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Policy uncertainty and stock market volatility revisited: The predictive role of signal quality

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Abstract

This paper provides novel insight into the growing literature on the policy uncertainty-stock market volatility nexus by examining the out-of-sample predictive ability of the quality of political signals over stock market volatility at various forecast horizons. Specifically, we examine whether or not accounting for the signal quality in forecasting models within a mixed frequency framework can improve forecast performance and help achieve economic gains for investors. Both in- and out-of-sample tests, based on a GARCH-MIDAS framework, show that the quality of the policy signal matters regarding the predictive role of policy uncertainty over subsequent stock market volatility. While high economic policy uncertainty (EPU) predicts high volatility, particularly when the signal quality is high, the positive relationship between EPU and volatility breaks down when the signal quality is low. The improved out-of-sample volatility forecasts obtained from the models that account for the quality of policy signals also help typical mean–variance investors achieve improved economic outcomes captured by higher certainty equivalent returns and Sharpe ratios. Although our results indicate clear distinctions between the US and UK stock markets in terms of how market participants process policy signals, they highlight the role of the quality of policy signals as a driver of volatility forecasts with significant economic implications.

KEYWORDS

economic policy uncertainty, forecasting, market volatility, signal quality

1 | INTRODUCTION

The role of economic policy uncertainty (EPU) as a driver of return and volatility dynamics in financial markets is well-established in the literature. The theoretical frameworks proposed by Gomes et al. (2012) and Pastor and Veronesi (2012, 2013) establish a link between policy uncertainty and stock market returns from various channels, including the effect of uncertainty on investment decisions, personal consumption and saving patterns, and labor supply. Some studies, including Bloom (2009) and Baker et al. (2016), argue that firms tend to reduce investments by delaying investment projects during periods of high uncertainty, which is consistent with the evidence in Pastor and Veronesi (2012, 2013) and Gilchrist et al. (2014) that the effect of uncertainty on stock market returns tends to be more pronounced during weaker economic conditions. At the same time, uncertainty surrounding policy changes creates a risk factor that investors seek compensation for when it comes to the valuation of risky assets, which, in turn, contributes to a risk-based channel that links policy uncertainty to financial market returns. Accordingly, a large number of studies have documented evidence of a significant EPU effect on stock market (e.g., Brogaard & Detzel, 2015; Dakhlaoui & Aloui, 2016; You et al., 2017) and institutional investment returns (Ali et al., 2022), whereas others have established a link to volatility and covariance patterns across the stock, bond, and commodity markets (Badshah et al., 2019; Liu et al., 2017; Liu & Zhang, 2015).

A number of studies in this strand of the literature, including Liu and Zhang (2015), Li et al. (2016), and Goodell et al. (2020), show that aggregate stock market volatility tends to co-move with EPU, whereas Pastor and Veronesi (2013) find that periods characterized by high EPU often experience more volatile stock returns. In a recent study, however, Białkowski et al. (2022) note that the positive link between policy uncertainty and volatility is more complicated than what the literature generally argues and that the quality of the policy signals plays a significant intermediary role in the effect of EPU on stock market volatility. Noting that the stock market experienced an extremely low level of volatility, captured by the CBOE VIX index, during much of 2017 despite the high level of EPU in the same period, the authors show that low-quality policy signals, coupled with high opinion divergence among investors, played a role in weakening the positive relationship between market volatility and policy uncertainty in the United States and the United Kingdom. We contribute to this emerging literature from a novel context by examining (i) the out-of-sample predictive ability of the quality of political signals over stock market volatility at various forecast horizons and (ii) whether or not augmenting the EPU-based predictive models with signal quality can help achieve economics gains by improving the accuracy of volatility forecasts. This is an important consideration given that stock market volatility is a key input for portfolio and hedging decisions, and the accuracy of volatility forecasts is critical for the effectiveness of portfolio and risk management strategies as well as the pricing of derivative securities (Poon & Granger, 2003; Rapach & Strauss, 2008; Rapach et al., 2008). Furthermore, considering that low-frequency events such as policy or earnings announcements often have lingering effects on financial markets as investors gradually process the information and reflect it in their trades, the mixed frequency framework adopted in our analysis provides an interesting perspective on the predictive role of policy uncertainty over future stock market volatility patterns.

The recent evidence from Białkowski et al. (2022) suggests that the relationship between policy uncertainty and market volatility is driven by the quality of political signals and divergence in investors' opinions. This argument supports the well-established evidence in the literature regarding the role of divergent beliefs across market participants on return volatility in financial markets. For example, Ajinkya and Gift (1985) show that the option implied volatility estimates reflect an incremental component of dispersion in EPS forecasts beyond that can be explained by historical volatility values, and Anderson et al. (2005) show that the disagreement among analysts over expected earnings can predict return volatility out-of-sample. Similarly, studies including Diether et al. (2002) and Berkman et al. (2009) establish a negative relationship between the level of dispersion in fund managers' beliefs and subsequent stock returns, whereas more recently, Jiang and Sun (2014) show that the dispersion in investors' beliefs positively predicts subsequent stock returns. These findings are further supported by Balcılar et al. (2018), who use active managers' dispersion in equity market exposures as a proxy for differences in opinion to show that the causal effect of divergent beliefs on subsequent returns is likely to be transmitted via the volatility channel. Accordingly, the literature provides ample evidence that relates divergence in investors' opinions to stock market volatility and subsequent returns. However, the issue has not yet been explored in the context of policy uncertainty. In this paper, we extend this strand of the literature to a new context by examining the predictive ability of EPU over stock market volatility conditional on the quality of the political signals that can be considered as a driver of ambiguity in policy expectations and thus divergence in beliefs across market participants.

