REPRICING POLICY UNCERTAINTY

NEWS-BASED AND PREDICTION-MARKET EVIDENCE ON U.S. EQUITY RISK PREMIA

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Abstract:

This paper studies the evolving relationship between economic and political uncertainty, equity prices, and risk premiums. We extend the methodology of Brogaard and Detzel (2015) based on the Economic Policy Uncertainty (EPU) index, enabling the incorporation of a novel entropy-based measure derived from prediction markets. With increased precision, we find that both the contemporaneous and predictive historical relationships between EPU and market returns remain, even as EPU has decoupled from business-cycle variables. Furthermore, our market-based entropy measure appears insufficiently distinct from continuous uncertainty proxies, ultimately failing to generalise as an uncertainty measure or reliably forecast equity returns.

Keywords:

Economic policy uncertainty, asset pricing, prediction markets, Polymarket, political uncertainty, equity risk premium

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I. INTRODUCTION

Asset prices reflect investors' beliefs about an intrinsically uncertain future, and the measurement of that uncertainty is therefore central to empirical asset pricing. Among the sources of uncertainty that investors face, government policy decisions concerning fiscal, monetary, and regulatory matters are economy-wide and hard to diversify against (Brogaard and Detzel, 2015; Pástor and Veronesi, 2013).

One specific challenge with pricing uncertainty lies in its measurement. The most widely used proxy is the Economic Policy Uncertainty (EPU) index of Baker et al. (2016), and Brogaard and Detzel (2015) develop the central asset-pricing test of it. They include EPU within Merton (1973)'s ICAPM framework as a state variable whose shocks shift the investment opportunity set, which generates both a contemporaneous price impact and a predictive risk premium.

Their sample ends in 2012, which predates more than a decade of structural shifts in monetary policy, an apparent rise in discrete political events driving uncertainty, and the emergence of prediction markets as a forward-looking measurement instrument.

In this paper, we test whether the asset-pricing relationship between EPU and equity returns survives a decade of structural change, and whether prediction markets capture a separately priced dimension of political uncertainty. We extend Brogaard and Detzel (2015)'s framework along three dimensions: a sample extension through 2024, a move to daily frequency, and the construction of a prediction-market-based measure of political uncertainty from Polymarket prices on the 2024 U.S. election cycle.

Each of these extensions is motivated by a development since Brogaard and Detzel (2015)'s sample period. First, they showed that a large share of the variation in the Economic Policy Uncertainty Index is explained by the business-cycle controls within their model. Major evolutions in the macroeconomic and monetary policy environment since 2012 such as the prolonged zero-interest-rate regime, quantitative easing and the macroeconomic shock of COVID-19 may have shifted that relationship, raising the question of whether EPU still behaves as a business-cycle-correlated process within their specification.

Second, recent work has noted that the nature of policy uncertainty itself as it is observed by standard, news-based measures has evolved. Davis (2019) notes qualitatively that EPU spikes now occur increasingly within expansions during discrete political events, when in previous decades they would mostly occur during recessions. Baker et al. (2021) document this quantitatively, showing that trade-policy news alone accounts for 36% of post-2010 daily market moves exceeding 2.5%, against just 0.6% over the previous century. If EPU variations have become more linked to short-lived political events, the monthly sample used by the original paper may aggregate away meaningful short-term variation.

Third, the 2024 U.S. election cycle saw Polymarket emerge as the most actively traded prediction market on record, with election-related contracts attracting several billion dollars in volume. Prediction markets have long been shown to aggregate dispersed information efficiently and to outperform some conventional forecasting tools (Wolfers and Zitzewitz, 2004), but 2024 is the first year to overlap both a consequential political event such as the U.S. presidential election as well as sufficient liquidity for a clean inference. Prediction markets price the probability distribution over policy outcomes directly and in a forward-looking manner while news-based indices proxy that distribution indirectly through realised media attention. A market-based measure may therefore capture variation in policy uncertainty that news indices miss.

We begin by replicating Brogaard and Detzel (2015)'s contemporaneous and predictive specifications for their original sample to make sure we have a common starting point. We then extend the sample to 2024 and note the major evolutions in coefficient magnitudes and run extra tests to understand them more deeply. Third, we reconstruct the specification using a daily frequency of EPU in order to observe more granularity and verify whether the same-day results of the contemporaneous specification are significant or if the market's reaction to EPU shocks is lagged. Finally, we produce an uncertainty measure using entropy for multiple Polymarket samples and incorporate them into our specification to see whether or not they contribute any information beyond the standard uncertainty measures and controls.

Our results show that the contemporaneous and predictive relationships between EPU and equity returns survive the post-2012 environment, appearing more robust in the extended sample. In the extended sample, the predictive coefficient on EPU is significant at all five monthly horizons, where the original sample yielded significance only at $h = 2$ and $h = 3$ when controlling for all macroeconomic state variables. At daily frequency, the predictive coefficient becomes significant at $h = 10$ trading days and remains significant through three months. This pricing relationship persists even as EPU has decoupled from business-cycle variables, with the joint explanatory power of standard cyclical controls having roughly halved in the sample extension, while the same regression with IV as the dependent variable is stable across samples, isolating the decoupling to EPU specifically. Our Polymarket analysis produces a structured null across all four tested contracts once a leverage diagnostic is applied; a single significant predictive result emerges on the Presidential contract at $h = 10$ trading days while the Senate, House, and Fed contracts are insignificant at all horizons.

A theoretical and empirical literature establishes that policy uncertainty earns a risk premium in equity markets. The equilibrium foundations were developed by Pástor and Veronesi (2012, 2013), who model political uncertainty as a priced risk whose magnitude varies with the economic conditions. Brogaard and Detzel (2015) then provided the central empirical test for U.S. equities, embedding the news-based EPU index in an ICAPM framework and documenting the contemporaneous and predictive pricing effects that it has. Brogaard et al. (2020) demonstrate that the result generalises internationally, with U.S. election cycles transmitting political-uncertainty premia to fifty non-U.S. equity markets. This literature shows that policy uncertainty is priced, but it does not address how the pricing relationship behaves as the macroeconomic and political environment shifts, nor the shorter term horizons at which it operates. We contribute by tracing the U.S. EPU pricing relationship through a decade of structural change and resolving it at daily frequency.

Parallel to this, a literature has documented that the nature of policy uncertainty itself has shifted over the past decade. Davis (2019) observes qualitatively that post-2009 EPU spikes tend to cluster in expansions around discrete political events rather than in recessions. Baker et al. (2021) offer a quantitative study which shows that policy-driven news now account for a disproportionate share of daily market jumps post-2010. A separate measurement issue was raised by Jurado et al. (2015). They argue that the popular uncertainty proxies which include news-based indices move independently of the forecast-error-based estimates of underlying uncertainty. These papers describe a shift in EPU's character, but they do not test whether it changes the pricing role that it has within Brogaard and Detzel (2015)'s specifications. We contribute by quantifying the business-cycle decoupling within that framework and by showing that the predictive relationship survives it.

Prediction markets and direct measures of political uncertainty form a third strand of literature. Kelly et al. (2016) take an early step toward a more direct measurement of the political-uncertainty construct by using Shannon entropy of election-outcome probabilities through option prices. However their measure is identified only around election windows. Relating to prediction markets, Wolfers and Zitzewitz (2004) and Arrow et al. (2008) established that they tend to aggregate dispersed information efficiently and often outperform polls and other forecasting tools. Tsang and Yang (2026) document Polymarket's 2024 election cycle in detail, including the liquidity necessary to make the data usable for statistical inference. The prediction-market literature has not been integrated with asset-pricing tests of political uncertainty, and no prior work uses Polymarket prices to test whether prediction-market-implied uncertainty earns a premium beyond what news-based EPU captures. We contribute by constructing entropy from Polymarket prices on the four major 2024 contracts and integrating it into the Brogaard and Detzel (2015) daily specification.

The remainder of the paper is structured as follows. Section II and III describe the data and empirical methodology. Section IV presents the contemporaneous and predictive results, the daily extension, and the prediction-market analysis. Section V discusses the findings, and Section VI concludes.

II. DATA & VARIABLE CONSTRUCTION

Our empirical methodology closely follows that of Brogaard and Detzel (2015). To establish a baseline, we begin by replicating their contemporaneous and predictive analyses to confirm the correctness of the methodology. Thereafter, we extend the sample period to 2024 to examine the continued predictive power of EPU. The methodology is then adapted to a daily frequency, creating the foundation for our analysis of prediction markets as aggregators of uncertainty.

A. Data Sources

Our empirical analysis uses a sample period from January 1985 to December 2024.

Our macroeconomic data, including all treasury yields, bond yields, implied volatility indices and other activity indices, were sourced from the Federal Reserve Bank of St. Louis (2026) library. At a monthly frequency, this includes: Aaa Moody's corporate bond yields (AAA), Baa Moody's corporate bond yields (BAA), three-month treasury bill yields (TB3MS), 10-year treasury bond yields (GS10), and the Chicago Fed national activity index (CFNAI, referred to as CFI).

At the daily frequency, we retrieved all the above indices, except for CFI, as it is only available in the monthly frequency, from the same source, with the addition of VXO and VIX; this includes: Aaa Moody's corporate bond yields (DAAA), Baa Moody's corporate bond yields (DBAA), three-month treasury bill yields (DTB3), 10-year treasury bond yields (DGS10), the CBOE S&P 100 implied volatility index (VXOCLS), and the CBOE S&P 500 implied volatility index (VIXCLS).

We retrieved the Economic Policy Uncertainty (EPU) index from the Economic Policy Uncertainty website (Baker et al., 2016). The monthly version we retrieved is the U.S.-based monthly EPU index, containing both the daily news-based index and the legacy three-component composite index. We also retrieved the U.S. daily version, which contains purely the news-based index.

We obtained monthly and daily equity market data, including the Center for Research in Security Prices (CRSP) value-weighted index (both including and excluding dividends) and the Fama risk-free rate, from Wharton Research Data Services (2026).

Finally, we collected the daily prediction market data directly from Polymarket (2026). We utilised their public Gamma and Central Limit Order Book (CLOB) APIs to retrieve historical time-series data for the Presidential (*presidential-election-winner-2024*), Senate (*which-party-will-control-the-us-senate-after-the-2024-election*), House (*house-control-after-2024-election*), and Federal Reserve (*fed-interest-rates-MONTH-2024*) contracts. This dataset captures daily implied probabilities over the 2024 prediction-market subsample.

B. Variable Construction

The dependent variable is the cumulative log-excess market return. The excess market return is calculated using the CRSP value-weighted market index (including dividends) as a proxy for aggregate market return and the Fama risk-free rate as a proxy for the risk-free rate. Both of these series are transformed into natural logarithms before any further calculations, constructing continuous compounding returns. For the longer horizon regressions, the dependent variable is thus summed over h time periods to represent the cumulative return. The same methodology was applied at both the daily and monthly frequencies.

The main independent variable, EPU, was constructed differently for the monthly and daily frequencies. For the monthly frequency, we used the legacy three-component index (Baker et al., 2016). This legacy index weights the standard newspaper-based index with an index for temporary tax code provisions and a measure of dispersion among surveyed professionals in their forecasts of key macroeconomic outcomes. However, as this is not available at a daily frequency, the purely newspaper-based index was used for daily regressions. EPU is scaled by 1/100 to ensure readability.

Realised market variance (VAR), for the monthly frequency, is calculated as the daily variance within each month scaled by 10,000. At the daily frequency, realised market variance is proxied by the squared daily log market return. While this measure is not without problems, including issues relating to noise, it is unbiased and appropriate for this use case (Andersen and Bollerslev, 1998).

Implied volatility (IV) is synthesised by splicing VIX and VXO, as no single implied-volatility measure is available for the full sample period. VXO is used up to its discontinuation in 2021, and VIX thereafter (CBOE, 2021). These two indices capture closely related dimensions of implied volatility with VIX tracking the S&P 500 and VXO the S&P 100. We refer to this spliced series as IV throughout the remainder of the paper. The monthly frequency version uses the last daily closing value of the month, while the daily version uses the daily closing value.

The log dividend price ratio (Log(D/P)) is calculated by using the 12-month rolling sum of dividends divided by the price level, both derived from the CRSP value-weighted market index with and without dividends, by extracting the difference (dividends). Log(D/P) is only utilised at a monthly frequency.

The remaining independent control variables enter our specifications without further transformation. The spread between the 10-year treasury bond yield and the three-month treasury bill yield is denoted TERM. The default probability is proxied using the spread in yields between Baa and Aaa-rated corporate bonds. The three-month treasury yield minus its trailing 12-month moving average and 252-day moving average for the monthly and daily frequencies, respectively, is denoted RREL. The Chicago National Activity Index is denoted CFI and is only available monthly.

Finally, we construct a prediction-market measure of uncertainty using data from Polymarket. We restrict the sample to four contracts covering the calendar year 2024: the Presidential election winner, Senate control, House control, and the Fed's rate decision. These were chosen because 2024 is the first year where institutional-grade liquidity was attained and the events surrounding the presidential election were highly contested, leading to spikes in uncertainty in congruence with EPU.

The Presidential contract is multi-outcome across the full set of active candidates and the remaining three are binary. For the Fed contract, which is implemented as a sequence of meeting-specific markets, we stitch consecutive contracts at each FOMC meeting date so that the series reflects a continuous forward-looking policy-rate expectation over the year.

