Volatility-of-Volatility Aligned Uncertainty and Return Predictability

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Abstract

We propose a novel approach to forecasting market returns by constructing economic uncertainty indices aligned with volatility-of-volatility (VOV). We employ the partial least squares (PLS) method to synthesize information from economic policy uncertainty (EPU) indices and macro-financial uncertainty measures into indices that best predict future VOV. This VOV alignment significantly enhances return predictability, delivering out-of-sample R^2 up to 14.5% for U.S. equities and generating substantial economic gains for mean-variance investors. Predictability extends beyond equities to hedge fund returns (R^2 up to 17.4%) and global markets (up to 19%). Our results clarify which uncertainty components—such as financial uncertainty, sovereign debt crises, and regulatory risk—drive predictive power, offering an interpretable and theoretically grounded tool for improving asset allocation across diverse asset classes and geographies.

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Abstract

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1. Introduction

Volatility-of-volatility (VOV) has emerged as a critical dimension of market risk, providing insights beyond traditional volatility measures. Since Bollerslev, Tauchen, and Zhou (2009) introduced VOV as an additional source of uncertainty, a growing literature has documented its strong link to asset pricing and return predictability across equities, options, and hedge funds (Agarwal, Arisoy, and Naik, 2017; Huang et al., 2019; Chen et al., 2022). VOV risk intensifies during market stress, reflecting investors' heightened demand for compensation against volatility risk, making its prediction essential for improving return forecasts and managing portfolio risk.

Parallel research highlights the role of economic uncertainty—captured by measures such as economic policy uncertainty (EPU) indices (Baker, Bloom, and Davis, 2016) and macro-financial uncertainty indicators (Jurado, Ludvigson, and Ng, 2015)—in shaping volatility dynamics and risk premia. While uncertainty shocks influence both expected returns and volatility (Pástor and Veronesi, 2012; Brogaard and Detzel, 2015; Kelly, Pástor, and Veronesi, 2016), their predictive power through risk premium effects varies across channels: volatility (VIX) or VOV. We argue that VOV offers the most stable and theoretically grounded conduit for extracting predictive information. Unlike VIX, which is noisy and influenced by transitory shocks, VOV reflects higher-order risk—uncertainty about volatility itself—making it more persistent and less prone to short-term noise.

Why align uncertainty with VOV? The rationale stems from both theory and empirical evidence. First, VOV exhibits a structural negative covariance with market returns (Bollerslev, Tauchen, and Zhou, 2009; Chen et al., 2022), making it a more stable and economically meaningful

anchor than VIX, which is noisy and influenced by transitory shocks. Second, VOV captures higher-order risk—uncertainty about volatility itself—which is more persistent and less sensitive to short-lived sentiment or liquidity shocks. This persistence improves the signal-to-noise ratio when filtering uncertainty measures. Third, aligning uncertainty with VOV isolates the component of uncertainty that drives volatility risk premia, rather than conflating unrelated factors affecting returns or volatility. By leveraging this alignment, we extract predictive information that is theoretically grounded, empirically robust, and economically interpretable, offering a superior channel for forecasting returns and managing risk.

To implement this idea, we use the partial least squares (PLS) method following Kelly and Pruitt (2013), which has been widely adopted in return predictability research (Huang et al., 2015; Jiang et al., 2019). PLS is particularly effective for synthesizing information from many correlated predictors because it extracts latent factors that maximize covariance with a target variable—in our case, future VOV. The procedure involves three passes: (i) time-series regressions of each uncertainty measure on future VOV to estimate loadings; (ii) cross-sectional regressions that aggregate these loadings into a single VOV-aligned index each month; and (iii) return-forecasting regressions using the constructed index as the predictor. By filtering out noise common across individual uncertainty measures and retaining only components most relevant for predicting VOV, this approach yields a stable informative index that improves both in-sample fit and out-of-sample performance. Relative to prior applications that align predictors directly with market returns, our alignment with VOV leverages a theoretically grounded and empirically more stable channel for extracting predictive content.

To construct the VOV-aligned indices, we draw on two comprehensive sets of measures widely used in the literature. The first set comprises ten Economic Policy Uncertainty (EPU) indices from Baker, Bloom, and Davis (2016), including one overall EPU index and nine categorical subindices. These indices capture policy-related risks that influence financial markets and have been shown to forecast equity risk premia (Brogaard and Detzel, 2015). The second set includes three macro-financial uncertainty measures developed by Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021): financial uncertainty (FIN), macroeconomic uncertainty (MACRO), and real uncertainty (REAL). Prior research documents that FIN is priced in the cross-section of stock returns (Bali, Brown, and Tang, 2017). We combine these measures in five predictor groups—(1) EPU; (2) EPU + FIN; (3) EPU + MACRO; (4) EPU + REAL; and (5) EPU + FMR (all three macro-financial measures)—to evaluate the incremental predictive content of each uncertainty dimension when aligned with VOV.

We find that VOV-aligned indices deliver strong and statistically significant predictability in both in-sample and out-of-sample tests. The EPU+FIN combination achieves an in-sample R^2 of 13.97% and an out-of-sample R^2 of 14.49%, both significant at the 1% level, substantially outperforming VIX-aligned counterparts. The economic value is considerable: mean-variance investors realize annualized certainty-equivalent return of above 20%, even after transaction costs, with Sharpe ratios exceeding 1.5. These results persist after controlling for the established predictors from Welch, Goyal (2008) and Welch, Goyal, and Zafirov (2024), and when the sample includes the global financial crisis.

We extend the VOV-alignment framework to tradable hedge fund indices across four strategy

groups—Event Driven, Equity Hedge, Macro, and Relative Value (HFR classification). VOV-aligned uncertainty significantly predicts hedge fund performance across most categories, with out-of-sample R^2 frequently above 10%. The Relative Value Multi-Strategy index achieves 17.41% out-of-sample R^2 (1% significance), while Event Driven and Equity Hedge strategies exhibit broad predictability consistent with their exposure to equity and credit volatility. Macro strategies show heterogeneous results—strong predictability in several discretionary and commodity-focused indices, but weaker in currency and systematic diversified indices—suggesting that some macro funds load on risks not fully captured by the VOV-aligned uncertainty index. These findings imply that VOV-aligned uncertainty captures systemic, volatility-linked risk that is especially salient for leveraged and arbitrage-based strategies, offering practical benefits for hedge-fund allocation and risk management.

We further test the generality of VOV-aligned uncertainty in 50 developed and emerging markets. Predictability is particularly strong in developed markets, where out-of-sample R^2 values often exceed 10%—for example, Australia approaches 19%—and remains robust across Europe and Asia-Pacific. Emerging markets display more modest but still significant gains in many cases; notably, South Africa reaches 16.88% out-of-sample R^2. This cross-market evidence indicates that VOV-aligned uncertainty is a globally relevant return predictor, consistent with VOV risk being a pervasive factor across international equity markets. For global investors, incorporating VOV-aligned uncertainty into allocation policies provides a scalable tool for improving risk-adjusted performance and mitigating drawdowns during episodes of heightened uncertainty.

We finally test whether the return predictability of the VOV-aligned EPU+FIN index extends beyond the aggregate market to characteristic-sorted equity portfolios. Using portfolios formed on book-to-market, size, profitability, investment, momentum, and industry classifications, we find strong and pervasive predictability. In-sample slope coefficients are uniformly negative and highly significant, with R^2 values around 9%–14%. Out-of-sample performance remains economically meaningful, with R^2_{OS} exceeding 15% for small-stock and manufacturing portfolios.

This paper contributes to the literature on return predictability and uncertainty in several aspects. First, we provide new evidence that VOV is an effective channel through which economic uncertainty translates into return predictability. Second, we extend the PLS framework of Kelly and Pruitt (2013) by aligning uncertainty measures with VOV rather than returns, demonstrating superior predictive performance and stability. Third, our framework enhances interpretability by decomposing aggregate uncertainty into economically meaningful components. The PLS weights reveal which uncertainty dimensions—such as financial uncertainty (FIN), sovereign debt and currency crises, and regulatory uncertainty—drive predictive power, and how their importance shifts during major economic shocks. This contribution clarifies why some uncertainty measures matter for asset pricing while others do not. Fourth, we show that VOV-aligned uncertainty indices predict not only U.S. equity returns but also hedge fund returns and global equity markets, offering practical insights for portfolio management across asset classes and geographies.

The remainder of the paper proceeds as follows. Section 2 summarizes the methodology for using VOV-aligned uncertainty to predict market returns. Section 3 describes the data and variable construction. Section 4 presents empirical results. Section 5 provides robustness checks, while

Section 6 shows extensions beyond forecasting aggregate U.S. market returns. Section 7 concludes.

2. Methodology

Our approach builds on the theoretical link between VOV and market returns. Prior research (Bollerslev, Tauchen, and Zhou, 2009; Chen et al., 2022) establishes that VOV exhibits a contemporaneous negative covariance with aggregate returns, making it a structural risk factor rather than a noisy outcome variable. This property motivates aligning economic uncertainty measures with VOV rather than with VIX, which are more susceptible to transitory shocks. By doing so, we isolate the component of uncertainty that drives volatility risk premium, improving signal extraction and forecast stability.

2.1. Alignment via Partial Least Squares

We adopt the PLS method (Kelly and Pruitt, 2013), which efficiently aggregates information from many correlated predictors by extracting latent factors that maximize covariance with a target variable—in our case, future VOV. This approach is particularly effective when predictors contain overlapping information and idiosyncratic noise. The procedure consists of three steps.

The first pass identifies how each uncertainty measure relates to the target variable (future VOV). Following Kelly and Pruitt (2013) and Huang et al. (2015), we regress each uncertainty measure $U_{i,t}$ on next month's VOV:

$$U_{i,t} = \eta_i + \gamma_i VOV_{t+1} + \varepsilon_{i,t}, \tag{1}$$

where VOV serves as the conditioning variable that determines which components of uncertainty

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matter for volatility risk pricing. Each uncertainty measure $U_{i,t}$ (e.g., EPU categories, FIN, MACRO, REAL, to be introduced in the following section of Data) is tested for its sensitivity to VOV. The estimated loading γ_i captures how strongly that measure co-moves with VOV. Intuitively, large loadings indicate that the uncertainty measure contains information relevant for volatility risk. This step filters out noise by discarding components unrelated to VOV.

The second pass uses the estimated loadings (γ_i) to construct a single VOV-aligned uncertainty index for each month:

$$U_{i,t} = a_t + F_t\gamma_i + e_{i,t}, \tag{2}$$

where the estimated coefficient F_t is the latent factor representing the VOV-aligned uncertainty index. That is, all uncertainty measures at time t are regressed on their previously estimated loadings. The fitted value F_t is the optimal linear combination of uncertainty measures that maximizes covariance with VOV. This aggregation reduces dimensionality and multicollinearity, producing a stable and interpretable predictor. This index becomes the predictor in the third pass for forecasting market returns.

The third pass conducts return forecasting. We define $\widehat{VOV}_t|U \equiv \mathbb{E}_t[VOV_{t+1}|U] = F_t$, where U denotes a set of uncertainty measures, and we then regress market returns on the VOV-aligned index:

$$r_{m,t+1} = \alpha + \beta\widehat{VOV}_t|U + \epsilon_{t+1}, \tag{3}$$

where theory predicts $\beta < 0$, consistent with the negative covariance between VOV and returns.

2.2. Out-of-Sample Market Return Predictions

To assess the real-time forecasting ability of VOV-aligned uncertainty indices, we implement a recursive out-of-sample prediction scheme. This approach expands the estimation window each time a new observation becomes available, ensuring that forecasts rely only on information available at the prediction date and mitigating look-ahead bias. The procedure follows three steps:

1) **Recursive Estimation of PLS Loadings:**

   For each month t, we re-estimate the first-pass regressions of individual uncertainty measures $U_{i,t-1}$ on VOV using all data up to t. This updates the loadings (γ_i) that capture the sensitivity of each uncertainty measure to VOV.