Banerjee (2011) argues that divergent beliefs can drive stock market return dynamics from two distinct channels, that is, the rational expectations and differences in opinion channels, and shows that each channel manifests itself across various horizons during which the impact of divergent beliefs is observed. While the rational expectation channel hypothesizes a positive relationship between dispersion in beliefs and stock market returns at longer horizons, Banerjee (2011) shows that this relationship reverses at shorter horizons, consistent with the differences-in-opinion model. Although the literature proposes various alternative proxies to capture divergent beliefs among investors, including the dispersion in analyst earnings forecasts (Diether et al., 2002), the breadth of mutual fund ownership (Chen et al., 2002), the dispersion in retail investor trading (Goetzmann & Massa, 2005), historical income volatility or stock return volatility (Berkman et al., 2009), mutual funds' active holdings (Jiang & Sun, 2014), and, more recently, the dispersion in equity market exposures of active managers (Balcılar et al., 2018), none of these studies have explored the nexus between stock market volatility and divergent beliefs in the context of political uncertainty. Furthermore, considering the evidence in Banerjee (2011) of an asymmetric relationship between divergent beliefs and stock market volatility depending on the forecast horizon, our study provides a broader insight into this literature by examining the role of ambiguity in policy expectations as a predictor of stock market volatility across the long and short forecast horizons.

Because our uncertainty-based predictors are at a monthly frequency, while we aim to predict daily returns, we use the generalized autoregressive conditional heteroskedasticity (GARCH) variant of mixed data sampling (MIDAS), that is, the GARCH-MIDAS model (Engle et al., 2013). The GARCH-MIDAS model avoids the loss of information that would have resulted from averaging the daily volatility to a lower monthly frequency (Das et al., 2019). The main idea behind the GARCH-MIDAS model is that volatility is not just volatility but that there are different components to volatility, one pertaining to short-term fluctuations and the other to a long-run component, with the latter likely to be affected by the monthly EPU and the associated quality of signal indexes in our context. Indeed, our findings show that the quality of the policy signal matters regarding the predictive role of policy uncertainty over subsequent stock market volatility. We find that high EPU predicts high volatility, particularly when the signal quality is high. In contrast, the positive relationship between EPU and volatility breaks down when the signal quality is low.

The out-of-sample analysis further confirms the in-sample findings in that the out-of-sample predictive performance of EPU over stock market volatility is indeed conditional on the level of signal quality as not taking into account signal quality in the predictive model does not yield any difference in the forecast performance as compared with the benchmark model. The improved volatility forecasts obtained from the forecasting models conditioned on signal quality also yield favorable economic gains for investors, captured by the certainty equivalent returns (CERs) and Sharpe ratios. Our results show that augmenting the forecasting model with a combination of EPU and signal quality predictors yields out-of-sample volatility forecasts and higher utility gains generated by the portfolios created from these forecasts. This is an important consideration as high-frequency forecasts are often utilized in trading and valuing derivative contracts. Finally, our analysis indicates clear distinctions between the US and UK stock markets regarding the predictive role played by the quality of political signals and how market participants process those signals.

The remainder of the paper is organized as follows. Section 2 presents the data and the description of the GARCH-MIDAS model that allows us to utilize mixed frequency variables in the same predictive model. Section 3 presents the in- and out-of-sample analysis findings, and Section 4 extends the analysis to economic implications for mean–variance investors. Finally, Section 5 concludes with directions for future research.

2 | DATA AND METHODOLOGY

2.1 | Data

Our dataset includes daily stock market log returns for S&P500 and FTSE100, with the underlying data obtained from the market data section of the Wall Street Journal at https://www.wsj.com/. The news-based EPU index developed by Baker et al. (2016) is used as a proxy for the overall EPU in the economy, and the monthly data are obtained from policyuncertainty.com. The EPU index captures EPU from three broad dimensions, including (i) news coverage of policy-related economic uncertainty, (ii) the number of federal tax code provisions about to expire in future years, and (iii) the dispersion in economic forecasts. Examining a sample of stock markets in 16 countries, Baker et al. (2021) show that journalists attribute one-third of large stock market fluctuations in the United States to news about government policies, thus establishing a link to stock market volatility. Similarly, the data for the quality of political signals (*Quality*) constructed by Białkowski et al. (2022) are sourced from qualityofpoliticalsignals.com. Like the EPU index, this index is also constructed via textual analysis of news articles from 10 leading newspapers in the United States and the United Kingdom. However, the articles are categorized with regard to the terms they contain about quality, signal, and policy. Further scaling and standardizing the raw counts, the authors generate the quality index such that the higher the index value, the lower the quality of political signals. Because our uncertainty-based predictors are monthly, while our stock returns are at daily frequency, our sample period involves both these frequencies of data covering (3rd) January 2000 to (31st) January 2022 for the United States and (2nd) January 2001 to (31st) January 2022 for the United Kingdom.

We offer some preliminary analyses (summary statistics and pre-tests) to understand the behavior of the variables of interest. We present the results of the summary statistics (mean, standard deviation, coefficient of variation, skewness, and kurtosis) in Table 1, whereas those of the pre-tests (serial correlation and conditional heteroscedasticity tests) are presented in Table 2. The summary

TABLE 1 Summary statistics.

