

Can Newspaper-Based Uncertainty Indices Improve Forecasts of S&P 500 Returns?

A News-Based Uncertainty Analysis of the Efficient Market Hypothesis

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Abstract

This dissertation evaluates whether newspaper-based uncertainty indices improve forecasts of S&P 500 returns, testing the semi-strong form of the Efficient Market Hypothesis (EMH). The analysis employs a recursive, expanding window forecasting framework, evaluating performance across 1-, 3-, 6-, and 12-month horizons using MAFE and MSFE loss functions.

Findings reveal that while aggregate measures struggle to consistently outperform benchmark models, category-specific indices demonstrate enhanced predictive power. Agricultural Policy Uncertainty (APU) emerges as the most robust predictor across all four forecast horizons. Importantly, including category-specific factors like Trade Policy Uncertainty (TPU) and Elections and Political Governance Uncertainty (EPGU) greatly improves forecasting accuracy, exposing distinct “pockets of predictability” where their predictive capacity improves due to escalating tariff frictions and political ambiguity. While outperforming benchmark models remains a challenge, specialised, category-specific news indices provide invaluable, forward-looking insights into shifting market dynamics, offering an assessment of market efficiency through the lens of time-varying predictive capacity.

AI Statement

I acknowledge the use of generative AI in *code development* in this paper. However, the work reported remains my own.

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1.0 Introduction

In an era defined by rapid political and economic transitions, news-based uncertainty indices have emerged as critical tools for understanding how uncertainty transmits into equity markets. Newspaper-based indices, such as the Economic Policy Uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016), quantify this risk by measuring the frequency of uncertainty-related terms within news coverage. While these indices are widely used by central banks, governments, firms, and financial institutions to monitor uncertainty around fiscal policy, regulation, and economic decisions, existing literature surrounding their predictive power remains mixed. Some studies suggest these metrics provide strong forecasting performance, while others show they struggle to beat simple benchmark models in out-of-sample settings. This division is the primary motivation for this dissertation, directly testing the Efficient Market Hypothesis (EMH) to determine if public news holds practical value for financial forecasting.

To investigate this ongoing debate, this dissertation investigates whether ten uncertainty measures can improve S&P 500 return forecasts. Equity Market Volatility (EMV) indices are integrated alongside traditional measures to capture terms directly linked to financial markets and investor sentiment. The analysis uses an expanding window out-of-sample forecasting framework using a monthly dataset from January 1985 to December 2025. The predictive models are trained on an initial sample period (1985-2010) before recursively generating one-step-ahead forecasts over a 16-year evaluation period (2010-2025) and are then evaluated via Mean Absolute Forecast Error (MAFE) and Mean Squared Forecast Error (MSFE) loss functions.

The results reveal that return predictability is highly structural and episodic rather than uniform. Agricultural Policy Uncertainty (APU) stands out as the most robust predictor, systematically outperforming the benchmark model across all horizons by capturing sector-specific structural risk. Furthermore, dynamic rolling windows of forecast errors expose distinct “pockets of predictability”, notably between 2018 and 2020. During this period of intense trade frictions and political gridlock, category-specific trackers like Trade Policy Uncertainty (TPU) and Elections and Political Governance Uncertainty (EPGU) experienced a surge in forecasting accuracy. By identifying these pockets of predictability within recent history, this research provides empirical evidence to challenge the efficient and unpredictable S&P 500.

2.0 Literature Review

Financial markets are highly sensitive to uncertainty due to its “effect on real economic decisions, including firms’ investment and hiring plans” (Jahan-Parvar , et al., 2024). This aligns with Knight’s (1921) view, where he famously argues that “profit arises out of the inherent, absolute unpredictability of things... where even a probability calculation is impossible and meaningless.” While Knight highlights the chaotic nature of true uncertainty, Fameliti and Skintzi (2024) link this to modern financial markets, arguing that quantifying uncertainty using news-based indices enhances forecasting performance.

The Efficient Market Hypothesis (EMH) serves as the main theoretical benchmark. Markets are said to be semi-strong-form efficient if “security prices at any time ‘fully reflect’ all available information” (Fama, 1970). Therefore, any predictability derived from news-based uncertainty indices directly challenges market efficiency and can have significant implications for financial markets. However, this predictability may not be the result of market failure; it could be a response to risk. The ICAPM framework (Merton,1973) provides a rational alternative for return predictability, implying that “expected excess returns should vary with conditional exposures to innovations in state variables that forecast investment opportunities” (Brogaard & Detzel , 2015). Therefore, if the EPU index represents such a state variable, it should include a risk premium. Brogaard and Detzel (2015) argue that EPU is “an economically important risk factor for equities”, suggesting that any predictive power represents compensation for non-diversifiable risk.

The development of newspaper-based indices has provided a way to quantify uncertainty. The EPU index is constructed by counting articles in leading newspapers that contain a specific triple of terms, “‘ economic’ or ‘economy’; ‘uncertain’ or ‘uncertainty’; and one or more of

‘congress’, ‘deficit’, ‘Federal Reserve’, ‘legislation’, ‘regulation’ or ‘White House’. (Baker, et al., 2016), and goes through a rigorous audit of 12,000 news articles to ensure the correlation between automated and human classification. Additionally, these indices are forward-looking and aim to “capture uncertainty about who will make economic policy decisions, what economic policy actions will be undertaken and when, and the economic effects” (Baker, et al., 2016). More recently, Baker et al. (2019) introduced the Equity Market Volatility (EMV) tracker, which “moves with the VIX and with the realised volatility of returns on the S&P 500” (Baker, et al., 2019). Unlike the EPU index, the EMV tracker is constructed by selecting terms in news coverage that achieve the “highest R-squared value” (Baker, et al., 2019), in regressions against the VIX. The EMV tracker allows researchers to break down volatility into thirty distinct categories, such as ‘Trade Policy’, ‘Fiscal Policy’, and ‘Commodity Markets’. This could lead the index to be more useful for forecasting due to its close link with financial markets. However, Baker et al. (2016) caution that aggregate indices often contain “informational noise”, which explains why these broader indices fail to outperform univariate benchmark models.