2) **Construction of VOV-Aligned Index:**

   Using the updated loadings, we perform the second-pass cross-sectional regression to aggregate uncertainty measures into a single VOV-aligned index F_t. This index represents the component of economic uncertainty most relevant for predicting volatility risk.

3) **Return Forecasting:**

   We substitute the expected VOV-aligned index into the predictive regression: $r_{m,t+1} = \alpha_t + \beta_t \widehat{VOV}_t | U + \varepsilon_{t+1}$, where α_t and β_t are estimated using data up to month t. We measure out-of-sample accuracy using the Campbell–Thompson (2008) statistic:

$$R_{OS}^2 = 1 - \frac{\sum_{t=s}^{T-1}(r_{m,t+1} - \hat{r}_{m,t+1})^2}{\sum_{t=s}^{T-1}(r_{m,t+1} - \bar{r}_{m,t+1})^2},$$

   where $\bar{r}_{m,t+1}$ is the historical average benchmark. Positive R_{OS}^2 values indicate that the model outperforms the historical mean forecast—a stringent benchmark in equity premium prediction. We also apply the Clark–West (2007) MSFE-adjusted test to assess statistical

significance.

3. Data

We use monthly U.S. stock market returns from Ken French's data library, computed as log excess returns on the CRSP value-weighted market portfolio. VOV is proxied by the CBOE Volatility-of-Volatility Index (VVIX), which measures the implied volatility of VIX options and reflects uncertainty about volatility itself. For comparison, we also use the CBOE Volatility Index (VIX) as a benchmark for market volatility. Both VVIX and VIX series are obtained from the CBOE database and transformed into logarithmic form.

Our predictor set comprises two widely used groups of economic uncertainty measures. We include ten newspaper-based indices from Baker, Bloom, and Davis (2016): one overall EPU index and nine categorical subindices covering monetary policy, taxes, government spending, health care, national security, entitlement programs, regulation, trade policy, and sovereign debt/currency crises. These indices capture policy-related risks that influence financial markets and have been shown to forecast equity risk premium. We also incorporate three model-based measures developed by Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021): (i) FIN: Financial uncertainty, reflecting shocks to financial conditions, (ii) MACRO: Macroeconomic uncertainty, capturing broad economic fluctuations, and (iii) REAL: Real uncertainty, associated with real activity and production. We collectively refer to these three measures as the FMR group. To evaluate their incremental predictive power, we augment the EPU base set by adding FIN, MACRO, and REAL individually, as well as the combined FMR set. This design yields five

predictor configurations: (1) EPU only; (2) EPU + FIN; (3) EPU + MACRO; (4) EPU + REAL; and (5) EPU + FMR (all three macro-financial measures combined).[1]

Our main sample spans July 2009 to December 2021, excluding the global financial crisis period to avoid extreme initial conditions. Robustness checks extend the sample back to March 2006, the earliest date for which VVIX data is available. We apply logarithmic transformations to market returns, VVIX, and VIX, and standardize all predictors to mitigate scale effects. All uncertainty measures are expressed as monthly log differences and standardized by their respective standard deviations to ensure comparability across predictors.

<Insert Table 1 here>

Table 1 presents descriptive statistics for market returns, volatility measures, and economic uncertainty indices. The U.S. market exhibits an average monthly excess return of 1.23% with a standard deviation of 4.11%, indicating substantial variability and negative skewness consistent with downside risk. VVIX, our proxy for volatility-of-volatility, shows a higher mean (4.53) but lower dispersion (0.16) than VIX (mean 2.87, SD 0.33), confirming its role as a persistent second-order risk measure rather than a transitory volatility indicator. Among uncertainty measures, sovereign debt and currency crises display extreme kurtosis and wide dispersion, reflecting episodic shocks, while financial uncertainty (FIN) is relatively stable, suggesting persistent but moderate fluctuations. Macroeconomic and real uncertainty exhibit higher skewness and kurtosis, particularly during systemic stress periods. Overall, these patterns underscore VVIX's suitability

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[1] Both the EPU and FMR datasets are obtained from the Economic Policy Uncertainty website: https://www.policyuncertainty.com/index.html

as an anchor for aligning uncertainty measures and highlight the heterogeneous nature of uncertainty components, which later informs the PLS-based variable importance analysis.

4. Empirical Results

The empirical analysis is designed to assess whether aligning economic uncertainty measures with volatility-of-volatility provides a more effective and theoretically grounded channel for predicting market returns than conventional approaches. VOV captures higher-order risk—uncertainty about volatility itself—which is more persistent and less sensitive to transitory shocks than realized volatility or VIX. This structural property suggests that VOV-aligned uncertainty indices may isolate the components of uncertainty most relevant for volatility risk premia, thereby improving forecast accuracy and stability. Beyond statistical performance, the investigation seeks to determine whether such alignment delivers economically meaningful gains for investors through enhanced portfolio allocation and risk management. Accordingly, the empirical tests evaluate predictive power, robustness across alternative specifications, and practical implications for asset allocation in both domestic and global markets.

4.1. Predictability of VOV-aligned Uncertainty Indices

We begin by assessing whether VOV alignment improves return predictability relative to raw uncertainty indicators. This test addresses the hypothesis that filtering uncertainty through VOV enhances signal extraction by focusing on volatility risk.

<Insert Table 2 here>

Table 2 reports results for five VOV-aligned indices constructed from different uncertainty

combinations. All indices exhibit negative slope coefficients significant at the 1% level, consistent with the theoretical prediction that VOV risk commands a negative price. The EPU+FIN specification delivers the strongest performance, with an in-sample R^2=13.97% and an out-of-sample R^2_{OS}=14.49%, both highly significant. Indices incorporating the full FMR group also perform well, while those augmented with MACRO or REAL uncertainty yield smaller gains.

To evaluate whether VOV provides a unique advantage, we compare its performance with indices aligned to VIX using identical predictor sets.

<Insert Table 3 here>

Table 3 demonstrates that VIX-aligned indices underperform markedly. Four of five specifications produce negative R^2_{OS} values, and only the EPU+FIN combination achieves a marginally positive 1.18% at the 10% level. These results underscore VOV's superiority as a predictive channel and suggest that VIX alignment suffers from transitory option-market noise, while VOV alignment leverages a more persistent risk factor.

4.2. Error Analysis and Dynamics of VOV-Aligned Forecasts

This section analyzes the cumulative squared prediction errors (CSPE) of VOV-aligned uncertainty, compares the VOV-aligned index with realized VOV, and evaluates the performance of VOV-aligned return forecasts relative to realized market returns. Following Rapach, Strauss and Zhou (2010) and Huang et al. (2015), we evaluate performance using differences in CSPE. For an out-of-sample month t, the CSPE for a return forecast $\hat{r}_{m,k+1}$ is computed as

$$\text{CSPE} = \sum_{k=s}^{t} \left(r_{m,k+1} - \hat{r}_{m,k+1} \right)^2. \tag{4}$$

<Insert Figure 1 here>

Figure 1 shows the difference in CSPE between the historical average benchmark and forecasts based on two alignment indexes: $\widehat{VOV}_t|\text{EPU}$ and $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$. Both forecasts lie above the zero-reference line, which signals cumulative outperformance relative to the HA benchmark. The $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ index remains consistently above $\widehat{VOV}_t|\text{EPU}$, indicating that it delivers stronger overall performance. This advantage is particularly pronounced during episodes of heightened uncertainty, such as the COVID-19 crisis, when competing forecasts exhibit sharp deterioration.

<Insert Figure 2 here>

Figure 2 compares the constructed VOV-aligned uncertainty index with realized VOV, both in-sample and out-of-sample. The close tracking between the two series validates the alignment approach and demonstrates that the index effectively captures the component of economic uncertainty most relevant for volatility risk. This alignment is critical because it ensures that predictive signals are grounded in a persistent risk factor rather than short-lived market noise. Table A1 in the Appendix further shows that three VOV-aligned uncertainty indices constructed from EPU alone, EPU+FIN, and EPU+REAL significantly predict realized VOV.

<Insert Figure 3 here>

Figure 3 plots market return forecasts from the best index, $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$, against realized returns. The realized returns exhibit substantial month-to-month volatility, highlighting the challenge of forecasting market returns. Despite this high noise, the VOV-aligned forecasts track the broad ups and downs of realized returns rather than short-term fluctuations. This comovement

is particularly evident in the out-of-sample period, where the forecasts display similar ups and downs to those observed in the in-sample predictions. The figure illustrates that while the VOV-aligned index does not replicate realized returns point by point, it contains meaningful information about the direction and variation of expected market returns.

In sum, VOV-aligned uncertainty indices consistently outperform the historical average benchmark in terms of CSPE, with the EPU+FIN index delivering the strongest gains, especially during periods of elevated uncertainty. Moreover, the VOV-aligned index closely tracks realized VOV and produces return forecasts that capture the broad ups and downs of market returns, indicating that the alignment approach extracts meaningful and persistent predictive information despite substantial return volatility.

4.3. Incremental Power Beyond Individual Uncertainty Measures and Established Predictors

We assess the effectiveness of our aggregate VOV-aligned index by comparing it with, and controlling for, the individual uncertainty predictors. We first examine the performance of each predictor using the univariate specification:

$$r_{m,t+1} = \alpha + \eta U_{i,t} + \epsilon_{t+1} \tag{5}$$

where $U_{i,t}$ denotes one of the fifteen uncertainty predictors listed in Table 1. We then add our VOV-aligned EPU+FIN uncertainty index and estimate the following bivariate regression:

$$r_{m,t+1} = \alpha + \eta U_{i,t} + \beta \widehat{VOV}_t|\{\text{EPU}, \text{FIN}\} + \epsilon_{t+1} \tag{6}$$

We focus on the statistical significance of the regression slop β and on the out-of-sample

performance of the bivariate specification.

Table 4 presents the forecasting results for the EPU+FIN VOV-aligned index when comparing with and controlling for the individual uncertainty measures listed in Table 1. Panel A shows that seven of the fifteen predictors yield significant in-sample slope coefficients, but only two—taxes and health care uncertainty—generate significant out-of-sample R_{OS}^2 values, both below 4%. Most other measures, including VVIX, provide weak or negative out-of-sample predictive performance.

Panel B reports the results after controlling for each individual uncertainty predictor. The index continues to exhibit strong in-sample performance, with R^2 values rising to roughly 15% across all predictors. Out of sample, the index also delivers significant R_{OS}^2 improvements for nearly all predictors; for example, controlling for VIX slightly increases R_{OS}^2 to 15.32%. An exception is the specification including MACRO uncertainty, which yields an insignificant positive R_{OS}^2 of 4.99%. This is because the MACRO measure itself produces a large negative R_{OS}^2 below -10%. Including this measure introduces substantial noise that dampens the predictive gains of the VOV-aligned index. In summary, the individual uncertainty predictors offer limited predictive power on their own, whereas the VOV-aligned EPU+FIN index provides significant predictive ability beyond each of these individual uncertainty predictors.