	Mean	SD	Skewness	Kurtosis	CV	*N*	Freq	Start date	End date
Stock returns									
USA	0.020	1.24	−0.40	14.02	60.77	5556	Daily	03-Jan-2000	31-Jan-2022
UK	0.003	1.17	−0.35	11.51	335.44	5423	Daily	02-Jan-2001	31-Jan-2022
Exogenous factors (USA)									
EPU	137.16	66.24	1.97	9.09	0.48	265	Monthly	Jan-2000	Jan-2022
EPU-Quality[Low]	9468.60	12,354.4	1.73	7.14	1.30	265	Monthly	Jan-2000	Jan-2022
EPU-Quality[High]	5187.94	5982.47	0.81	2.74	1.15	265	Monthly	Jan-2000	Jan-2022
Exogenous factors (UK)									
EPU	129.09	70.30	1.96	10.80	0.54	253	Monthly	Jan-2001	Jan-2022
EPU-Quality[Low]	9384.88	11,798.93	1.54	6.73	1.26	253	Monthly	Jan-2001	Jan-2022
EPU-Quality[High]	4435.03	5344.67	0.89	2.61	1.21	253	Monthly	Jan-2001	Jan-2022

Note: This table shows the summary statistics of daily stock returns (log return of stock price index) and monthly exogenous factors. The latter involves economic policy uncertainty (EPU) and its interaction with high and low-quality political signals. The high quality of political signals (EPU-Quality[High]) denotes values of the actual index for political signals below its median, whereas those above it are for the low quality (EPU-Quality[Low]). In other words, the higher the value of the index, the lower the quality of political signals. SD is the standard deviation of the variables; CV is the coefficient of variation, obtained as the ratio of the standard deviation to the mean; *N* is the sample size in each case.

TABLE 2 Results for conditional heteroscedasticity and serial correlation tests.

Stock returns	$ARCH(5)$	$ARCH(10)$	$ARCH(20)$	$Q(5)$	$Q(10)$	$Q(20)$	$Q^2(5)$	$Q^2(10)$	$Q^2(20)$
USA	398.67***	222.91***	124.00***	8.48	28.81***	97.37***	2974.2***	5281.9***	7643.0***
UK	260.15***	148.95***	82.30***	65.51***	118.58***	173.35***	1569.70***	2263.50***	2800.30***
Exogenous factors (USA)	$ARCH(1)$	$ARCH(2)$	$ARCH(3)$	$Q(1)$	$Q(2)$	$Q(3)$	$Q^2(1)$	$Q^2(2)$	$Q^2(3)$
EPU	7.96***	19.20***	12.85***	5.02**	8.28**	11.37**	7.90***	38.94***	43.52***
EPU-Quality[Low]	19.30***	30.76***	21.00***	34.23***	48.63***	49.23***	18.36***	62.78***	76.86***
EPU-Quality[High]	88.86***	44.02***	29.17***	18.80***	42.53***	44.191***	67.74***	84.75***	90.59**
Exogenous factors (UK)									
EPU	22.96***	15.99***	11.30***	1.62	4.29	4.29	21.49***	37.47***	46.84***
EPU-Quality[Low]	8.26***	7.99***	5.31***	3.68*	5.97*	6.61*	8.18***	18.27***	19.99***
EPU-Quality[High]	4.03**	5.99***	4.00***	0.14	1.51	2.19	4.06**	13.14***	14.34***

Note: See note to Table 1 on the description of variables. The applied tests consist of the autoregressive conditional heteroscedasticity (ARCH) effect test, which is a formal test for volatility; and the *Q*-statistic and Q^2-statistic testing for the presence of autocorrelation and higher order autocorrelation, respectively; at lags 5, 10, and 20 for stock returns and lags 1, 2, and 3 for the exogenous factors.
***Indicates significance of tests at 1% level.
**Indicates significance of tests at 5% level.
*Indicates significance of tests at 10% level.

statistics are based on daily stock returns (log return of stock price index) and monthly exogenous factors. The latter involves EPU and its interaction with high and low-quality political signals. The high quality of political signals (EPU-Quality[High]) denotes values of the actual index for political signals below its median, whereas those above it are used to capture low quality EPU-Quality[Low]. In other words, the higher the value of the index, the lower the quality of political signals. We find that the mean value of stock returns for the United States is higher than that of the United Kingdom, whereas the latter is riskier than the former, judging by the coefficient of variation. Both stock markets are, however, observed to be negatively skewed and heavy-tailed.

Regarding EPU and its variants, the United States is observed to record higher values than the United Kingdom, implying that EPU is more pronounced in the former and interacting EPU with the quality of political signals does not seem to change the outcome. In other words, the values of the interaction terms are larger for the United States than for the United Kingdom. The pre-tests reported in Table 2 yield evidence of serial correlation and heteroscedasticity for the variables of interest, and therefore accounting for these salient features in the estimation process is crucial for robust outcomes. In this regard, the GARCH-MIDAS framework indeed comes in handy in addition to its ability to accommodate mixed data frequencies.

2.2 | Methodology

As our dataset includes variables in mixed frequencies (i.e., daily stock returns and monthly EPU index and signal quality series), we adopt a framework that is simultaneously suitable for volatility modeling and incorporation of mixed frequencies within the same predictive model. The GARCH-MIDAS model offers a major advantage in this regard, and so our empirical application builds a mixed-frequency model to predict high-frequency (daily) stock market volatility using the predictive information captured by EPU and signal quality index that is available at a lower frequency (monthly). The GARCH-MIDAS model hinges on the merits that it preserves the originality of the data frequency, thus circumventing information loss as all possible available information inherent in the data is more adequately harnessed. This framework also reduces the likelihood of estimation biases occasioned by aggregation and disaggregation often employed by the extant uniform frequency-based methods. GARCH-MIDAS uses every piece of information, regardless of how minute, captured by the EPU and quality of signal indexes to improve the model's predictive performance for daily stock market volatility.

