RESEARCH PROJECT

Optimization of Financial Risk: How Economic Policy Uncertainty (EPU) impacts risky asset returns and volatility

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Abstract

Recent economic recessions and financial market failures have indicated that markets are unstable and drastic changes deemed seemingly unexpected. The traditional indicators investors and economists utilize no longer have the full capability to predict major changes in the market. While the modern-day internet infrastructure allows investors to have unlimited information, asymmetric information exists in the market; noise in the market prevents investors from being fully exposed to true factor signals. The economic policy uncertainty engineered by Baker, Bloom, and Davis captures market sentiment and expectations of economic policy to estimate the level of market uncertainty. Thus, borrowing on techniques often used by hedge funds to capture market signals, this paper attempts to study and decompose the relationship of uncertainty towards risky asset returns and volatility. By the EPU index along with macroeconomic indicators, the model attempts to regress cumulative absolute returns, studying both lag effects in the market and volatility of risky assets, through an event study analysis of various past recessions.

Keywords:

Economic policy uncertainty, EPU, beta, volatility, returns, effects of recession, risky assets, asset classes, uncertainty

1 | INTRODUCTION

Financial markets are deeply sensitive to shifts in economic policy, and uncertainty around these policies can ripple across global asset prices, investor sentiment, and overall market stability. The main question posed to all types of investors – *Buy or Sell* – becomes an often-debated topic in the financial market. Given the oversaturation of the market and misleading signals investors use, uncertainty is a topic to consider. Policies change and politics spin in ways the market cannot expect, how would it alter investors' decisions?

The underlying research topic for this capstone project revolves around the fluctuations of the Economic Policy Uncertainty (EPU) index; more specifically, how does EPU influence the returns and volatility of risky assets? Using various models, this paper attempts to study the relationship between the dynamic economic environment and risky asset pricing returns and volatility that can be a deciding factor for investment portfolios. For investors and firms, understanding how such uncertainty translates into asset price movements is crucial; even small miscalculations lead to significant financial losses.

By looking at the EPU index historically, we get a sense that EPU both fluctuates with the business cycle, but also during macroeconomic events, referring to *Figure 2*. Policies change dramatically when economic recessions occur, such as the impact we see during the COVID-19 pandemic and the past financial crisis. Although the research question focuses narrowly on the connection between EPU and risky asset classes, the broader implications are highly practical. As economic and political uncertainties become more frequent and complex, both institutional investors and policymakers need clearer tools to anticipate market reactions. This study aims to contribute meaningful insights, offering a nuanced view of how uncertainty shapes market behavior across traditional and alternative asset classes.

2 | LITERATURE REVIEW

Researching the impact of various economic indicators on investment decisions is not a new topic; in fact, this study has been repeated, altered, and improved throughout with using different approaches and data. An older Princeton publication written by Dixit and Pindyck (1994) titled, "Investment Under Uncertainty" dives into the theory behind Baker, Bloom, Davis's (2013) methodology. It becomes the basis of why uncertainty provides much volatility for firms on both the micro and macro level. However, this was theoretical and not driven by quantitative data. Years after Baker, Bloom, Davis (2013) took this into their consideration and provides a study that becomes a central methodology for many literatures.

Authors Baker, Bloom, and Davis initially created the methodology to calculate the economic policy uncertainty using 3 main components of data: newspaper sources indicating policy-related uncertainty, "reports by the Congressional Budget Office (CBO) that compile lists of temporary federal tax code provisions", and lastly, "the dispersion between individual forecasters' predictions about future levels of the Consumer Price Index, Federal Expenditures, and State and Local Expenditures" from various Federal Reserve Banks in the United States, but mainly the Philadelphia Fed Reserve. Along with their unique methodology, the authors have analyzed times of uncertainties during recessions, wars, terrorist attacks, and other events. The paper summarizes the following that the index "broadly [remains] consistent with theories that highlight negative economic effects of uncertainty shocks". While the paper hypothesizes the general trend that supports commonly held beliefs, it does not provide enough assertion for the stock market, more specifically risky asset pricings. One critique of the methodology is that an overreliance of using the frequence of newspaper-related mentions of market sentiment uncertainty may add to the noise in the data.

In a publication, Brogaard and Detzel (2015) critique similar features in their journal, citing the need for supplemental factors to aid in determining the uncertainties in the market. Through their journal, they provided a supported hypothesis that “portfolios with the greatest EPU beta underperforms the portfolio with the lowest EPU beta by 5.53% per annum” as a measurement of impact towards the stock market. Relying on Baker, Bloom, and Davis’ methodology too, journal authors Al-Thaqeb and Algharabali find parallelism in their works, supporting the impact of EPU on the markets, but more so focusing on quantifying the “dynamic and grows and changes quickly. One thing that the paper admits to lack is the study on the impact of actual interest and inflation rates of the EPU, which will be addressed in this paper surrounding EPU and event study asset pricing models. Meanwhile, a journal written by Kang, Lee, and Ratti (2014) using the EPU index focuses on a different aspect of the market by studying the time lags and lasting period of impact of policy uncertainty. One of the strengths of performing an event study analysis allows researchers to examine cross sectional events with time series data, which is also incorporated in this research project.

