model. We estimate dynamic factor betas using 24-month rolling regressions for each industry portfolio, with factors such as the market excess return and macroeconomic uncertainty. To ensure robust estimation, we apply a shrinkage adjustment, pulling each beta toward economically motivated targets: a prior of 1 for the market beta, and 0 for all uncertainty-related factors.

The portfolio optimization itself is based on the same soft-constrained quadratic program. Rather than strictly forcing exposures to match target levels, the optimization penalizes large deviations from desired factor sensitivities, primarily ensuring that the market beta closely tracks a user-selected target value while still permitting flexibility on secondary factors. Optimization weights are recalculated at a semi-annual frequency to strike a balance between responsiveness and minimizing turnover.

From a user experience perspective, the app provides two main interactive controls: a slider allowing users to select the target market beta between 0.5 and 1.5, and a dropdown menu enabling users to filter the analysis to specific crisis periods such as the Dot-Com Crash, the Global Financial Crisis, or the COVID-19 shock. Changes in user input dynamically trigger the backend engine to rerun the rolling beta estimation, optimization, and performance calculation procedures without requiring manual reloading or reprogramming.

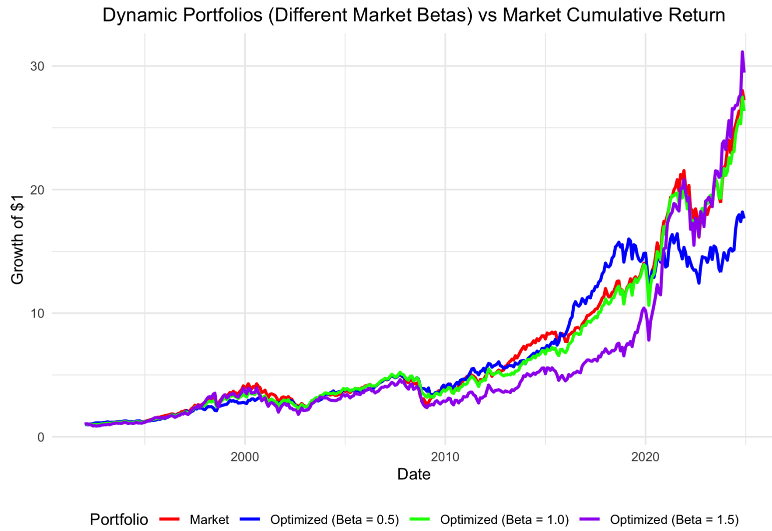
The outputs generated include a cumulative return plot comparing the optimized portfolio to the broad market, and recalculated annualized performance metrics (return, volatility, and Sharpe ratio) for both portfolios. All outputs are reactive, meaning they update instantly in response to user changes.

Overall, the Shiny application not only replicates but extends our portfolio construction methodology into a flexible, interactive environment, demonstrating the practical applicability of dynamic trade policy-sensitive investment strategies.

Results

In this section, we evaluate the performance of our optimized portfolios and analyze their dynamic behavior relative to the market. We examine key portfolio metrics such as cumulative returns, Sharpe ratios, and realized factor exposures across different target market betas. Additionally, we explore industry-level sensitivity to uncertainty, factor attribution, and the effectiveness of our optimization in achieving desired exposures over time.