We then test whether VOV-aligned indices add information beyond widely used established predictors, addressing concerns about omitted-variable bias. We begin with a univariate regression to evaluate the predictive power of each established variable:

$$r_{m,t+1} = \alpha + \eta Z_t + \epsilon_{t+1}, \tag{7}$$

where Z_t denotes one of the twenty established predictors from Welch and Goyal (2008) and Goyal, Welch, Zafirov (2024). We consider fourteen variables from Welch and Goyal (2008): dividend-price ratio (DP), dividend yield (DY), earnings-price ratio (EP), dividend-payout ratio (DE), stock return variance (SVAR), book-to-market ratio (BM), net equity issuance (NTIS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), and inflation (INFL). These variables capture valuation ratios, interest rate spreads, credit risk, and macroeconomic conditions commonly used in equity premium prediction. We also include six predictors from Goyal, Welch, and Zafirov (2024): output gap of industrial production (OGAP), tail risk from cross-section (TAIL), the PLS index extracted from fourteen technical indicators (TCHI), the PLS index extracted from B/M cross-section (FBM), the average correlation of daily stock returns (AVGCOR), and short stock interest (SHTINT).[2] We next examine whether the predictive power of $\widehat{VOV}_t | \text{EPU, FIN}$ persists after controlling for these established variables. We estimate the following bivariate regression to assess the incremental power of the $\widehat{VOV}_t | \{\text{EPU, FIN}\}$ index:

$$r_{m,t+1} = \alpha + \beta \widehat{VOV}_t | \{\text{EPU, FIN}\} + \eta Z_t + \epsilon_{t+1}. \tag{8}$$

Our primary interest is whether the slope coefficient β remain statistically significant based on the Newey-West t-statistics and the out-of-sample performance using the bivariate regression.

<center><Insert Table 5 here></center>

Table 5 reveals that most established variables have limited standalone predictive power, with out-of-sample R^2 values typically negative or not significant. Only OGAP, TAIL, TCHI, and AVGCOR exhibit significant R^2_{OS} values, ranging from 2.31% to 3.25%. When combined with the VOV-aligned index, explanatory power rises sharply, with R^2 exceeding 10% in most cases. The slope on the VOV-aligned index remains negative and significant at the 1% level, confirming that its predictive content is not subsumed by established predictors. This finding reinforces the argument that VOV alignment captures a distinct and economically relevant dimension of uncertainty.

4.4. Variable Importance

The objective in this subsection is to enhance the interpretability of the VOV-alignment framework by uncovering the underlying drivers of its predictive power. While aggregate indices provide a convenient summary of uncertainty, they mask the relative influence of individual components. We therefore examine variable importance to identify which measures—such as financial uncertainty, sovereign risk, or regulatory factors—consistently shape volatility risk premia. By doing so, we aim to demonstrate that VOV-aligned indices are not black-box predictors, but interpretable tools grounded in economic theory.

Figure 4 provides a heatmap of time-varying weights assigned to individual uncertainty measures within the VOV-aligned index. The analysis reveals that three components—financial uncertainty (FIN), sovereign debt and currency crises, and regulatory uncertainty—consistently dominate across the sample period. These measures capture systemic financial risk and institutional instability, both of which are theoretically linked to volatility risk premium and

investor demand for hedging against higher-order uncertainty. Their persistent prominence suggests that these risks are priced continuously rather than episodically, reinforcing the economic rationale for their inclusion. This is further confirmed by the following findings.

The periods when the VOV-aligned index exhibited superior forecast performance relative to VIX-aligned index correspond to the onset of persistent and policy-driven systematic risk, which traditional VIX measures structurally underestimate. The imposition of U.S. sanctions on Russia in March 2014 created the largest forecasting divergence, as regulation uncertainty instantly translated into systematic financial uncertainty. A similar underestimation of VIX measures occurred in April 2020, where the COVID-19 amplified financial uncertainty to its peak following the complex and uncertain regulatory responses of the CARES Act. A third major peak in July 2016 was characterized by the period's highest regulatory uncertainty, immediately following the UK Brexit Referendum, which introduced massive and structural policy risk into the global financial system.

Furthermore, the VOV-aligned framework also proves superior in integrating risks transmitted via sovereign debt and currency crises. For instance, global market turmoil culminating in November 2015 tracked the sustained uncertainty following the Greek default on the IMF in July and the Chinese yuan devaluation in August, signaling the critical role of VOV-based forecasts capturing sovereign debt and currency crises. [3] In all these cases, the VOV-aligned index

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[3] The VOV-aligned index also validated its dominant predictability when systematic stress is compounded by domestic policy friction in late 2018 and early 2019. Systematic pressure first escalated in October 2018 due to a sharp combination of US-China trade war and investor fears over the Federal Reserve's accelerated rate hikes, contributing to the initial failure of VIX-based forecasts. This market stress was then critically compounded in January 2019 by the prolonged U.S. government shutdown, which directly fueled financial uncertainty and exacerbated the failure of VIX-aligned index.

successfully captured the realized volatility jump induced by these unforeseen event shocks.

Conversely, several Economic Policy Uncertainty (EPU) categories, such as monetary policy, entitlement programs, and trade policy, exhibit persistently low weights, indicating limited relevance for explaining return variation under normal market conditions. This pattern underscores the selective nature of predictive content: not all policy-related uncertainties translate into volatility risk premium. The concentration of predictive power in measures reflecting financial fragility and sovereign risk highlights the structural channels through which uncertainty affects asset pricing.

Overall, the variable importance analysis demonstrates that VOV-aligned indices are not opaque statistical constructs, but interpretable tools grounded in economic theory. By isolating the uncertainty dimensions most relevant for volatility risk, the framework enhances transparency and provides a foundation for refining predictive models to emphasize economically meaningful sources of risk.

4.5. Asset-Allocation Implications

Statistical significance must translate into economic value to matter for investors. By computing CER gains and Sharpe ratios under realistic constraints, this section tests whether VOV-aligned forecasts improve risk-adjusted performance enough to justify implementation costs, especially during high-uncertainty episodes.

We further assess the economic value of forecasting market returns with VOV-aligned uncertainty indices from an asset allocation perspective. We consider a mean-variance investor who allocates across equities and the risk-free bills using these return forecasts. Following

Campbell and Thompson (2008), we compare the annualized certainty equivalent return (CER) gains and Sharpe ratios of VOV-based strategies against those of the HA forecast strategy. The investor's optimal equity weight at the end of month t is $\omega_t = \frac{1}{\gamma} \frac{\mathbb{E}_t[R_{t+1}]}{\mathbb{E}_t[\sigma_{t+1}^2]}$, where γ denotes the investors' degree of risk aversion, $\mathbb{E}_t[R_{t+1}]$ is a forecast of simple excess stock returns of time t+1 using a VOV-aligned uncertainty index of time t, and $\mathbb{E}_t[\sigma_{t+1}^2]$ denotes the forecast of return variance of time t+1 recursively estimated using the excess stock returns observed up to month t. We exclude short sales and allow for at most 200% leverage, thus constraining the equity weight to lie between 0 and 3. The weight allocated to risk-free bills is $1 - \omega_t$, and the portfolio return (R_{t+1}^p) at month $t + 1$ is given by $R_{t+1}^p = \omega_t R_{t+1} + r_{t+1}^f$, where R_{t+1} and r_{t+1}^f are the realized simple excess market return and the risk-free return, respectively.

The CER of the portfolio is $\text{CER} = \bar{R}^p - \frac{1}{2}\gamma\sigma^2(R^p)$, where $\bar{R}^p$ and $\sigma^2(R^p)$ denote the mean and variance of portfolio returns over the out-of-sample period, respectively. We also compute the annualized Sharpe ratios to assess investment performance. A higher CER or Sharpe ratio suggests greater economic value of predictability.

<Insert Table 6 here>

Table 6 reports the asset allocation results for a mean-variance investor with risk aversion of 3 or 5. We compare the strategy performance based on the best performing index, $\widehat{VOV}_t | \{\text{EPU, FIN}\}$ with the historical average (HA) forecast. Under both risk-aversion levels and with no transaction costs, the strategy using the EPU+FIN VOV-aligned index consistently delivers higher CER gains and Sharpe ratios. This index produces annualized CER gains of 35.86% and 26.66% for $\gamma = 3$ and 5, with Sharpe ratios above 1.5, indicating strong economic value and

better performance than the HA benchmark. Introducing a 50-basis point transaction cost weakens performance for both indices, but the qualitative ranking remains unchanged. The EPU+FIN index continues to produce the higher CER gain and Sharpe ratio in each panel.

<Insert Figure 5 here>

Figure 5 compares cumulative portfolio returns for strategies based on VOV-aligned uncertainty indices (EPU+FIN) with two benchmarks: the HA forecast and a buy-and-hold strategy. This visualization complements Table 6 by showing how performance evolves over time in the out-of-sample period. During 2015–2018, all four strategies move closely together, with cumulative returns rising from 1 to about 2. However, the VOV-aligned strategy maintains the top position by marginally outperforming the HA forecast and the buy-and-hold strategy. Around 2019, the VOV-aligned strategies begin to pull ahead, while the buy-and-hold strategy remains lower. The sharpest divergence occurs during the COVID-19 period: the EPU+FIN strategy climbs to above 10 by the end of 2021. In contrast, the HA benchmark ends closer to 4, and the buy-and-hold strategy remains below 3. The figure shows that VOV-aligned strategies track benchmarks during normal periods but outperform significantly during the COVID-19 episode, indicating that these strategies deliver higher cumulative returns in times of heightened uncertainty.

Overall, Figure 5 demonstrates that the VOV-aligned uncertainty indices (EPU+FIN) achieve the largest cumulative gains by the end of the sample, surpassing both HA and buy-and-hold benchmarks.

5. **Robustness**

To ensure that the predictive power of VOV-aligned uncertainty indices is not driven by specific sample conditions or modeling choices, we conduct a series of robustness checks. These analyses examine two dimensions: (i) whether incorporating additional uncertainty measures enhances performance; (ii) whether results persist when the sample includes the global financial crisis. By addressing these aspects, we validate stability, flexibility, and practical relevance of our approach across different economic environments.

5.1. Incorporating Additional Uncertainty Measures

To test robustness, we augment the best-performing VOV-aligned index (EPU+FIN) with four widely cited uncertainty measures: MRU, capturing macroeconomic risk (Bali et al., 2014); MPU, reflecting monetary policy uncertainty (Husted et al., 2020); ESGUI, measuring sustainability-related uncertainty (Ongan et al., 2025); and EMV, a news-based equity volatility tracker (Baker et al., 2026). These measures are relevant because prior studies link macro risk, policy uncertainty, sustainability concerns, and volatility shocks to asset pricing and market volatility, suggesting potential incremental predictive power when aligned to VOV.

<Insert Table 7 here>

Table 7 shows that all augmented indices maintain significant negative slopes and strong out-of-sample performance. The EPU+FIN+MRU specification delivers the largest improvement, raising R_{OS}^2 from 14.49% to 16.6%. MPU, ESGUI, and EMV also improve performance, with R_{OS}^2 values between 11.32% and 12.85%, all significant at the 1% level. These findings confirm that VOV alignment is robust and benefits from integrating broader uncertainty dimensions. The largest gain from MRU underscores the role of macro-risk uncertainty, while MPU, ESGUI, and

EMV provide complementary signals consistent with their documented influence on financial markets. Overall, these results indicate that outperformance of VOV-aligned indices is robust and can be marginally enhanced by incorporating additional uncertainty measures.

5.2. Including the Global Financial Crisis Period

We extend the sample back to VVIX inception (March 2006) to include the global financial crisis, testing whether aligning uncertainty measures to VOV—proxied by VVIX, which applies the VIX methodology to VIX options—retains predictive power under extreme regimes. We construct the indices via PLS regression to maximize covariance with future VVIX and filter common noise in many predictors. This choice is motivated by evidence that model-based uncertainty episodes are rare but large and persistent, making the VOV channel theoretically appealing for equity-premium prediction (Jurado, Ludvigson, and Ng, 2015).