A newer study done on the stock market of Croatia looks into how the economic environment of recent Agrokor Case in Croatia has fluctuated levels of uncertainty, causing rippling effects onto the stock market – Škrinjarić, and Orlović (2019). This paper breaks down the hundreds of factor signals that come to play when deciding the movement or momentum of the stock market in response to uncertain stimuli. Unlike other papers mentioned before, this paper uses an event study analysis to look at the periods in which the uncertainty takes into effect on the market. Similar techniques are absorbed in this research project.

Even more recently, based on an article written by Jiang, Kang, Meng (2024), authors also write about the uncertainty index on the stock market; however, the paper does not go into depth about other risky assets and only applies time series analysis. Therefore, we can dissect further in this paper in comparison with other prior research, a strength in using the event study analysis and Two-Way Fixed Effect model.

Opportunities for Research

After looking at historical journals and articles published by other authors, we see some strengths and some critiques as well. Many of the articles cite that the EPU index provides a satisfactory factor into asset pricing models; however, it isn't enough. We combine other factors like CPI index, short and long-term bond pricing, volume and liquidity of the market to find the cumulative absolute returns, and ultimately the attractiveness of asset investments. We also find that in many articles, only time series analysis is used for financial data. While that is applicable, we choose instead to focus on the event study analysis to cover a wide array of market shocks, over a large period of time to be able to detect lags in events of uncertainty. We apply this methodology across numerous types of assets which would make it more realistic within a firm setting to allow diversification of a portfolio. Looking at past journals is crucial to set apart methodologies that need improvements and methodologies that can be implemented within this research paper. All in all, this paper hopes to achieve a tool that can be implemented by firms to study how different types of events, reaching varying degrees of uncertainty, can affect the returns gained by risky assets, regardless of the type of asset.

3 | CONCEPTUAL FRAMEWORK

This paper is grounded in two key areas of theory: financial asset pricing models and broader economic theories of uncertainty. In finance, the fundamental concept of the risk-return trade-off tells us that investors demand higher expected returns for holding riskier assets. According to Modern Portfolio Theory (Markowitz, 1952) and the Capital Asset Pricing Model (CAPM)[1], any rise in perceived risk, such as an increase in economic policy uncertainty (EPU), leads investors to readjust or rebalance their portfolios. Typically, they reduce exposure to risky assets like stocks, commodities, and cryptocurrencies, and shift funds toward safer investments like government bonds or generally fixed incomes. This reallocation is expected to drive down the returns of risky assets and increase their volatility, as markets react more sensitively to unpredictable news.

A core theory behind these adjustments is investor risk aversion. Risk aversion refers to the tendency of investors to prefer more certain outcomes over uncertain ones, even if the expected returns are the same. When uncertainty increases, risk-averse investors are likely to flee from volatile assets, or assets that may fluctuate overnight, amplifying price declines and pushing up volatility. This behavior is also reinforced by institutional investors – such as mutual funds and pension funds – that often have strict risk management guidelines. As EPU rises, the market as a whole becomes more cautious in which liquidity may tighten, and bid-ask spreads can widen, creating further instability. This risk-averse reaction is a critical driver that transmits economic uncertainty into financial market outcomes.

[1] These are financial models often cited for portfolio techniques

Economic theory further strengthens this expectation. The Real Options Theory (Dixit & Pindyck, 1994) explains that firms, when faced with increasing uncertainty, tend to delay investment and hiring decisions, waiting for clearer signals about future policy or market conditions. This contraction in investment can slow economic growth, reduce corporate earnings expectations, and weigh on overall market performance. Similarly, consumers may hold back on major purchases, and confidence in the broader economy can dramatically reduce, as described in Keynesian economics' "*animal spirits*" idea (Tardi, C. 2023). When markets are calm, markets behave the way that theories; however, the combined effect of these behaviors contributes to deteriorating economic fundamentals and theories and may lead to unexplained market movements.

This link between risk aversion, economic behavior, and financial market dynamics suggests that periods of high EPU should correspond with declines in risky asset returns and increases in volatility. However, while traditional asset classes like stocks and bonds fit neatly within this framework, some asset classes present ambiguities (Bradley, Richard). For example, gold and certain commodities are sometimes viewed as safe havens during periods of uncertainty, potentially rising in value. More recently, cryptocurrencies have sparked debate: do they behave like risky tech stocks, or are they evolving into a form of "digital gold" that could act as a hedge against uncertainty? This paper will explore this theory as well. Economic and financial theories offer competing predictions here, making empirical analysis essential. This paper tests these theoretical expectations using a rich dataset of daily returns across multiple asset classes from 1999 to 2025, aiming to clarify how different markets respond to rising policy uncertainty, especially during recessions and other market shocks.