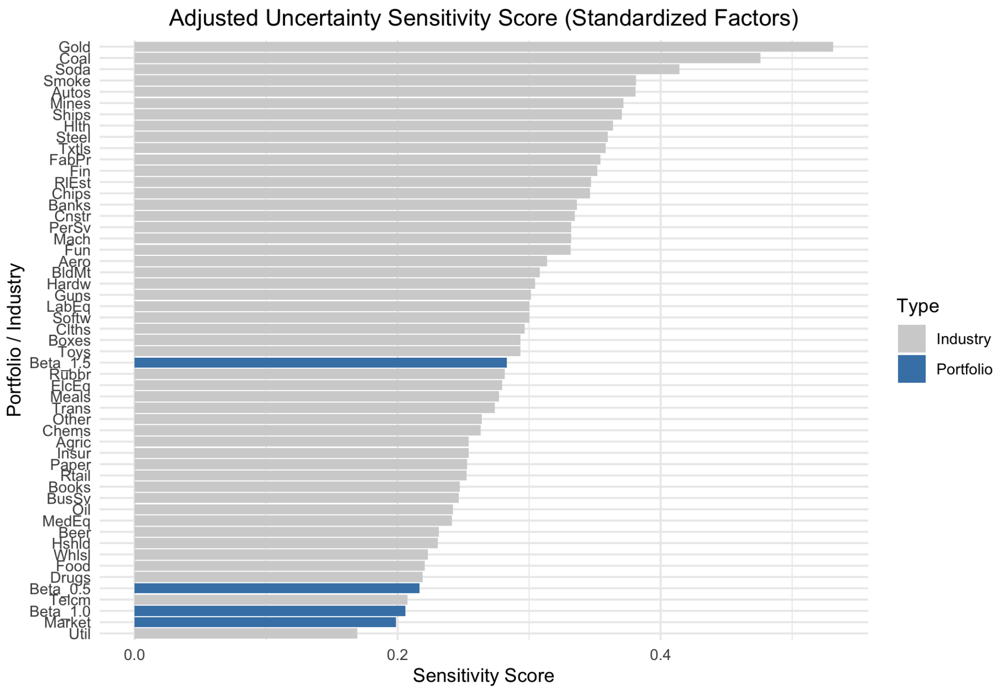
The chart below shows the cumulative returns of the optimized portfolios targeting different market betas (0.5, 1.0, 1.5) versus the market. The lower-beta portfolio (0.5) grows more steadily with smaller drawdowns, while the higher-beta portfolio (1.5) exhibits greater volatility and sharper swings. The beta 1.0 portfolio closely tracks the market, but with slight differences due to uncertainty factor penalties.



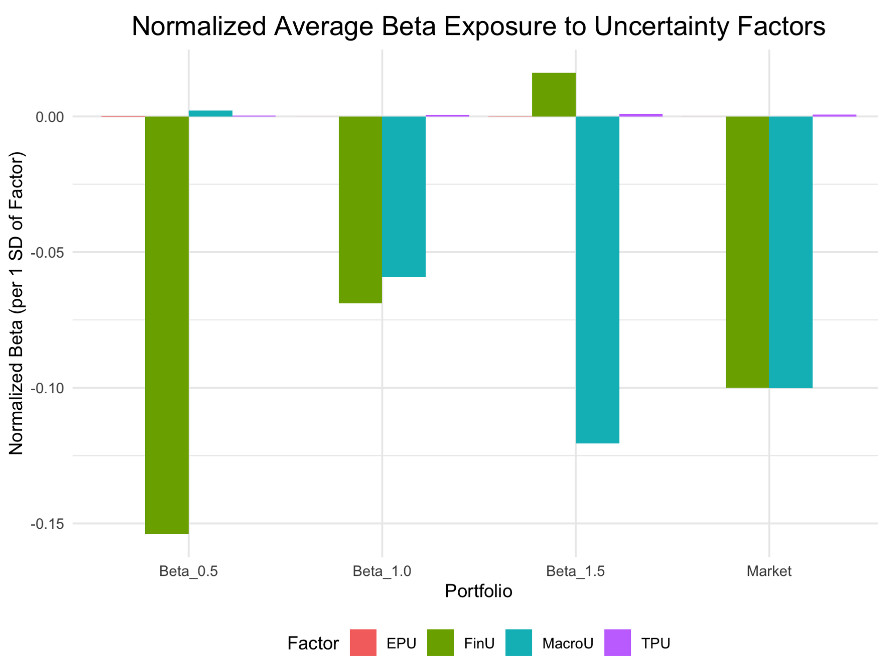
This table below summarizes the annualized performance metrics for each portfolio. The optimized portfolio with a target beta of 1.0 achieves a Sharpe ratio comparable to the market, while the portfolio with a target beta of 0.5 shows slightly lower risk-adjusted returns. The portfolio targeting a beta of 1.5 delivers higher returns but at the cost of significantly higher volatility and a lower Sharpe ratio, indicating less efficient risk-taking.