<Insert Table 8 here>

Table 8 shows that across specifications, slopes remain negative and generally significant in-sample, consistent with a negative price of VOV risk. Out-of-sample (OOS) performance weakens for most indices once the GFC is included: EPU (-3.02%), EPU+MACRO (-3.98%), EPU+REAL (-7.04%), and EPU+FMR (2.94%, statistically insignificant). In contrast, $\widehat{VOV}_t|\{EPU, FIN\}$ remains robust, delivering R^2_{OS} = 5.55% with Clark-West MSFE-adjusted significance at the 5% level. This pattern is consistent with the literature's characterization of macro/financial uncertainty as persistent during major episodes, and with the idea that the VVIX anchor captures the higher-order volatility risk component that remains priced even through severe dislocations. These findings confirm that financial uncertainty filtered through the VVIX/VOV

anchor is the most resilient source of predictive content in crisis-inclusive samples.

6. Extensions

This section investigates the generality of our VOV-aligned uncertainty framework beyond the aggregate U.S. market returns. First, we examine tradable hedge fund indices to test whether hedge fund strategies are systematically sensitive to volatility-of-volatility risk captured by the VOV-aligned uncertainty index. Second, we assess international scope by evaluating the index's forecasting power across global equity markets including developed and emerging markets. Third, we explore the index's predictive ability for other equity portfolios in U.S. markets. Across all three extensions, we maintain the same real-time out-of-sample design and report statistical (in-sample R^2, R^2_{OS}) and economic relevance, while exploring heterogeneity by strategy and region to clarify when and why VOV-aligned uncertainty is most informative.

6.1. Forecasting hedge fund returns with VOV-aligned uncertainty

We extend the VOV-alignment framework to tradable hedge fund indices to test portability across asset classes where leverage, dynamic hedging, and relative-value arbitrage should be acutely sensitive to VOV risk. Prior evidence shows that VOV exposure is priced in hedge fund returns—constructed via investable lookback-straddle proxies on VIX—implying a negative VOV premium and material performance effects across strategies (Agarwal, Arisoy, and Naik, 2017). We evaluate performance on HFR-classified indices, which offer standardized, investable strategy families for Event Driven, Equity Hedge, Macro, and Relative Value.

<Insert Table 9 here>

Table 9 presents the in-sample and out-of-sample performance for forecasting various hedge fund index returns using the $\widehat{VOV}_t | \{EPU, FIN\}$ index. We find that that in-sample slopes are negative and significant for most indices. Out of sample, roughly half of the Event Driven/Equity Hedge/Relative Value sub-indices achieve $R^2_{OS} > 10\%$. We find that VOV-aligned uncertainty predicts hedge-fund returns most strongly in leverage/arbitrage-intensive styles (Relative Value; selected Event Driven and Equity Hedge), consistent with VOV being a priced systemic factor that transmits through financing frictions and hedging convexity. The mixed Macro results suggest mandates tied to FX or systematic multi-asset signals may require non-equity volatility anchors (e.g., rates or FX vol) to capture their dominant risk channels.

In sum, Table 9 shows that the $\widehat{VOV}_t | \{EPU, FIN\}$ index is a parsimonious, interpretable timing tool across hedge-fund styles, delivering double-digit R^2_{OS} in many indices and peaking at 17.41% for Relative Value Multi-Strategy, while highlighting where anchor tailoring could further improve Macro forecasts. To sum up, these results indicate that the predictive power of VOV-aligned uncertainty extends beyond the aggregate stock market to a variety of hedge fund returns.

6.2. Forecasting global market returns with VOV-aligned uncertainty

We examine whether the predictive power of the VOV-aligned EPU+FIN index generalizes beyond U.S. equities to international markets, addressing the question of global scope. Prior research documents that U.S. information often forecasts non-U.S. returns through lead-lag effects and news diffusion (Rapach, Strauss, Zhou, 2013). If VOV risk is a pervasive factor, the same signal should improve return predictability across developed and emerging markets, making it relevant for global asset allocation. We construct country-level equity market returns following

Bessembinder et al. (2023). That is, we identify common stocks in each market (GVKEY mapping) from Compustat Global/WRDS, compute buy-and-hold total returns (including dividends and splits) in USD, and aggregate to country portfolios. Markets are then grouped into Developed and Emerging based on the MSCI Market Classification Framework to align with investability and accessibility standards. This design lets us test whether VOV-aligned uncertainty is a systemic predictor that scales across geographies and market structures.

<Insert Table 10 here>

Table 10 presents the forecasting results using the $\widehat{VOV}_t|\{EPU, FIN\}$ index in the global stock markets. We find that the EPU+FIN index delivers significant negative slopes in nearly all countries. Out-of-sample performance is strongest in Developed markets, where many achieve R_{OS}^2>10%; for example, Australia reaches 19.33%, while several European markets exceed 12%. Among Emerging markets, results are more heterogeneous but still notable: South Africa posts 16.76%, and Brazil and Chile exceed 7%, with Clark–West MSFE-adjusted significance supporting the gains.

In sum, we show that the VOV-aligned signal is a scalable global allocation tool—delivering double-digit out-of-sample R^2 in many Developed markets and meaningful gains in selected Emerging markets.

6.3. Forecasting returns on characteristic portfolios with VOV-aligned uncertainty

We also examine whether the return predictability of the VOV-aligned EPU+FIN index extends beyond the aggregate market to other equity portfolios. Following Kelly and Pruitt (2013), we forecast returns for portfolios formed on six stock characteristics: book-to-market ratios, firm size,

operating profitability, investment, momentum (decile portfolios), and industry classification (10 industry portfolios). Return data for all portfolios are obtained from Ken French's website.

<Insert Table 11 here>

Table 11 shows that the $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ index delivers strong and pervasive return predictability across characteristic-sorted portfolios. In-sample slope coefficients are uniformly negative and highly significant, with R^2 generally between 9% and 14%. Out-of-sample results are also economically meaningful, with significantly positive R_{OS}^2 for nearly all portfolios; the largest R_{OS}^2 exceeds 17% for manufacturing industry portfolios and is around 15% for small-stock portfolios. The only exception is utility industry portfolios, which do not exhibit significant out-of-sample performance. This likely reflects their stable cash flows, low volatility, and limited sensitivity to uncertainty shocks. In summary, the VOV-aligned uncertainty index delivers broad and robust return predictability across firm characteristics and industries.

7. Conclusion

This paper investigates how economic uncertainty translates into return predictability through the lens of VOV. Motivated by the structural negative covariance between VOV and market returns documented in prior research, we construct VOV-aligned uncertainty indices using the PLS approach and evaluate their forecasting ability in both in-sample and out-of-sample settings. Our results show that aligning uncertainty measures to future VVIX—rather than to returns or VIX—substantially improves predictive accuracy and stability.

The empirical evidence highlights several key findings. First, VOV-aligned indices

consistently outperform VIX-aligned counterparts, confirming that higher-order volatility risk is a more persistent and theoretically grounded channel for extracting predictive content. Second, among all specifications, the EPU+FIN VOV-aligned index delivers the strongest performance, achieving out-of-sample R^2 values up to 14.5% for U.S. equities and generating economically meaningful gains for mean-variance investors, even after transaction costs. Third, variable-importance analysis reveals that financial uncertainty, sovereign debt/currency crises, and regulatory uncertainty are the dominant drivers of predictive power, offering interpretability and insight into the structural channels through which uncertainty affects risk premia.

Robustness checks confirm that these results persist after controlling for Welch-Goyal established predictors, when incorporating additional uncertainty measures such as MRU, MPU, ESG, and EMV, and even when the sample includes the Global Financial Crisis. Furthermore, the predictive power of VOV-aligned uncertainty extends beyond equities to hedge fund strategies, where leverage and arbitrage amplify sensitivity to volatility shocks, and to global equity markets, where the signal achieves double-digit out-of-sample R^2 in many developed economies and meaningful gains in selected emerging markets. In addition, the signal predicts returns across characteristic-sorted equity portfolios, with robust in- and out-of-sample performance for size, value, momentum, profitability, investment, and most industry portfolios, highlighting the broad and systematic nature of VOV-aligned uncertainty.

Overall, this study advances the literature by demonstrating that VOV alignment is a powerful and interpretable framework for forecasting returns. It provides a scalable tool for portfolio management across asset classes and geographies, particularly valuable during periods of

heightened uncertainty. Future research could assess dynamic integration of VOV-aligned signals

into multi-asset allocation strategies.

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Table 1: Summary statistics

This table presents summary statistics for the log market return (r_m), the log of the Cboe Volatility Index (VIX), the log of the Cboe Volatility-of-Volatility Index (VVIX), and two sets of economic uncertainty measures. The first set, from Baker, Bloom and Davis (2016), includes one overall economic policy uncertainty and nine categorical policy uncertainty subindices (monetary policy, taxes, government spending, health care, national security, entitlement programs, regulation, trade policy, and sovereign debt and currency crises). The second set, from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021), comprises three uncertainty measures: financial uncertainty (FIN), macro uncertainty (MACRO), and real uncertainty (REAL). All uncertainty measures are constructed as differences in log-transformed values. For each variable, we report the time-series mean (Mean), standard deviation (Std), maximum (Max), minimum (Min), skewness (Skew), and kurtosis (Kurt). The sample period spans from July 2009 to December 2021.

Variables	Mean	Std	Min	Max	Skew	Kurt
r_m	0.0123	0.0411	-0.1423	0.1280	-0.5263	1.4313
VVIX	4.5316	0.1565	4.1665	5.0299	0.4574	0.5951
VIX	2.8739	0.3256	2.2523	3.9804	0.6746	0.2957
Economic policy uncertainty	0.0014	0.2614	-0.8128	1.1983	0.6532	2.6906
Monetary policy	0.0080	0.4675	-0.8685	1.4545	0.5111	0.3208
Taxes	-0.0001	0.3169	-0.8676	1.0018	0.1130	0.6067
Government spending	-0.0014	0.5114	-1.9646	1.3285	-0.2460	1.1833
Health care	-0.0016	0.3882	-1.3654	1.6079	0.2142	1.8818
National security	0.0009	0.4796	-1.2250	1.3010	0.2496	0.0902
Entitlement programs	0.0036	0.4812	-1.4264	1.9343	0.3301	1.0114
Regulation	-0.0007	0.3384	-0.7298	1.4283	0.8296	1.8620
Trade policy	0.0016	0.7394	-1.9878	2.0273	0.1122	0.0720
Sovereign debt and currency crises	0.0024	1.8716	-13.7733	12.3693	-0.7417	31.3905
FIN	-0.0010	0.0364	-0.1065	0.1063	0.1751	0.9627
MACRO	-0.0009	0.0327	-0.0933	0.1949	1.6722	10.2594
REAL	0.0002	0.0352	-0.1042	0.2131	1.5760	10.6666

Table 2: Forecasting market returns with VOV-aligned uncertainty indices

This table presents the regression slope (β), Newey-West t-statistic (t-stat), in-sample R^2, and out-of-sample R^2_{OS} for forecasting market returns using VOV-aligned uncertainty:
$$r_{m,t+1} = \alpha + \beta\widehat{VOV}_t|U + \epsilon_{t+1},$$
where $r_{m,t+1}$ denotes the market return in month $t+1$, and $\widehat{VOV}_t|U$ is a VOV-aligned uncertainty index extracted using partial least squares from a set of economic uncertainty measures U. We first include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) as the base group. We then add financial uncertainty (FIN), macroeconomic uncertainty (MACRO), real uncertainty (REAL), as well as the FMR group (the three measures added jointly) from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021). The significance of R^2_{OS} is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

Predictor	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
$\widehat{VOV}_t\|$EPU	-3.46***	-4.38	4.92	3.87**	1.78
$\widehat{VOV}_t\|\{$EPU, FIN$\}$	-5.45***	-4.74	13.97	14.49***	3.14
$\widehat{VOV}_t\|\{$EPU, MACRO$\}$	-3.82***	-4.31	7.07	5.81*	1.37
$\widehat{VOV}_t\|\{$EPU, REAL$\}$	-3.5***	-3.97	5.42	2.77	1.19
$\widehat{VOV}_t\|\{$EPU, FMR$\}$	-4.36***	-4.95	11.33	10.65**	1.75