4 | DATA & VARIABLES

The dataset combines various assets stacked together in a panel that has daily prices collected from Jan 1, 1999, to Feb 28, 2025. Several assets have been selected carefully: choosing assets with high betas or volatility and a long historical price. Essential commodities are used as well, namely Gold, Oil, and Wheat. The S&P data has also been collected to act as a benchmark or base reference for equity returns, accounting for the general trend of the market[2]. With this, continuous returns are calculated, along with both forward and backwards volatility in different day intervals. Using raw price data is ineffective and generally unaccepted as comparison between risky assets and asset classes become challenging. Furthermore, prices are hard to compare between equities and commodities, thus justifying the use of returns.

The main dependent variables used are the continuous returns and forward rolling standard deviations of 2 and 3 days. As for the independent variables, the daily EPU index has been collected and matched with the daily stock prices. Previous volatility has also been captured using a backwards standard deviation, looking at the past 3, 5, 10, 30, 60-day intervals. Monthly inflation, from CPI and PCEPI indexes, interest rates, and the unemployment rate is also recorded. Acknowledging macroeconomic indicators that are provided by month, the daily asset data takes for the respective month's indicators. Lastly, expectations of inflation are also used to capture market sentiment and given a dummy variable when the actual inflation exceeds expectations.

Asset Classes:

- ETFs

[2] Bloomberg L.P – All prices are taken and referenced from Bloomberg.

- Single Stocks
- Treasury Notes (5-10 Years)
- Government Bonds
- Commodities (Oil, Gold, Wheat)
- Cryptocurrencies (Bitcoin, Ethereum, DOGE)
- REITs (Real Estate Equities)
- Mutual Funds

Dependent Variables:

- Continuous returns (%)[3]
- Forward rolling volatility in 2 and 3-day intervals

Independent Variables:

- EPU index (baseline = 0),
- Macroeconomic Indicators (CPI, Interest Rate, Unemployment Rate, all with % units represented as decimal numbers),
- 3, 5, 10, 30, 60-day standard deviation (%)
- Dummy variable for inflation expectations
  (0 – Actual not exceeding expectations, 1 – Actual exceeding expectations)

Unit of analysis is performed at a national level in the US, reflecting the financial market.

Time Span: Daily prices across Jan 1, 1999, until Feb 28, 2025.

Structure: Panel Data with approx. 150,000 observations, and an estimated 1-million-dimension size, accounted for multiple variables in Stata.

[3] Calculated by taking the natural logarithm of prices change

5 | EMPIRICAL METHODOLOGY

This paper is designed to test the key predictions of the theoretical framework found in the prior section. Generally, rising EPU leads to lower returns and higher volatility in risky asset markets. However, we want to quantify and check for this, but at the same time, see if there are any discrepancies between asset classes that may disagree with this theory.

To capture these dynamics or changes, I am using a panel data approach with daily data across multiple asset classes such as Stocks, ETFs, Commodities, Cryptocurrencies, and numerous Fixed Incomes, from January1999 to February 2025. Using daily prices over 20 years taken from Bloomberg, we are able to see changes within each asset class and over time periods, and various recessions.

To control both time-invariant asset characteristics, in other words, each asset's inherent risk behavior, and common shocks such as macroeconomic events, we employ a Two-Way Fixed Effects (TWFE) model. This allows us to isolate the effects of EPU from other factors. We hope that from this, we are able to see not only the changes for each asset class and how they react to higher levels of EPU, but the movements from one asset class to another. For example, investors who are risk averse may choose to reallocate their portfolio to fixed incomes or commodities for a more certain, but lower return.

The main TWFE model to see the impact of EPU on returns is listed below:

$$Returns_{it} = \beta_0 + \beta_1 \cdot EPU_{t-1} + \beta_2 \cdot (EPU_{t-1} \cdot AssetClass_i +$$
$$\beta_3 \cdot (Macroeconomic\ Indicators_{it}) + \alpha_i + \lambda_t + \varepsilon_{it}$$

$Returns_{it}$ – Continuous Returns

This is the main dependent variable that is tested. We take continuous returns of prices. Price data does not reflect the true nature of stocks, due to undervalued or overvalued assets, and using returns allow us to compare for different asset classes.

β_0 – Constant Coefficient

This constant refers to the baseline return if all factors are zero.

EPU_{t-1} – Economic Policy Uncertainty Index at time (t-1)

We capture this index at a given time of t minus 1 as we would like to capture the forward effect of uncertainty on the next price/return term. Uncertainty affects only the next terms, and not the returns before it.

$EPU_{t-1} \cdot AssetClass_i$ – Main Interaction Term

Our EPU index and the Asset Classes are multiplied to achieve the heterogeneous effects of EPU across different asset classes we have chosen. This allows us to get a better understanding into how the effects change.