For a binary contract with implied probability p_t, we measure uncertainty through Shannon entropy,

$$H_t = -p_t \cdot \ln(p_t) - (1 - p_t) \cdot \ln(1 - p_t) \tag{1}$$

which is bounded by $\ln(2) \approx 0.693$ at $p_t = 0.5$ and falls to zero as the outcome becomes certain. For the multi-outcome Presidential contract, entropy is computed over the full set of active candidates,

$$H_t = -\sum_{i=1}^{k} p_{i,t} \cdot \ln(p_{i,t}) \tag{2}$$

with a time-varying upper bound of $\ln(k)$ which reflects the effective candidate count (roughly four in January 2024 and collapsing to two by November).

Table I presents summary statistics for all constructed variables, reporting observation counts, means, standard deviations, and sample extrema.

Table I. Summary Statistics

This table presents summary statistics for all key constructed variables as presented in Section II in their original data units. EPU is shown in raw index units, but enters all regressions scaled by 1/100. Log excess returns are shown here in decimal form while interpretations are expressed in percentage form. Panel A reports monthly observations, Panel B reports daily observations, and Panel C reports daily Polymarket entropy measures. N denotes the number of observations.

Panel A. Monthly Sample

Variable	N	Mean	Std. Dev.	Min	Max
Log Excess Return	480	0.01	0.05	-0.26	0.12
EPU	495	119.73	47.43	57.20	460.11
EPU News	495	131.88	74.53	44.78	724.94
VAR	480	1.24	2.61	0.08	32.60
IV	483	20.12	8.13	7.87	61.41
TERM	494	1.59	1.22	-1.57	3.76
DEFAULT	494	0.97	0.36	0.51	3.38
RREL	494	-0.06	0.69	-2.36	2.48
CFI	493	-0.05	1.06	-18.26	6.30
Log(D/P)	492	-3.84	0.31	-4.51	-3.14

Panel B. Daily Sample

Variable	N	Mean	Std. Dev.	Min	Max
Log Excess Return	10080	0.00	0.01	-0.19	0.11
EPU	10080	104.59	76.34	3.32	1026.38
VAR	10080	1.24	5.59	0.00	353.26
IV	9828	20.09	8.88	6.32	150.19
TERM	10080	1.63	1.22	-1.73	3.94
DEFAULT	9828	0.97	0.36	0.50	3.50
RREL	10080	-0.06	0.73	-3.10	2.71

Panel C. Polymarket Entropy Sample

Variable	N	Mean	Std. Dev.	Min	Max
Election Entropy	252	0.83	0.41	0.00	1.34
Senate Entropy	252	0.49	0.21	0.00	0.69
House Entropy	252	0.49	0.31	0.00	0.69
Fed Entropy	252	0.43	0.29	0.00	0.98

III. EMPIRICAL METHODOLOGY

A. *Contemporaneous Analysis*

We begin our contemporaneous analysis by regressing EPU on the independent control variables. We first estimate a univariate regression for each control variable followed by a multivariate regression including all control variables. To ensure readability, we standardize the independent control variables before the regression, $W_i^* = \frac{W_i}{\sigma_{W_i}}$. We then estimate the multivariate regression,

$$\text{EPU}_t^* = \alpha + \sum_{i=1}^{k} \beta_i W_{i,t}^* + \epsilon_t \tag{3}$$

Next, we estimate the effects of uncertainty shocks on excess market returns. We first difference the standardised independent variables, such that $\Delta W_{i,t}^* = W_{i,t}^* - W_{i,t-1}^*$. Then we regress log excess market returns on ΔEPU_t^* in a univariate regression, followed by a multivariate regression:

$$xr_t^* = \alpha + \beta\Delta\text{EPU}_t^* + \sum_{i=1}^{k} \gamma_i \Delta W_{i,t}^* + \epsilon_t \tag{4}$$

where xr_t^* is the standardised log excess market return at time t, ΔEPU_t^* captures the economic policy uncertainty shock, and $\Delta W_{i,t}^*$ represents the shock in control variables. We use the same Newey-West standard errors as for Equation (3).

Finally, to examine the time-series persistence of the data, we estimate autoregressive AR(p) models for our key uncertainty and control variables. The model is specified as,

$$y_t = \alpha + \sum_{i=1}^{p} \rho_i y_{t-i} + \gamma \text{MKT}_{t-1} + \epsilon_t \tag{5}$$

where y_t represents the uncertainty variable of interest (EPU, VAR, or IV), p is the number of autoregressive lags, and MKT_{t-1} is the lagged log excess market return, capturing potential feedback loops between uncertainty and market returns. We use the same Newey-West standard errors as for Equation (3) and (4). To confirm stationarity, we also perform a Dickey-Fuller Generalized Least Squares (DF-GLS) test.

In order to deduce whether the relationship between EPU and different variables statistically changed, we employ a structural break test (Chow, 1960). We specifically followed the framework described by Gujarati (1970), utilizing dummy variables. This allows us to seamlessly integrate Newey-West standard errors to account for autocorrelation. We estimate

$$\text{EPU}_t = \alpha_1 + \alpha_2 D_t + \sum_{i=1}^{k} \beta_{1,i} W_{i,t} + \sum_{i=1}^{k} \beta_{2,i} (D_t W_{i,t}) + \epsilon_t \tag{6}$$

where D_t is the dummy variable indicating if the data point belongs to the post-2012 subsample, and $\beta_{2,i}$ measures the post-2012 shift for each variable independently.

B. Predictive Analysis

Following the contemporaneous analysis, we conduct a predictive analysis which investigates whether future stock market returns can be predicted using current levels of EPU with, and without, controls. We regress cumulative log excess market return on EPU with different subsets of control variables from those used in the contemporaneous analysis (vector W). These regressions are repeated for different prediction periods h. We estimate

$$xr_{t,t+h} = \alpha + \beta \text{EPU}_t + \sum_{i=1}^{k} \gamma_i W_{i,t} + \epsilon_{t+h} \tag{7}$$

where $xr_{t,t+h}$ is the cumulative log excess market return between the time period t and $t+h$, h is the length of the period: $h \in \{1, 2, 3, 6, 12\}$ and $h \in \{1, 5, 10, 21, 63\}$ for the monthly and daily versions, respectively, and ϵ_{t+h} is the error term. We use Hodrick (1992) standard errors with h lags to account for autocorrelation due to overlapping observations.

To facilitate comparison across horizons and against benchmark dynamics, we report the per-period premium $\beta(h)/h$, where $\beta(h)$ is the cumulative coefficient from Equation (7) at horizon h. The AR(p)-implied benchmark used in Tables B.4 and B.5 is defined in the appendix notes.

C. Prediction Market Analysis

The Polymarket analysis adapts both the daily contemporaneous and predictive specifications to a prediction-market measure of uncertainty that we construct using entropy. Where the EPU aggregates newspaper attention across a broad range of policy topics, our measure captures continuous trader sentiment on specific events. If prediction markets aggregate uncertainty-relevant information more efficiently, this analysis should add explanatory power over the standard controls at a daily level.

Our goal is to measure whether a shock to uncertainty has an impact on asset prices. Because past entropy carries information into today's entropy, we must isolate the component that was not predictable from the previous day. We fit a first-order autoregression to each entropy series and keep the residual which represents the genuine surprise to uncertainty. This constitutes our innovation variable Innov_t. The innovation in each market is standardised to unit variance within that market's active sample before entering the regression.

To test whether these innovations carry information about equity returns, we add Innov_t to the daily multivariate specification from Section A:

$$xr_t = \alpha + \beta_1 \text{Innov}_t + \beta_2 \Delta\text{EPU}_t + \sum_{i=1}^{k} \gamma_i \Delta W_{i,t} + \epsilon_t \tag{8}$$

where the dependent variable and controls follow the daily contemporaneous construction described in Section A: the return is the daily log excess market return, ΔEPU_t is the first-differenced news-based EPU, and $\Delta W_{i,t}$ denotes first-differenced daily controls. Standard errors are Newey-West with 21 lags, corresponding to 21 trading days.

We then run a predictive regression to test whether innovations in entropy predict returns over subsequent trading days, following the daily predictive framework in Section B. The regression is estimated first without controls and then with the daily level controls EPU, VAR, IV, TERM, DEFAULT, and RREL. We estimate

$$xr_{t,t+h} = \alpha + \beta_1 \text{Innov}_t + \sum_{i=1}^{k} \gamma_i W_{i,t} + \epsilon_{t+h} \tag{9}$$

where $h \in \{1, 5, 10, 21\}$ trading days. We omit the 63-day horizon used in the EPU specification because the Polymarket samples are too short to support it. Standard errors are Hodrick (1992) with h lags.

Because prediction markets can process information gradually and because daily innovations in an election year are highly concentrated around certain events, we complement this regression with three diagnostics:

First, we use a leverage check by dropping the days with the largest innovations and re-estimating the regression. We do this to verify whether the t-statistics are mainly driven by extreme days rather than a year-round relationship.

The second diagnostic establishes whether the framework has enough resolution to detect economically meaningful effects in the first place, given that daily Polymarket innovations are heavily concentrated around a small number of political events. We run a Monte Carlo simulation in which we plant a known effect of size β into the dependent variable, re-estimate the specification, and record whether the coefficient on Innov is significant at the 5% level. Repeating this 1,000 times for each β in a grid of 0.01 to 0.35 gives the probability that the framework detects a true effect of that magnitude. A null result is informative only if the simulation shows that the framework would catch a real relationship of similar size.

Third, we apply a permutation test to our predictive results to verify the robustness of our results. We implement this because of the limited size of our sample and the concentration of innovations within a few days, for which Hodrick standard errors are not well suited. We therefore shuffle the innovation series 5,000 times, which breaks the temporal alignment between entropy and returns while preserving the marginal distribution of the two series. The regression is then re-estimated at each iteration, which yields an empirical distribution of t-statistics under the null hypothesis of no relationship. The fraction of permuted t-statistics that exceed the observed value in absolute terms yields a p-value that does not depend on the asymptotic assumptions underlying the Hodrick standard errors.

IV. EMPIRICAL RESULTS

A. Contemporaneous Results

A.1. Study Replication

Table II, Panel A reports EPU regressed on the macroeconomic state variables. The panel reveals that all univariate regressions are significant at a 1% level, with a positive relationship for all variables except RREL and CFI. This broadly aligns with the economic intuition: a decreasing RREL (falling interest rate) and a decreasing CFI (diminishing economic activity), both signal economic slowdowns. Conversely, IV and VAR represent uncertainty in the form of financial volatility, and are, as expected, positively correlated with EPU. Bond risk and uncertainty are captured in TERM and DEFAULT, which are also positive, as expected. Log(D/P) functions as a proxy for the equity risk premium; if it increases, it indicates that investors demand higher yield as compensation for higher risk.

The multivariate regression, however, alters the significance of the control variables. IV, TERM, CFI, and Log(D/P) are now the only significant variables, while remaining positive. IV absorbs all financial volatility present in EPU, indicating that the forward-looking implied volatility is a main component captured by the EPU. To contextualize the magnitude, the multivariate coefficient of 0.27 translates to a 12.8 point increase in EPU in response to a one-standard-deviation increase in IV.

Additionally, bond risk is exclusively captured by TERM, suggesting that, while EPU has a correlation with the bond environment, it is more so with the macroeconomic yield curve, rather than any corporate default probabilities. Log(D/P) and CFI remain significant, meaning it successfully captures aspects of EPU which the other control variables do not.

Ultimately, Table II is therefore broadly consistent with the original Brogaard and Detzel (2015) paper which shows the same signs and significance for all variables, with the sole exception that their DEFAULT variable was significant in the multivariate regression and ours had CFI as significant as well, even while magnitudes remained close.

Panel B examines the contemporaneous relationship by regressing the log excess market return on the change in EPU and the macroeconomic state variables. The univariate regression suggests a strong correlation as the coefficient is significant at a 1% level with a negative sign, meaning stock market returns decrease as uncertainty, as measured by the EPU, increases. More precisely, using Table I, we know that a one-standard-deviation increase in EPU is associated with a 1.4% decline in contemporaneous market return. Crucially, this relationship remains robust when the full suite of macroeconomic state variables are introduced in the multivariate regression. The EPU coefficient remains significant at a 5% level, however, with a decreasing magnitude, representing a 0.55% drop in market returns in response to a one-standard-deviation increase in EPU. This is congruent with Brogaard and Detzel (2015)'s core findings.

Finally, Panel C concludes the contemporaneous section by examining the time-series properties of EPU, IV and VAR. Principally, the Dickey–Fuller Generalized Least Squares test rejects the null hypothesis for all time series at a 1% level. This indicates that the variables are stationary and suitable for the predictive regressions that follow.

For EPU, the AR(1) coefficient in Column (2) of 0.71 suggests that 71% of the previous month's EPU persists into the next. This corresponds to a half-life of 2 months. This implies large month-over-month stickiness. The variables are, however, below 1, and are therefore stationary, in congruence with the DF-GLS test.

Additionally, the previous month's market return is significantly, and negatively, correlated with EPU and VAR. This suggests a feedback loop where positive market returns decrease uncertainty in the form of EPU and VAR the following month and subsequent months, due to the stickiness. EPU is also significantly affected by the fourth order autoregressive coefficient, however, to a lesser extent as the coefficient is smaller.