Despite the theoretical frameworks, empirical evidence on the forecasting value of these indices remains fragmented. Katsouris (2023) notes that return predictability is often episodic and structural rather than permanent over time. This suggests that the struggle to find consistent predictive power may arise from models that ignore these “threshold effects and nonlinearities”. As a result, this creates a large divide in the literature. While many studies find news-based uncertainty indices perform well with an in-sample focus testing historical data, this performance significantly reduces when applied to current data with an out-of-sample focus. This is often due to overfitting by incorporating historical informational noise, rather than predictive signals, causing them to struggle to forecast future stock returns.

Within the existing literature, in-sample studies confirm the predictive power of news-based uncertainty indices, with Brogaard and Detzel (2015) finding that EPU “positively forecasts log excess market returns” at short horizons. Similarly, Jahan-Paravar et al. (2024) show that “foreign EPU possesses significant incremental predictive power for U.S. returns”. However, the out-of-sample results are not as positive. Nonejad (2022) shows that many indices fail to provide meaningful improvements in forecasting power relative to the “historical average benchmark”.

An evaluation framework based on “conditional relative predictive ability”, using real-time information to account for changing economic conditions, is presented by Nonejad (2022). His research shows that multiple EMV indices provide meaningful forecasting improvements, with some measures producing a 15% lower Mean Squared Error (MSE) relative to the benchmark. Importantly, this framework tests whether improved forecasts translate into “economic gains” for investors. This directly links to the aim of this dissertation, which not only examines whether uncertainty indices contain predictive power for S&P 500 returns but also whether this power has meaningful economic value.

The literature highlights a clear misalignment between theoretical models and practical out-of-sample forecasting gains. While in-sample returns are often successful, out-of-sample predictive power is often weak, especially when compared to simple benchmark models. This dissertation addresses this disagreement by testing the out-of-sample performance of EPU and EMV indices. By comparing different measures of uncertainty and accounting for the persistence in stock returns, it aims to identify which indices, if any, contain accurate and reliable values for forecasting.

3. Methodology

This section outlines the empirical framework that is used to evaluate whether newspaper-based uncertainty indices can be used to forecast S&P 500 returns. Although monthly S&P 500 returns often reflect market efficiency, this study explores whether news-based uncertainty indices contain additional information that can enhance forecasting performance. The analysis follows a standard forecasting approach, using a benchmark model and predictive models that incorporate uncertainty indices.

To assess whether these indices hold economically meaningful predictive power, an out-of-sample evaluation framework is used, consistent with the approach of Nonejad (2022). Forecast performance is compared against an effective benchmark model using multiple horizons and evaluated with loss functions.

3.1 Data

S&P 500 returns are a key index in examining the performance of the U.S. equity market. Therefore, understanding the predictability of these returns is important for both investors and policymakers. Newspaper-based uncertainty indices are incorporated into the analysis, and they capture changes in policy and market sentiment in real time, allowing for the assessment of whether uncertainty acts as a reliable predictor for future S&P 500 returns.

3.1.1 Data Sources and Variable Construction

Monthly S&P 500 price data was obtained from Yahoo Finance and used to compute monthly log returns, which act as the dependent variable. Log returns have been used to ensure stationarity and allow for consistent and comparable interpretations over the sample period.

The independent variables are newspaper-based uncertainty indices sourced from the Federal Reserve Economic Data (FRED) database, which provide widely used measures of economic policy uncertainty and financial market volatility. All EPU indices are log-transformed to account for their large magnitude and to reduce skewness. EMV indices, however, are kept at levels due to their moderate scale. Monthly observations have been obtained for all variables over the full sample period of January 1985 to December 2025, ensuring consistency among the datasets.

3.1.2 Uncertainty Indices

Newspaper-based uncertainty indices capture different dimensions of policy-related uncertainty. The EPU index provides a general measure of uncertainty related to economic policy, whereas the category-specific EPU indices capture uncertainty across policy areas. EMV measures are also incorporated as they are directly linked to movements in financial markets and may provide more meaningful information for forecasting stock returns. In addition, the Oil Price Uncertainty (OPU) index captures uncertainty associated with fluctuations in oil prices. The full set of uncertainty measures used within this study is summarised in Table (3.1).

By incorporating both EPU and EMV measures, the analysis allows for a comparison between general policy uncertainty and market-specific volatility, providing a more comprehensive assessment of the role of news-based information in forecasting S&P 500 returns.

Table 3.1: Uncertainty Indices

Index	Type	Description
EPU	General EPU	Broad Measure of overall economic policy uncertainty
Fiscal Policy	EPU	Uncertainty related to government budget decisions, deficits, and fiscal planning
Government Spending	EPU	Uncertainty around public expenditure and government spending policies
National Spending	EPU	Uncertainty in national-level spending priorities and allocations
Trade Policy	EPU	Uncertainty related to tariffs, trade agreements, and international trade policy
Oil Price	OPU	Market volatility associated with uncertainty in oil price movements
Agricultural Policy	EMV	Uncertainty affecting agricultural markets and policy decisions
Elections and Political Governance	EMV	Uncertainty linked to elections and political leadership changes
Interest Rates	EMV	Measures volatility related to uncertainty in monetary policy and interest rate decisions
Taxes	EMV	Uncertainty surrounding taxation policy and changes in tax regulations

3.1.3 Data Observations

An initial analysis of S&P 500 returns against the EPU and FPU indices reveals distinct volatility clustering, where periods of economic stability alternate with extreme shocks. As seen in Figure (3.1) and Figure (3.2), significant spikes of uncertainty, notably during the 2008 Financial Crisis and the 2020 COVID-19 pandemic, align with sharp, negative shocks in S&P 500 returns.

These visual trends demonstrate an inverse relationship between market performance and news-based uncertainty, where abrupt movements in policy uncertainty indices consistently coincide with periods of heightened market volatility. Furthermore, these patterns suggest that policy-related uncertainty is closely linked to financial market instability, providing a strong motivation for testing the forecasting performance of these indices.