α_i – Asset Fixed Effects

This term captures all time-invariant characteristics specific to each asset class, allowing a control for differences between assets that do not change over time.

λ_t – Time Fixed Effects

This term controls for shocks or factors that hit all assets at a specific time, t, such as COVID news, Fed Announcements, or other macroeconomic events.

ε_{it} – Error Term

This term refers to the unexplained part of the model, capturing random shocks or factors that affect asset returns at a given time but are not included in the model's variables. We expect that the unexplained variances in our model can be large but would largely be justified by unrelated noise or movement in the market caused by large hedge funds or other factors.

We also apply a TWFE model for a forward volatility to see how increasing EPU affects volatility for the next several days or weeks. Again, we employ a similar model, but change the dependent variable that is regressed.

$$Volatility_{it} = \beta_0 + \beta_1 \cdot EPU_{t-1} + \beta_2 \cdot (EPU_{t-1} \cdot AssetClass_i + \\ \beta_3 \cdot (Macroeconomic\ Indicators_{it}) + \alpha_i + \lambda_t + \varepsilon_{it}$$

$Volatility_{it}$ – Forward Volatility of Assets

This other dependent variable looks into the 3 or 5 day forward rolling volatility at a time of t on each asset. This measures the standard deviation. While a backwards rolling volatility is a independent variable integrated as part of the controls, we are still integrating it into the model to see previous effects on the current EPU.

By using Two-Way Fixed Effects[4], the analysis controls for differences between assets and for events that affect all assets at the same time. This helps make sure that the effect of EPU is measured accurately and isn't distorted by hidden factors, giving a stronger test of the idea that policy uncertainty lowers returns and increases market volatility. Please refer to Figure 3 on expectations and sign predictions for the variables in the model.

[4] Used the xtreg command on Stata for the TWFE

Event Study Analysis Extension

To complement the panel regressions, we conduct an event study focusing on the impact of uncertainty around the onset of the COVID-19 pandemic. This event was not only a shock to the financial market, but also reverberates across factors economically, politically, and socially.

Modeling this, we get the estimated model:

$$Returns_{it} = \sum_{k} (\beta_k \cdot EventTime_k) + \alpha_i + \lambda_t + \varepsilon_{it}$$

$\sum_k (\beta_k \cdot EventTime_k)$ – Effect Impact within time frame

In this model, we bin daily returns into weeks leading up to and trailing the COVID-19 announcement that occurred in March of 2020. We set the week of the announcement as the base reference so we can compare changes related to it.

We can expect that the parallel trends assumption holds prior to the announcement and experience drastic changes in returns based on the fluctuations and amplification of EPU.

6 | RESULTS

The results of our analysis largely confirm the predictions laid out in our conceptual framework. We expected that increases in EPU would lead to lower returns and higher volatility across risky asset markets, and the data supports this for most asset classes. In the returns model, EPU has mostly a negative and statistically significant effect on assets like ETFs and treasuries, aligning with the prediction that heightened uncertainty prompts risk-averse investors to pull back from risky assets. Similarly, the volatility model shows a positive and significant relationship between EPU and realized volatility, confirming that uncertainty contributes to greater price instability. However, one interesting exception emerged: cryptocurrencies displayed a positive and significant return to EPU, suggesting that in contrary to traditional risky assets, cryptocurrencies may behave more like a hedge in times of policy uncertainty. On the other hand, investors may also see the potential to drive returns by correctly interpreting momentum. Overall, the main theoretical predictions stay consistent in the empirical tests, with a notable nuance for newer asset classes. Because we were handling daily returns, the effect on returns were scaled by about 47 points, reflecting the average net change in daily EPU.

Returns TWFE Model

One of the main findings is that commodities and Treasuries (10Y notes) show significant and substantial sensitivity to increases in economic policy uncertainty. Specifically, the model estimates that a typical rise in the EPU index leads to a 0.02% daily loss for commodities with a p-value = 0.036 and a much larger 0.56% daily loss for Treasury notes with a p-value = 0.000, both of which are statistically significant.

For example, our model predicts that, on average, a 47-point increase in the EPU index leads to a 0.56% percentage point loss for treasury notes, relative to the base returns, holding all other factors constant. This was tested at the statistically significant level of 1%, in which the test returned a p-value = 0.000, concluding that treasury notes showed a statistical decrease in returns in response to increasing EPU.

In contrast, cryptocurrencies behave very differently and the results diverge from the theoretical framework. The model estimates, on average, a 0.53% daily gain in response to a 47-point gain in EPU, which is both statistically significant at the 1% level and economically significant. This suggests that cryptocurrencies may serve as a hedge or a speculative outlet during periods of high uncertainty, standing apart from the pattern observed in more traditional risky assets. Despite being a newer asset class, risk in cryptocurrency is seen as a positive signal in the market, a chance to gain profit from economic uncertainty.