Ultimately, the results are highly congruent with Brogaard and Detzel (2015). The signs and significance levels of

Table II. Replicated contemporaneous relationship between EPU and macroeconomic state variables

Contemporaneous specification on the replicated 1985–2012 monthly sample. Panel A reports standardised regressions of composite EPU on the macroeconomic state variables (Eq. (3)); column (8) reports the multivariate regression on the business-cycle subset (TERM, DEFAULT, RREL, CFI), and column (9) reports the multivariate regression on the full control set. Panel B reports the contemporaneous return regression (Eq. (4)) in univariate and multivariate form. Panel C reports AR(p) coefficients with the lagged log excess market return and DF-GLS test statistics for EPU, IV, and VAR (Eq. (5)). EPU is the legacy three-component composite index (Baker et al., 2016), scaled by 1/100. Newey and West (1987) standard errors with 4 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. standardised regressions of EPU on state variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IV	0.42***								0.27***
	(5.83)								(2.94)
VAR		0.34***							-0.02
		(4.35)							(-0.23)
TERM			0.40***					0.27***	0.28***
			(5.75)					(3.92)	(4.13)
DEFAULT				0.52***				0.36***	0.20
				(5.62)				(3.71)	(1.49)
RREL					-0.33***			-0.08	-0.08
					(-5.24)			(-1.33)	(-1.31)
CFI						-0.33***		-0.09	-0.10*
						(-7.32)		(-1.46)	(-1.69)
Log(D/P)							0.21***		0.18***
							(2.98)		(2.64)
N	324	336	336	336	336	336	336	336	324
Adj. R^2	0.17	0.11	0.16	0.27	0.11	0.11	0.04	0.35	0.39

Panel B. Regression of log excess market return on ΔEPU

	Multivariate	Univariate
Δ EPU	-0.11**	-0.28***
	(-2.05)	(-3.51)
Δ VAR	0.20**	
	(2.45)	
Δ IV	-0.78***	
	(-12.63)	
Δ TERM	-0.10***	
	(-2.58)	
Δ DEFAULT	-0.19***	
	(-2.96)	
Δ RREL	-0.05	
	(-1.08)	
Δ Log(D/P)	-0.10**	
	(-2.27)	
N	323	335
Adj. R^2	0.53	0.08

Panel C. AR(p) coefficients and DF-GLS statistics

	EPU		IV		VAR	
	(1)	(2)	(3)	(4)	(5)	(6)
AR(1)	0.77***	0.71***	0.83***	0.83***	0.57***	0.51***
	(13.31)	(11.02)	(23.33)	(22.95)	(3.14)	(2.90)
AR(2)	-0.02	0.00				
	(-0.19)	(0.03)				
AR(4)	0.19***	0.18***				
	(3.11)	(2.97)				
MKT_{t-1}		-0.78***		1.18		-6.45***
		(-3.25)		(0.20)		(-2.74)
DF-GLS	-2.29***		-3.86***		-5.16***	
N	332	332	323	323	335	335
Adj. R^2	0.74	0.75	0.68	0.68	0.32	0.33

all variables are broadly equivalent. The only changes are minor magnitude deviations in certain coefficients and exact significance level.

A.2. Time Extension

Table III extends the baseline contemporaneous results with an extended sample period from 2012 to 2024. Panel A reveals substantial shifts in significance and magnitude, both for the univariate and multivariate specifications. However, the coefficient signs remain constant in congruence with the economic intuition.

Specifically, IV and VAR remain largely unchanged in the univariate case while only IV remains significant in the multivariate case. The decrease in IV from 0.27 to 0.17 corresponds to a drop from a 12.8 to 8.1 effect on EPU due to a one-standard-deviation change in IV.

Bond risk also exhibits crucial differences. TERM is no longer significant in either specification, while DEFAULT remains significant in the univariate specification and has gained significance at a 5% level in the multivariate specification. In the same manner, RREL has demonstrated changes. Its magnitude and significance have decreased in the univariate specification while remaining insignificant in the multivariate specification. Bond risk therefore remains correlated, but components have shifted importance.

Additionally, CFI has lost all significance in both cases and even changed signs in the multivariate specification, although with a small magnitude. Lastly, Log(D/P) has seen a decreasing magnitude in both specifications, losing significance in both specifications.

The multivariate regression of EPU on purely business variables (TERM, DEFAULT, RREL, CFI) in Table II and Table III reveals a structural decoupling. The explanatory power of these independent variables falls from 0.35 to 0.16 when extending the sample from 2012 to 2024. A regression on purely business-cycle variables therefore explains roughly half as much of EPU variation in the extended sample as it did in the original.

We re-estimate the business-cycle regression on a 1985–2019 subsample to exclude COVID (Table A.3, Appendix B). The adjusted R^2 is 0.26, sitting between the 0.35 of the original sample and the 0.16 of the full extended sample. We also re-estimate the business-cycle regression with IV as the dependent variable in place of EPU to verify if this decoupling is specific to EPU or generalises beyond it (Table A.5, Appendix C). The adjusted R^2 on IV is 0.304 in 1985–2012 and 0.285 in 1985–2024.

Panel B exhibits a notable shift yet core findings remain consistent. Nevertheless, all variables previously significant in both the univariate and multivariate case remain significant. However, coefficient magnitudes and significance levels have decreased for multiple variables. The univariate EPU regression has seen its coefficient decrease from -0.28 to -0.22, while the multivariate regression coefficient drops from -0.11 to -0.08, both keeping their significance. In practical terms, this corresponds to a changed effect on market returns, from a drop of 1.4% to 1.1%, and 0.55% to 0.4%, in response to a one-standard-deviation change in EPU, for the univariate and multivariate regression, respectively. Other variables, including IV, VAR, and TERM, are all seeing lower magnitudes. Overall, while adjusted R2 has increased slightly, moving from 0.53 to 0.55, EPU predicts a smaller share of the market downturn.

Regarding Panel C, the significance of coefficients remains largely unchanged, with the sole exception of the second-order autoregressive coefficient (AR(2)), now being significant at a 10% level (Column 2). EPU, IV and VAR therefore remain stationary, enabling valid predictive regressions. However, notably, the stickiness of all variables has decreased, primarily for EPU and VAR. For EPU specifically, the AR(1) coefficient drops to 0.61 (Column 2), reducing the half-life from 2 to 1.4 months. This suggests a more dynamic, faster-reverting uncertainty environment post-2012.

Table III. Extended contemporaneous relationship between EPU and macroeconomic state variables

Contemporaneous specification on the extended 1985–2024 monthly sample. Panel A reports standardised regressions of composite EPU on the macroeconomic state variables (Eq. (3)); column (8) reports the multivariate regression on the business-cycle subset (TERM, DEFAULT, RREL, CFI), and column (9) reports the multivariate regression on the full control set. The drop in column (8) adjusted R^2 from 0.35 in the replicated sample to 0.16 documents the structural decoupling of EPU from business-cycle variables. Panel B reports the contemporaneous return regression (Eq. (4)) in univariate and multivariate form. Panel C reports AR(p) coefficients with the lagged log excess market return and DF-GLS test statistics for EPU, IV, and VAR (Eq. (5)). EPU is the legacy three-component composite index (Baker et al., 2016), scaled by 1/100. Newey and West (1987) standard errors with 4 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. standardised regressions of EPU on state variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IV	0.38***								0.17*
	(5.13)								(1.74)
VAR		0.34***							0.12
		(5.03)							(1.24)
TERM			0.05					-0.06	-0.06
			(0.70)					(-0.67)	(-0.67)
DEFAULT				0.39***				0.37***	0.24**
				(4.46)				(3.94)	(2.14)
RREL					-0.20*			-0.11	-0.09
					(-1.88)			(-1.02)	(-0.84)
CFI						-0.13		0.00	0.03
						(-1.23)		(0.03)	(0.26)
Log(D/P)							0.05		0.06
							(0.91)		(0.94)
N	468	480	480	480	480	480	480	480	468
Adj. R^2	0.14	0.11	0.00	0.15	0.04	0.02	0.00	0.16	0.20

Panel B. Regression of log excess market return on ΔEPU

	Multivariate	Univariate
Δ EPU	-0.08**	-0.22***
	(-2.18)	(-3.32)
Δ VAR	0.04	
	(0.40)	
Δ IV	-0.72***	
	(-11.63)	
Δ TERM	-0.09***	
	(-2.67)	
Δ DEFAULT	-0.17***	
	(-3.74)	
Δ RREL	-0.02	
	(-0.38)	
Δ Log(D/P)	-0.10***	
	(-2.64)	
N	467	479
Adj. R^2	0.55	0.05

Panel C. AR(p) coefficients and DF-GLS statistics

	EPU		IV		VAR	
	(1)	(2)	(3)	(4)	(5)	(6)
AR(1)	0.66***	0.61***	0.80***	0.82***	0.46***	0.39**
	(11.40)	(11.14)	(24.73)	(25.49)	(2.95)	(2.47)
AR(2)	0.17	0.20*				
	(1.59)	(1.84)				
AR(4)	0.17***	0.16***				
	(3.97)	(3.77)				
MKT_{t-1}		-1.13***		7.70		-9.34**
		(-4.39)		(1.53)		(-2.29)
DF-GLS	-3.59***		-4.74***		-6.73***	
N	476	476	467	467	479	479
Adj. R^2	0.71	0.72	0.64	0.64	0.21	0.23

A.3. Structural Break Test

Table IV statistically compares the replicated and extended regressions from Panel A of Tables II and III, respectively. The F-tests in the table reveal that the EPU has significantly decoupled from both the full controls (F = 7.50, $p < 0.001$) and the macroeconomic ones (F = 3.58, $p = 0.007$), both at the 1% level.

Table IV. Chow test for post-2012 coefficient stability

Interaction coefficients $\beta_{2,i}$ from Eq. (6), measuring the change in slope between the 1985–2012 and 2013–2024 subsamples. The dependent variable is standardised EPU. The full specification interacts a post-2012 dummy with all seven regressors from Table II Panel A column (9); the business-cycle specification interacts the dummy with the four business-cycle regressors only (TERM, CFI, DEFAULT, RREL). The joint F-statistic tests $H_0 : \beta_{2,i} = 0$ for all interactions in the specification. Newey and West (1987) standard errors with 4 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

	Full specification		Business-cycle only	
Variable	Interaction coef.	t-statistic	Interaction coef.	t-statistic
TERM	−0.396***	(−2.73)	−0.508***	(−2.99)
CFI	0.259**	(2.23)	0.218*	(1.69)
Log(D/P)	−0.508*	(−1.87)	–	–
IV	0.348*	(1.84)	–	–
RREL	−0.300	(−1.49)	−0.349	(−1.31)
DEFAULT	0.398	(0.93)	0.549	(1.34)
VAR	0.071	(0.65)	–	–
Joint F-statistic	7.50***		3.58***	
p-value	(< 0.001)		(0.007)	

The table also provides insight into which variables are behind this decoupling. The full specification suggests that TERM and CFI have significantly decoupled at the 1% and 5% level, respectively. The interaction coefficient of -0.396 for TERM indicates a decreased effect on EPU by 18.8 points in response to a one-standard-deviation change in TERM, displaying the magnitude of the structural decoupling. Simultaneously, Log(D/P) and IV show suggestive evidence of a shift at the 10% level.

The business-cycle-only specification reveals that the macroeconomic decoupling also stems from TERM at the 1% level; however, the effect is even stronger with a coefficient at -0.508 corresponding to a decreased response from EPU due to a one-standard-deviation shift in TERM of 24.1. Additionally, CFI is now only suggestively significant at a 10% level. The rest of the variables have remained stable, either due to lack of change, or due to lack of statistical power.

A.4. Frequency Extension

Table V investigates the same contemporaneous regressions with the time extended sample in a daily frequency. Generally, Panel A exhibits the same significance and signs across variables with minor changes. In the univariate specifications, the magnitude of VAR has decreased noticeably, largely explained by VAR now being estimated using the daily return. The multivariate instead departs from the monthly version as RREL remains significant. DEFAULT remains significant, however, exhibits a diminished magnitude. Notably, IV remains the strongest predictor of EPU with a multivariate coefficient of 0.22 translating to a 16.8 point rise in EPU in response to a one-standard-deviation increase in IV. Crucially, this represents a larger point impact than both monthly regressions in Table II and III despite not having the largest coefficient due to the larger standard deviation for the daily EPU as presented in Table I.