Portfolio	Annualized Return	Annualized Volatility	Sharpe Ratio
Optimized (Beta = 0.5)	0.10	0.14	0.52
Optimized (Beta = 1.0)	0.11	0.15	0.58
Optimized (Beta = 1.5)	0.12	0.21	0.48
Market	0.11	0.15	0.58

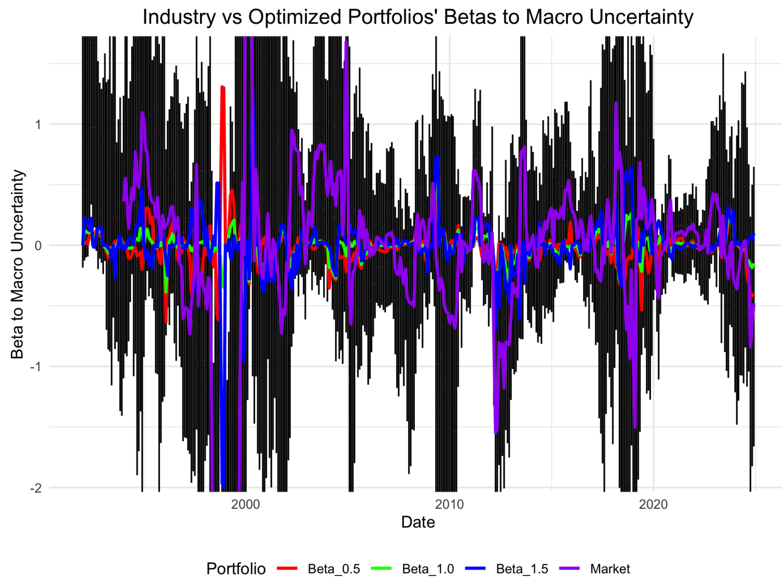
The chart below ranks industries and optimized portfolios based on their average standardized sensitivity to macroeconomic and policy uncertainty factors. Higher scores indicate greater exposure to uncertainty. Consistent with our goal, the optimized portfolios (in blue) exhibit significantly lower sensitivity compared to most industries, demonstrating that our strategy effectively minimizes exposure to uncertainty shocks while maintaining desired market beta targets.



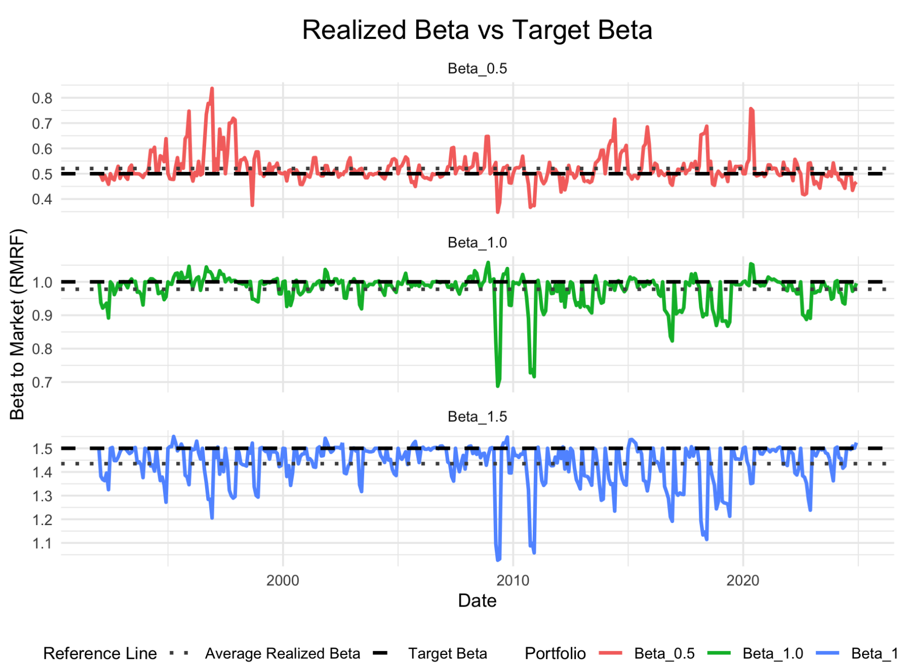
This plot shows the normalized average beta exposures of each optimized portfolio to different uncertainty factors. It highlights that the portfolios primarily load on Macro and Financial Uncertainty factors, while exposures to Trade Policy Uncertainty (TPU) and Economic Policy Uncertainty (EPU) are close to zero, suggesting that TPU and EPU risks are largely insignificant compared to broader macro-financial uncertainties.



This figure shows the realized beta to macroeconomic uncertainty for each industry and the optimized portfolios over time. The optimized portfolios maintain consistently lower and more stable macro uncertainty exposures compared to the market and most industries, demonstrating the effectiveness of the optimization in controlling macro risk sensitivity. All other factors are all in the appendix.



This figure below compares the realized market beta of each optimized portfolio to its target beta over time. The realized betas closely track their respective targets (0.5, 1.0, and 1.5) on average, with some fluctuations, particularly during periods of market stress, confirming that the optimization effectively controls market exposure over time.