We define daily stock returns $(r_{i,t})$ as the log-returns of the stock price index. As we deal with mixed frequency series, note that $i = 1, \ldots, N_t$ and $t = 1, \ldots, T$, respectively, denote daily and monthly frequencies with N_t representing the number of days in a month t. The GARCH-MIDAS model is then formulated in the following form:

$$r_{i,t} = \tau + \sqrt{\mu_t \times g_{i,t}} \times e_{i,t}, \forall i = 1, \ldots, N_t, \tag{1}$$

$$e_{i,t} | \Sigma_{i-1,t} \sim N(0,1), \tag{2}$$

where τ denotes the unconditional mean of stock returns; the term $\sqrt{\mu_t \times g_{i,t}}$ represents the conditional variance that comprises the two main components—the GARCH(1,1)-based short-run component $(g_{i,t})$ that is characterized by a higher frequency and a long-run component that captures the long-run volatility by the parameter (μ_t); $e_{i,t}$ is the error distribution defined in Equation (2), with $\Sigma_{i-1,t}$ denoting the information that is available at day $i-1$ of month t.[1] The short-run component of the conditional variance is given in Equation (3):

$$g_{i,t} = (1-\alpha-\beta) + \alpha \frac{(r_{i-1,t}-\tau)^2}{\mu_i} + \beta g_{i-1,t}, \tag{3}$$

where α and β are the ARCH and GARCH terms, respectively, with $\alpha > 0$, $\beta \geq 0$, and $\alpha + \beta < 1$. In alignment with Engle et al. (2013), the monthly frequency series (EPU and quality of signal index) are transformed to a daily frequency without loss of originality of the model. We transform the monthly varying long-term component (μ_t) to daily, rolling back the days across the months without keeping track of it. Equations (4) and (5), respectively, define the daily long-term component (μ_i) for the realized volatility (RV) and the exogenous factor:

$$\mu_i = m + \theta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) RV_{i-k}, \tag{4}$$

$$\mu_i = m + \theta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{i-k}, \tag{5}$$

where m is the intercept for the long-run component and θ is the coefficient of the predictor (whether RV or an exogenous factor). Essentially, we consider four variants of the long-run component of the GARCH-MIDAS, where the models are differentiated in terms of the choice of predictors. These variants, respectively, incorporate the following predictors: (i) RV, and this is considered as the benchmark (or the conventional GARCH-MIDAS) model; (ii) RV and EPU; (iii) RV, EPU, and low quality of political signal index; and (iv) RV, EPU, and high quality of the political signal index. For the variants interacted with RV, the principal components analysis (PCA) is employed to combine them into a single factor.[2] Note that the principal component factor, rather than the PCA itself, is incorporated within the rolling window framework.

Note further in Equations (4) and (5) that the beta polynomial weights $\phi_k(w_1, w_2) \geq 0$, $k = 1, \ldots, K$ are constrained to sum to unity to achieve identification of the model's parameters. We filter the secular component of the MIDAS weights using 40 ($K=40$) MIDAS months, which is the optimal lag for our specification based on the log-likelihood statistics.[3] We adopt the one-parameter beta polynomial, hinging on the flexibility of the beta weighting scheme (Colacito et al., 2011). The weighting scheme allows for the transformation of a two-parameter beta weighting function $\left[\phi_k(w_1,w_2)=\frac{[k/(K+1)]^{w_1-1}\times[1-k/(K+1)]^{w_2-1}}{\sum_{j=1}^{K}[j/(K+1)]^{w_1-1}\times[1-j/(K+1)]^{w_2-1}}\right]$ to a one-parameter beta weighting function $\left[\phi_k(w)=\frac{[1-k/(K+1)]^{w-1}}{\sum_{j=1}^{K}[1-j/(K+1)]^{w-1}}\right]$ by constraining w_1 to unity and setting $w=w_2$, to ensure that the weighting function will be monotonically decreasing (Engle et al., 2013), where the weights (ϕ_k) are positive and sum to one $\left(\sum_{k=1}^{K}\phi_k=1\right)$. Also, the comprising parameter (w) is constrained to be greater than unity $(w>1)$ to ensure that larger weights are assigned to more recent than distant lags of the observations.

We ascertain the in-sample predictability of the incorporated predictors by testing the statistical significance of the slope parameter (θ) such that a significant estimate would imply the predictability of the corresponding predictor for stock return volatility. Following the evidence in the literature that aggregate stock market volatility tends to co-move with EPU (e.g., Goodell et al., 2020; Li et al., 2016; Liu & Zhang, 2015), we expect that the EPU and the quality of signal indexes to be positively related to stock market volatility, which suggests that higher political uncertainty is associated with higher volatility, while improved quality of political signals (i.e. low values for the signal quality index) reduces it.

However, the out-of-sample forecast performance of the contending model variants in comparison with the conventional GARCH-MIDAS model used as the benchmark model is of more importance to this study. Therefore, we employ the modified Diebold and Mariano (Harvey et al., 1997) test, an extension of the conventional Diebold and Mariano (1995) test for paired model comparisons. The former test is of the following form:

$$DM^*=\left(\sqrt{\frac{T+1-2h+T^{-1}h(h-1)}{T}}\right)DM, \qquad (6)$$

where T is the length of the out-of-sample periods of the forecast errors; and h denotes the forecast horizon, which is usually set to 1. The conventional DM test is defined as $DM=\overline{d}/\sqrt{V(d)/T}\sim N(0,1)$, where $\overline{d}=1/T\left[\sum_{t=1}^{T}d_t\right]$ is the average loss differential defined by $d_t\equiv g(\varepsilon_{it})-g(\varepsilon_{jt})$ with $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$, respectively, denoting the loss functions of the forecast errors, $\varepsilon_{it}\varepsilon_{jt}$ corresponding to returns forecasts, $\widehat{r}_{it}$ and $\widehat{r}_{jt}$ of contending models; and $V(d_t)$ denotes the unconditional variance of d_t. The null hypothesis $(H_0:E(d_t)=0)$ of equality of contending models' precisions is tested against a mutually exclusive alternative $(H_1:E(d_t)<0)$ that a model variant (with one or more of the exogenous factors) yields more precise forecasts than the specified benchmark model. To that end, we adopt the iterative 1-day ahead forecast and therefrom estimate the forecast performance using the period between t and $t+h$, where $h=30,60\&120$. In other words, the forecast performance is evaluated at 30-, 60-, and 120-day out-of-sample forecast periods, using a 50:50 data split under a one-day ahead rolling window framework.