Figure 3.1: S&P 500 Log Returns vs Economic Policy Uncertainty (EPU) index

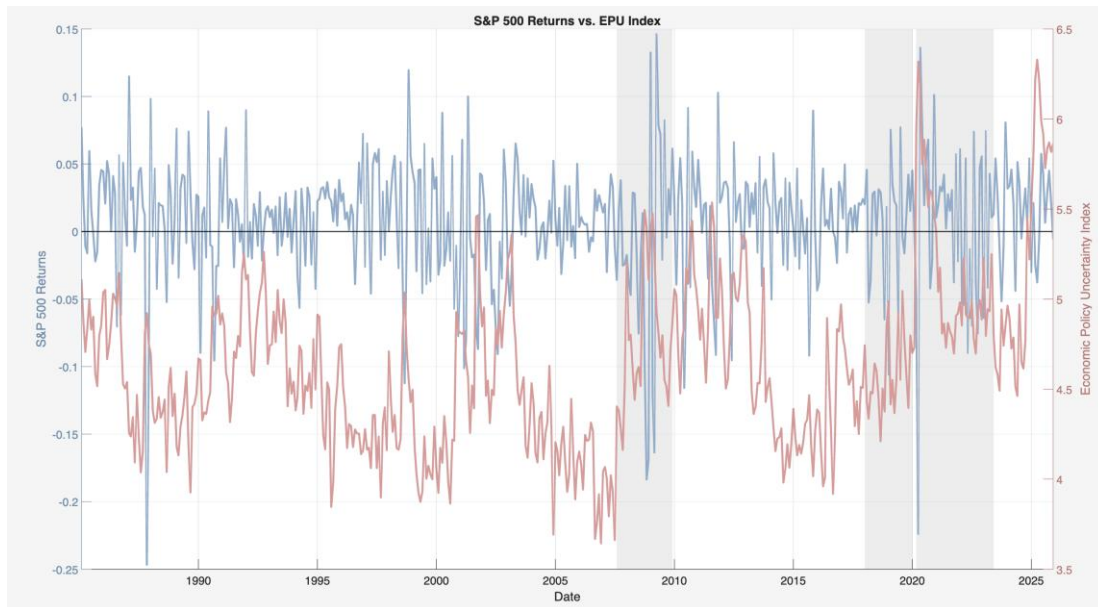


Figure 3.2: S&P 500 Log Returns vs Fiscal Policy Uncertainty (FPU) index

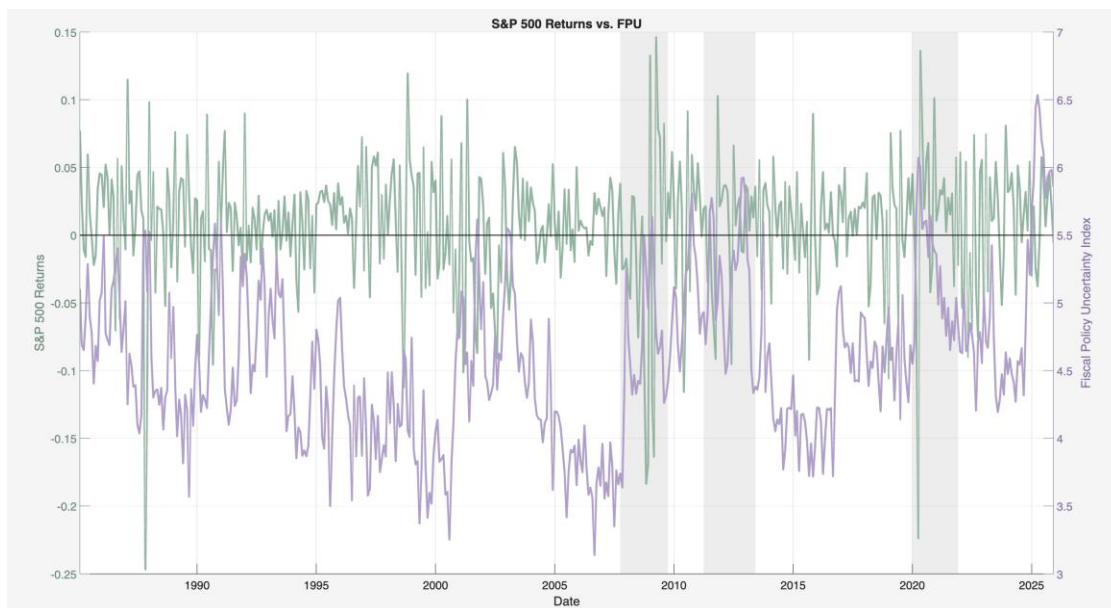


Figure 3.1 displays S&P 500 log returns (blue line) against the EPU index (red line). Figure 3.2 displays S&P 500 log returns (green line) against the FPU index (purple line). The shaded regions highlight periods where policy uncertainty and returns exhibit synchronicity, showing the inverse relationship between heightened uncertainty and market instability.

3.2 Forecasting Models

This study evaluates the predictive power of newspaper-based uncertainty indices using a set of benchmark and predictive models.

3.2.1 Benchmark: AR (3)

The benchmark model is an autoregressive model of order three:

$$y_{t+h} = c_0 + \varphi_1 y_t + \varphi_2 y_{t-1} + \varphi_3 y_{t-2} + \varepsilon_{t+h} \quad (3.1)$$

- where c_0 represents the intercept, φ_1 , φ_2 , and φ_3 capture the persistence in returns across three lagged values, and ε_{t+h} is the error term.

To determine the most accurate benchmark specification, autoregressive models from order 1 to 4 were estimated. For each model, the average Mean Squared Forecast Errors (MSFE) were calculated across forecast horizons. The AR (3) model was selected as the benchmark specification due to having the lowest average MSFE, indicating that using three lags of past S&P 500 returns provides the most accurate baseline for forecasting future returns in this setting.

3.2.2 Predictive Models

To address the research question, the predictive models are augmented AR (3) models, incorporating newspaper-based uncertainty indices:

$$y_{t+h} = c_0 + \varphi_1 y_t + \varphi_2 y_{t-1} + \varphi_3 y_{t-2} + \theta X_t + \varepsilon_{t+h} \quad (3.2)$$

- where y_{t+h} denotes the S&P 500 return at time $t + h$, X_t represents the individual uncertainty index, and the coefficient θ captures the predictive power it may hold.