Conclusion

In this project, we set out to explore whether trade policy uncertainty and other related economic factors are significant enough to require a specially constructed portfolio. Using clean and reputable data sources, including Ken French's data library and Sydney Ludvigson's macro and financial uncertainty indexes, we managed to construct a unified dataset sampling from 1990 to 2024 by combining asset returns and multiple uncertainty factors.

Then, we implemented a dynamic portfolio optimization framework that allowed us to control various exposures, from the market factor to multiple forms of uncertainty including the TPU and EPU. Our methodology incorporated rolling window regressions, beta shrinkage, and soft penalty optimization to keep exposures aligned with target values while maintaining a fully vested portfolio. On top of this, we built an R Shiny application that made the optimization process dynamic. Indeed, it allowed the adjustment of target betas interactively.

Ultimately, our optimized portfolios, especially designed to manage trade policy sensitivity, did not materially outperform the market. In terms of Sharpe ratios and overall risk-adjusted returns, the optimized portfolios closely matched the market's performance, for target market betas close to 1. This result suggests that, at least over the period we studied, the broad equity market already does a reasonably efficient job at absorbing and pricing in trade policy risks.

Although industries such as Steel, Autos, and Fabricated Products showed notable sensitivity to trade policy uncertainty individually, this did not translate into meaningful inefficiencies when diversified across sectors. Markets appear resilient to trade shocks at the aggregate level, and specialized portfolio construction to hedge TPU does not seem to yield superior performance when compared to simply holding the market.

Looking forward, while past trade wars (such as the U.S.–China escalation) produced only moderate and transient distortions, the structure of global supply chains continues to evolve. If future policy shifts, such as more persistent de-globalization or regional trade blocs, were to reshape industries more profoundly, TPU-sensitive strategies might become more valuable. However, based on the historical evidence, a well-diversified market portfolio remains a robust choice even amid trade-related uncertainties.

References

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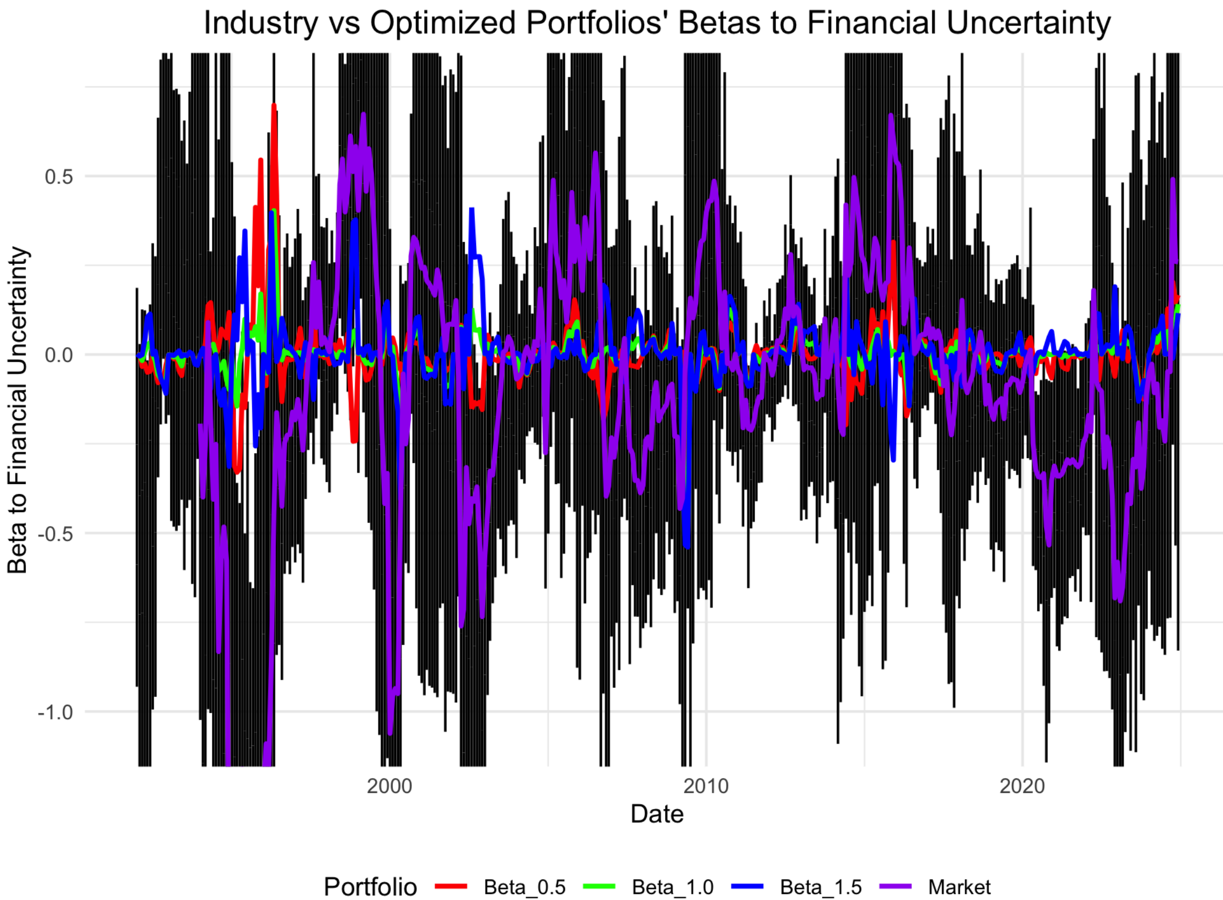
Ludvigson, Sydney C. (2025). *Uncertainty Data: Macro and Financial Indexes*. Retrieved from. https://www.sydneyludvigson.com/