Table 3: Forecasting market returns with VIX-aligned uncertainty indices

This table presents the regression slope (β), Newey-West t-statistic (t-stat), in-sample R^2, and out-of-sample R^2_{OS} for forecasting market returns using the VIX-aligned uncertainty indices:

$$r_{m,t+1} = \alpha + \beta \widehat{VIX}_t | U + \epsilon_{t+1}.$$

Here, $r_{m,t+1}$ denotes the market return in month $t+1$, and $\widehat{VIX}_t | U$ is a VIX-aligned uncertainty index. The VIX-aligned uncertainty indices are extracted using partial least squares from a set of economic uncertainty measures U. We first include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) as the base group. We then add financial uncertainty (FIN), macroeconomic uncertainty (MACRO), real uncertainty (REAL), as well as the FMR group (the three measures added jointly) from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021). The significance of R^2_{OS} is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
$\widehat{VIX}_t | EPU$	-1.47	-1.28	0.99	-3.81	0.14
$\widehat{VIX}_t | \{EPU, FIN\}$	-4.10***	-4.05	7.26	1.18*	1.33
$\widehat{VIX}_t | \{EPU, MACRO\}$	-2.00*	-1.66	1.73	-11.73	-1.93
$\widehat{VIX}_t | \{EPU, REAL\}$	-1.94	-1.64	1.76	-17.13	-1.99
$\widehat{VIX}_t | \{EPU, FMR\}$	-3.80***	-3.63	6.77	-15.96	-1.80

Table 4: Comparison with and control for individual uncertainty measures

This table provides the in-sample and out-of-sample results when comparing with and controlling for the individual uncertainty measures listed in Table 1. Panel A presents the univariate regressions:

$$r_{m,t+1} = \alpha + \eta U_{i,t} + \epsilon_{t+1},$$

where $r_{m,t+1}$ is the monthly aggregate stock market return, and $U_{i,t}$ is the one of the log VVIX, the log VIX, or the two sets of economic uncertainty measures. The first set, from Baker, Bloom and Davis (2016), includes one overall economic policy uncertainty and nine categorical policy uncertainty subindices (monetary policy, taxes, government spending, health care, national security, entitlement programs, regulation, trade policy, and sovereign debt and currency crises). We denote this set of ten uncertainty measures as EPU. The second set, from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021), comprises three uncertainty measures: financial uncertainty (FIN), macro uncertainty (MACRO), and real uncertainty (REAL). Panel B reports the bivariate regressions:

$$r_{m,t+1} = \alpha + \eta U_{i,t} + \beta \widehat{VOV}_t | \{EPU, FIN\} + \epsilon_{t+1},$$

where $\widehat{VOV}_t | \{EPU, FIN\}$ is the VOV-aligned index extracted using partial least squares with EPU and FIN as input measures. We report slope coefficients (η and β), in-sample R^2, and out-of-sample R_{OS}^2 for each uncertainty measure. The significance of η and β is evaluated using their respective p-values of Newey-West t-statistics, while the significance of R_{OS}^2 is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-sample period spans January 2014 to December 2021.

	In-sample			Out-of-sample	
	η (%)	β (%)	R^2 (%)	R_{OS}^2 (%)	CW-stat
Panel A: Performance of individual uncertainty measures					
VVIX	0.39		0.92	-2.54	-0.62
VIX	0.76**		3.47	2.04	1.24
Economic policy uncertainty	0.69*		2.86	0.96	0.84
Monetary policy	0.31		0.55	-3.61	-1.13
Taxes	0.74**		3.22	3.47**	1.98
Government spending	0.42		1.07	-1.12	-0.30
Health care	0.73**		3.09	3.45*	1.50
National security	0.28		0.45	-2.88	-0.96
Entitlement programs	0.37		0.82	-1.30	-0.85
Regulation	0.00		0.00	-3.83	-1.00
Trade policy	0.50*		1.47	1.04	1.07
Sovereign debt and currency crises	-0.44*		1.14	0.84	0.83
FIN	-0.99***		5.76	0.56	0.97
MACRO	-0.40		0.97	-12.37	-0.19
REAL	-0.10		0.06	-14.21	-0.80

	In-sample			Out-of-sample	
	η (%)	β (%)	R^2 (%)	R^2_{OS} (%)	CW-stat
Panel B: $\widehat{VOV}_t|\{EPU, FIN\}$ performance controlling for individual uncertainty measures					
VVIX	0.50*	-5.58***	15.45	13.49***	3.11
VIX	0.64**	-5.26***	16.37	15.32***	3.99
Economic policy uncertainty	0.20	-5.21***	14.18	7.30**	2.02
Monetary policy	-0.12	-5.57***	14.04	7.40**	2.32
Taxes	0.17	-5.22***	14.12	11.38**	2.40
Government spending	-0.11	-5.59***	14.03	9.75**	2.42
Health care	0.18	-5.22***	14.13	10.60**	2.20
National security	-0.54	-6.32***	15.31	8.62**	2.37
Entitlement programs	0.11	-5.39***	14.04	10.23**	2.28
Regulation	0.11	-5.48***	14.04	11.14***	2.63
Trade policy	-0.12	-5.61***	14.03	14.73***	3.39
Sovereign debt and currency crises	-0.29	-5.35***	14.46	15.04***	3.27
FIN	-0.19	-5.07***	14.12	11.09**	2.30
MACRO	-0.12	-5.37***	14.05	4.99	1.23
REAL	0.11	-5.51***	14.03	4.31*	1.38

Table 5: Comparison with and control for individual established predictors

This table provides the in-sample and out-of-sample results when comparing with and controlling for established predictors. Panel A presents the univariate regressions:

$$r_{m,t+1} = \alpha + \eta Z_t + \epsilon_{t+1},$$

where $r_{m,t+1}$ is the monthly aggregate market return, and Z_t is drawn from two groups of established predictors in the prior literature. The first group consists of fourteen variables from Welch and Goyal (2008): dividend-price ratio (DP), dividend yield (DY), earnings-price ratio (EP), dividend-payout ratio (DE), stock return variance (SVAR), book-to-market ratio (BM), net equity issuance (NTIS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), and inflation (INFL). These variables capture valuation ratios, interest rate spreads, credit risk, and macroeconomic conditions commonly used in equity premium prediction. The second group comprises six predictors from Goyal, Welch, and Zafirov (2024): output gap of industrial production (OGAP), tail risk from cross-section (TAIL), the PLS index extracted from fourteen technical indicators (TCHI), the PLS index extracted from B/M cross-section (FBM), the average correlation of daily stock returns (AVGCOR), and short stock interest (SHTINT). Panel B reports the bivariate regressions:

$$r_{m,t+1} = \alpha + \eta Z_t + \beta \widehat{VOV}_t|\{\text{EPU}, \text{FIN}\} + \epsilon_{t+1},$$

where $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ is a VOV-aligned uncertainty index. This index is extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) index from Jurado, Ludvigson and Ng (2015). We report slope coefficients (η and β), in-sample R^2, and out-of-sample R^2_{OS} for each established variable. The significance of η and β is evaluated using their respective p-values of Newey-West t-statistics, while the significance of R^2_{OS} is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-sample period spans January 2014 to December 2021.

	In-sample			Out-of-sample	
	η (%)	β (%)	R^2 (%)	R^2_{OS} (%)	CW-stat
Panel A: Performance of individual established predictors					
DP	0.52		1.48	-5.46	1.04
DY	0.39		0.82	-4.31	0.62
EP	-0.13		0.11	-0.14	-0.23
DE	0.32		0.59	0.45	0.98
SVAR	0.86***		4.41	-28.78	-0.97
BM	0.22		0.27	-1.84	0.42
NTIS	-0.05		0.02	-1.76	-1.41
TBL	-0.44		1.14	-2.81	-0.78
LTY	-0.57*		1.94	-0.14	0.52
LTR	0.13		0.10	-1.34	-0.50
TMS	-0.17		0.18	-3.09	-1.85
DFY	0.51		1.51	0.49	1.07
DFR	0.20		0.24	-4.01	-0.81
INFL	-0.30		0.54	-2.32	-0.49
OGAP	-0.65***		2.47	2.47**	1.74
TAIL	-0.68*		2.70	2.83**	1.93
TCHI	-0.74**		3.25	3.42*	1.57
FBM	0.07		0.03	-1.00	-0.67
AVGCOR	0.62*		2.31	2.37**	1.70
SHTINT	-0.17		0.18	-1.67	-1.14

	In-sample			Out-of-sample	
	η (%)	β (%)	R^2 (%)	R^2_{OS} (%)	CW-stat
Panel B: $\widehat{VOV}_t$|EPU, FIN performance controlling for individual established predictors					
DP	0.37	-5.33***	14.70	10.01***	2.71
DY	0.19	-5.37***	14.16	11.10**	2.52
EP	-0.07	-5.44***	14.00	14.18***	3.05
DE	0.20	-5.40***	14.20	14.37***	3.15
SVAR	0.87***	-5.48***	18.50	-3.60	0.65
BM	0.05	-5.44***	13.98	13.15***	2.87
NTIS	0.05	-5.47***	13.98	12.98***	2.94
TBL	-0.17	-5.35***	14.14	10.64***	2.67
LTY	-0.48**	-5.35***	15.32	13.02***	3.38
LTR	0.00	-5.45***	13.97	13.11***	3.23
TMS	-0.26	-5.51***	14.37	12.13***	3.20
DFY	0.18	-5.32***	14.14	13.46***	3.06
DFR	0.24	-5.47***	14.30	10.62**	2.22
INFL	-0.25	-5.43***	14.35	12.04***	2.88
OGAP	-0.39**	-5.21***	14.83	13.80***	3.09
TAIL	-0.56*	-5.30***	15.82	15.47***	3.34
TCHI	-0.60**	-5.26***	16.11	16.25***	3.37
FBM	0.06	-5.45***	13.98	13.50***	2.88
AVGCOR	0.47*	-5.28***	15.23	15.42***	3.36
SHTINT	-0.29	-5.53***	14.46	13.35***	3.15

Table 6: Asset allocation results

This table reports the annualized certainty equivalent returns (CER) and annualized Sharpe ratios for a mean-variance investor. The investor with a risk-aversion (γ) of 3 or 5 allocates between the stock market and risk-free bills using either the return forecast based on the $\widehat{VOV}_t|\{EPU, FIN\}$ index or the historical average (HA) return forecast. The $\widehat{VOV}_t|\{EPU, FIN\}$ index is extracted using partial least squares from a set of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) from Jurado, Ludvigson and Ng (2015). The portfolio weight in the stock market is recursively estimated and constrained between 0 and 1.5. The CER is computed as $CER = \bar{R}^p - 0.5\gamma\sigma^2(R^p)$, where $\bar{R}^p$ and $\sigma^2(R^p)$ denote the mean and variance of portfolio returns over the out-of-sample period, respectively. Sharpe ratio is calculated as the average monthly portfolio excess return divided by its standard deviation. We present results under two transaction-cost assumptions: zero cost and 50 basis points (bps) per trade. The out-of-sample period ranges from January 2014 to December 2021.