3 | EMPIRICAL RESULTS

3.1 | In-sample analysis

Table 3 presents the in-sample predictability results for US stock market volatility based on the alternative models described earlier. The conventional GARCH-MIDAS model that includes *RV* is considered the benchmark, and each pane corresponds to the model variation augmented with the predictor variable(s) listed in the first column. As our focus is the role of EPU on volatility conditional on the high and low signal quality, we present in the table the model variations for [*RV* + *EPU*] and its two variations for *Quality[High]* and *Quality [Low]*, corresponding to market states when the signal quality is high and low, respectively.[4] The positive slope coefficient captured by θ in the benchmark GARCH-MIDAS model that includes *RV* is consistent with the evidence in the literature on volatility clustering effects that associate past occurrences of volatility with subsequent market fluctuations. The positive and highly significant θ estimate in the (*RV* + *EPU*) variation is also in line with our prior expectation that links high policy uncertainty to stock market volatility, consistent with the evidence that aggregate stock market volatility tends to co-move with EPU (e.g., Goodell et al., 2020; Li et al., 2016; Liu & Zhang, 2015). These patterns are consistent both for the US and UK markets (reported on the right-hand panel of Table 3), confirming our prior expectations on the EPU–volatility nexus.

When we examine the model variations that incorporate signal quality, however, we consistently observe a positive and highly significant slope coefficient in both the full and 50% samples for the *RV* + *EPU-Quality[High]* model. This confirms the inferences in Białkowski et al.

TABLE 3 In-sample predictability results.

Response variable	RV	RV + EPU	RV + EPU-Quality[High]	RV + EPU-Quality[Low]	RV	RV + EPU	RV + EPU-Quality[High]	RV + EPU-Quality[Low]
	USA				UK			
Full data sample								
μ	0.0680***	0.0658***	0.0671***	0.0669***	0.0402***	0.0384***	0.0392***	0.0392***
	[0.0113]	[0.0114]	[0.0111]	[0.0112]	[0.0119]	[0.0119]	[0.0117]	[0.0118]
α	0.1380***	0.1253***	0.1304***	0.1319***	0.1269***	0.1015***	0.1045***	0.1073***
	[0.0094]	[0.0086]	[0.0084]	[0.0083]	[0.0095]	[0.0067]	[0.0067]	[0.0071]
β	0.8074***	0.8457***	0.8401***	0.8422***	0.7945***	0.8800***	0.8773***	0.8723***
	[0.0132]	[0.0095]	[0.0094]	[0.0091]	[0.0172]	[0.0077]	[0.0076]	[0.0080]
θ	0.0186***	0.0380***	0.0389***	0.0552	0.0297***	0.0237***	−0.0069	0.1080**
	[0.0024]	[0.0054]	[0.0086]	[0.0532]	[0.0029]	[0.0078]	[0.0157]	[0.0449]
w	11.3640***	49.9910**	31.5190	1.0031	14.1510***	49.9970	13.7180	11.6420
	[2.6541]	[21.7120]	[21.1540]	[1.8408]	[2.8279]	[34.9900]	[70.3410]	[14.1860]
m	0.5038***	0.0333	0.0385	0.0943	0.3133***	0.1117	0.1285	0.1120
	[0.0555]	[0.1123]	[0.1069]	[0.1237]	[0.0466]	[0.1277]	[0.1309]	[0.1235]
50% data sample								
μ	0.0523***	0.0504***	0.0504***	0.0532***	0.0604***	0.0572***	0.0590***	0.0600***
	[0.0194]	[0.0191]	[0.0191]	[0.0192]	[0.0194]	[0.0193]	[0.0192]	[0.0196]
α	0.0772***	0.0633***	0.0669***	0.0766***	0.1250***	0.0921***	0.1058***	0.1114***
	[0.0119]	[0.0089]	[0.0091]	[0.0092]	[0.0177]	[0.0137]	[0.0119]	[0.0134]
β	0.8827***	0.9195***	0.9201***	0.9139***	0.8224***	0.8854***	0.8792***	0.8669***
	[0.0316]	[0.0116]	[0.0107]	[0.0106]	[0.0292]	[0.0169]	[0.0131]	[0.0173]
θ	0.0230***	0.1145***	0.0875***	−1.0020***	0.0368***	0.1337***	0.2466***	0.6661***
	[0.0075]	[0.0239]	[0.0258]	[0.3375]	[0.0059]	[0.0186]	[0.0933]	[0.1426]
w	20.2690	49.9960*	49.9960*	1.0010**	13.4430**	49.9990**	3.4469**	9.1116
	[13.2830]	[26.2600]	[27.0050]	[0.4157]	[5.2836]	[24.1410]	[1.6117]	[6.3561]
m	0.4075***	0.3921**	−0.0547	−0.2187	0.2613***	0.5661***	−0.0376	0.6435***
	[0.1429]	[0.1612]	[0.1933]	[0.2751]	[0.0955]	[0.1710]	[0.2883]	[0.2094]

Note: Each cell contains the estimated GARCH-MIDAS parameter, the corresponding standard error, and an indication of statistical significance. The conventional GARCH-MIDAS model that includes realized volatility (RV) is considered the benchmark, and each pane corresponds to the model variation augmented with the predictor variable listed in the first column.
***Represents significance at 1%.
**Represents significance at 5%.
*Represents significance at 10%.