This predictive model allows for the evaluation of whether newspaper-based indices improve the forecasting performance relative to the AR (3) benchmark model.

3.2.3 Forecast horizons

The analysis focuses on monthly S&P 500 returns across four forecast horizons ($h = 1, 3, 6, \& 12$). When observing a one-step-ahead horizon, both direct and iterative forecasting methods lead to the same result. However, when extended to multi-period horizons, the two approaches differ. The iterative approach is adopted here, as it recursively generates forecasts using all available information, resulting in more efficient forecasts.

3.2.4 Out-of-Sample Forecasting Procedure

The full dataset spans from January 1985 to December 2025. Ataei (2025) highlights that “at the daily frequency, the semi-strong form of EMH is rejected... but supported at the monthly frequency”, as information is “rapidly and fully incorporated into asset prices” at this scale. This justifies the use of monthly data for this research, as the difficulty in consistently outperforming the AR (3) benchmark is an expected outcome of market efficiency at this level.

The analysis uses an expanding window out-of-sample forecasting framework, with the following split of data:

- Training Period: January 1985 – December 2009
- Evaluation Period: January 2010 – December 2025

The procedure begins by estimating each predictive model using the training sample (1985M1 to 2009M12) to generate a one-step-ahead forecast for 2010M1. The training sample is then recursively expanded by one observation, the observation for 2010M1, and the model is then re-estimated to produce the subsequent forecast for 2010M2. This process is repeated until the final forecast is generated for 2025M12. This ensures that each forecast generated uses all historical information available at that point in time, replicating a real-time forecasting environment.

3.2.5 Evaluation Framework

The forecast performance is evaluated using Mean Absolute Forecast Error (MAFE) and Mean Squared Forecast Error (MSFE).

$$MAFE = \frac{1}{T-h-T_0+1} \sum |y_{t+h} - \hat{y}_{t+h}| \quad (3.3)$$

$$MSFE = \frac{1}{T-h-T_0+1} \sum (y_{t+h} - \hat{y}_{t+h})^2 \quad (3.4)$$

- where y_{t+h} denotes the S&P 500 log return at time $t + h$, $\hat{y}_{t+h}$ is the h -step ahead forecast of the log return, given all information up to time t . T_0 represents the end of the training sample and T is the total number of observations in the dataset.

Both loss functions calculate the difference between actual and predicted returns. The MAFE provides a linear measure of forecast error, whereas the MSFE places a greater weight on larger errors. The MSFE is essential for this study as it penalises larger errors more, which will allow for the analysis of how well the predictive models perform during extreme market spikes.

3.2.6 Data Limitations

Finally, it is important to acknowledge certain limitations within this study. Firstly, the analysis assumes constant parameters and homoscedastic errors, which may not fully capture the time-varying nature of uncertainty and stock return relationships. Furthermore, newspaper-based indices contain potential measurement error and media bias. Due to the predictive models having a two-step estimation process, in which indices are first estimated and subsequently used in the forecasting models, means that initial estimation errors may accumulate and carry into the final out-of-sample return forecasts.

4.0 Results

This section evaluates whether the newspaper-based uncertainty indices hold predictive power to improve the out-of-sample forecasts of S&P 500 stock returns relative to the benchmark specification. Forecasts are evaluated at the 1, 3, 6, and 12-month horizons using MSFE and MAFE, where lower values indicate a stronger forecasting performance. The analysis focuses on time-varying pockets of predictability and the comparison of EPU and EMV indices.

To establish a means for comparison, the out-of-sample performance metrics for the AR (3) benchmark model, along with the full set of results for all individual uncertainty indices, are documented in Appendix A. These baseline results reveal that forecast errors are highest at the short-term 1-month horizon and decline as the forecast horizon extends to 12 months. The variations in both MSFE and MAFE across all horizons remain minimal, demonstrating that the predictive performance of the AR (3) benchmark is relatively stable throughout the evaluation period. The following analysis compares the various uncertainty measures to identify any that provide significant forecasting gains.

4.1 Relative Performance

Table (4.1) presents the relative forecast performance of the uncertainty-based predictive models relative to the AR (3) benchmark. Predictive power varies considerably across the ten uncertainty measures, with only one index outperforming the benchmark at all four horizons.

Table 4.1: Predictive Model Relative Performance

Index	h=1	h=3	h=6	h=12
Economic Policy Uncertainty (EPU)	1.8251	2.5231	2.7540	2.8581
Fiscal Policy (FPU)	1.2662	1.2385	1.275	1.3047
Government Spending (GSU)	1.0468	1.0382	1.0412	1.0539
National Spending (NSU)	1.4188	1.3615	1.4107	1.4307
Trade Policy (TPU)	1.0058	1.0010	1.0050	1.0052
Oil Price (OPU)	1.3465	1.295	1.3297	1.3536
Agricultural Policy (APU)	0.9990	0.9954	0.9942	0.9968
Elections and Political Governance (EPGU)	0.9926	0.9955	0.9915	1.2692
Interest Rates (IRU)	1.3086	1.2246	1.2523	1.3628
Taxes (TU)	1.4394	1.3051	1.3398	1.3628

Table 4.1 displays the ratio of Mean Squared Forecast Error (MSFE) of the augmented predictive models to the AR (3) benchmark model. Values below 1 (highlighted in green) indicate that the uncertainty-augmented model outperforms the benchmark, while values above 1 indicate the benchmark remains more accurate. The colour scale provides a visual representation of performance relative to the benchmark, where green signifies outperformance of the benchmark model, yellow shows equal performance and red indicates that the benchmark model remains superior.

The strongest-performing uncertainty measure is Agricultural Policy Uncertainty (APU), which outperforms the AR (3) benchmark model across all forecast horizons, although the forecasting gains are modest. This predictive power arises from the way shifts in agricultural policy disrupt the real economy. Bakas and Triantafyllou (2018) argue that uncertainty related to the macroeconomy serves as a “common(latent) factor” for volatility within agricultural markets, and therefore the APU index is able to identify structural shifts that impact the performance of the S&P 500, unlike the broader measures. Similarly, Garcia et al. (2024) observe that “policy changes are essential elements of the risk environment of farmers affecting market prices, production possibilities, costs, and income,” further supporting the idea that agricultural policy can offer a key insight into financial market fluctuations.