	No transaction cost		50pbs transaction cost	
Strategy	CER (%)	Sharpe ratio	CER (%)	Sharpe ratio
Panel A: Risk aversion $\gamma = 3$				
HA	35.86	1.62	27.91	1.36
$\widehat{VOV}_t|\{EPU, FIN\}$	13.47	0.91	12.25	0.88
Panel B: Risk aversion $\gamma = 5$				
HA	7.65	0.88	7.09	0.86
$\widehat{VOV}_t|\{EPU, FIN\}$	26.66	1.72	19.31	1.39

Table 7: Forecasting performance of VOV-aligned uncertainty indices using additional uncertainty measures

This table presents the in-sample and out-of-sample market return forecasting performance for VOV-aligned uncertainty indices constructed with additional uncertainty measures. We report the regression slope (β), Newey-West t-statistic (t-stat), in-sample R^2, and out-of-sample R_{OS}^2 for each VOV-aligned uncertainty index $\widehat{VOV}_t|U$, where U denotes a set of economic uncertainty measures. These indices are extracted using partial least squares from various combinations of economic uncertainty measures. EPU refers to the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016), while FIN denotes the financial uncertainty from Jurado, Ludvigson and Ng (2015). The additional uncertainty measures include macroeconomic risk-based uncertainty (MRU) from Bali, Brown and Caglayan (2014); monetary policy uncertainty (MPU) from Husted, Rogers and Sun (2020); environmental, social, and governance (ESGUI)-based sustainability uncertainty from Ongan, Gocer and Işık (2025); and the overall equity market volatility tracker (EMV) from Baker et al. (2026). The significance of R_{OS}^2 is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

Predictor	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R_{OS}^2 (%)	CW-stat
$\widehat{VOV}_t|\{EPU, FIN, MRU\}$	-6.48***	-5.87	17.85	16.60***	2.73
$\widehat{VOV}_t|\{EPU, FIN, MPU\}$	-6.09***	-6.44	14.79	12.85***	2.75
$\widehat{VOV}_t|\{EPU, FIN, ESGUI\}$	-5.88***	-5.20	13.26	12.53***	2.80
$\widehat{VOV}_t|\{EPU, FIN, EMV\}$	-5.47***	-4.22	12.07	11.32***	2.76

Table 8: Forecasting performance of VOV-aligned uncertainty indices including the global financial crisis period

This table presents the in-sample and out-of-sample market return forecasting performance for VOV-aligned uncertainty indices when the sample includes the global financial crisis period. We report the regression slope (β), Newey-West t-statistic (t-stat), in-sample R^2, and out-of-sample R^2_{OS} for each VOV-aligned uncertainty index $\widehat{VOV}_t|U$, where U denotes a set of economic uncertainty measures. The base group consists of the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016). We then add financial uncertainty (FIN), macroeconomic uncertainty (MACRO), real uncertainty (REAL), as well as the FMR group (the three measures added jointly) from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021). The significance of R^2_{OS} is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from March 2006 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

Predictor	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
$\widehat{VOV}_t|$EPU	-1.61	-1.46	0.97	-3.02	-0.85
$\widehat{VOV}_t|\{$EPU, FIN$\}$	-4.88***	-4.07	9.06	5.55**	1.91
$\widehat{VOV}_t|\{$EPU, MACRO$\}$	-3.52**	-2.35	4.96	-3.98	0.55
$\widehat{VOV}_t|\{$EPU, REAL$\}$	-2.73**	-2.00	2.77	-7.04	0.05
$\widehat{VOV}_t|\{$EPU, FMR$\}$	-4.10***	-3.35	9.08	2.94	1.18

Table 9: Forecasting hedge fund index returns with VOV-aligned uncertainty indices

This table presents the in-sample and out-of-sample performance for forecasting various hedge fund index returns using the $\widehat{VOV}_t|\{EPU, FIN\}$ index. We group the hedge fund indices into four main strategies according to the Hedge Fund Research classification: (1) Event Driven; (2) Equity Hedge; (3) Macro; and (4) Relative Value. The $\widehat{VOV}_t|\{EPU, FIN\}$ index is extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) index from Jurado, Ludvigson and Ng (2015). We report the regression slope (β), in-sample R^2, and out-of-sample R^2_{OS} for each hedge fund index. The significance of β is evaluated using the p-values of Newey-West t-statistics, while the significance of R^2_{OS} is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

	In-sample		Out-of-sample	
	β (%)	R^2 (%)	R^2_{OS} (%)	CW-stat
Panel A: Event Driven				
Activist Index	-4.82***	13.18	13.40***	2.59
Credit Arbitrage Index	-2.20**	11.11	8.59**	2.18
Distressed/Restructuring Index	-2.43***	12.88	11.95***	2.75
Merger Arbitrage Index	-1.24**	7.87	6.65**	2.13
Multi-Strategy Index	-1.86***	8.58	9.86***	2.47
Special Situations Index	-3.17***	14.02	13.01***	2.61
Event-Driven (Total) Index	-2.56***	13.83	12.99***	2.65
Panel B: Equity Hedge				
Equity Market Neutral Index	-0.70***	7.30	0.38	1.01
Fundamental Growth Index	-3.67***	13.38	13.97***	3.06
Fundamental Value Index	-3.86***	14.91	13.64***	2.93
Long/Short Directional Index	-3.54***	14.21	13.95***	3.04
Multi-Strategy Index	-3.24***	13.64	14.43***	3.22
Quantitative Directional Index	-2.54***	12.46	10.43***	2.66
Energy/Basic Materials Index	-4.34***	10.89	8.45***	2.68
Healthcare Index	-2.03**	3.70	2.92**	1.72
Technology Index	-2.12***	7.93	7.28***	2.59
Technology/Healthcare (Total) Index	-2.07***	6.12	5.65**	2.28
Equity Hedge (Total) Index	-3.22***	14.18	13.64***	3.01

	In-sample		Out-of-sample	
	β (%)	R^2 (%)	R^2_{OS} (%)	CW-stat
Panel C: Macro				
Active Trading Index	-0.60**	2.35	1.41*	1.32
Commodity Index	-1.17**	5.27	5.98***	2.51
Currency Index	-0.08	0.06	-2.11	-0.86
Discretionary Directional Index	-0.81***	5.26	3.06**	2.00
Discretionary Thematic Index	-1.07***	5.93	3.78**	2.06
Multi-Strategy Index	-1.27***	6.97	5.07**	1.90
Systematic Directional Index	-0.87*	1.60	0.11	0.69
Systematic Diversified Index	-0.91*	1.51	0.14	0.69
Macro (Total) Index	-0.95***	4.22	2.92**	1.71
Panel D: Relative Value				
Fixed Income Directional Index	-1.79***	13.51	10.24**	2.21
Fixed Income-Asset Backed Index	-1.52*	9.28	5.96**	1.82
Fixed Income-Convertible Arbitrage Index	-1.62***	10.74	10.68***	2.46
Fixed Income-Corporate Index	-2.07***	14.71	12.37***	2.48
Fixed Income-Sovereign Index	-1.82***	12.69	9.36**	2.22
Multi-Strategy Index	-1.48***	15.75	17.41***	3.04
Volatility Index	-1.34***	8.94	0.47	0.95
Yield Alternatives Index	-4.17***	14.50	11.59***	2.79
Relative Value (Total) Index	-1.86***	17.12	13.59***	2.50

Table 10: Forecasting results using VOV-aligned uncertainty in global markets

This table presents the forecasting results using the $\widehat{VOV}_t|\{EPU, FIN\}$ index in the global stock markets. The $\widehat{VOV}_t|\{EPU, FIN\}$ index is extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) index from Jurado, Ludvigson and Ng (2015). We report the regression slope (β), Newey-West t-statistic (t-stat), in-sample R^2, and out-of-sample R^2_{OS} for 50 stock markets included in the MSCI Developed and Emerging Markets Indices. The significance of R^2_{OS} is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
Global	-5.30***	-4.95	14.02	15.30***	3.24
Global (Excl. US)	-5.24***	-4.77	12.61	14.00***	3.15
By Development					
Developed	-5.42***	-5.04	14.70	15.96***	3.21
Developed (Excl. US)	-5.45***	-4.99	13.88	15.63***	3.12
Emerging	-4.70***	-3.78	6.97	6.95***	2.72
By Region					
North America	-5.46***	-4.92	14.35	14.76***	3.22
Europe	-5.82***	-4.37	12.01	13.37***	2.95
Asia Pacific	-4.84***	-5.30	13.12	13.88***	3.03
Asia Pacific (Excl. Japan)	-6.09***	-5.75	13.27	13.88***	3.17

	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
By Market					
Developed: North America					
United States	-5.37***	-4.89	14.01	14.48***	3.20
Canada	-6.70***	-4.40	14.25	13.15***	2.99
Developed: Europe					
Austria	-6.81***	-3.74	9.62	11.06***	2.85
Belgium	-6.95***	-3.74	12.82	12.19***	2.65
Denmark	-3.70***	-2.86	4.60	4.52**	1.96
Finland	-5.70***	-3.83	7.19	11.65***	3.09
France	-6.03***	-3.98	10.75	11.60***	2.82
Germany	-6.29***	-4.34	11.50	13.02***	2.94
Greece	-6.07**	-2.52	3.57	2.29	1.30
Ireland	-4.32**	-2.61	5.60	4.69*	1.69
Italy	-5.24***	-3.10	6.43	5.84**	2.15
Netherlands	-6.45***	-4.87	12.67	15.29***	3.28
Norway	-6.47***	-3.48	8.17	7.20**	2.27
Portugal	-3.50**	-2.21	3.14	1.68	1.22
Spain	-5.08**	-2.80	5.47	5.84**	2.20
Sweden	-6.21***	-4.31	9.73	13.33***	3.19
Switzerland	-5.42***	-6.30	14.49	12.73***	3.17
United Kingdom	-5.72***	-3.92	12.24	12.65***	2.62
Developed: Asia Pacific					
Australia	-8.46***	-4.73	16.19	19.33***	3.39
Hong Kong	-5.53***	-4.75	9.84	8.41***	2.81
Israel	-5.19***	-3.87	8.03	8.27**	2.54
Japan	-3.19***	-3.20	6.41	7.33**	2.04
New Zealand	-5.88***	-3.87	10.16	10.56***	2.67
Singapore	-4.78***	-3.56	8.18	5.35**	1.82
South Korea	-6.15***	-5.01	8.62	8.10**	2.47
Taiwan	-5.77***	-4.32	10.53	11.25***	2.80

	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
Emerging					
Argentina	-6.77**	-2.10	2.60	-0.21	0.67
Brazil	-9.83***	-3.27	11.05	7.61**	2.29
Chile	-6.44***	-4.17	8.52	7.65**	2.32
China	-2.86*	-1.69	1.27	1.09	1.02
Colombia	-7.59***	-3.04	7.11	3.42*	1.69
Czech Republic	-4.38**	-2.36	4.29	4.22**	1.93
Egypt	-6.35***	-3.64	7.40	0.85*	1.35
Hungary	-3.81*	-1.85	2.16	-0.09	0.69
India	-6.01***	-3.05	7.38	4.25*	1.48
Indonesia	-5.35**	-2.34	6.46	7.34**	2.11
Kuwait	-3.84**	-2.32	5.34	2.83**	1.71
Malaysia	-4.65***	-4.01	8.82	7.03***	2.65
Mexico	-5.57***	-3.55	8.10	7.37**	2.20
Nigeria	-1.74	-0.60	0.44	-1.47	-1.44
Pakistan	-5.39**	-2.55	6.25	4.24**	1.72
Peru	-5.21***	-4.41	5.89	5.75***	2.75
Philippines	-5.06***	-3.21	8.42	6.15**	2.21
Poland	-7.13***	-3.91	8.20	9.84***	2.77
Russia	-5.34**	-2.34	4.04	4.31**	1.82
Saudi Arabia	-3.99**	-2.47	4.52	2.22**	1.90
South Africa	-8.52***	-4.52	14.64	16.76***	3.26
Thailand	-6.58***	-4.11	9.86	6.87**	2.27
Turkey	-6.98***	-2.93	5.32	5.44**	2.12
United Arab Emirates	-2.43**	-2.25	2.08	1.54*	1.42

Table 11: Forecasting results using VOV-aligned uncertainty for characteristic-sorted portfolio returns