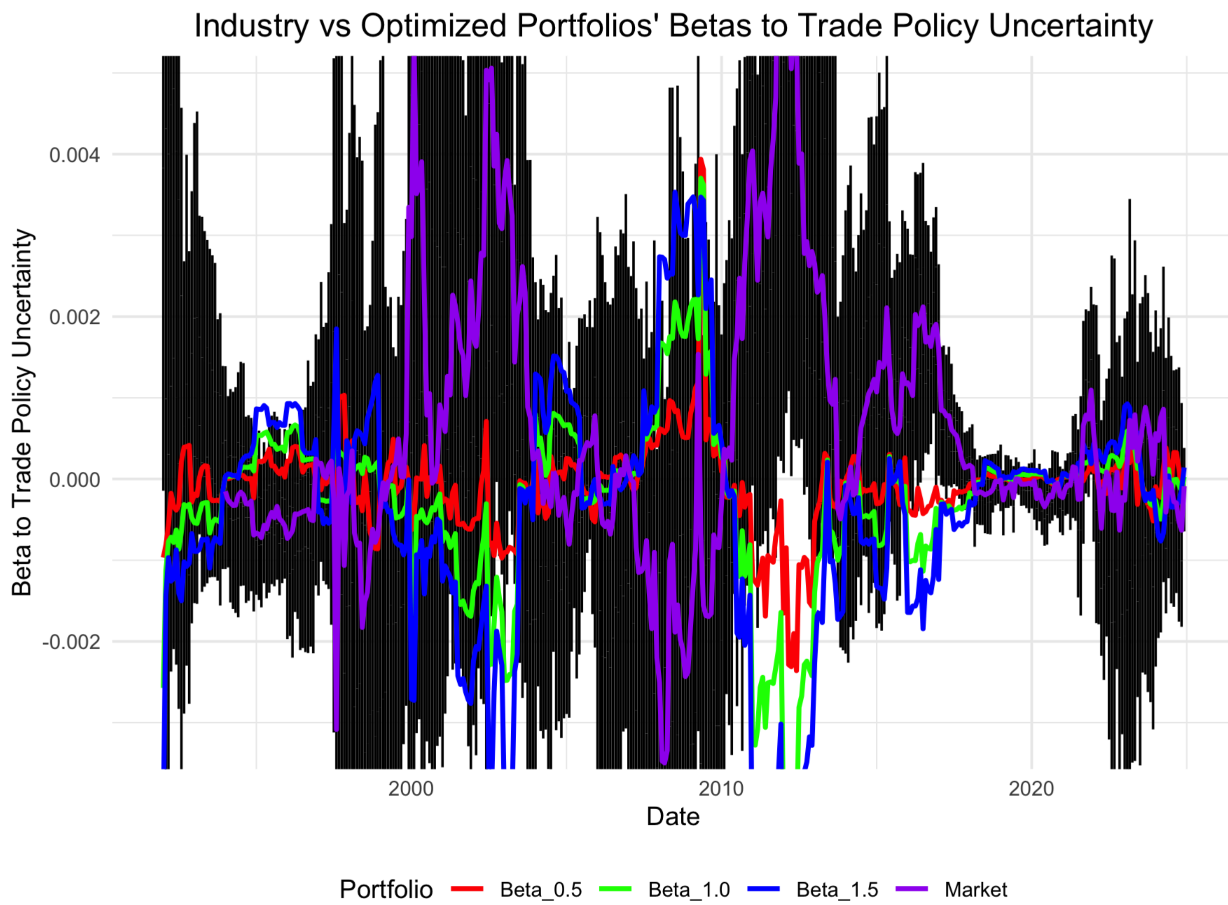
Appendix

1.