Panel B exhibits extensive changes. EPU diverges from monthly results as it is neither significant in the univariate nor multivariate specification, and is essentially zero in both coefficient and real-world interpretation. This might, however, be an artifact of EPU consisting only of the news-based index rather than the three-component one, which

Table V. Daily contemporaneous relationship between EPU and macroeconomic state variables

Contemporaneous specification at daily frequency on the extended 1985–2024 sample. Panel A reports standardised regressions of news-based EPU on the macroeconomic state variables (Eq. (3)); columns (1)–(5) report univariate regressions and column (6) reports the multivariate regression on the full daily control set (IV, VAR, TERM, DEFAULT, RREL). CFI and Log(D/P) are excluded as they are unavailable at daily frequency. Panel B reports the contemporaneous return regression (Eq. (4)) in univariate and multivariate form, with VAR proxied by the squared daily log market return. Panel C reports AR(p) coefficients with the lagged log excess market return and DF-GLS test statistics for EPU, IV, and VAR (Eq. (5)). EPU is the news-based daily index (Baker et al., 2016), scaled by 1/100; the daily composite index is unavailable. Newey and West (1987) standard errors with 21 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. standardised regressions of EPU on state variables

	(1)	(2)	(3)	(4)	(5)	(6)
IV	0.32***					0.22***
	(6.38)					(4.79)
VAR		0.15**				0.02
		(2.56)				(0.94)
TERM			0.05			-0.05
			(1.55)			(-1.34)
DEFAULT				0.25***		0.09***
				(6.53)		(2.77)
RREL					-0.24***	-0.15***
					(-5.13)	(-3.80)
N	9828	10080	10080	9828	10080	9828
Adj. R^2	0.10	0.02	0.00	0.06	0.06	0.13

Panel B. Regression of daily market return on ΔEPU

	Multivariate	Univariate
Δ EPU	-0.00	-0.01
	(-0.65)	(-0.61)
Δ VAR	0.08**	
	(2.26)	
Δ IV	-0.77***	
	(-5.53)	
Δ TERM	0.03	
	(1.57)	
Δ DEFAULT	-0.01	
	(-0.73)	
Δ RREL	0.01	
	(0.72)	
N	9827	10079
Adj. R^2	0.54	-0.00

Panel C. AR(p) coefficients and DF-GLS statistics

	EPU		IV		VAR	
	(1)	(2)	(3)	(4)	(5)	(6)
AR(1)	0.30***	0.30***	0.97***	0.97***	0.20**	0.19**
	(18.98)	(19.02)	(108.29)	(104.41)	(2.44)	(2.19)
AR(2)	0.13***	0.13***				
	(9.47)	(9.56)				
AR(5)	0.14***	0.14***				
	(10.79)	(10.79)				
MKT_{t-1}		-2.41***		17.84**		-30.04**
		(-3.49)		(2.46)		(-2.00)
DF-GLS	-2.17***		-7.13***		-14.21***	
N	10075	10075	9827	9827	10079	10079
Adj. R^2	0.43	0.43	0.93	0.93	0.04	0.04

would mean the two indices capture different types of uncertainty. To check whether index composition drives the divergence, we re-estimate the monthly Panel B specification using only the news-based component (Table A.1, Appendix A). The news-only monthly ΔEPU coefficient remains significant at −0.09 ($t = -2.42$), nearly identical to the composite. The monthly-to-daily divergence is therefore not driven by index construction.

Panel C reveals results validating the daily frequency methodology allowing predictive regressions. Crucially, the DF-GLS still remains significant at a minimum 5% level confirming stationarity for IV, VAR and EPU. The market return feedback loop remains intact; the same is true for stickiness which remains significant. The lagged-return effect on EPU (MKT_{t-1}) is revisited in Section B as a candidate mechanism for the contemporaneous null in Panel B. The magnitude of the autoregressive coefficients decreased for EPU and VAR, while they increased for IV; the uncertainty environment has therefore shifted, with EPU experiencing larger day-to-day deviations, while implied volatility remains highly sticky. However, these values are not comparable to that of the monthly version as the first-order coefficients are defined using the daily frequency, meaning the stickiness is measured over a shorter time period. The AR(1) coefficient of EPU can therefore be represented as a half-life of 0.58 trading days.

B. Predictive Results

B.1. Study Replication

Table VI presents the predictive forecasting regressions assessing the capability of current EPU to predict future log excess market return. Table VI, Panel A examines this relationship without macroeconomic state variables as controls. EPU exhibits a positive predictive effect on total returns for all time periods h, however, the coefficients are only significant for three- and six-months at a 10% level. The positive association stands in stark contrast to the negative contemporaneous relationship identified in Table II. This suggests that heightened uncertainty is indicative of increased expected returns which are realised over these time horizons.

Consequently, Panel A is broadly congruent with the Brogaard and Detzel (2015) study, despite minor magnitude and significance deviations. Specifically, the original paper saw the two-month time period being significant and generally had slightly lower coefficient magnitudes than the replication.

Panel B introduces the control variables VAR and IV to isolate the unique effect associated with EPU, which remains significant, however, at the time periods two- and three-months and a higher 5% significance level for the three month time period. Both VAR and IV are significant for horizons of three-months and less with VAR being negative and IV positive. The positive implied volatility (IV) aligns with the EPU interpretation that both demand a higher expected return. Conversely, realised volatility (VAR) exhibits a significant negative correlation with future excess returns. This finding indicates that high historic volatility is associated with lesser future returns, an apparent paradox, however, this is congruent with existing literature. Bollerslev et al. (2009) presents precisely this idea identifying the spread between implied and realised volatility as a driver of future returns. These results are highly aligned with the original paper with only slight deviations in EPU magnitudes and exact significance levels.

Panel C incorporates the full suite of macroeconomic state variables, resulting in minor shifts in EPU coefficients. The two- and three-month horizons are still significant. Except for the 12-month coefficient, EPU saw increased coefficient magnitudes, while IV and VAR results and interpretations remain consistent. Among remaining controls, only RREL remains significant, which it is for all time horizons in excess of one-month. This suggests that current deviations in short-term interest rates capture uncertainty and risk premium not present in EPU, VAR or IV.

To quantify this risk premium, the multivariate coefficient of 5.51 at the three month horizon in Panel C implies that a one-standard-deviation increase in EPU predicts a roughly 2.61% rise in cumulative returns in the subsequent three-month period. This equates to a roughly 10.4% annualized equity risk premium commanded due to the EPU

Table VI. Replicated predictive regressions of cumulative log excess market return on EPU

Predictive regressions of cumulative log excess market returns from t to $t+h$ on EPU at time t (Eq. (7)), estimated on the replicated 1985–2012 monthly sample. Horizons are $h \in \{1, 2, 3, 6, 12\}$ months. Panel A reports univariate forecasts; Panel B adds the volatility controls VAR and IV; Panel C adds the full control set (VAR, IV, TERM, DEFAULT, RREL, Log(D/P)). EPU is the legacy three-component composite index (Baker et al., 2016), scaled by 1/100. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. Univariate forecasts

	$(h=1)$	$(h=2)$	$(h=3)$	$(h=6)$	$(h=12)$
EPU	0.70	2.68	3.93*	6.60*	10.12
	(0.72)	(1.57)	(1.74)	(1.70)	(1.47)
N	336	336	336	336	336
Adj. R^2	-0.00	0.01	0.02	0.03	0.04

Panel B. EPU forecasts with IV and VAR

	$(h=1)$	$(h=2)$	$(h=3)$	$(h=6)$	$(h=12)$
EPU	1.25	3.12*	4.38**	6.11	10.08
	(1.48)	(1.95)	(2.01)	(1.52)	(1.28)
VAR	-0.58***	-0.76**	-1.06**	-0.65	0.03
	(-3.49)	(-2.56)	(-2.54)	(-0.86)	(0.03)
IV	0.10**	0.15*	0.22*	0.18	-0.04
	(2.05)	(1.83)	(1.89)	(0.87)	(-0.10)
N	324	324	324	324	324
Adj. R^2	0.04	0.04	0.06	0.03	0.03

Panel C. EPU forecasts with controls

	$(h=1)$	$(h=2)$	$(h=3)$	$(h=6)$	$(h=12)$
EPU	1.27	3.97*	5.51**	6.96	6.78
	(1.12)	(1.89)	(1.99)	(1.51)	(0.88)
VAR	-0.60***	-0.75**	-1.09***	-0.81	-0.54
	(-3.58)	(-2.57)	(-2.70)	(-1.20)	(-0.57)
IV	0.13**	0.23***	0.34***	0.42*	0.40
	(2.51)	(2.63)	(2.86)	(1.88)	(0.90)
TERM	-0.10	-0.30	-0.39	-0.08	2.61
	(-0.41)	(-0.61)	(-0.54)	(-0.06)	(1.13)
DEFAULT	0.11	-1.32	-1.33	-0.67	3.13
	(0.09)	(-0.60)	(-0.43)	(-0.13)	(0.39)
RREL	0.59	1.46*	2.49**	5.40**	10.58**
	(1.38)	(1.80)	(2.13)	(2.37)	(2.43)
Log(D/P)	1.10	2.48	3.47	6.28	9.59
	(1.32)	(1.46)	(1.38)	(1.23)	(0.95)
N	324	324	324	324	324
Adj. R^2	0.04	0.07	0.10	0.13	0.22

levels at $t = 0$.

Broadly, these results corroborate the original findings, with only minor magnitude differences in most variables.

B.2. Time Extension

Table VII extends the original findings by utilizing a sample period through 2024. Panel A indicates that the extended sample further strengthens EPU's predictive ability, as all coefficients are now significant compared to the three- and six-month horizons in the original sample. However, the coefficient magnitudes remain consistent overall. A Chow-style test on the extended sample confirms this stability: no statistically significant shift in the EPU predictive coefficient appears at any monthly horizon (Table B.1, Appendix A).

TABLE VII. Extended predictive regressions of cumulative log excess market return on EPU

Predictive regressions of cumulative log excess market returns from t to $t + h$ on EPU at time t (Eq. (7)), estimated on the extended 1985–2024 monthly sample. Horizons are $h \in \{1, 2, 3, 6, 12\}$ months. Panel A reports univariate forecasts; Panel B adds the volatility controls VAR and IV; Panel C adds the full control set (VAR, IV, TERM, DEFAULT, RREL, Log(D/P)). EPU is the legacy three-component composite index (Baker et al., 2016), scaled by 1/100. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. Univariate forecasts

	$(h = 1)$	$(h = 2)$	$(h = 3)$	$(h = 6)$	$(h = 12)$
EPU	1.19*	2.74**	3.82**	6.30**	10.73**
	(1.88)	(2.49)	(2.54)	(2.25)	(2.22)
N	479	478	477	474	468
Adj. R^2	0.01	0.02	0.03	0.05	0.07

Panel B. EPU forecasts with IV and VAR

	$(h = 1)$	$(h = 2)$	$(h = 3)$	$(h = 6)$	$(h = 12)$
EPU	1.48**	2.92***	4.03**	6.05**	10.60*
	(2.57)	(2.63)	(2.55)	(1.96)	(1.88)
VAR	-0.20	-0.25	-0.43	-0.17	0.38
	(-0.82)	(-1.01)	(-1.45)	(-0.36)	(0.59)
IV	0.02	0.05	0.10	0.07	-0.10
	(0.40)	(0.73)	(1.06)	(0.42)	(-0.31)
N	467	466	465	462	456
Adj. R^2	0.01	0.03	0.04	0.04	0.07

Panel C. EPU forecasts with controls

	$(h = 1)$	$(h = 2)$	$(h = 3)$	$(h = 6)$	$(h = 12)$
EPU	1.51**	3.14***	4.27**	6.18*	10.14*
	(2.39)	(2.59)	(2.48)	(1.87)	(1.71)
VAR	-0.18	-0.21	-0.40	-0.18	0.23
	(-0.77)	(-0.88)	(-1.43)	(-0.41)	(0.40)
IV	0.05	0.13*	0.21**	0.25	0.16
	(0.93)	(1.77)	(2.22)	(1.51)	(0.50)
TERM	-0.16	-0.32	-0.45	-0.47	0.91
	(-0.85)	(-0.88)	(-0.83)	(-0.43)	(0.43)
DEFAULT	-0.81	-2.30	-2.59	-2.03	1.65
	(-0.72)	(-1.12)	(-0.89)	(-0.42)	(0.21)
RREL	0.15	0.60	1.21	3.21	7.14*
	(0.40)	(0.82)	(1.15)	(1.57)	(1.91)
Log(D/P)	1.65*	3.60**	5.11**	8.74*	13.32
	(1.91)	(2.14)	(2.07)	(1.76)	(1.36)
N	467	466	465	462	456
Adj. R^2	0.01	0.05	0.08	0.12	0.20

Panel B corroborates this result, as EPU is significant across all horizons. Still, the magnitudes remain consistent with the original sample. Notably, both VAR and IV have lost all statistical significance and decreased in magnitude; despite this, their signs remain consistent.

The introduction of the full suite of control variables further strengthens the findings. All EPU coefficients are still significant. VAR loses all significance, while IV is inconsistently significant. Finally, RREL remains significant and Log(D/P) gains significance at certain time periods. Overall, the extended sample strengthens the evidence for a relationship between EPU and cumulative returns, likely reflecting the greater precision afforded by the longer samples.

Quantifying the risk premium, the fully controlled three-month horizon EPU coefficient of 4.27 in Panel C translates to an additional cumulative market return of 2.03%. This equates to an annualized risk premium of 8.1% which is a reduction from the 10.4% observed in the pre-2012 sample. This confirms that EPU continues to command a highly significant risk premium in modern equity markets. Furthermore, the 12-month horizon EPU coefficient of 10.14 indicates an annual equity risk premium of 4.81%. However, instead of being contradictory, this confirms previous work by Bollerslev et al. (2009) who concludes that risk premium tapers with time.

B.3. Frequency Extension

Table VIII uses the extended sample period, while using daily frequency data, to reveal the shorter-term prediction ability of EPU. Panel A reveals that the predictive power is overall weaker for the shorter time periods, as it is only significant for the 1-, 21- and 63-day horizons.