The time-varying nature of these gains validates the phenomenon of ‘pockets of predictability’ described by Lansing, LeRoy, and Ma (2022), which are “interspersed with longer intervals that exhibit little to no evidence of predictable excess stock returns.” The APU index isolates sudden, unanticipated shocks rather than general information noise, which allows it to serve as a reliable predictor for S&P 500 returns and systematically

outperform the autoregressive benchmark model. Trade Policy (TPU), Government Spending (GSU), Elections and Political Governance (EPGU), and Oil Price (OPU) uncertainty also emerge as stronger performing measures. OPU demonstrates stronger predictive power at longer forecast horizons, whereas TPU and EPGU exhibit stable, near-benchmark performances across all horizons.

In contrast, the broad EPU index exhibits the weakest performance across all horizons, suggesting that it is too generalised to provide meaningful forecasting power for S&P 500 returns. This pattern is consistent across several of the broader uncertainty measures, illustrating the differences in forecasting performance between aggregate and targeted uncertainty measures, suggesting that more targeted forms of uncertainty contain greater forecasting information for S&P 500 returns. Furthermore, the fluctuations in relative forecast errors indicate that the predictive relationship between uncertainty indices and stock returns is unstable over time. This outcome aligns with the findings of Nonejad (2022), who observes that predictive performance differs substantially across uncertainty categories and uncertainty horizons.

4.2 Pockets of Predictability

To evaluate how forecasting performance evolves, moving averages of forecast errors are computed for both the predictive models and the AR (3) benchmark model across the evaluation period. This rolling analysis highlights specific windows of heightened predictive power.

Figure (4.2) illustrates the moving-average forecast errors across the evaluation sample. The results highlight that the forecasting performance of uncertainty measures is time-varying,

rather than static across the sample period. Several uncertainty measures appear to outperform the benchmark during distinct intervals of heightened economic and financial instability. This pattern indicates that predictive performance manifests in “pockets of predictability”, revealing that newspaper-based uncertainty indices provide improvements in specific periods rather than consistently throughout the sample. This structural variation in predictive power, which fluctuates across the timeframe, aligns with the findings of Cong et al. (2024), who argue that “return predictability is an intrinsic and time-varying asset characteristic” that creates “patterns reminiscent of a mosaic.” By targeting these distinct clusters, the rolling average framework captures the episodic nature of stock returns.

Figure 4.2: Moving Average Forecast Errors

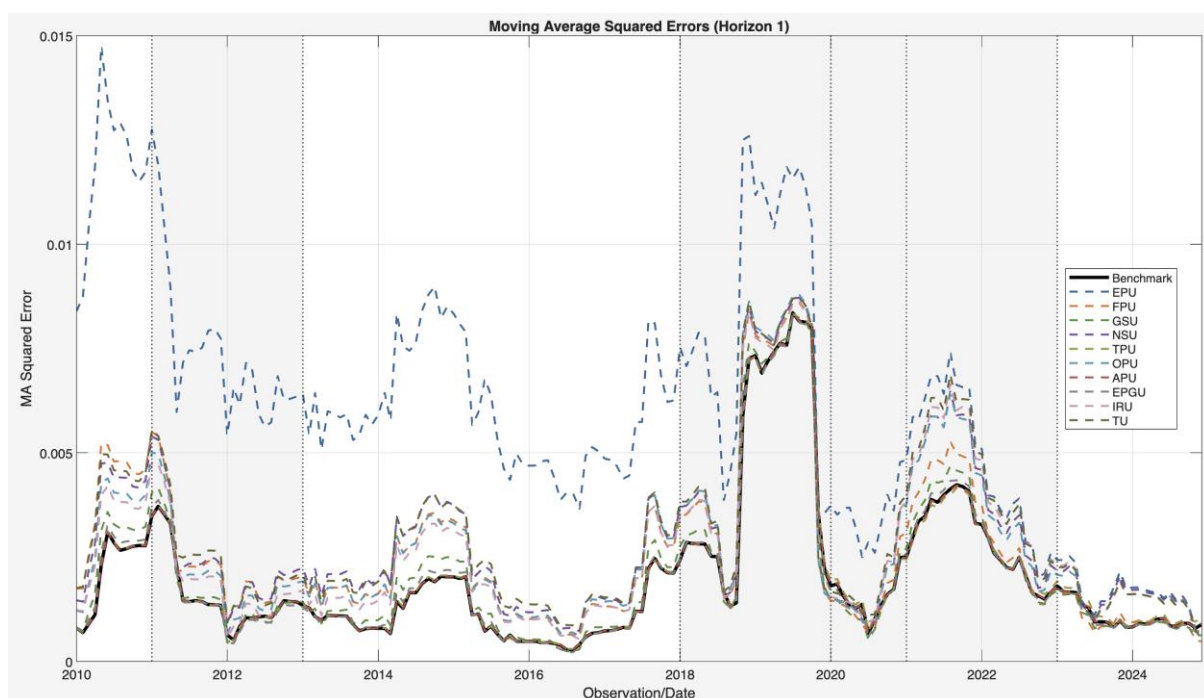


Figure 4.2 tracks the moving average squared error for $h = 2$ from 2010 to 2025. The solid black line represents the AR (3) benchmark, while the coloured dashed lines represent the uncertainty predictive models. Periods where a dashed line falls below the benchmark indicate the predictive model outperforming the benchmark model. The shaded areas isolate distinct pockets of predictability where the inclusion of uncertainty indices provides additional economically meaningful value. The performance analysis for longer forecast horizons is provided in Appendix B.

4.2.1 The 2011-2013 Post-Crisis Recovery

The first distinct pocket of predictability occurs between 2011 and 2013, an interval characterised by post-financial crisis recovery, quantitative easing, U.S. debt ceiling negotiations, as well as the downgrade of U.S. sovereign debt by Standard & Poor's.