(2022) that the positive association between policy uncertainty and market volatility is robust when the signal quality is high, that is, when political signals are more informative. In contrast, we find that the positive association between EPU and stock market volatility breaks down when the signal quality is low, implied by the insignificant θ estimate for the *RV + EPU-Quality[Low]* model, whereas the coefficient turns even negative in the 50% data sample. Pastor and Veronesi (2013) argue that investors will be less likely to update their beliefs when exposed to noisy political signals with many reversals and contradictions, implied by low signal quality, even in a state of high EPU, thus leading to lower risk premia and market volatility. Accordingly, our findings support the argument that the quality of political signals indeed matters when it comes to the predictive relationship between policy uncertainty and subsequent stock market volatility. While high EPU predicts high volatility in all specifications, particularly when the signal quality is high, our findings indicate that this positive relationship between EPU and volatility breaks down in the *RV + EPU-Quality[Low]* model when the quality signal is low.

Interestingly however, although the results for the United States are fully in line with the evidence in Białkowski et al. (2022), we find that the distinction between high and low signal quality is not as robust for the United Kingdom reported on the right-hand panel of Table 3. In contrast to the evidence for the United States, we find that low-quality policy signals, in fact, contribute to higher stock market volatility in the United Kingdom, indicated by the positive and significant slope coefficients in the *RV + EPU-Quality [Low]* model. In the 50% sample, however, we observe that the positive EPU–volatility relationship is maintained irrespective of the signal quality, although the positive effect of policy uncertainty on volatility is relatively strong when the signal quality is low. This suggests that high policy uncertainty drives stock market volatility in the United Kingdom, particularly when policy signals are noisy and less informative. While an in-depth examination of the structural differences that might be causing the different results is beyond the scope of this particular study, one can argue that the differences in the political settings in the two countries can provide some useful hints. The parliamentary system in Britain allows the prime minister and his cabinet to pursue his economic agenda with relative ease without too much compromise with the opposition (Dadush & Stancil, 2011). Once a coalition is established, the government can act more decisively towards the desired economic policies. In such an environment, it is not surprising to find that stock market volatility responds only when the quality of political signals is low; that is, the policymakers provide noisy signals, as investors experience greater disagreement when the signal quality is low, thus leading to higher volatility (e.g., Anderson et al., 2005).

In contrast, the political setting in the United States is based on the system of checks and balances in which the Senate depends on supermajorities to pursue the economic agenda promised by the president, which becomes even more complicated with biannual congressional elections that can change the balance of power and create greater uncertainty regarding the realization of promised economic policies. This, in turn, creates an environment wherein investors update their beliefs regarding economic outcomes only when policymakers' policy signals are strong, hence the high signal quality effect that we observe in our results. In the case of the United Kingdom, however, the parliamentary system eases some of the uncertainties driven by the process in which economic policies are passed through the legislative system, thus easing the role of the signal quality on volatility dynamics, as we observe in the results for the 50% sample. In other words, whereas investors in the United States need high-quality policy signals to update their beliefs regarding economic policy actions, investors in the United Kingdom do not face the same level of uncertainty as their counterparts in the United States, thus rendering the signal quality effect relatively less important as we observe in the 50% sample results. In contrast, noisy policy signals, implied by low signal quality, have a greater effect on stock market volatility in the United Kingdom as investors experience greater divergence in their expectations in such an environment, thus contributing to volatility (e.g., Balcılar et al., 2018).

3.2 | Out-of-sample analysis

Having observed encouraging results from the in-sample tests that support the role of signal quality in the propagation of policy uncertainty to the stock market, we next extend our analysis to the out-of-sample predictive ability of the quality of political signals over stock market volatility at various forecast horizons. Table 4 presents the out-of-sample forecast evaluation statistics, which compare the row labeled GARCH-MIDAS variants with the benchmark model indicated in the heading of each panel. For this purpose, we employ the modified Diebold and Mariano (Harvey et al., 1997) (modified DM) test where a rejection of the null hypothesis would imply that the forecasts of the paired contending model variants (i.e., the benchmark model and any of the other variants that incorporate one or more of the exogenous factors) are significantly different. A negative and statistically significant modified DM statistic in the table indicates that the row labeled augmented model is preferred over the benchmark model under all standard significance levels.

Examining Panel A in Table 4, where the benchmark model is the conventional GARCH-MIDAS model that includes *RV*, we find that all model variants, with the exception of the variant involving RV and EPU, significantly outperform the benchmark model that uses RV as the only exogenous factor to predict the US stock return volatility. This is an interesting result suggesting that the out-of-sample predictive performance of EPU over stock market volatility is indeed conditional on the level of signal quality, as not taking into account signal quality in the predictive model does not yield any significant improvements compared with the benchmark model. This result is consistently observed across all three specified forecast horizons (30-, 60-, and 120-day). In other words, the model variants that incorporate the quality of the political signal index, combined with RV and EPU, offer statistically significant improvements in the out-of-sample US stock return volatility forecasts over the benchmark model. However, the model variant that excludes the quality of the political signal index (the variant with strictly RV and EPU) does not offer additional information that could substantially improve the out-of-sample forecast performance of the benchmark model (with RV only). This finding indeed provides new insight into the EPU–volatility nexus, suggesting that incorporating EPU in stock market volatility models without considering the signal quality will not help improve the out-of-sample forecasting performance of these models.

Motivated by the findings discussed above, we next analyze another scenario in Panel B where the model variant with RV and EPU only is considered the benchmark model. In essence, under this scenario, we evaluate the model variants' forecast performance that includes signal quality against the one with RV and EPU rather than with RV only. This comparison allows us to ascertain the predictive information captured by the signal quality over and above that is contained in EPU alone. We observe in Panel B that all the quality (of political signal)-based model variants consistently outperform the new benchmark model across the specified forecast horizons (except for 120-day when signal quality is low). These results further highlight the relevance of the quality of political signals for the out-of-sample predictability of stock market volatility across both the short and long forecast horizons, although with a reduction in the outperformance stance as the forecast horizon lengthens. Therefore, our results show that augmenting the RV- and EPU-based GARCH-MIDAS models with the quality of the political signal index yields better out-of-sample forecasts, which is an important consideration for forward-looking investment strategies. Interestingly, however, while the findings for the United Kingdom, reported on the right-hand panel of Table 4, support the predictive role of low signal quality over and above the EPU index alone (except at the 120-day forecast horizon), we see that the improvement, though not significant, in the forecasting performance for the United Kingdom only applies to models when the signal quality is low. Thus, the results further confirm the heterogeneity across the two stock markets, reported in the in-sample analysis on the right-hand panel of Table 3, with respect to how market participants process policy signals.