When controlling for VAR and IV, as seen in Panel B, the statistical significance of the EPU coefficient increases for the longer horizons and disappears for the short horizons. VAR and IV on their own remain insignificant, in alignment with Table VII.

Panel C further corroborates the results from Table VII. EPU remains significant; however, only for longer horizons of 10, 21, and 63-days. Crucially, this reveals new information, as the increased expected return is tangible after only 10 days. Quantifying this impact, the fully controlled 10-day coefficient of 0.27 implies that a one-standard-deviation change in EPU increases cumulative excess returns by 0.21% over the subsequent 10 trading days. Without the resolution enabled by the daily data, this relationship could not have been identified due to its sub-one-month nature. Furthermore, all control variables remain insignificant generally in alignment with the monthly 2024 sample (Table VII).

We then compare the predictive profile against its AR-implied benchmark, i.e., how it would look if EPU were a state variable that raised required returns by a constant amount and then mean-reverted according to its AR(20) rate. $\beta(h)/h$ should decay in the following manner: falling from 0.0077 at $h = 10$ to 0.0025 at $h = 126$. The actual profile is roughly stable around 0.025–0.032 across this range (Table B.5), and lies several times above the AR(20)-implied benchmark throughout this range, reaching roughly an order of magnitude by $h = 126$. The same regularity appears at monthly frequency in lesser form (Table B.4): the composite-EPU profile sits 15% above its AR(4) benchmark at $h = 6$ while the news-only profile sits 30% above its own. The implications of this gap are discussed in Section B.

The daily extension reveals two features of the news-based EPU that motivate the prediction-market test which follows. First, ΔEPU carries no contemporaneous information at daily frequency once the standard volatility controls are included (Table V, Panel B), despite it remaining significant at the monthly horizon. Second, EPU's predictive power concentrates at horizons of ten trading days and beyond (Table VIII, Panel C), indicating that whatever information EPU carries plays out over weeks rather than at the point of impact. We will be testing whether a continuously traded, forward-looking measure of political probability is well-suited to capture the variation that EPU misses at daily resolution, by using Polymarket implied uncertainty.

TABLE VIII. Daily predictive regressions of cumulative log excess market return on EPU

Predictive regressions of cumulative log excess market returns from t to $t+h$ on EPU at time t (Eq. (7)), estimated at daily frequency on the extended 1985–2024 sample. Horizons are $h \in \{1, 5, 10, 21, 63\}$ trading days, ranging from one day to roughly three months. Panel A reports univariate forecasts; Panel B adds the volatility controls VAR and IV; Panel C adds the daily control set (VAR, IV, TERM, DEFAULT, RREL). CFI and Log(D/P) are excluded as they are unavailable at daily frequency. EPU is the news-based daily index (Baker et al., 2016), scaled by 1/100; the daily composite index is unavailable. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. Univariate forecasts

	$(h=1)$	$(h=5)$	$(h=10)$	$(h=21)$	$(h=63)$
EPU	0.04*	0.13	0.28	0.64*	1.85**
	(1.74)	(1.31)	(1.51)	(1.95)	(2.48)
N	10079	10075	10070	10059	10017
Adj. R^2	0.00	0.00	0.00	0.01	0.03

Panel B. EPU forecasts with IV and VAR

	$(h=1)$	$(h=5)$	$(h=10)$	$(h=21)$	$(h=63)$
EPU	0.03	0.12	0.26*	0.61**	1.79***
	(1.40)	(1.37)	(1.69)	(2.20)	(2.70)
VAR	0.00	-0.02	-0.01	-0.01	-0.03
	(0.70)	(-0.83)	(-0.21)	(-0.28)	(-0.37)
IV	0.00	0.01	0.01	0.02	0.04
	(0.26)	(0.65)	(0.24)	(0.37)	(0.35)
N	9827	9823	9818	9807	9765
Adj. R^2	0.00	0.00	0.00	0.01	0.03

Panel C. EPU forecasts with controls

	$(h=1)$	$(h=5)$	$(h=10)$	$(h=21)$	$(h=63)$
EPU	0.03	0.13	0.27*	0.65**	1.97***
	(1.53)	(1.49)	(1.80)	(2.39)	(3.04)
VAR	0.00	-0.02	-0.01	-0.02	-0.04
	(0.66)	(-0.88)	(-0.24)	(-0.36)	(-0.52)
IV	0.00	0.01	0.01	0.03	0.09
	(0.50)	(0.83)	(0.43)	(0.74)	(0.85)
TERM	-0.01	-0.04	-0.07	-0.10	-0.23
	(-0.79)	(-0.77)	(-0.70)	(-0.51)	(-0.38)
DEFAULT	-0.04	-0.08	-0.10	-0.47	-0.87
	(-0.55)	(-0.23)	(-0.16)	(-0.37)	(-0.25)
RREL	0.01	0.03	0.05	0.14	1.02
	(0.30)	(0.29)	(0.27)	(0.35)	(0.89)
N	9827	9823	9818	9807	9765
Adj. R^2	0.00	0.00	0.00	0.01	0.04

C. Prediction Market Results

We begin by estimating the baseline Panel B specification of Brogaard and Detzel (2015) separately for each of the four markets, adding the Polymarket innovation as the final regressor. The dependent variable is the daily log excess market return, standardised by its full-sample standard deviation, with results presented in Table IX.

TABLE IX. Contemporaneous regressions of Polymarket innovations

OLS regressions of the daily standardised log excess market return on first-differenced standardised macroeconomic state variables and Polymarket-implied uncertainty innovations (Eq. (8)). Each column is a separate regression in which Innovation is constructed from a different Polymarket contract. Innovation is the residual from an AR(1) fit on the daily Shannon-entropy series of that contract, standardised to unit variance over the active sample; entropy is constructed from Eq. (1) for the binary Senate, House, and Fed contracts and from Eq. (2) for the multi-outcome Presidential contract. Macroeconomic controls are first-differenced and standardised. Sample periods and observations: Presidential January 5–November 6, 2024 (N = 211); Senate January 2–November 7, 2024 (N = 215); House February 22–November 18, 2024 (N = 187); Fed January 2–December 31, 2024, with a six-week gap between FOMC-meeting contracts in March–May (N = 222). Newey and West (1987) standard errors with 21 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

	Presidential	Senate	House	Fed
Δ EPU	−0.01	−0.00	0.02	0.00
	(−0.28)	(−0.13)	(0.76)	(0.13)
Δ VAR	0.27***	0.23***	0.25***	0.26***
	(3.56)	(2.92)	(3.49)	(5.83)
Δ IV	−0.86***	−0.84***	−0.83***	−0.83***
	(−6.86)	(−7.01)	(−7.95)	(−9.68)
Δ TERM	−0.16***	−0.16***	−0.17***	−0.14***
	(−4.08)	(−4.52)	(−3.76)	(−4.37)
Δ DEFAULT	0.03	0.03	0.06	0.07
	(0.53)	(0.47)	(0.87)	(1.57)
Δ RREL	0.02	0.01	0.02	−0.00
	(0.28)	(0.13)	(0.30)	(−0.06)
Innovation	−0.03	−0.10***	−0.09***	0.04
	(−0.86)	(−4.02)	(−5.54)	(0.78)
N	211	215	187	222
Adj. R^2	0.557	0.558	0.590	0.586

Two of the four contracts yield null results. The Presidential election produces a coefficient on Innovation of −0.03 (t = −0.86), which is statistically indistinguishable from zero. The Fed rate produces a coefficient of +0.04 (t = 0.78), also null. In both cases the standard controls behave as expected: ΔIV is strongly negative, ΔVAR positive, and ΔTERM negative at the 1% level, with the model explaining roughly 56–59% of the variation in daily excess returns. Polymarket innovations in these two contracts contribute nothing beyond what the standard controls already capture.

The Senate and House contracts present a different picture. The Senate innovation coefficient is −0.10 (t = −4.02) and the House innovation coefficient is −0.09 (t = −5.54), both significant at the 1% level. The signs are negative, as one would expect if rising political uncertainty depresses contemporaneous returns, and the magnitudes imply that a one-standard-deviation shock to Senate or House entropy is associated with roughly a 0.09–0.10 standard-deviation decline in same-day excess returns, holding standard controls fixed. These estimates suggest that congressional-control uncertainty, measured through prediction markets, carries information about equity returns beyond what standard uncertainty variables provide.

The remainder of this section argues that these two apparent positives do not survive scrutiny. We first show that both coefficients collapse when a small number of election-period observations are removed from the sample. We then use a Monte Carlo simulation to establish that the null results are not artifacts of low statistical power.

A standard OLS regression weights observations by their leverage, so a small number of days with unusually large innovations can potentially drive the entire estimated coefficient. If these days coincide with exogenous events which affect both the prediction market and the equity markets, we need to make sure the relationship is causal rather than just a parallel relationship on these particular high-leverage days. To verify if our House and Senate results are valid we therefore drop the 5 days with the most leverage (concentrated in November when the election results are announced) and reestimate the regression for the rest of the year.

Table X. Leverage diagnostic

Coefficient on the Polymarket Innovation term and its t-statistic from the contemporaneous specification of Table IX (Eq. (8)), before and after dropping the five observations with the largest $|\text{Innov}_t|$ in each market. Coefficients on the macroeconomic controls are unreported. Post-drop sample sizes: Presidential $N = 206$, Senate $N = 210$, House $N = 182$, Fed $N = 217$. The five dropped Presidential observations are June 28 (Biden–Trump debate), July 15 (Trump assassination attempt), July 18, July 22 (Biden withdrawal), and November 6 (election night). The five dropped Senate observations are November 6 together with four early-year observations (January 29, January 30, February 15, and February 20) from the pre-September window before Polymarket's depth had matured (Tsang and Yang, 2026). The five dropped House observations cluster in election week (November 6, 7, 11, 15, and 18). The five dropped Fed observations are January 10, February 2, February 20, August 1, and November 8. Newey and West (1987) standard errors with 21 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

	Baseline		After drop	
	Coef.	t-stat	Coef.	t-stat
Presidential	−0.03	(−0.86)	+0.21	(+1.84)
Senate	−0.10***	(−4.02)	−0.07	(−0.43)
House	−0.09***	(−5.54)	+0.24	(+0.70)
Fed	+0.04	(+0.78)	+0.01	(+0.20)

Table X reports the Innov coefficient before and after the drop. For the House contract the coefficient moves from −0.09 ($t = -5.54$) to +0.24 ($t = +0.70$), a sign reversal with total loss of significance. For the Senate contract the coefficient moves from −0.10 ($t = -4.02$) to −0.07 ($t = -0.43$), with the dropped dates being November 6 together with four early-year observations from a thin-liquidity period. The Presidential coefficient also loses its baseline sign, and the Fed baseline was null throughout. These 5 dropped days represented around 2.3% to 2.7% of each market's sample, yet the disproportionate effect they had on Senate and House shows that the previous relationship we found was almost entirely carried by these high-leverage dates.

All four markets therefore yield null results. A concern with this null is that daily Polymarket innovations are concentrated in a small number of event-driven days, and a standard regression may lack the resolution to detect a real relationship in such a sample. A Monte Carlo simulation on the House innovation series (the most concentrated of the four, and therefore the most plausible candidate for an underpowered sample) makes this unlikely as detection probability reaches 71% at $\beta = 0.05$, 95% at $\beta = 0.10$, and 100% at $\beta \geq 0.20$, the null is therefore well powered for moderate-sized effect but could miss smaller ones. Full results are reported in Appendix C.

Taken together, the four contracts produce a structured null. Across the Presidential, Senate, House, and Fed markets, daily Polymarket innovations show no robust contemporaneous relationship to equity returns beyond what standard volatility, term-spread, and newspaper-EPU controls already capture. Both apparent positives (Senate and House) appear to be driven by a handful of election-week days on which both the prediction market and the equity market reacted to the same external news, and the power analysis partially rules out the possibility that the four nulls reflect an underpowered test rather than a genuine absence of a relationship.

We then complete this analysis with a predictive regression to test whether these innovations predict returns at longer horizons. We therefore run a predictive specification on the AR(1) innovations of Polymarket entropy to verify whether the measure we have constructed adds explanatory power when controlling for the standard volatility indices and macro indicators. These forecasts are reported in Table XI.