We also found that bonds, longer term fixed incomes, had a more subtle effect. With the same 47-point increase in EPU, the model predicts that on average, bonds experienced a 0.0075%-point daily loss, holding all other factors constant. This shows that while EPU fluctuates daily, the "appetite" for uncertainty becomes marginal on the long run. Bonds are typically 30 years, and changes in the short term do not expect expectations as much.

The findings found from the TWFE returns model are broadly consistent with existing research on the impact of economic policy uncertainty (EPU) on financial markets. Baker, Bloom, and Davis established that rising EPU tends to depress stock market returns and increase volatility, nothing that "elevated policy uncertainty is associated with declines in equity prices and increases in stock price volatility" (Baker, Bloom, Davis, 2016). This pattern echoed in our results for commodities and treasuries, where we observe significant daily losses of around

0.02% and 0.56%, respectively. Similarly, Bloom emphasizes that "uncertainty shocks generate large and rapid drops in investment and output," supporting our observation that policy uncertainty negatively affects traditional asset classes (Bloom, 2009). The International Monetary Fund's Global Financial Stability Reports also routinely highlight that "surges in policy uncertainty tend to tighten financial conditions and weigh on risky assets," reinforcing the theoretical expectation of lower returns during turbulent periods (*Global Financial Stability Report,* 2025).

The one notable divergence in our results is the behavior of cryptocurrencies, which exhibit a significant positive return response to EPU shocks. This aligns with Bouri et al., who argue that "Bitcoin exhibits safe haven properties against global uncertainty at certain times," suggesting that crypto may play a different role in financial markets compared to traditional assets (Bouri, 2017). While Smales highlights that "gold has long been viewed as a safe haven asset during periods of financial uncertainty," our broader commodity category showed a negative reaction to EPU, indicating that not all commodities respond in the same way (Smales, 2018). In our dataset, we did not just include gold, but also oil and wheat. Overall, our empirical results fit well within the existing literature, while also providing potentially new insight into how emerging asset classes like cryptocurrencies behave when policy uncertainty rises.

<u>Volatility Model</u>

The volatility model results align closely with the patterns we observed in the returns model, showing that increases in economic policy uncertainty leads to heightened volatility for most asset types. For example, bonds, notes (10Y Treasuries), REITs, and stocks all show a statistically significant rise in their 3-day forward volatility following EPU shocks. This indicates that uncertainty not only dampens returns but also destabilizes asset prices, making them more volatile in the short term. Stocks, in particular, experience widening price swings, which explains why investors often retreat from equities during periods of high uncertainty; as the standard deviation of returns grows, the risk of large losses becomes more pronounced, reinforcing risk-averse behavior.

This model predicts that when a typical 47-point EPU shock occurs, bonds experience an average increase of 0.0374% in 3-day realized volatility, while 10Y Treasury notes see a slightly higher increase of 0.0094%. Stocks also show a meaningful rise in volatility, with a 0.0031% increase, confirming that economic uncertainty makes these traditional assets more unstable and riskier to hold. These effects highlight why investors tend to shy away from equities and fixed-income assets when policy uncertainty rises.

Interestingly, commodities and cryptocurrencies do not exhibit a significant increase in volatility in response to EPU changes. This suggests that, while these asset classes may still react to broader market forces, they are less sensitive to policy-driven uncertainty in terms of price instability. Cryptocurrency's minimal volatility response, despite its strong positive return to EPU, highlights its unique role in the market, possibly reflecting speculative dynamics or its emerging status as an alternative asset during market downturns.

The model shows no significant volatility response for commodities or cryptocurrencies, with changes of -0.0041% and -0.0008%, respectively, both of which are statistically insignificant. This suggests that these asset classes may be less sensitive to policy-driven uncertainty in terms of their short-term volatility, even though crypto displayed a strong positive return response in the returns model.

Overall, these volatility findings strengthen the argument that economic policy uncertainty discourages investment in traditional risky assets by making their future returns less predictable and more volatile.

Event Study Analysis

Next, we also wanted to see the impact of EPU over time. In this case, we chose to focus on the impact of EPU surrounding the COVID-19 pandemic. Due to the index and returns we have chosen based on the daily prices of assets, we binned the returns to a weekly period and looked at their average returns. For an event study analysis to work, we would expect the parallel trends assumption to hold before the event itself occurred. The time period we chose to look at was 5 weeks prior and 5 weeks after the event.

We ran for different asset classes and found different results among the 11-week period. Among the results, we found interesting, yet consistent data. Please refer to figures 7 and 8 to see the event study analysis plotted onto a graph. On figure 7, we see the movement of returns for ETFs vs Commodities. The returns for ETFs drastically dropped on the week and after the pandemic was announced and slowly bounced back up. However, commodities showed only a small, yet gradual decrease in returns over time, after the announcement. This followed our understanding found in the TWFE model that shows the more negative effect that ETFs had over commodities.