Finally, we further conduct additional comparisons in Panels C and D to formally test whether the asymmetry effect concerning signal quality indeed exists between high and low-quality political signals. The results for the US stock market do not yield any evidence of asymmetry between low and high-quality political signals when combined with RV, indicated by the insignificant DM statistics in both panels. This result is suggestive of the similarity in the precision of the GARCH-MIDAS models that incorporate either the low or high quality of the signal index. In modeling US stock market volatility using the quality of the political signal as a predictor, the aggregate quality of political signal may not necessarily be decomposed as both low and high-quality signal indexes can be modeled in the same way. This feat is consistent across the forecast horizons and indicates the robustness of the result to the forecast horizons.

Similarly, when the high and low-quality signals are combined with RV and EPU, we find no evidence of a significant asymmetry effect across the specified forecast horizons. This stance indicates the insignificance of accounting for asymmetry in the quality of political signals. In other words, the outcome favoring no asymmetry appears to be consistent. In contrast, the results for the United Kingdom, reported in Panels C and D on the right-hand side of Table 4, show that signal quality indeed matters for the United Kingdom such that low (high) quality of political signals yield improved forecast performance compared to high (low) quality signals across all forecast horizons, when quality of political signal is combined with RV (RV and EPU). These findings highlight clear distinctions between the two markets regarding the predictive role of the quality of political signals and the information they capture regarding future volatility patterns.

4 | ECONOMIC SIGNIFICANCE

In the last step of our analysis, we examine the economic significance of our forecast outcomes using several utility metrics popularly employed in the literature. Essentially, the interest is ascertaining the economic gains of incorporating exogenous predictor variable(s) for predicting stock market volatility. This provides economic-based confirmation that lends support to the statistical conclusions earlier reached by the modified DM statistics. The economic gains of different GARCH-MIDAS-X model variants that incorporate EPU and the quality of signal index quality singly and jointly are compared with the conventional GARCH-MIDAS based on RV.

We consider a characteristic mean–variance utility investor who optimizes the available portfolio in contrast to a risk-free asset by apportioning shares among investment options, with optimal weight, w_t, defined as

$$w_t = \frac{1}{\gamma} \frac{\theta \widehat{r}_{t+1} + (\theta - 1)\widehat{r}^f_{t+1}}{\theta^2 \widehat{\sigma}^2_{t+1}}, \tag{7}$$

where γ is the risk aversion coefficient; θ is a leverage ratio that is set to 6 and 8, premised on a 10% margin maintained by investors; $\widehat{r}_{t+1}$ is the stock market RV forecast at time $t+1$; $\widehat{r}^f_{t+1}$ is a risk-free asset (3-month Treasury bill rate); and $\widehat{\sigma}^2_{t+1}$ is an estimate of return volatility, obtained as a 30-day moving window of daily returns. The CER for the investor's optimal portfolio allocation is defined in Equation (8):

TABLE 4 Diebold and Mariano out-of-sample forecast evaluation.

Model	Volatility					
	USA			UK		
	$h=30$	$h=60$	$h=120$	$h=30$	$h=60$	$h=120$
Panel A: Benchmark model: *GARCH-MIDAS[RV]*						
RV + EPU	−0.5838	−0.5792	−0.5069	−0.3973	−0.3476	−0.3074
RV + EPU-Quality[High]	−2.3043**	−2.1617**	−2.0533**	2.2581**	1.7704*	1.2199
RV + EPU-Quality[Low]	−2.0794**	−2.2491**	−2.0348**	−2.5676**	−2.4125**	−1.4371
Panel B: Benchmark model: *GARCH-MIDAS[RV + EPU]*						
RV + EPU-Quality[High]	−1.8300*	−1.6921*	−1.1443*	1.9429*	1.7627*	1.3873
RV + EPU-Quality[Low]	−2.7650***	−2.1497**	−1.5243	−1.2184	−1.1531	−0.8095
Panel C: Benchmark model: *GARCH-MIDAS[RV + Quality[Low]*						
RV + Quality[High]	1.0808	0.9300	0.8247	3.9226***	2.8178**	1.9550*
Panel D: Benchmark model: *GARCH-MIDAS – [RV + EPU-Quality[Low]*						
RV + EPU-Quality[High]	−0.1201	−0.1011	−0.0481	−4.1473***	−3.2492***	−2.0785**

Note: The table presents the modified Diebold and Mariano test statistics, which compares the row labeled GARCH-MIDAS variant with the benchmark model indicated in the heading of each panel by testing the equality of their predictions. The statistical significance at 1%, 5%, and 10% are denoted by ***, ** and *, respectively, with a negative and statistically significant modified DM statistic indicating that the row labeled model is preferred over the benchmark model, under all the standard significance levels.
***Represents significance at 1%.
**Represents significance at 5%.
*Represents significance at 10%.

TABLE 5 Economic significance.