TABLE XI. Predictive regressions of cumulative log excess market return on Presidential entropy innovations

Predictive OLS regressions of cumulative log excess market returns from t to $t+h$ on the AR(1) innovation in Presidential Shannon entropy (Eq. (9)). The innovation series is constructed via Eq. (2) on the multi-outcome Presidential contract and standardised to unit variance over the active sample. Panel A is univariate; Panel B adds the level controls EPU, VAR, IV, TERM, DEFAULT, and RREL. Sample: January 5–November 6, 2024 ($N = 211$). The corresponding regressions on Senate, House, and Fed innovations are statistically insignificant at every horizon $h \in \{1, 5, 10, 21\}$ and are omitted to conserve space. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout is adapted from Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. Univariate

	($h = 1$)	($h = 5$)	($h = 10$)	($h = 21$)
Innov(Presidential)	−0.04	0.05	0.33***	0.06
	(−1.01)	(0.73)	(2.77)	(0.44)
N	211	211	211	211
Adj. R^2	−0.002	−0.004	0.016	−0.004

Panel B. With controls

	($h = 1$)	($h = 5$)	($h = 10$)	($h = 21$)
Innov(Presidential)	−0.06	0.01	0.26*	0.04
	(−1.14)	(0.15)	(1.87)	(0.18)
EPU	0.02	0.01	−0.04	−0.21
	(0.50)	(0.14)	(−0.29)	(−0.87)
VAR	−0.06	−0.06	−0.06	−0.06
	(−0.61)	(−0.53)	(−0.43)	(−0.34)
IV	0.04	0.18	0.31*	0.36
	(1.33)	(1.38)	(1.70)	(1.51)
TERM	0.18	0.50	0.78	2.14
	(0.60)	(0.37)	(0.31)	(0.49)
DEFAULT	1.76	2.93	7.31	11.92
	(1.05)	(0.42)	(0.57)	(0.47)
RREL	0.22	1.04	1.91	2.06
	(0.72)	(0.72)	(0.74)	(0.46)
N	211	211	211	211
Adj. R^2	−0.012	0.047	0.136	0.159

The only market which preserved significance after the controls were added was the Presidential market (Senate, House and Fed are null at all horizons). Presidential innovations are significant at $h = 10$ ($t = 2.77$) with a coefficient of 0.33 in the univariate regression, and the effect weakens to 0.26 but remains significant with the controls in Panel B.

We next verify whether the $h = 10$ horizon is robust. We tested only 4 different horizons in Table XI, so to distinguish whether $h = 10$ is a genuine informative window or a lucky horizon choice we estimate the specification at every horizon window from $h = 1$ to $h = 30$. Figure 1 reports the results.

The coefficient rises from near-zero at $h = 1$–5, climbs sharply at $h = 6$, peaks across $h = 7$–11 with t-statistics exceeding the 5% critical value, and decays back to insignificance by $h = 12$. The observed $h = 10$ result from Table XI is therefore not an isolated spike. The shape across the full horizon range is suggestive of a smooth hump, but the coefficients outside $h = 7$–11 are not statistically distinguishable from zero, so the hump interpretation rests on the significant window rather than the surrounding pattern.

As with the contemporaneous analysis, daily Polymarket innovations are concentrated in a small number of event-driven days. A leverage drop of the five largest |Innov| observations at $h = 10$ reduces the coefficient modestly from 0.27 to 0.18 but collapses the t-statistic from 1.87 to 0.53, indicating the signal is concentrated within these five

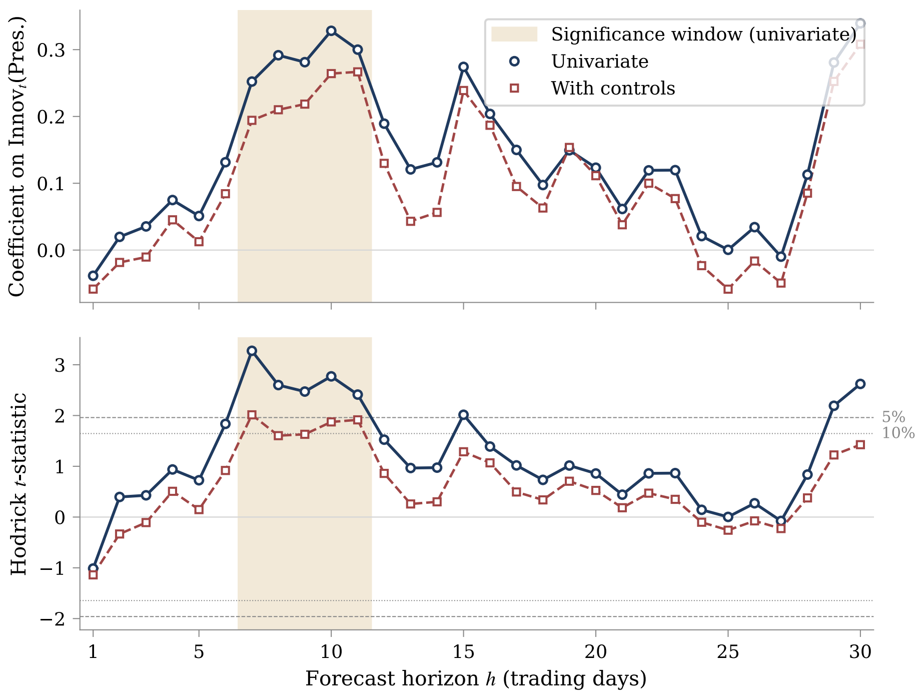

Figure 1. Horizon sweep of Presidential entropy innovations on cumulative excess returns. Each marker estimates the predictive specification of Eq. (9) at horizon $h \in \{1, 2, \ldots, 30\}$ trading days. The solid (univariate) series corresponds to Panel A of Table XI; the dashed (with controls) series corresponds to Panel B and includes the level controls EPU, VAR, IV, TERM, DEFAULT, and RREL. Top panel: estimated coefficient on the standardised AR(1) Presidential entropy innovation. Bottom panel: corresponding Hodrick (1992) t-statistic. The shaded band marks $h = 7$ to $h = 11$, where the univariate $|t|$ exceeds the two-sided 5% critical value of 1.96. Sample: January 5–November 6, 2024 ($N = 211$).

observations. A permutation test confirms that the relationship within these days is genuine: only 11 of 5,000 shuffles produce a $|t|$ as extreme as the observed 2.77 ($p = 0.002$). Both diagnostics are reported in Appendix C.

V. DISCUSSION

A. EPU and the Business-Cycle Decoupling

The most robust finding from our sample extension is the business-cycle decoupling. EPU has become less explained by business-cycle variables (TERM, DEFAULT, RREL, CFI), with the adjusted R^2 falling from 0.35 to 0.16, as seen in Tables II and III. Davis (2019) made a similar qualitative observation: he noted that EPU spikes, which historically clustered around recessions and economic crises, have increasingly coincided with discrete political events. We verify this quantitatively using the Brogaard and Detzel (2015) framework, as the R^2 decline is consistent with Davis's theory but not unique to it.

To assess whether this decline is driven by COVID-era outliers, we re-estimate the regression on the 1985–2019 subsample, which is presented in Table A.3 (Appendix B), thus excluding the pandemic entirely. The R^2 for this sample is 0.26, which is at the mid-point between the samples ending in 2012 and 2024. This indicates that while the decoupling also took place post-COVID, it was already underway before.

We run a further diagnostic, reported in Appendix C, which sharpens the interpretation. When replacing EPU with IV as the dependent variable, the business-cycle R^2 is essentially unchanged across samples: 0.304 and 0.285 for the samples ending in 2012 and 2024, respectively (Table A.5). This means that option-implied volatility still tracks the business cycle and has not decoupled. The divergence is therefore specific to EPU and cannot be attributed to a generic shift in the relationship between uncertainty and macroeconomic conditions.

However, this decoupling did not seem to have impacted EPU's predictive power for equity returns. The predictive coefficient is statistically unchanged across samples, as showcased by the Chow-style test in Tables B.1 and B.2 (Appendix A), while the business-cycle component of EPU has fallen substantially. This suggests that EPU's predictive content is not primarily driven by its business-cycle component, because we could have expected that if it had been, the predictive coefficient would have weakened with the decoupling. This is consistent with Davis (2019)'s observation that post-2009 EPU spikes have become increasingly correlated with discrete political events; however, our framework does not decompose EPU by source, and we therefore cannot directly test his hypothesis.

Further research could test this directly by adding political-event indicators alongside the business-cycle variables, for example the trade-policy uncertainty sub-index constructed by Baker et al. (2016). If R^2 recovers when political variables are added to the extended sample, it would confirm that political events replaced cyclical drivers rather than EPU simply becoming disconnected from fundamentals.

B. EPU's Contemporaneous and Predictive Power

The contemporaneous extension confirms the robustness of the original finding. The monthly ΔEPU remains significant in the extended sample at -0.08^{**} (Table III), compared to the original -0.11^{**} (Table II), displaying only a modest decrease in magnitude. At a daily frequency, ΔEPU is insignificant in the extended sample. We interpret this as reflecting, at least in part, the fact that at daily frequency EPU is partly endogenous to the prior day's market reaction: today's EPU change partly reflects yesterday's price movement rather than independent uncertainty news, so it cannot covary cleanly with today's return. This is visible in Table V Panel C, where the lagged log excess market return enters the EPU equation with a coefficient of -2.41 ($t = -3.49$), substantially larger than its monthly counterpart of -1.13. A second contributing factor is that the daily news-based index is structurally noisier than its monthly aggregate. Future research could isolate the signal by restricting the regression to large-uncertainty-shock days, where the EPU change is more likely to reflect a genuine same-day uncertainty event than residual response to the prior day's market move.

Our extension of the predictive results revealed a more precise picture of EPU's predictive power. In the original sample, EPU levels significantly predict cumulative excess returns only at the one- to three-month horizons with controls, while in the extension they become significant at all horizons. At the horizons where both samples were significant the coefficient magnitudes are similar, and the Chow-style test (Appendix A) finds no statistically distinguishable shift at any horizon. The results are consistent with the underlying relationship being present throughout the entire sample period, and that the 1985–2012 sample simply lacked the precision to detect it at short and long horizons.

The daily predictive results show a richer pattern. Coefficients become significant at $h = 10$ and remain so through $h = 63$ trading days. A horizon sweep extending to $h = 126$ (Table B.5, Appendix C) shows that $\beta(h)/h$, the implied per-day return premium per unit of EPU elevation, is approximately stable around 0.030 from $h = 10$ to $h = 63$ and declines only gradually to 0.026 by $h = 126$. This decay is much slower than EPU's measured persistence would mechanically deliver; if EPU raised required returns by a constant amount and then mean-reverted at its AR(20) rate, $\beta(h)/h$ at $h = 126$ should fall to 0.0025. The observed value is roughly an order of magnitude larger. The same regularity is visible at monthly frequency in attenuated form: extended-sample $\beta(h)/h$ at $h = 6$ months is 0.83 against an AR(4)-implied 0.64, roughly 30% above the prediction.

Part of this gap reflects index composition. Table B.4 (Appendix B) shows that the monthly composite sits 15% above its AR(4) benchmark at $h = 6$ while the news-only version sits 30% above its own. The composite blends the news-based component with measures of expiring tax provisions and forecaster disagreement, which appear to capture slower-moving uncertainty. The daily extension uses news-only data so part of the daily gap inherits this composition issue. But composition cannot account for the full daily 10x ratio.

Another reading is that the AR-based benchmark is itself the wrong null, as it assumes that EPU operates as a state variable whose mean reversion governs the structure of the premium. Pástor and Veronesi (2013) develop a different mechanism in which political and policy uncertainty earn a premium that is tied to the anticipated resolution of that uncertainty. This would suggest that the horizon over which the premium is earned is set by when the underlying policy question resolves, not by the mean reversion of newspaper attention to it. A flat $\beta(h)/h$ profile is consistent with this channel. We cannot identify the mechanism formally without decomposing EPU spikes by event type and resolution horizon, which is beyond this paper's scope.

C. Prediction Market

We now turn to our Polymarket results, where we attempted to construct a forward-looking index using entropy-implied uncertainty. The contemporaneous analysis provided a structured null across the four contracts after a leverage drop of the five days with the most innovation (see Table X). However, our predictive results showed that the Presidential market retained a stable point estimate across the leverage drop (Table C.1, Appendix B), although with collapsed significance, indicating that the relationship is concentrated in a small number of event-driven days. The permutation test indicates that the observed timing relationship is unlikely to arise under random reassignment of innovations (Figure C.2, Appendix C).

The predictive analysis shows a hump-shaped information absorption (see Figure 1). More specifically, there is a smooth hump-shape pattern from $h = 1$ to $h = 10$; however, the relationship becomes significant only at $h = 7$, so we cannot reliably infer the coefficients before this horizon. The hump then decays until $h = 12$, where it becomes insignificant again. This is consistent with a discrete resolution window, spanning roughly 1–2 trading weeks after the innovation shock.

Both diagnostics are consistent with the interpretation that prediction-market entropy carries predictive information about future equity returns during major political events, with the relationship operating at the event level rather than as a continuous channel. However, this inference rests on a small number of event-driven days and cannot be extrapolated beyond them. Prediction-market entropy is also structurally less variable than newspaper attention. The entropy level is close to a unit root and produces few large innovations outside event windows, which is why the predictive specification uses innovations rather than levels. This in turn limits direct comparability with the EPU $\beta(h)/h$ profile, which prices the level of a mean-reverting state variable. Further research could attempt to reproduce these findings on other markets; the difficulty lies in finding liquid markets which carry enough weight to reflect real economic policy uncertainty.

VI. CONCLUSION

This paper set out to re-evaluate the asset-pricing implications of economic policy uncertainty in the post-2012 era and to test whether the unprecedented liquidity seen in prediction markets captures dimensions of uncertainty missed by traditional measures. By extending the framework of Brogaard and Detzel (2015) through 2024, moving to daily frequency, and integrating Polymarket-based entropy measures, this paper reaches three main conclusions.

First, the pricing relationship between EPU and aggregate equity returns remains intact in the modern sample. At the monthly frequency, EPU continues to predict future excess returns, now estimated with greater precision in the extended sample. At the daily frequency, predictive effects emerge at horizons of 10 trading days, indicating that the return premium is realized earlier than could previously be identified using monthly data.