Throughout this window, Government Spending (GSU) and Fiscal Policy (FPU) uncertainty measures generate relatively lower forecast errors. Predictive accuracy appears to improve gradually following the initial post-crisis instability as economic conditions and policy expectations stabilise. Additionally, periods surrounding debt ceiling negotiations and heightened fiscal uncertainty are followed by an improvement in forecasting performance. This could suggest that during the recovery of financial markets following a shock, fiscal and monetary policy expectations become increasingly important for forecasting stock returns.

4.2.2 The 2018-2020 Trade and Political Turmoil

A second prominent pocket arises between 2018 and 2020. This period was dominated by U.S.-China trade tensions and political ambiguity surrounding the Trump administration. Amidst this heightened tariff friction, TPU appears to perform strongly. This aligns seamlessly with the findings of Baker, Bloom, Davis and Kost (2025), who observe that trade policy news “went from a virtual non-factor for equity market volatility in the twenty years before Donalds Trump’s first election to a leading source afterwards” The predictive power of TPU during this window can be explained by its ability to capture supply chain disruptions in real-time and provide a forward-looking perspective that the benchmark model does not capture until after a shock materialises. EPGU also appears to outperform the benchmark during this elevated political uncertainty. The improvement in predictive ability is supported by Baker, Davis and Levy (2022), who demonstrate that “close elections elevate policy uncertainty much more than the average election.”, largely due to rapid shifts in investor

expectations that the benchmark model fails to capture, explaining why forecasting gains for the EPGU index are apparent around highly competitive political cycles.

This interval also coincided with high volatility in commodity markets and shifting global growth forecasts, during which OPU produced lower forecast errors. Interestingly, the overall forecasting performance of these uncertainty measures weakens during periods of intensified market uncertainty and volatility but then improves as economic conditions begin to stabilise. This dynamic suggests that targeted uncertainty measures become more informative when uncertainty shocks directly affect investor expectations and corporate profitability.

4.2.3 The 2020-2023 Pandemic and Inflationary Shocks

Following the onset of COVID-19, a final pocket of predictability spans from 2020 to 2023. This is driven by supply chain disruptions and subsequent spikes in inflation. This period illustrates Knight's (Knight, 1921) view on uncertainty. When a major crisis hits, markets shift instantly from predictable risk to absolute uncertainty. During the initial stages of the pandemic shock, forecast errors increased substantially, reflecting the extreme volatility and unpredictability of financial markets. However, in the subsequent period of slow economic growth and rising inflation, OPU demonstrates strong performance, beating the AR (3) benchmark due to energy market disruption and commodity price volatility. Interest rate uncertainty (IRU) also becomes increasingly informative during the Federal Reserve's monetary tightening and rising inflation.

This pattern suggests that predictive relationships strengthen after major economic shocks begin to stabilise rather than during the period of peak uncertainty. In contrast, periods of extreme volatility and rising uncertainty generally produce weaker forecasts. It is also apparent that category-specific uncertainty measures perform stronger during periods where

uncertainty is directly linked to individual economic risks such as trade, fiscal policy, and inflation. These findings are consistent with previous literature showing that uncertainty rises sharply during economic shocks before gradually declining as financial conditions stabilise.

4.3 Comparison of EPU and EMV Indices

These results show noticeable differences in forecasting performance between EPU and EMV uncertainty measures. The aggregate EPU index was initially constructed under the premise that it is “associated with heightened stock market volatility and potential for a downturn in stock market performance” (Baker, Bloom and Davis, 2016). However, these empirical findings demonstrate that the broad index lacks predictive power. Furthermore, Baker, Bloom and Davis note that “economic policy uncertainty typically raises the risk premium that people and firms must deal with,” causing EPU to spike during major political and economic events. This explains why the indices struggle to maintain predictive power during stable economic conditions, as they are designed to capture episodic economic shocks. Generally, EMV measures produce stronger forecasting performance, occasionally outperforming the benchmark results and producing lower forecast errors, particularly during periods of heightened uncertainty, while most EPU measures remain closer to or below the benchmark performance.

Although aggregate EPU measures underperform, category-specific measures demonstrate higher predictive power, reinforcing that these targeted measures contain greater information for forecasting S&P 500 stock returns. As Baker, Bloom, Davis and Kost (2025) find, “news about policy matters is an important and growing contributor to volatility,” noting that the share of EMV articles containing policy-centric terms has been steadily rising since the 1980s. This shows that EMV indices can outperform aggregate indices due to their ability to isolate policy-driven shocks.

5. Conclusion

This dissertation has investigated the out-of-sample predictive power of news-based uncertainty indices for S&P 500 stock returns. By comparing various measures of uncertainty and accounting for the persistence in stock returns, this study addresses the lack of consensus regarding whether news-based indices can meaningfully improve forecast accuracy. The Efficient Market Hypothesis (EMH) has been tested through an expanding window-out-of-sample forecasting framework, using a training sample from January 1985 to December 2009 and an evaluation period from January 2010 to December 2025.

Empirical results reveal that asset return predictability is highly episodic. Within the out-of-sample framework, Agricultural Policy Uncertainty (APU) emerges as the most consistent predictor, systematically outperforming the AR (3) benchmark model across all forecast horizons. While broad aggregate indices fail to perform as well due to informational noise, the performance of APU highlights the value of targeted uncertainty measures. Additionally, other category-specific measures, including Trade Policy Uncertainty (TPU) and Government Spending Uncertainty (EPGU), demonstrated powerful periods of forecasting capability, particularly during the 2018-2020 pocket of predictability driven by U.S.-China tariff friction.

These findings bridge a vital gap between the foundational asset pricing theories. Under the EMH, if publicly available news indices can systematically predict returns, it implies a direct contradiction to market efficiency. However, Merton's (1973) ICAPM framework provides a rational explanation. When an uncertainty index acts as an economically important risk factor, its predictive power represents compensation for bearing non-diversifiable risk, rather than market inefficiency. Considering these findings, the overall modest forecasting gains reinforce the conclusion reached by Chowdhury and Ifft (2024) that the U.S. stock market

adheres to the semi-strong form of the Efficient Market Hypothesis, where asset prices often cause uncertainty indices to shift.

The superiority of APU is supported by the mechanism where agricultural policy changes act as essential elements of the risk environment, fundamentally altering market prices and corporate cash flows. By isolating sudden, unanticipated institutional innovations, the APU index captures structural shifts that a backwards-looking autoregressive model cannot anticipate.