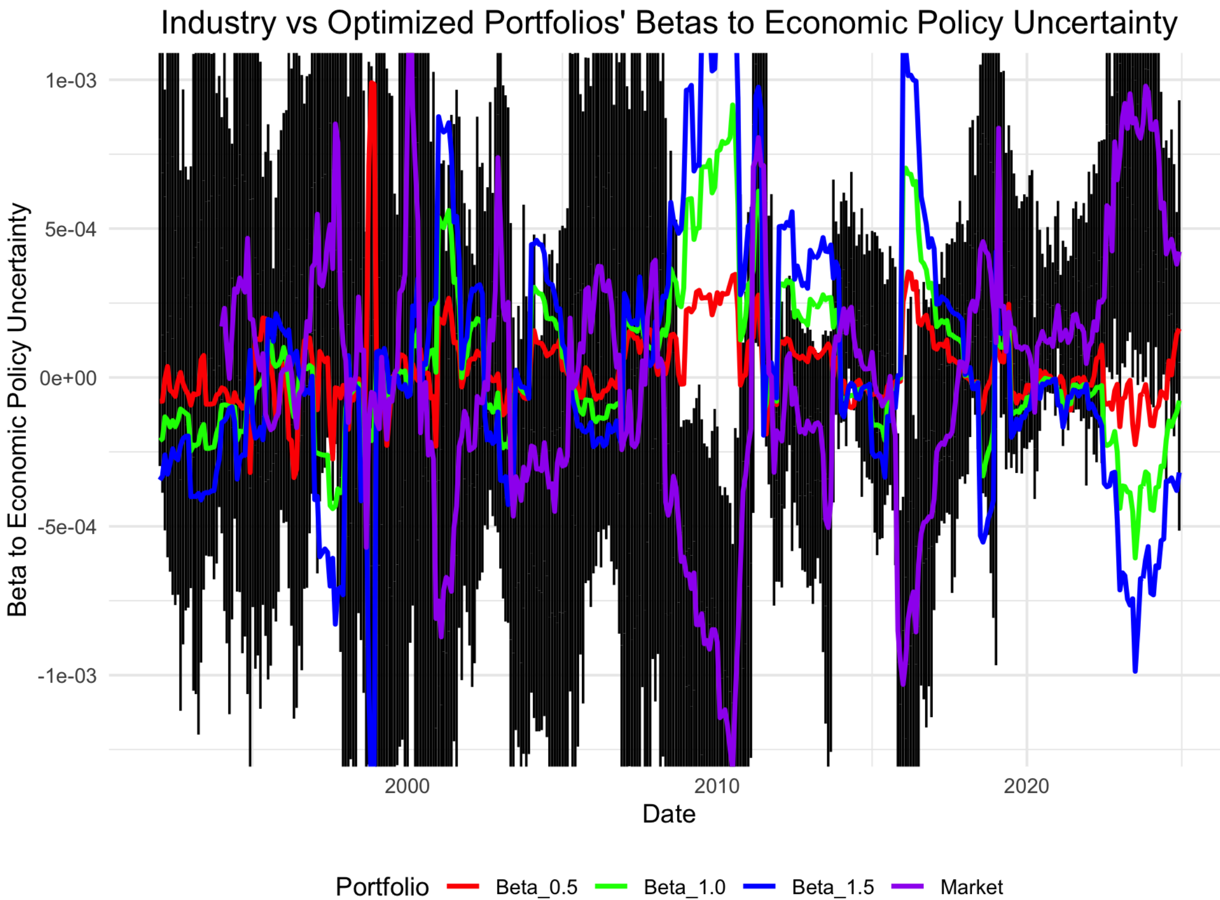


Industry vs Optimized Portfolios' Betas to Financial Uncertainty
Beta to Financial Uncertainty
0.5
0.0
-0.5
-1.0
2000
2010
2020
Date
Portfolio
Beta_0.5
Beta_1.0
Beta_1.5
Market