Second, the macroeconomic character of EPU has changed materially. The explanatory power of traditional business-cycle controls falls sharply in the post-2012 period, a phenomenon confirmed not to be due to COVID-era outliers. Despite this, the predictive and contemporaneous power has remained stable, suggesting that EPU's relation with market returns does not primarily stem from its business-cycle content. Cautiously, the evidence is consistent with the idea that EPU instead has become increasingly shaped by discrete political events not captured in standard uncertainty or cyclical measures.

Third, we find that prediction-market-based entropy does not function as an independent uncertainty measure within our methodology. The contemporaneous regressions across the Presidential, Senate, House, and Fed contracts produce a structured null. In predictive regressions the results remain broadly insignificant, with a fragile signal on the Presidential contract around major event dates. The evidence therefore points to prediction-market-based uncertainty measures capturing discrete events but failing to function as consistent uncertainty measures.

However, the conclusions drawn are subject to limitations that motivate additional future research. First, the identified structural break is not yet fully explained. Future studies could remedy this through a complete analysis centered around this structural break with novel regressions that include a wider range of variables, and decomposing EPU into its sub-components. Second, prediction markets inherently face two limitations: restricted sample size and the discrete nature of the markets. These factors both weaken statistical power and reduce the practical utility of prediction markets as an uncertainty indicator. Future research could utilize new data while exploring the possibilities of forming an index capturing the full spectrum of uncertainty present in the prediction markets.

Despite these limitations, the evidence in this paper suggests that while EPU has become less tied to traditional business-cycle dynamics, it has not become less relevant for expected market returns.

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A. ROBUSTNESS OF THE EPU BASELINE SPECIFICATIONS

This appendix collects three diagnostics that defend the headline EPU results in Sections A and B against alternative explanations: the choice of EPU index variant (A), the inclusion of the COVID period in the extended sample (B) and the possibility that the business-cycle decoupling is generic to uncertainty proxies rather than EPU-specific (C).

A. News-based-only monthly regressions

Because the daily-frequency regressions are forced to use the news-based-only EPU index, the monthly–daily divergence in significance could reflect either index construction or measurement frequency. We re-estimate the monthly contemporaneous and predictive specifications using the news-based-only EPU index in place of the composite three-component index. Tables A.1 and A.2 report the results.

B. Pre-COVID subsample, 1985–2019

If the divergence between the original 1985–2012 sample and the extended 1985–2024 sample reflects the macroeconomic shocks of the COVID period rather than a continuous structural trend, dropping post-2019 observations should restore the original-sample patterns. We re-estimate the contemporaneous and predictive specifications on a 1985–2019 subsample. Tables A.3 and A.4 report the results.

C. IV as alternative dependent variable

The decoupling of EPU from business-cycle variables in the column (8) specification could in principle reflect a generic weakening of the relationship between uncertainty proxies and macroeconomic conditions, rather than something specific to EPU. To distinguish these, we re-estimate column (8) with IV as the dependent variable in place of EPU. Business-cycle variables continue to track IV across all three subsamples while losing their grip on EPU, isolating the decoupling to EPU specifically.

Table A.1. Contemporaneous relationship between news-based EPU and macroeconomic state variables

Re-estimation of Table III using the news-based-only EPU index in place of the composite three-component index. Monthly data, 1985–2024. Newey and West (1987) standard errors with 4 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. standardised regressions of EPU on state variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IV	0.36***								0.11
	(4.41)								(1.20)
VAR		0.37***							0.22**
		(4.48)							(2.29)
TERM			-0.11					-0.21**	-0.17*
			(-1.36)					(-2.11)	(-1.86)
DEFAULT				0.25***				0.23***	0.11
				(3.31)				(2.80)	(1.15)
RREL					-0.18			-0.17	-0.15
					(-1.57)			(-1.43)	(-1.34)
CFI						-0.16		-0.05	-0.00
						(-1.37)		(-0.42)	(-0.04)
Log(D/P)							-0.13**		-0.06
							(-2.41)		(-0.97)
N	468	480	480	480	480	480	480	480	468
Adj. R^2	0.12	0.13	0.01	0.06	0.03	0.02	0.02	0.11	0.19

Panel B. Regression of log excess market return on ΔEPU

	Multivariate	Univariate
Δ EPU	-0.09**	-0.22***
	(-2.42)	(-3.27)
Δ VAR	0.04	
	(0.43)	
Δ IV	-0.72***	
	(-11.61)	
Δ TERM	-0.09***	
	(-2.66)	
Δ DEFAULT	-0.17***	
	(-3.72)	
Δ RREL	-0.02	
	(-0.40)	
Δ Log(D/P)	-0.10***	
	(-2.65)	
N	467	479
Adj. R^2	0.55	0.05

Panel C. AR(p) coefficients and DF-GLS statistics

	EPU		IV		VAR	
	(1)	(2)	(3)	(4)	(5)	(6)
AR(1)	0.63***	0.58***	0.80***	0.82***	0.46***	0.39**
	(9.88)	(9.80)	(24.73)	(25.49)	(2.95)	(2.47)
AR(2)	0.16	0.20*				
	(1.62)	(1.89)				
AR(4)	0.18***	0.17***				
	(4.43)	(4.25)				
MKT_{t-1}		-2.07***		7.70		-9.34**
		(-4.77)		(1.53)		(-2.29)
DF-GLS	-3.89***		-4.74***		-6.73***	
N	476	476	467	467	479	479
Adj. R^2	0.62	0.64	0.64	0.64	0.21	0.23

Table A.2. Predictive regressions of cumulative log excess market return on news-based EPU

Re-estimation of Table VII using the news-based-only EPU index as the forecaster. Monthly data, 1985–2024. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. Univariate forecasts

	$(h = 1)$	$(h = 2)$	$(h = 3)$	$(h = 6)$	$(h = 12)$
EPU	0.81*	1.91***	2.65***	4.13**	7.07**
	(1.86)	(2.63)	(2.69)	(2.21)	(2.19)
N	479	478	477	474	468
Adj. R^2	0.01	0.03	0.03	0.04	0.06

Panel B. EPU forecasts with IV and VAR

	$(h = 1)$	$(h = 2)$	$(h = 3)$	$(h = 6)$	$(h = 12)$
EPU	1.07***	2.15***	3.01***	4.21**	7.21*
	(2.76)	(2.94)	(2.90)	(2.03)	(1.90)
VAR	-0.22	-0.29	-0.49	-0.24	0.27
	(-0.91)	(-1.19)	(-1.64)	(-0.50)	(0.41)
IV	0.03	0.06	0.11	0.09	-0.06
	(0.49)	(0.87)	(1.20)	(0.56)	(-0.21)
N	467	466	465	462	456
Adj. R^2	0.01	0.03	0.05	0.04	0.07

Panel C. EPU forecasts with controls

	$(h = 1)$	$(h = 2)$	$(h = 3)$	$(h = 6)$	$(h = 12)$
EPU	1.17***	2.41***	3.40***	4.98**	8.91**
	(2.88)	(3.18)	(3.16)	(2.35)	(2.27)
VAR	-0.21	-0.27	-0.48*	-0.30	-0.01
	(-0.90)	(-1.13)	(-1.73)	(-0.70)	(-0.02)
IV	0.06	0.14*	0.22**	0.27	0.18
	(1.00)	(1.88)	(2.33)	(1.60)	(0.56)
TERM	-0.09	-0.19	-0.25	-0.18	1.46
	(-0.49)	(-0.51)	(-0.47)	(-0.16)	(0.69)
DEFAULT	-0.64	-1.96	-2.14	-1.38	2.57
	(-0.59)	(-0.98)	(-0.76)	(-0.29)	(0.34)
RREL	0.22	0.73	1.41	3.51*	7.73**
	(0.57)	(1.00)	(1.33)	(1.72)	(2.05)
Log(D/P)	1.91**	4.13**	5.84**	9.82**	15.17
	(2.20)	(2.46)	(2.38)	(1.99)	(1.57)
N	467	466	465	462	456
Adj. R^2	0.02	0.06	0.09	0.13	0.23

TABLE A.3. Pre-COVID sample contemporaneous relationship between EPU and macroeconomic state variables

Re-estimation of Table III on the pre-COVID subsample, excluding observations after December 2019. Monthly data, 1985–2019. Newey and West (1987) standard errors with 4 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. standardised regressions of EPU on state variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IV	0.35***								0.14
	(5.01)								(1.55)
VAR		0.32***							0.05
		(4.33)							(0.63)
TERM			0.28***					0.17**	0.16**
			(3.55)					(2.17)	(1.97)
DEFAULT				0.48***				0.36***	0.23**
				(5.89)				(3.98)	(1.96)
RREL					-0.29***			-0.07	-0.08
					(-4.80)			(-1.17)	(-1.21)
CFI						-0.31***		-0.09	-0.10*
						(-7.57)		(-1.58)	(-1.74)
Log(D/P)							0.19***		0.16**
							(2.93)		(2.56)
N	408	420	420	420	420	420	420	420	408
Adj. R^2	0.12	0.10	0.08	0.22	0.08	0.10	0.04	0.26	0.28

Panel B. Regression of log excess market return on ΔEPU

	Multivariate	Univariate
Δ EPU	-0.08**	-0.25***
	(-2.09)	(-3.65)
Δ VAR	0.17**	
	(2.08)	
Δ IV	-0.79***	
	(-13.77)	
Δ TERM	-0.08**	
	(-2.33)	
Δ DEFAULT	-0.18***	
	(-2.97)	
Δ RREL	-0.04	
	(-0.85)	
Δ Log(D/P)	-0.09**	
	(-2.41)	
N	407	419
Adj. R^2	0.54	0.06

Panel C. AR(p) coefficients and DF-GLS statistics

	EPU		IV		VAR	
	(1)	(2)	(3)	(4)	(5)	(6)
AR(1)	0.67***	0.61***	0.83***	0.84***	0.57***	0.52***
	(12.18)	(10.84)	(25.84)	(26.03)	(3.23)	(2.99)
AR(2)	0.04	0.07				
	(0.53)	(0.96)				
AR(4)	0.18***	0.18***				
	(3.74)	(3.62)				
MKT_{t-1}		-1.09***		5.85		-5.43***
		(-4.34)		(1.04)		(-2.61)
DF-GLS	-3.00***		-4.10***		-5.75***	
N	416	416	407	407	419	419
Adj. R^2	0.66	0.67	0.69	0.69	0.32	0.33

Table A.4. Pre-COVID sample predictive regressions of cumulative log excess market return on EPU

Re-estimation of Table VII on the pre-COVID subsample. Monthly data, 1985–2019. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level. The table layout follows Brogaard and Detzel (2015) for comparability with the original study, while all estimates reported here are our own.

Panel A. Univariate forecasts

	(h = 1)	(h = 2)	(h = 3)	(h = 6)	(h = 12)
EPU	1.05	2.83*	3.81*	6.13*	10.24*
	(1.21)	(1.90)	(1.94)	(1.81)	(1.69)
N	420	420	420	420	420
Adj. R^2	0.00	0.02	0.02	0.03	0.04

Panel B. EPU forecasts with IV and VAR

	(h = 1)	(h = 2)	(h = 3)	(h = 6)	(h = 12)
EPU	1.63**	3.36**	4.34**	5.98*	10.55
	(2.24)	(2.47)	(2.34)	(1.75)	(1.57)
VAR	-0.57***	-0.71**	-0.98**	-0.51	0.14
	(-3.49)	(-2.44)	(-2.37)	(-0.68)	(0.14)
IV	0.09**	0.12*	0.19*	0.12	-0.10
	(2.05)	(1.72)	(1.83)	(0.63)	(-0.29)
N	408	408	408	408	408
Adj. R^2	0.04	0.04	0.05	0.03	0.04

Panel C. EPU forecasts with controls

	(h = 1)	(h = 2)	(h = 3)	(h = 6)	(h = 12)
EPU	1.75**	4.02**	5.11**	6.49*	8.87
	(1.99)	(2.51)	(2.40)	(1.77)	(1.37)
VAR	-0.58***	-0.69**	-0.99**	-0.65	-0.33
	(-3.44)	(-2.37)	(-2.52)	(-0.97)	(-0.35)
IV	0.12***	0.21***	0.32***	0.35*	0.25
	(2.62)	(2.69)	(2.94)	(1.72)	(0.65)
TERM	-0.12	-0.21	-0.16	0.22	2.21
	(-0.56)	(-0.52)	(-0.26)	(0.19)	(1.08)
DEFAULT	-0.27	-1.66	-1.72	-0.93	2.79
	(-0.26)	(-0.82)	(-0.59)	(-0.20)	(0.37)
RREL	0.57	1.43*	2.55**	5.42**	10.15**
	(1.38)	(1.82)	(2.26)	(2.45)	(2.39)
Log(D/P)	1.13	2.57	3.65	6.41	9.57
	(1.38)	(1.54)	(1.46)	(1.26)	(0.95)
N	408	408	408	408	408
Adj. R^2	0.04	0.07	0.10	0.12	0.21

Table A.5. Business-cycle regression staging: EPU vs. IV as dependent variable

Adjusted R^2 from regressing each dependent variable on the standardised business-cycle controls TERM, DEFAULT, RREL, and CFI, across three sample periods. EPU is the composite three-component index. Newey and West (1987) standard errors with 4 lags.