As with our results in the TWFE model, we wanted to see how cryptocurrencies reacted, differently to other traditional assets. Cryptocurrencies reacted positively to the EPU indexes and increased. While the trend on figure 8 shows a reversion to the average returns, the returns generally increased, showing a potentially bullish market, reflected through prices and returns.

Considering a myriad of factors, a decrease in investments in one asset class may indirectly increase the investments in another asset class. Reiterating this point, however, an increase in returns does not always hold as cryptocurrencies are also traded mainly by sentiment, and not traditional fundamentals. Even something as simple as updates on news platforms or social media may be enough to cause dramatic changes in the market.

Validity of Models

Both models appeared to be statistically robust and well-specified, with strong predictors and coefficients that are statistically significant for most asset classes. The use of the TWFE helps control for both asset-specific and time-specific shocks. The R^2 for both models were good, but especially substantial in the volatility TWFE model; it achieved a between asset-class R^2 of 0.9394 and a within R^2 of 0.4023. Between Asset Classes, the R^2 suggests that the model is able to explain 93.94% of the variation by using the variables used.

Additionally, the global utility test achieved an F-test of 172.77, leading to a P-Value of 0.000, or essentially zero. Without going into the hypothesis testing itself, this means that the model is significant, and we can conclude that there is enough evidence to reject the null, supported by the data we have.

Even though we clustered for both TWFE models, we still tested for autocorrelation and heteroskedasticity. Autocorrelation and heteroskedasticity are problematic because they can distort the accuracy of your standard errors, leading to incorrect p-values and confidence intervals. If present in the model, they can skew the data and lead to predictions or coefficients that are seemingly more significant than they actually are.

To test for heteroskedasticity, we ran a Modified Wald test that works with a TWFE model. It is used to detect groupwise heteroskedasticity in the residuals of a fixed effects panel model. This checks is the variance of the errors are the same across all the asset classes, which shows that the p-value is marginally greater than a level of 5% which shows that heteroskedasticity does not exist[5].

We also ran the Woldridge test to check for autocorrelation and both models showed that no autocorrelation was present. However, based on the data and variables integrated within the model, this could change as well. Thus, it is always good to check for both.

[5] Used xttest3 command on Stata to achieve heteroskedasticity test

7 | CONCLUSION

This paper attempts to reach meaningful conclusion by looking at the impact that Economic Policy Uncertainty (EPU) has on various asset classes. Before attempting to analyze data, though, we looked at previous studies done. Through a close examination of past literature and existing studies, this paper recognizes both strong findings and areas that needed more improvement in prior research. While many authors highlight the usefulness of the EPU index as a core component in asset pricing models, it becomes evident that relying solely on EPU is insufficient to capture the full complexity of market behavior. In response, this study incorporates additional macroeconomic factors, such as CPI measures, bond yields across different maturities, and liquidity and volume indicators, to create a more holistic view of asset returns and volatility, particularly during times of heightened uncertainty.

Although time series methods provide valuable insights, this research pivots toward a Two-Way Fixed Effect model and an event study framework, allowing for the assessment of asset behavior across a diverse range of market shocks and over extended periods. By applying the methodology across various asset classes, the study reflects realistic investment conditions and provides insight into how portfolios may be strategically adjusted in uncertain environments. In short, not all asset classes behave the same way: this is to be expected. However, we found most interesting that cryptocurrencies, volatile and often unreliable by nature, had positive returns in response to EPU and other macroeconomic factors.

While other asset classes had a varying degree of change in return stimulated by EPU, the 10-year treasury notes had a substantial change. Although it was surprising at first, it might make sense as restructuring of treasury notes occur frequently when overnight interest rates change over time. This may affect the volume and price at which investors may rebalance their portfolios. Bonds on the other hand had a small, yet negligible decrease in returns. Thus, unexplained variances in the error term may suggest other factors that have yet to be explored, which leads to extensions in future studies.

A valuable extension of this study would be to explore cross-country comparisons by applying the same methodology to international markets, allowing for an analysis of how EPU impacts differ across economic systems and regulatory environments. Future research could also examine sector-specific effects within asset classes, such as technology or energy stocks, to uncover more granular insights. Additionally, integrating high-frequency intraday data could provide a deeper understanding of how uncertainty shocks move within shorter time frames.

Another promising direction would be to assess the role of investor sentiment and media influence – particularly through social media platforms – which may amplify or dampen the effects of policy uncertainty, especially for emerging assets like cryptocurrencies. Lastly, linking EPU impacts to long-term portfolio performance and risk-adjusted returns would offer practical insights for institutional investors and asset managers aiming to optimize strategies under varying levels of economic uncertainty. Studying uncertainty at the daily level, however, may deter individual investors as fees to buy and sell assets become too high.