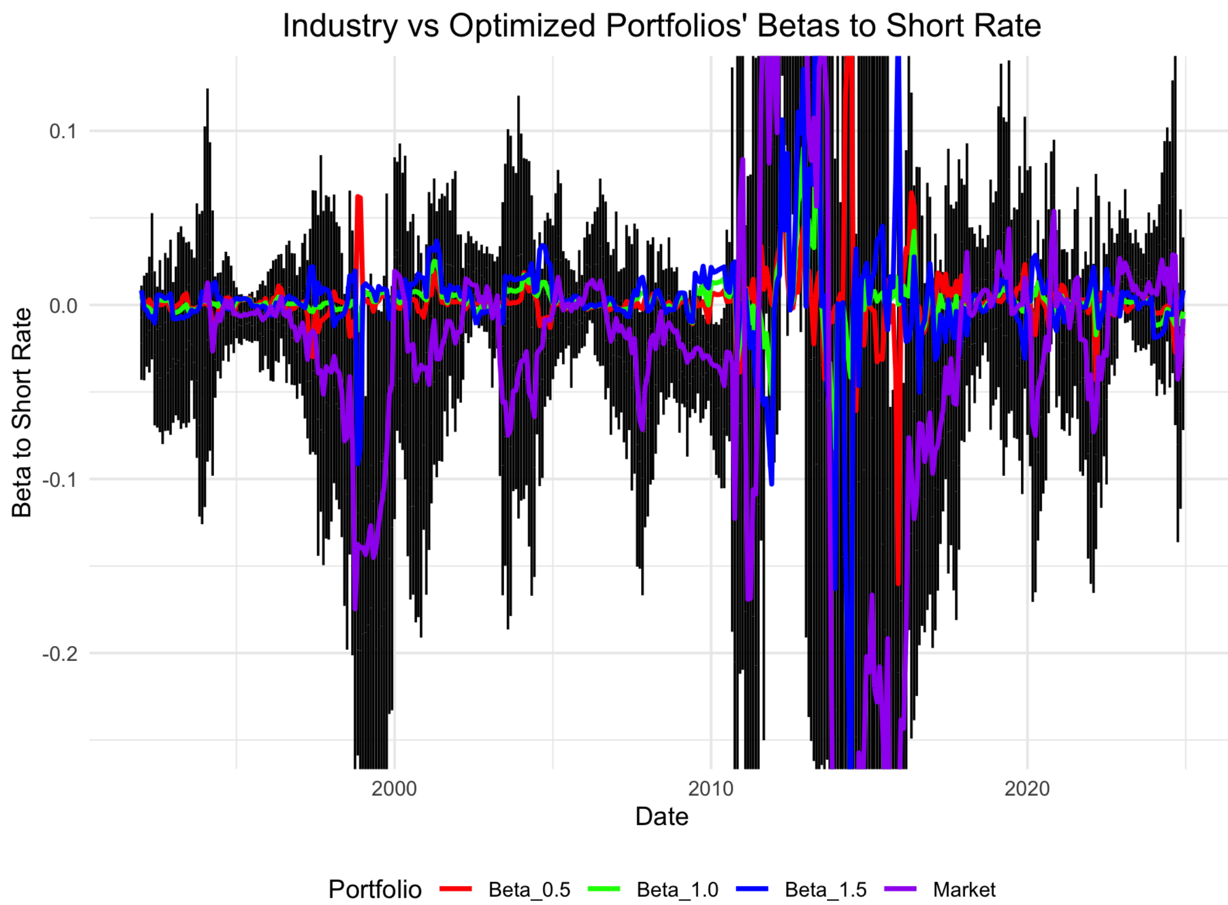
2.