	Dependent: EPU		Dependent: IV	
Sample	N	Adj. R^2	N	Adj. R^2
1985–2012	336	0.347	324	0.304
1985–2019	420	0.259	408	0.313
1985–2024	480	0.156	468	0.285

B. PREDICTIVE STRUCTURE OF EPU

This appendix collects three diagnostics that characterize the predictive relationship between EPU and cumulative excess returns: a Chow-style test of coefficient stability across the original and extended samples (A), a comparison of composite versus news-only $\beta(h)/h$ profiles against AR(4)-implied benchmarks (B), and the daily $\beta(h)/h$ profile against an AR(20) persistence benchmark (C).

A. Chow-style test of post-2012 coefficient stability

The extended-sample predictive coefficients on EPU could in principle differ statistically from the 1985–2012 estimates, in which case the apparent robustness of the relationship would be a coincidence of similar point estimates rather than a stable underlying parameter. We test stability by fitting the full extended sample with a post-2012 indicator and the full set of interactions:

$$xr_{t,t+h} = \alpha + \beta_{\text{pre}}\,\text{EPU}_t + \delta\,(\text{EPU}_t \times \mathbb{1}_{t\geq 2013}) + \gamma' X_t + \boldsymbol{\eta}'(X_t \times \mathbb{1}_{t\geq 2013}) + \epsilon_{t+h}.$$

The t-statistic on δ tests $H_0 : \beta_{\text{post}} = \beta_{\text{pre}}$. Tables B.1 and B.2 report results at monthly and daily frequencies; no interaction reaches the 10% critical value at any horizon.

TABLE B.1. Chow-style test of post-2012 shift in EPU predictive coefficient: monthly

β_{pre} is the coefficient on EPU in the pre-2013 subsample; δ is the post-2012 interaction; the implied β_{post} is their sum. The specification includes the monthly Panel C controls (VAR, IV, TERM, DEFAULT, RREL, Log(D/P)) and their post-2012 interactions. EPU is the composite index, scaled by 1/100. Monthly data, 1985–2024. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. No interaction t-statistic exceeds the 10% critical value of 1.645.

Horizon	β_{pre}	$\beta_{\text{post}} - \beta_{\text{pre}}$	t-stat on δ	Implied β_{post}
$h = 1$	1.27	+0.22	(+0.14)	1.49
$h = 2$	3.97	−2.03	(−0.72)	1.94
$h = 3$	5.51	−3.24	(−0.88)	2.27
$h = 6$	6.96	−3.14	(−0.49)	3.82
$h = 12$	6.78	+0.61	(+0.06)	7.39

TABLE B.2. Chow-style test of post-2012 shift in EPU predictive coefficient: daily

Daily counterpart of Table B.1. The specification includes the daily controls (VAR, IV, TERM, DEFAULT, RREL) and their post-2012 interactions. EPU is the news-based index, scaled by 1/100. Daily data, 1985–2024. Hodrick (1992) standard errors with h lags; t-statistics in parentheses. No interaction t-statistic exceeds the 10% critical value of 1.645.

Horizon	β_{pre}	$\beta_{\text{post}} - \beta_{\text{pre}}$	t-stat on δ	Implied β_{post}
$h = 1$	+0.018	+0.029	(+0.66)	0.048
$h = 5$	−0.031	+0.283	(+1.60)	0.252
$h = 10$	−0.002	+0.533	(+1.59)	0.531
$h = 21$	+0.269	+0.540	(+0.90)	0.809
$h = 42$	+1.040	+0.090	(+0.09)	1.130
$h = 63$	+1.782	−0.484	(−0.38)	1.297

B. Composite vs. news-only $\beta(h)/h$ profile

Because the daily extension uses the news-only EPU index while the monthly results use the composite three-component index, the gap between observed and AR(4)-implied $\beta(h)/h$ could reflect either index construction or measurement frequency. Table B.3 reports BIC-selected AR(4) coefficients estimated separately on the composite and news-only series; Table B.4 compares the implied $\beta(h)/h$ profile against the actual coefficients from the Brogaard–Detzel Panel C specification. Both indices are estimated on the same monthly dataset.

Table B.3. AR(4) coefficients for monthly EPU, 1985–2024

BIC-selected AR(4) coefficients estimated by OLS on the composite and news-only monthly EPU series. Lag order matches Brogaard and Detzel (2015).

	φ_1	φ_2	φ_3	φ_4
Composite	0.664	0.167	−0.115	0.172
News-only	0.631	0.160	−0.122	0.179

Table B.4. Predictive $\beta(h)/h$ versus AR(4)-implied benchmark: composite vs. news-only

Actual $\beta(h)/h$ from the Brogaard–Detzel Panel C specification (Table VII); the AR(4) prediction is computed as $\beta(h)/h = \beta(1) \cdot \sum_{s=0}^{h-1} \mathrm{IRF}(s)/h$ using the coefficients from Table B.3, calibrated at $h = 1$. Ratios above one indicate that the observed profile decays slower than AR(4) would predict. Monthly data, 1985–2024.

	Composite			News-only		
h	Actual	AR(4) pred.	Ratio	Actual	AR(4) pred.	Ratio
1	1.513	1.513	1.00	1.166	1.166	1.00
2	1.569	1.258	1.25	1.206	0.951	1.27
3	1.423	1.145	1.24	1.135	0.851	1.33
6	1.030	0.895	1.15	0.830	0.636	1.30
12	0.845	0.698	1.21	0.743	0.468	1.59

C. Daily $\beta(h)/h$ profile and AR(20) benchmark

The daily horizon sweep extends the Brogaard–Detzel predictive specification to $h = 126$ trading days. Under the simple state-variable assumption that EPU raises required returns by a constant amount and then mean-reverts at its measured AR(20) rate, $\beta(h)/h$ should decay with the implied impulse-response. The benchmark is calibrated as $\beta(h)/h = \beta(1) \cdot \sum_{s=0}^{h-1} \mathrm{IRF}(s)/h$ at $h = 1$. Ratios above one indicate that the observed profile decays slower than AR(20) would predict.

Table B.5. Daily $\beta(h)/h$ profile and AR(20)-implied benchmark

Actual $\beta(h)/h$ comes from the daily Panel C specification (Table VIII) at each horizon. The AR(20) prediction is $\beta(1) \cdot \sum_{s=0}^{h-1} \mathrm{IRF}(s)/h$, where IRF is the impulse response of EPU under its measured AR(20) dynamics, calibrated at $h = 1$. Significance levels for the actual coefficients at $h = 10$, 21, and 63 correspond to those reported in Table VIII Panel C. Daily data, 1985–2024.

h (days)	Months	Actual $\beta(h)/h$	AR(20) prediction	Ratio
10	0.5	0.0271	0.0077	3.5
21	1.0	0.0308	0.0056	5.5
42	2.0	0.0321	0.0044	7.4
63	3.0	0.0312	0.0037	8.5
84	4.0	0.0287	0.0032	9.0
105	5.0	0.0266	0.0028	9.5
126	6.0	0.0257	0.0025	10.3

C. POLYMARKET ROBUSTNESS DIAGNOSTICS

This appendix collects three robustness diagnostics for the Polymarket results in Section C: a Monte Carlo power curve supporting the contemporaneous structured null (A), a leverage diagnostic for the predictive Presidential regression at $h = 10$ (B), and a permutation test for the same regression (C).

A. Monte Carlo power curve, House contract

The contemporaneous null across the four Polymarket contracts could reflect low statistical power rather than a genuine absence of relationship, since daily innovations are concentrated in a small number of event-driven days. To rule this out, we run a Monte Carlo simulation on the House innovation series, the most concentrated of the four contracts and therefore the most plausible candidate for an underpowered sample. We plant a synthetic effect of size β ranging from 0.05 to 0.35 (in standardised units) into the dependent variable, re-estimate the contemporaneous specification, and record the rejection rate at the 5% level over 1,000 simulations per β.

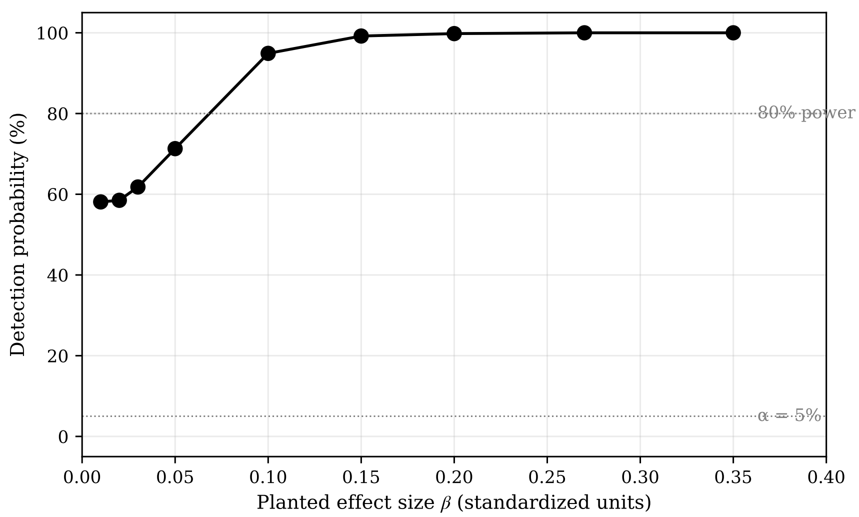

Figure C.1. Monte Carlo power curve for the House Polymarket contract. For each β on a grid of nine planted effect sizes between 0.01 and 0.35 in standardised units, a synthetic effect $\beta \cdot \text{Innov}_t$ is added to the dependent variable, the contemporaneous specification of Eq. (8) is re-estimated, and the null on the Innovation coefficient is tested at the 5% level using Newey–West standard errors with 21 lags. Each point is the rejection rate over 1,000 simulations. The House contract is selected because its innovations are the most concentrated of the four markets and therefore the most plausible candidate for an underpowered test. Detection probability is 71% at $\beta = 0.05$, 95% at $\beta = 0.10$, 99% at $\beta = 0.15$, and reaches 100% at $\beta \geq 0.27$. Sample: February 22–November 18, 2024 ($N = 187$).

B. Predictive leverage diagnostic at $h = 10$

The predictive Presidential result at $h = 10$ *is concentrated in a small number of event-driven days, so the apparent significance could be entirely carried by a handful of high-leverage observations.* We re-estimate the regression after dropping the five observations with the largest $|\text{Innov}|$ values to test whether the relationship survives outside these dates. Table C.1 reports both estimates.

TABLE C.1. Leverage diagnostic: Presidential $h = 10$ predictive regression before and after dropping the five largest |Innov| days

Re-estimation of the Presidential predictive regression at $h = 10$ from Table XI after dropping the five observations with the largest $|\text{Innov}_t|$ values. The five dropped dates are June 28 (Biden–Trump debate), July 15 (Trump assassination attempt), July 18 (aftermath), July 22 (Biden withdrawal), and November 6 (election night). Hodrick (1992) standard errors with 10 lags; t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level.

	Full sample ($N = 211$)		After drop ($N = 206$)	
	Coef.	t-stat	Coef.	t-stat
Univariate	+0.328	(2.77)***	+0.276	(0.82)
With controls	+0.264	(1.87)*	+0.182	(0.53)

C. Permutation test on Presidential $h = 10$

Hodrick (1992) standard errors rely on asymptotic approximations that may be unreliable in a sample of $N = 211$ with most innovation variance concentrated in five days. A permutation test provides a non-asymptotic complement.

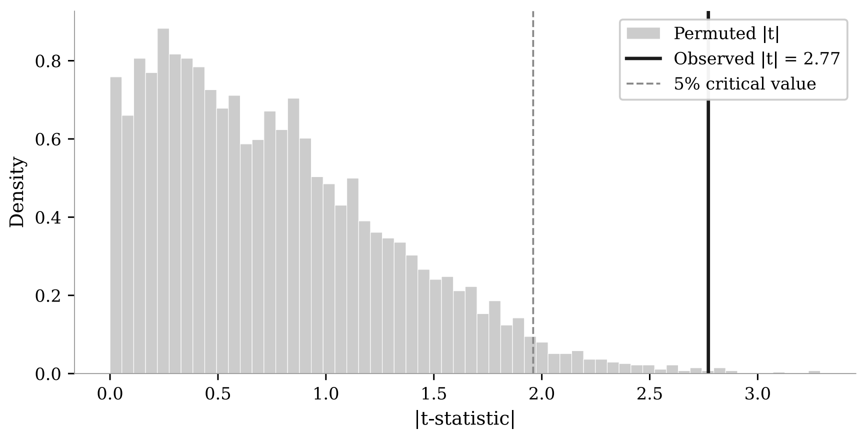

Figure C.2. Permutation distribution of $|t|$ on Innov(Presidential) at $h = 10$. The standardised AR(1) Presidential entropy innovation series is shuffled across dates 5,000 times, breaking temporal alignment with cumulative returns while preserving the marginal distribution of each series; the univariate predictive regression of Eq. (9) is re-estimated at each iteration. The vertical line marks the observed $|t| = 2.77$ from Table XI; only 11 of 5,000 shuffles produce a value at least as extreme, yielding $p = 0.002$. Sample: January 5–November 6, 2024.