All in all, though, while EPU provides an insightful signal into how markets react to uncertainty, it should not be used as a sole factor. An increase in EPU does not always lead to a decrease in return. Investors who only use EPU as the only metric may see a declining value in their portfolio at the cost of ignorance. Inherently, the goal of this research is not to determine whether investors should buy or sell; instead, it highlights the importance of looking at uncertainty too. Financial markets often behave erratically to economic theory.

By building atop established theory while introducing new data dimensions and methods, this research project offers a different picture of how uncertainty shapes market behavior. As global markets continue to evolve, understanding these dynamics will remain essential for both academic research and practical investment decision-making.

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9 | Appendix

Figure 1 -

	Variable	Description	Mean	Min	Max	Stdev	S.Size
Independent	EPU Index (t minus 1)	The main indicator used to quantitate market sentiment and uncertainty from policies	110.174	3.32	1026.38	81.86	9,125
Independent	Interest (%)	Effective rate from treasury bonds	2.05	0.05	6.54	2.06	300
Independent	Inflation (%)	Inflation rate found from change of CPI index	2.56	-2	9	1.72	300
Independent	UNRATE (%)	Unemployment rate	5.63	3.4	14.8	1.94	300
Independent	HigherInfl.	Compares expected vs. actual inflation; dummy variable	0.61	0	1	0.49	300
Independent	3D Vol	Rolling standard deviation from the past 3 days, volatility index	0.018	0	4.76	0.041	145,510
Independent	90D Vol	Rolling standard deviation from the past 90 days, volatility index	0.022	0.0032	0.715	0.032	140,651
Dependent	Returns (%)	Continuous returns on stock prices using natural log	0.00014	-4.74	4.79	0.041	149,601
Dependent	3/5 Day Forward Volatility	Volatility is measured by taking the standard deviation of the next 3 or 5 days.		0.00		0.008	149,601

Figure 2 – Historical EPU

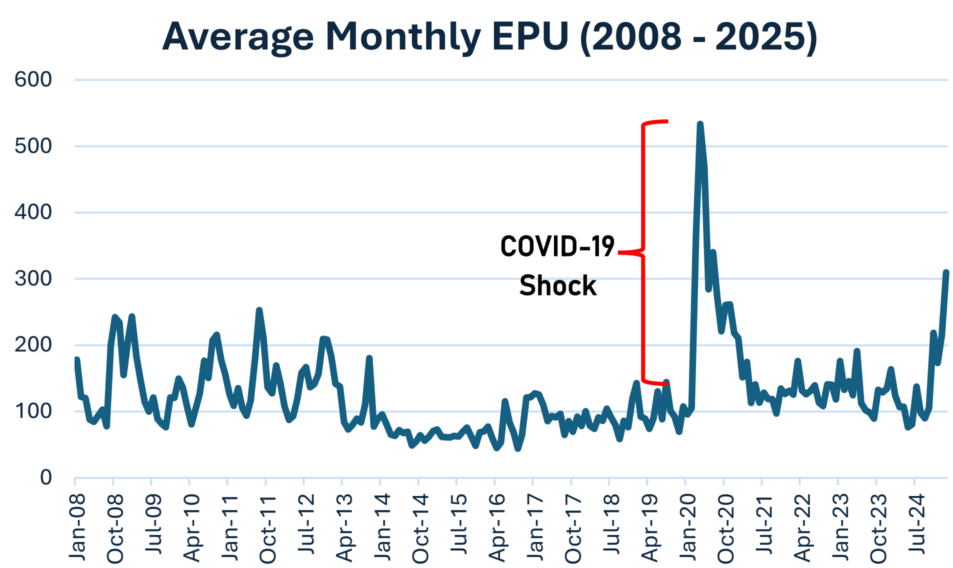

Figure 3 – Expectation & Theoretical Sign Prediction

Variable	Expected Effect on Returns	Expected Effect on Volatility	Reasoning
EPU(t-1)	Negative (↓)	Positive (↑)	Increased uncertainty leads to risk aversion which lowers returns & amplifies volatility.
EPU(t-1) × (AssetClass)	Ambiguous	Ambiguous	Stocks fluctuate. Bonds and Notes are often seen as safer assets. Crypto may act as either a risky asset or a hedge ("digital gold").
Interest Rate	Negative (↓)	Possibly Positive (↑)	Higher rates dampen risky asset performance; may increase volatility.
Inflation	Negative or Neutral	Possibly Positive (↑)	High inflation weakens returns; may increase volatility. Depends on Asset Class
Unemployment Rate	Negative (↓)	Possibly Positive (↑)	Reflects broader economic weakness, a market signal often used.

Lagged Volatility (for returns)	Possibly Positive (↑ short-term)	Persistence (↑)	Higher recent volatility can boost short-term returns and persist over time.