Industry vs Optimized Portfolios' Betas to Trade Policy Uncertainty
Beta to Trade Policy Uncertainty
0.004
0.002
0.000
-0.002
2000
2010
2020
Date
Portfolio
Beta_0.5
Beta_1.0
Beta_1.5
Market

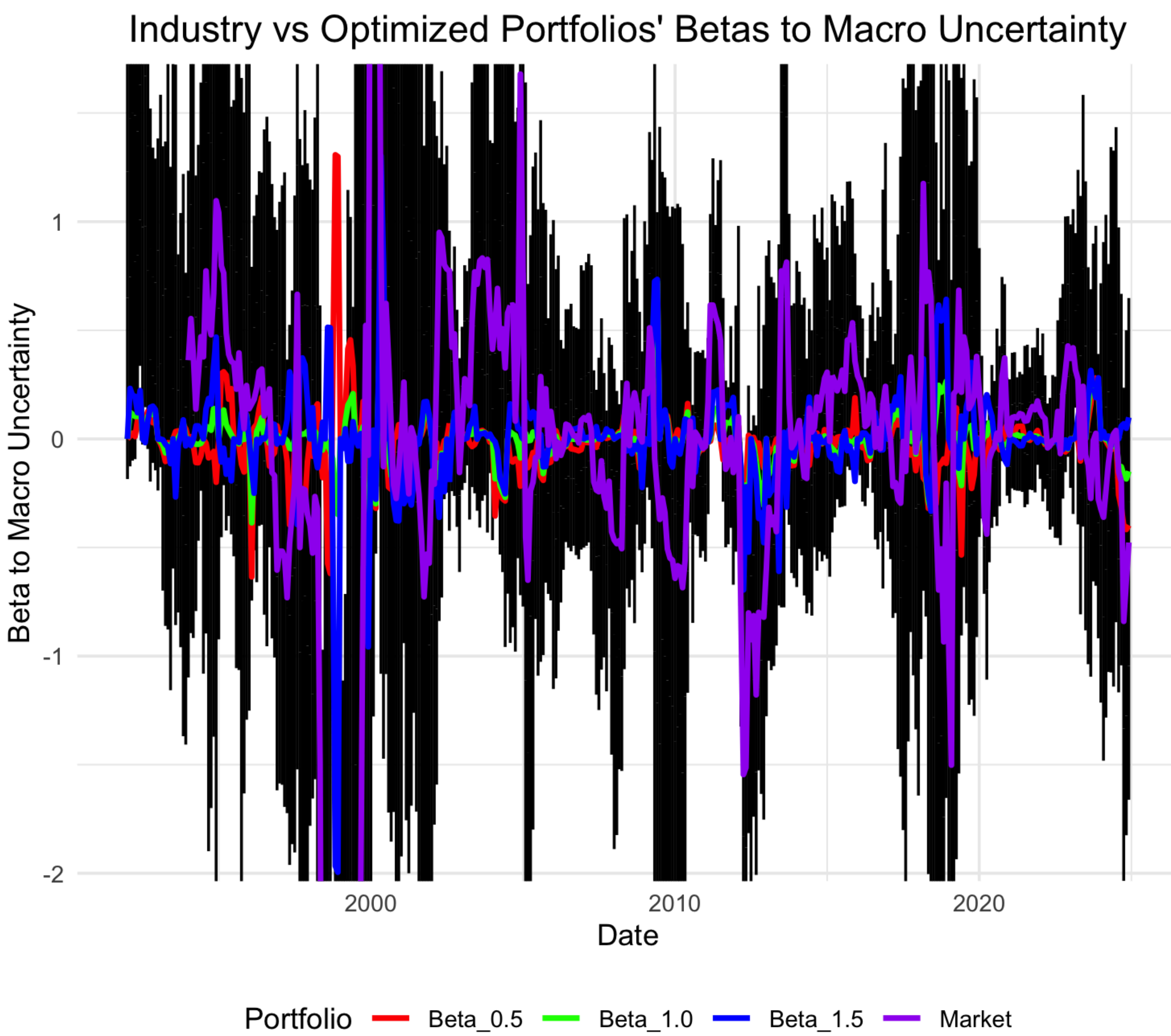
3.


Industry vs Optimized Portfolios' Betas to Economic Policy Uncertainty
1e-03
5e-04
0e+00
-5e-04
-1e-03
Beta to Economic Policy Uncertainty
2000
2010
2020
Date
Portfolio
Beta_0.5
Beta_1.0
Beta_1.5
Market

4.


Industry vs Optimized Portfolios' Betas to Short Rate
Beta to Short Rate
0.1
0.0
-0.1
-0.2
2000
2010
2020
Date
Portfolio
Beta_0.5
Beta_1.0
Beta_1.5
Market

5.


Industry vs Optimized Portfolios' Betas to Macro Uncertainty
Beta to Macro Uncertainty
1
0
-1
-2
2000
2010
2020
Date
Portfolio
Beta_0.5
Beta_1.0
Beta_1.5
Market