This table presents the in-sample and out-of-sample results using the $\widehat{VOV}_t|\{EPU, FIN\}$ index for forecasting six sets of characteristic-sorted portfolio returns. The $\widehat{VOV}_t|\{EPU, FIN\}$ index is extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) index from Jurado, Ludvigson and Ng (2015). We report the regression slope (β), Newey-West t-statistic (t-stat), in-sample R^2, and out-of-sample R^2_{OS} for each portfolio. The significance of R^2_{OS} is based on the p-values of the Clark and West (2007) MSFE-adjusted test statistic (CW-stat). ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

Portfolio	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
Panel A: Value Portfolios					
1 Growth	-4.92***	-4.64	11.27	11.05***	3.00
2	-5.05***	-4.67	13.11	13.35***	2.95
3	-5.61***	-4.18	13.56	12.64***	2.69
4	-6.24***	-3.84	14.05	13.49***	2.66
5 Value	-8.25***	-3.77	12.60	12.77***	2.74
Panel B: Size Portfolios					
1 Small	-7.67***	-4.33	12.57	15.09***	3.38
2	-7.48***	-4.06	13.31	14.92***	3.16
3	-7.16***	-4.25	14.04	14.37***	3.04
4	-6.39***	-4.19	13.82	13.74***	2.92
5 Big	-5.10***	-4.72	13.37	13.46***	3.06
Panel C: Operating Profitability Portfolios					
1 Robust	-6.26***	-4.57	11.25	11.43***	3.12
2	-6.31***	-4.41	14.00	13.25***	2.80
3	-5.52***	-4.00	12.71	13.85***	2.81
4	-5.02***	-4.55	13.22	12.88***	2.97
5 Weak	-5.24***	-5.01	13.43	13.00***	3.12
Panel D: Investment Portfolios					
1 Conservative	-5.79***	-5.64	13.61	13.75***	3.32
2	-5.35***	-4.28	13.11	14.61***	3.04
3	-5.36***	-4.15	13.32	13.43***	2.75
4	-4.82***	-4.40	11.24	11.18***	2.96
5 Aggressive	-5.86***	-4.77	12.95	12.13***	3.06

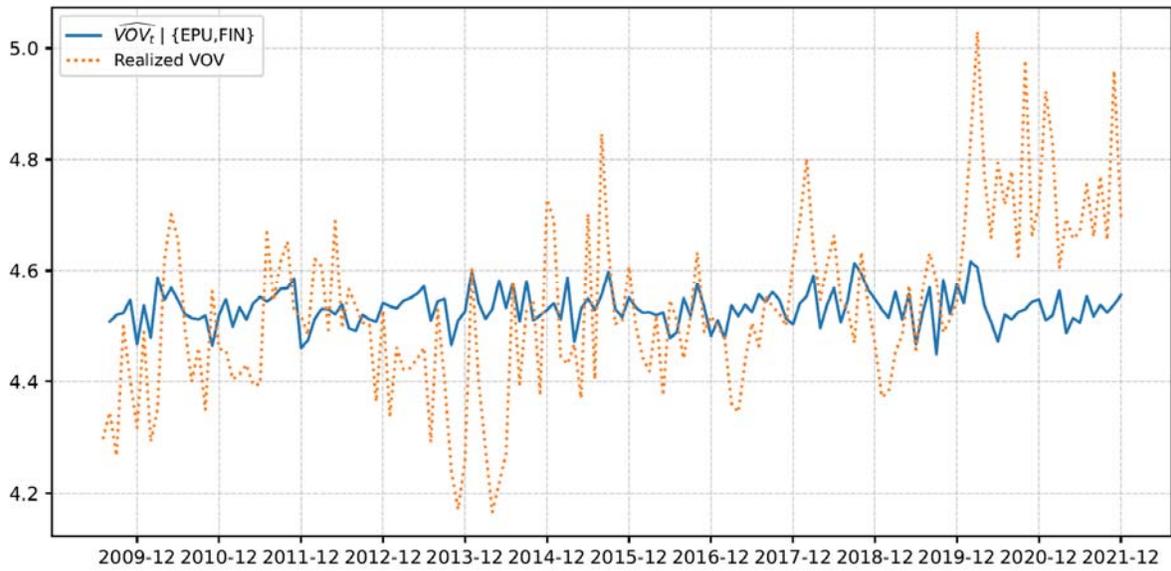|	In-sample			Out-of-sample	
	β (%)	t-stat	R^2 (%)	R^2_{OS} (%)	CW-stat
Panel E: Momentum Portfolios					
1 Past losers	-11.41***	-4.84	12.72	13.63***	3.38
2	-7.92***	-3.49	11.17	10.64***	2.73
3	-5.93***	-4.02	10.39	8.38**	2.51
4	-6.37***	-4.28	14.14	13.55***	2.90
5	-5.47***	-4.49	12.86	11.39***	2.75
6	-5.58***	-4.75	13.66	11.65***	2.72
7	-5.12***	-5.08	11.84	12.18***	2.92
8	-4.94***	-4.16	11.30	12.24***	2.83
9	-4.93***	-4.14	11.08	11.88***	2.75
10 Past winners	-5.79***	-4.00	9.05	8.71**	2.51
Panel F: Industry Portfolios					
Cons. nondur.	-4.03***	-3.67	10.09	7.95**	2.36
Cons. dur.	-8.86***	-4.21	9.63	9.52***	3.08
Manufacturing	-6.29***	-4.37	14.08	17.09***	3.20
Energy	-8.58***	-3.22	9.72	7.30**	2.36
Technology	-5.52***	-4.91	10.92	10.91***	3.13
Telecom	-4.46***	-3.86	8.86	6.90**	2.35
Retail	-5.05***	-5.04	12.41	10.81***	3.09
Healthcare	-3.66***	-3.72	6.66	6.86**	2.33
Utilities	-2.79**	-2.08	4.67	2.84	1.14
Other	-5.97***	-3.81	11.16	11.32***	2.61

Figure 1: Cumulative squared prediction error (CSPE) for the historical average benchmark minus that of return forecasts based on VOV-aligned indices

The solid line shows the difference in percentage between the cumulative squared prediction error (CSPE) of the historical average (HA) benchmark and that of the out-of-sample return forecast based on the $\widehat{VOV}_t|\{EPU, FIN\}$ index ($\Delta CSPE(HA, \widehat{VOV}_t|\{EPU, FIN\})$), while the dot line exhibits the difference in percentage between the CSPE of the HA forecast and that of the out-sample return forecast based on the $\widehat{VOV}_t|EPU$ index ($\Delta CSPE(HA, \widehat{VOV}_t|\{EPU\})$). Both indices are recursively extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) from Jurado, Ludvigson and Ng (2015). The horizontal black solid line at y = 0 represents the performance level of the HA benchmark, and forecast lines that lie above this reference line indicate cumulative outperformance relative to the HA benchmark. The out-of-sample period ranges from January 2014 to December 2021.
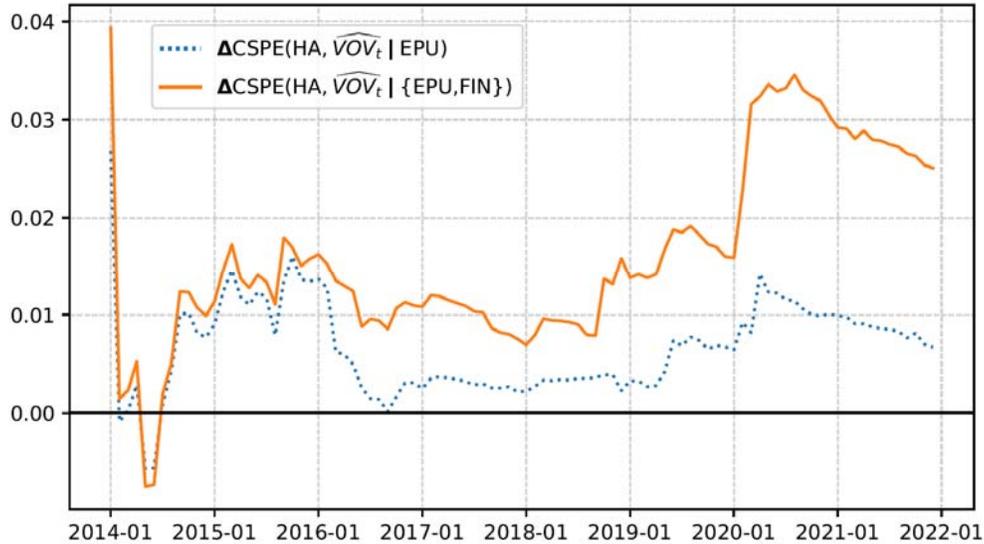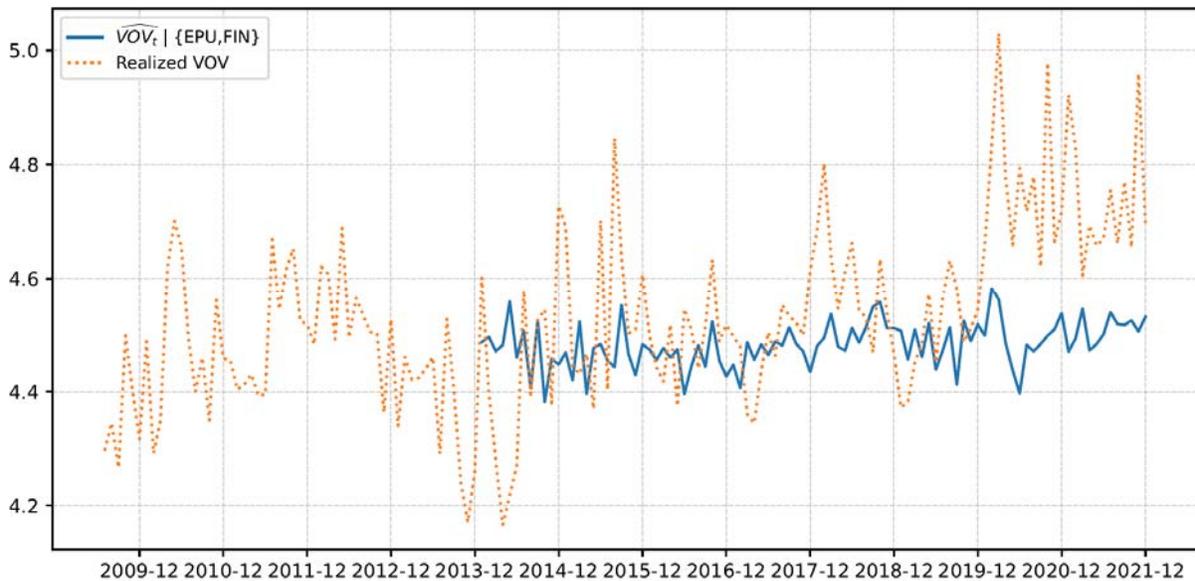
Figure 2: Comparing $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ with realized VOV

This figure compares the in-sample (Panel A) and out-of-sample (Panel B) $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ (solid line) with realized VOV (dashed line). The $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ index is recursively extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) from Jurado, Ludvigson and Ng (2015). The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.