Figure 4 – Output: EPU on Returns for Key Asset Classes (Adjusted using mean EPU change)

Variable	β Coefficient	P-Value
Bond	- 0.0075% daily loss	0.0635
Commodity	- 0.02% daily loss	0.036
Crypto	+ 0.53% daily gain	0.002
Note (10Y)	- 0.56% daily loss	0.000
Stocks	+ 0.0015% daily loss	0.422

Figure 5 – Output: EPU on 3 day forward volatility

Asset Type	% Change in 3-Day Vol	P-Value
Bond	0.0374%	0.000
Commodity	-0.0041%	0.044
Cryptocurrency	-0.0008%	0.094
ETF	0.0071%	0.067
Mutual Fund	0.0065%	0.236
Note	0.0094%	0.000
REIT	0.00395%	0.000
Stock	0.0031%	0.000

Figure 6 – Impact of EPU on Returns Visuall

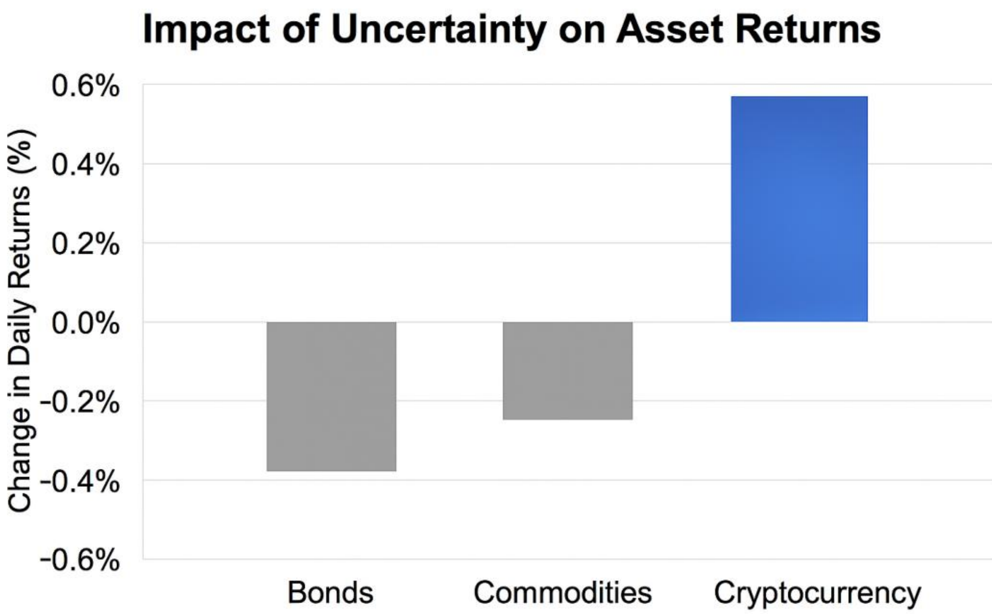

Figure 7 –

Event Study of ETF vs Commodities

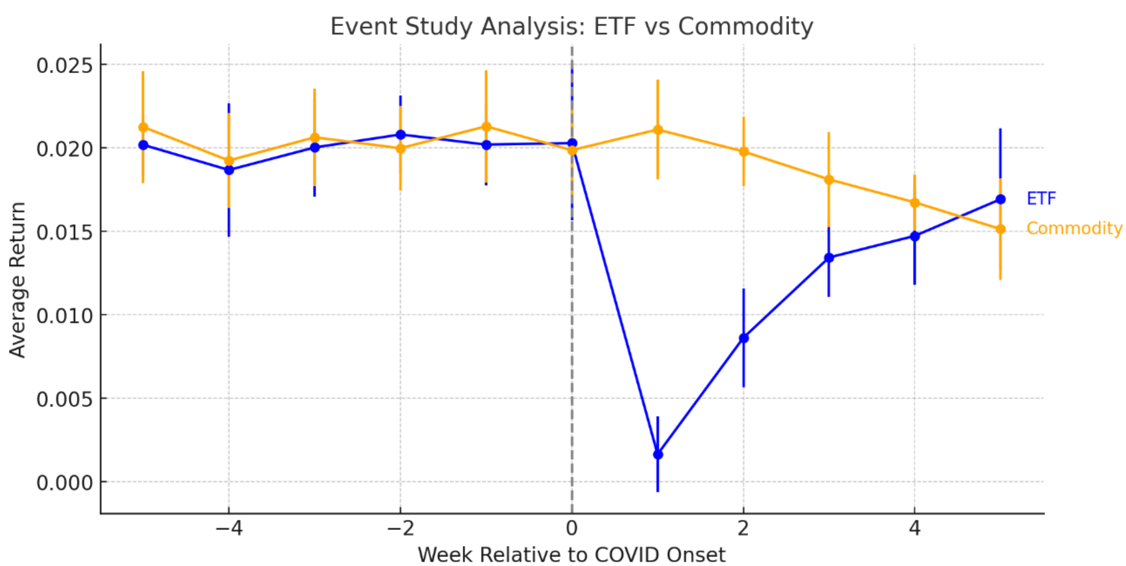

Figure 8 – Event Study of Crypto vs Commodities