This performance confirms the “mosaic” topology of predictability presented by Cong et al. (2025), where return predictability manifests in distinct, historical clusters. Future research could adopt the spatial autoregressive model proposed by Costola et al. (2023). This model moves beyond fixed rules by using a multilayer structure to separate different news types, such as cooperation from political conflicts. Since news relevance shifts, the model employs a time-varying network as a dial, allowing researchers to “discern the relative significance of each network” layer in real-time. Rather than assuming uniform reactions, the framework uses country-specific network exposure weights to compute individual sensitivity scores. Furthermore, “incorporating stochastic volatility” ensures settings evolve smoothly over time, reflecting stock market dynamics. This approach could formally explain the Post-Shock Stabilisation Effect by providing a rigorous mechanism validating why the U.S. exhibits a “diminished G7 influence” during crises, essentially pulling away from global trends when policy uncertainty is high.

Ultimately, this dissertation demonstrates that while out-of-sample market forecasting remains incredibly challenging, specialised newspaper-based indices provide invaluable, forward-looking insights into the market’s shifting intertemporal price of risk.

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7. Appendix

Appendix A: Forecast Performance Metrics

Table A.1: AR (3) Benchmark Forecast Performance

Horizon	MSFE	MAFE
h=1	0.0021	0.0342
h=3	0.0021	0.0343
h=6	0.0020	0.0337
h=12	0.0020	0.0332

Table A.1 displays the mean squared and absolute forecast errors of the benchmark AR (3) model across all four horizons. These metrics provide the reference point for which the errors of the uncertainty-augmented models are measured. This allows for consistent comparison to determine if adding news-based uncertainty indices provides additional predictive power in forecasting S&P 500 returns.

Table A.2: Predictive Model Forecast Performance

Full Index-by-Index Predictive AR(3) models								
Index	h=1 MSFE	h=1 MAFE	h=3 MSFE	h=3 MAFE	h=6 MSFE	h=6 MAFE	h=12 MSFE	h=12 MAFE
Economic Policy Uncertainty (EPU)	0.0058	0.0618	0.0052	0.0581	0.0055	0.0606	0.0056	0.0617
Fiscal Policy (FPU)	0.0026	0.0370	0.0025	0.0363	0.0025	0.0368	0.0025	0.0370
Government Spending (GSU)	0.0022	0.0331	0.0021	0.0326	0.0021	0.0323	0.0021	0.0322
National Spending (NSU)	0.0029	0.0392	0.0028	0.0383	0.0028	0.039	0.0028	0.0390
Trade Policy (TPU)	0.0021	0.0345	0.0021	0.0343	0.0020	0.0340	0.0020	0.0336
Oil price (OPU)	0.0028	0.0338	0.0020	0.0336	0.0020	0.0332	0.0019	0.0328
Agricultural Policy (APU)	0.0021	0.0379	0.0027	0.0368	0.0026	0.0373	0.0026	0.0026
Elections and Political Governance (EPGU)	0.0020	0.0334	0.0020	0.0332	0.0020	0.0328	0.0019	0.0324
Interest Rates (IRU)	0.0027	0.0365	0.0025	0.0352	0.0025	0.0355	0.0025	0.0353
Taxes (TU)	0.0030	0.0391	0.0027	0.0370	0.0027	0.0373	0.0027	0.0372

Table A.2 provides the mean squared and absolute forecast errors for each predictive model across all four forecast horizons. The colour shading from light to dark provides a visual gradient of the errors, where lighter shades indicate lower error values and darker shades highlight higher error values. This allows for the assessment of whether specific uncertainty indices enhance predictive power over the benchmark model.

Appendix B: Moving Average Squared Error Visualisations

Figure B.1 Moving Average Squared Errors (Horizon 2)

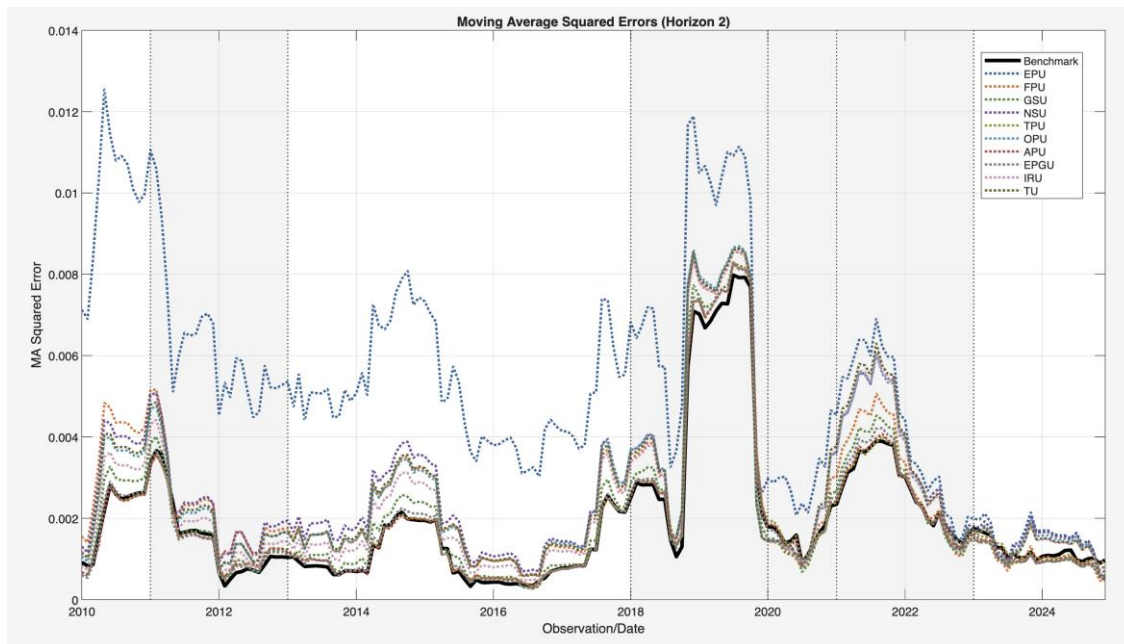


Figure B.1 tracks the Moving average Squared Error for the $h = 2$ horizon from 2010 to 2025. Consistent with the $h = 1$ results, the solid black line represents the AR (3) benchmark, while the coloured dashed lines denote the uncertainty predictive models. The shaded areas isolate pockets of predictability where the uncertainty indices provide additional forecasting information over the benchmark model.