Panel A: In-sample $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ compared with realized VOV
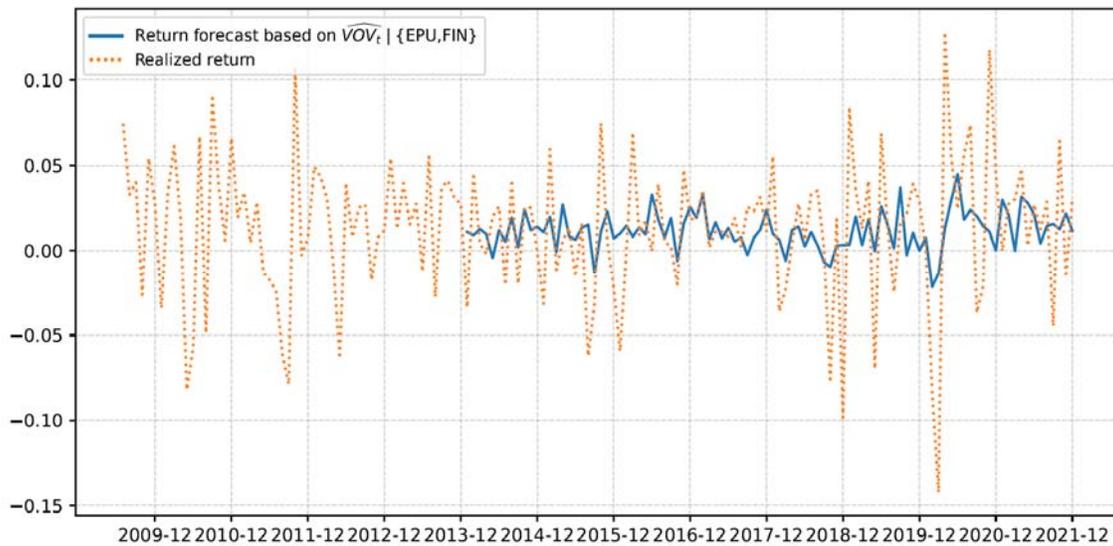

Panel B: Out-of-sample $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ compared with realized VOV

Figure 3: Comparing market return forecasts based on the $\widehat{VOV}_t|\{EPU, FIN\}$ index with realized market returns

This figure compares the in-sample (Panel A) and out-of-sample (Panel B) market return forecasts based on the $\widehat{VOV}_t|\{EPU, FIN\}$ index (solid line) with realized market returns (dashed line). The $\widehat{VOV}_t|\{EPU, FIN\}$ index is recursively extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) from Jurado, Ludvigson and Ng (2015). The in-sample period ranges from July 2009 to December 2021, while the out-of-sample period ranges from January 2014 to December 2021.
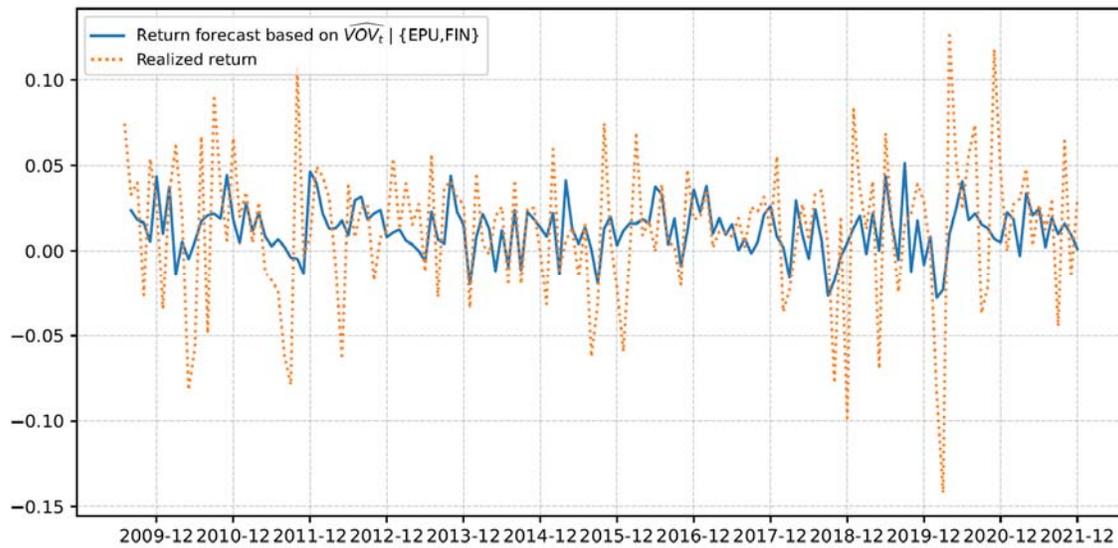

Panel A: In-sample return forecast based on $\widehat{VOV}_t|\{EPU, FIN\}$ compared with realized returns

Panel B: Out-of-sample return forecast based on $\widehat{VOV}_t|\{EPU, FIN\}$ compared with realized returns

Figure 4: Heatmap of weights on individual uncertainty measures
for the $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ index

This figure depicts the absolute weights on individual uncertainty measures for the $\widehat{VOV}_t|\{\text{EPU}, \text{FIN}\}$ index. This index is extracted using partial least squares from a combination of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) from Jurado, Ludvigson and Ng (2015). We recursively estimate weights for each uncertainty measure and scale the absolute weights to the 0-1 range in each month. Darker shades of red indicate higher weights. The sample period ranges from January 2014 to December 2021.
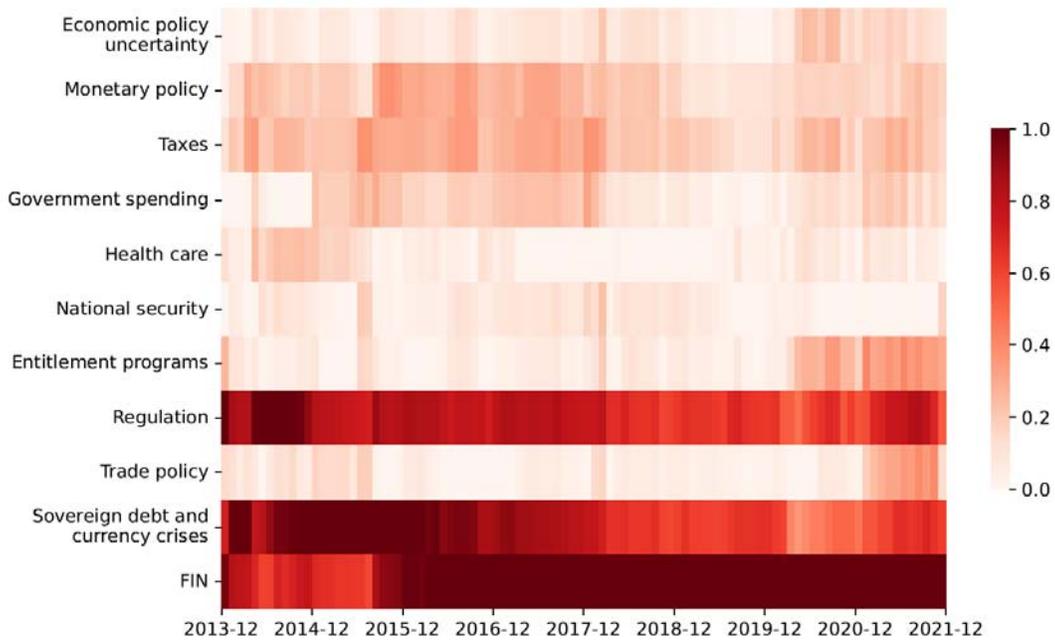
Figure 5: Cumulative portfolio returns for asset allocation strategies

This figure plots the cumulative portfolio returns of a mean-variance investor who allocates between the stock market and risk-free bills. Th investor has a risk-aversion (γ) of 3 or 5 and determines the stock market portfolio weight using either the return forecast based on the $\widehat{VOV}_t|\{EPU, FIN\}$ index or the historical average (HA) return forecast. The $\widehat{VOV}_t|\{EPU, FIN\}$ index is extracted using partial least squares from a set of economic uncertainty measures. Input measures include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) and the financial uncertainty (FIN) from Jurado, Ludvigson and Ng (2015). The portfolio weight in the stock market is constrained to lie between 0 and 3. For comparison, the buy-and-hold strategy continuously invests all wealth in the stock market. The out-of-sample period spans January 2014 to December 2021.
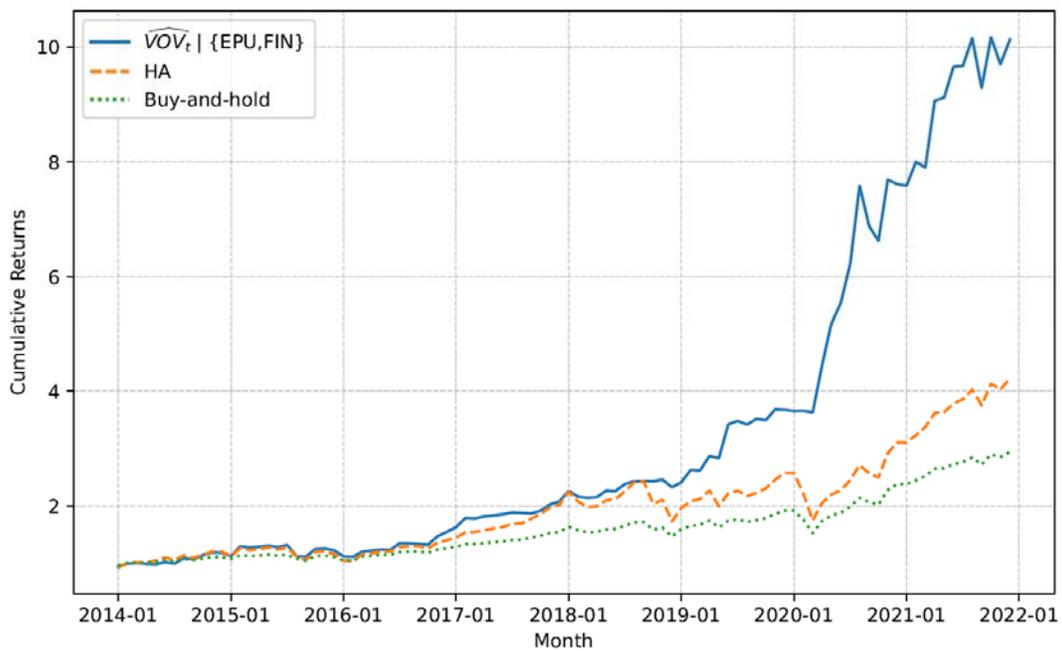
Appendix

A1. Forecasting market VOV with VOV-aligned uncertainty indices

Table A1 reports the in-sample forecasting performance of VOV-aligned uncertainty indices. Among the five specifications, three indices constructed from EPU alone, EPU with FIN, and EPU with REAL exhibit statistically significant slope coefficients at the 10% significance level or better. In terms of explanatory power, the EPU+FIN combination delivers the highest R^2 value of 4.29%, followed by the EPU+FMR index at 3.47%.

Table A1: Forecasting VOV with VOV-aligned uncertainty indices

Predictor	δ_1	t-stat	R^2 (%)
$\widehat{VOV}_t\|$EPU	0.10***	3.29	2.83
$\widehat{VOV}_t\|\{$EPU, FIN$\}$	0.11**	2.5	4.29
$\widehat{VOV}_t\|\{$EPU, MACRO$\}$	0.1	1.52	3.17
$\widehat{VOV}_t\|\{$EPU, REAL$\}$	0.09*	1.79	2.76
$\widehat{VOV}_t\|\{$EPU, FMR$\}$	0.09	1.56	3.47

Notes: This table presents the in-sample estimation results of forecasting market VOV with VOV-aligned uncertainty indices:

$$VOV_{t+1} = \delta_0 + \delta_1\widehat{VOV}_t|U + \epsilon_{t+1},$$

where VOV_{t+1} denotes the market VOV in month $t + 1$, and $\widehat{VOV}_t|U$ is a VOV-aligned uncertainty index extracted using partial least squares from a set of economic uncertainty measures U. We first include the ten economic policy uncertainty (EPU) indices from Baker, Bloom and Davis (2016) as the base group. We then add financial uncertainty (FIN), macroeconomic uncertainty (MACRO), real uncertainty (REAL), as well as the FMR group (the three measures added jointly) from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021). For each VOV-aligned uncertainty index, we report the regression slope (δ_1), their corresponding Newey-West t-statistics, and in-sample R^2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period ranges from July 2009 to December 2021.