Figure B.2 Moving Average Squared Errors (Horizon 3)

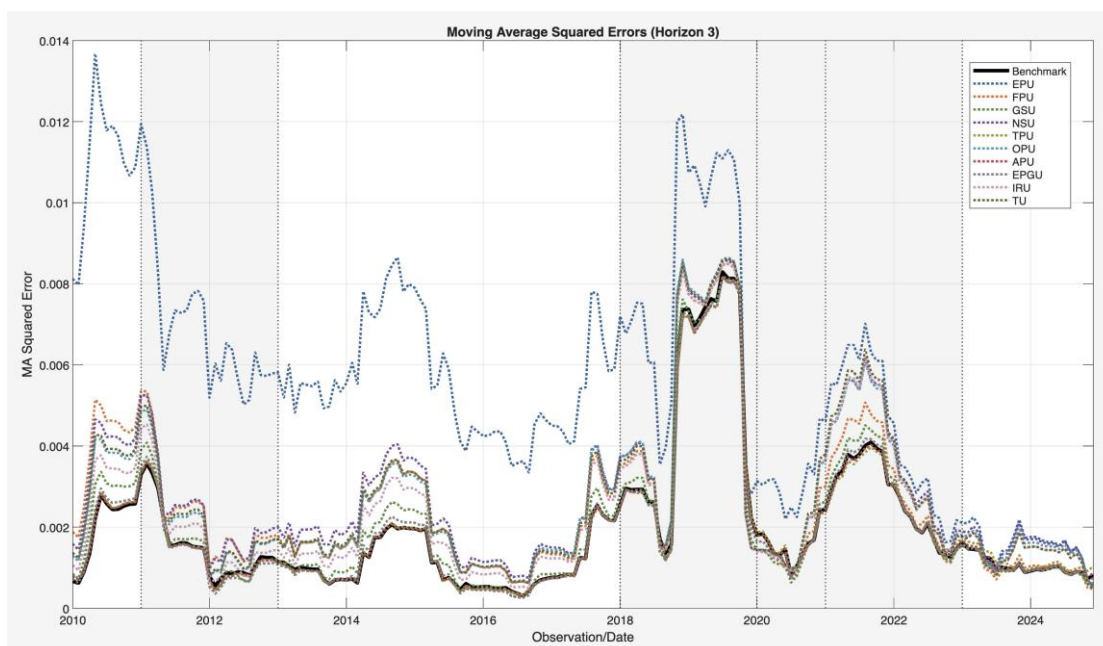


Figure B.3 tracks the Moving Average Squared Error for the $h = 3$ horizon from 2010 to 2025. Similar to the $h = 2$ results, the solid black line represents the AR (3) benchmark, and the coloured dashed lines represent the predictive models. Shaded areas again show the pockets of predictability, showing how the predictive models perform relative to the benchmark model along the sample period.

Figure B.3 Moving Average Squared Errors (Horizon 4)

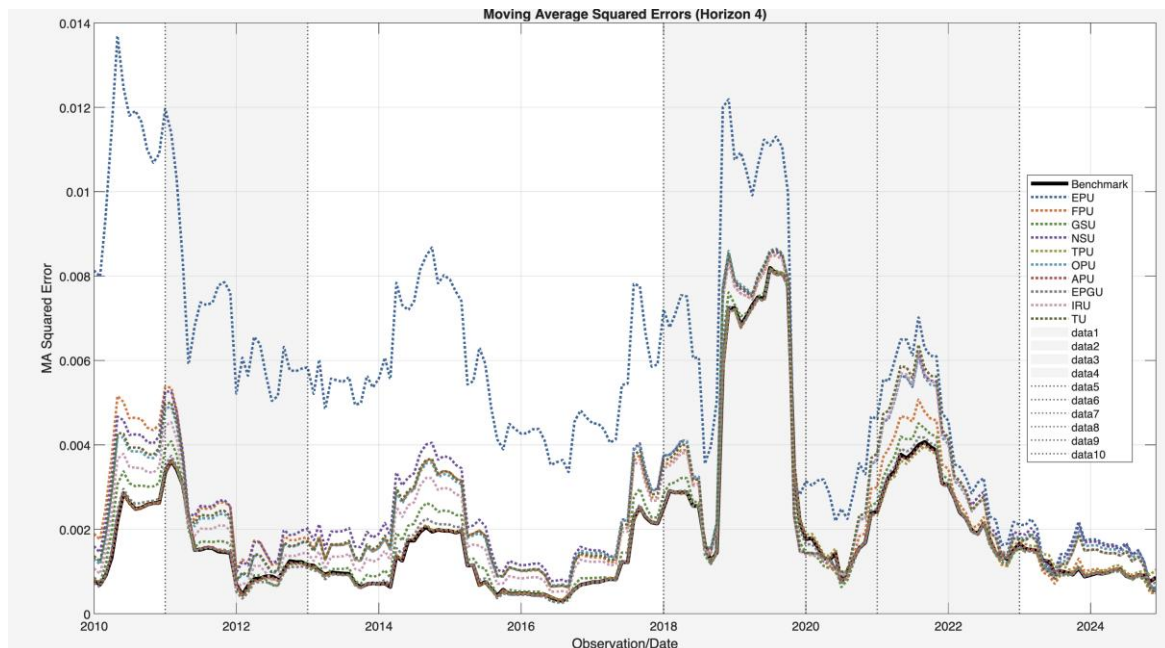


Figure B.3 shows the Moving Average Squared Errors for the $h = 4$ horizon across the evaluation period. Consistent with the previous horizons, the solid black line represents the AR (3) benchmark model and the coloured dashed lines represent the predictive models. The shaded areas continue to highlight pockets of predictability, demonstrating that the forecasting gains arising from the inclusion of uncertainty indices appear in specific windows of time rather than across the total sample period.