Model	Returns	Volatility	CER	SR	Returns	Volatility	CER	SR
	USA				UK			
Panel A: $\gamma=3\,and\,\theta=6$								
RV	0.5246	23.1850	0.4154	0.0983	0.3593	17.9426	0.1193	0.0783
RV + EPU	0.5946	25.2613	0.4850	0.1081	0.3653	18.1274	0.1253	0.0793
RV + EPU-Quality[High]	0.5982	25.3398	0.4888	0.1087	0.3684	18.1942	0.1284	0.0799
RV + EPU-Quality[Low]	0.5328	23.3970	0.4235	0.0996	0.3427	17.4661	0.1032	0.0754
Panel B: $\gamma=3\,and\,\theta=8$								
RV	0.5228	23.1292	0.4136	0.0981	0.3586	17.9159	0.1186	0.0782
RV + EPU	0.5928	25.2022	0.4832	0.1079	0.3646	18.1014	0.1246	0.0792
RV + EPU-Quality[High]	0.5964	25.2800	0.4870	0.1084	0.3677	18.1680	0.1277	0.0798
RV + EPU-Quality[Low]	0.5310	23.3407	0.4217	0.0993	0.3419	17.4398	0.1025	0.0753

Note: For each model variation, there are four measures—return, volatility, certainty equivalent return (CER), and Sharpe ratio (SR). The leverage ratio is denoted by θ with a value of one indicating no leverage. We set the leverage ratio to 6 and 8 and set the risk aversion level to 3.

$$CER=\overline{R}_p-0.5(1/\gamma)\sigma_p^2, \tag{8}$$

where $\overline{R}_p$ and σ_p^2 are, respectively, the out-of-sample mean and variance of the portfolio return, defined as $R_p=w\theta\left(r-r^f\right)+(1-w)r^f$. The economic significance is determined by maximizing an objective function of a utility as in Equation (9):

$$\begin{aligned}U\left(R_p\right)&=E\left(R_p\right)-0.5(1/\gamma)Var\left(R_p\right)\\&=w\theta\left(r-r^f\right)+(1-w)r^f-0.5(1/\gamma)w^2\theta^2\sigma^2,\end{aligned} \tag{9}$$

where the variance of the portfolio return is defined as $Var\left(R_p\right)=w^2\theta^2\sigma^2$ and σ^2 denotes excess return volatility. The model with the most favorable economic gains is the model that yields the highest returns, CER, and Sharpe ratio that is defined as $SR=\left(R_p-r^f\right)/\sqrt{Var\left(R_p\right)}$ and minimum volatility (see Liu et al., 2019). The economic significance computed above does not take cognizance of the cost of implementing the portfolio investment strategy. We subsequently incorporate the transaction cost in the computation of the economic significance for the contending models. Drawing from Callot et al. (2017), we estimate the average portfolio turnover for the out-of-sample period using the Equation (10):

$$TO_t = \left|\widehat{w}_t - \widehat{w}_{t-1}^{hold}\right|, \tag{10}$$

where $\widehat{w}_{t-1}^{hold} = \widehat{w}_{t-1}\left[(1+r_{t-1})/(1+R_{p,t-1})\right]$ is the weight of the hold portfolio and the turnover measures the average change in the portfolio weights. Equation (10) is suited for a case where we consider a risky asset against a risk-free asset, such that only the transaction cost (c) for the risky asset is required. The adjusted portfolio returns for the risky asset is defined as $R_p^{adjust} = R_p - cTO$, and the corresponding volatility, CER, and Sharpe ratio are computed for the adjusted portfolio returns.

Table 5 presents the mean portfolio returns, volatility, CERs, and Sharpe ratios obtained from the volatility

TABLE 6 Economic significance with transaction cost.

	TO	Adj. returns	Volatility	CER	SR	TO	Adj. returns	Volatility	CER	SR
	USA					UK				
Transaction cost: 1%										
Panel A: $\gamma = 3\, and\, \theta = 6$										
RV	0.1030	0.5246	23.1850	0.4154	0.0983	0.0711	0.3593	17.9426	0.1193	0.0783
RV + EPU	0.1030	0.5267	23.3526	0.4173	0.0984	0.0651	0.2959	16.0935	0.0555	0.0669
RV + EPU-Quality[High]	0.1021	0.5106	22.8896	0.4015	0.0960	0.0714	0.3714	18.2816	0.1315	0.0804
RV + EPU-Quality[Low]	0.1029	0.5242	23.1500	0.4149	0.0983	0.0699	0.3120	16.5643	0.0721	0.0699
Panel B: $\gamma = 3\, and\, \theta = 8$										
RV	0.0772	0.5228	23.1292	0.4136	0.0981	0.0533	0.3586	17.9159	0.1186	0.0782
RV + EPU	0.0772	0.5249	23.2977	0.4156	0.0982	0.0488	0.2952	16.0706	0.0549	0.0667
RV + EPU-Quality[High]	0.0765	0.5089	22.8355	0.3998	0.0958	0.0535	0.3707	18.2552	0.1307	0.0803
RV + EPU-Quality[Low]	0.0771	0.5224	23.0943	0.4131	0.0981	0.0501	0.3113	16.5399	0.0714	0.0698
Transaction cost: 0.5%										
Panel C: $\gamma = 3\, and\, \theta = 6$										
RV	0.1030	0.5251	23.1850	0.4159	0.0984	0.0711	0.3597	17.9426	0.1197	0.0784
RV + EPU	0.1030	0.5952	25.2613	0.4856	0.1083	0.0651	0.3657	18.1274	0.1257	0.0794
RV + EPU-Quality[High]	0.1021	0.5988	25.3398	0.4894	0.1088	0.0714	0.3688	18.1942	0.1288	0.0800
RV + EPU-Quality[Low]	0.1029	0.5333	23.3970	0.4240	0.0997	0.0699	0.3430	17.4661	0.1036	0.0755
Panel D: $\gamma = 3\, and\, \theta = 8$										
RV	0.0772	0.5232	23.1292	0.4140	0.0982	0.0533	0.3588	17.9159	0.1188	0.0782
RV + EPU	0.0772	0.5932	25.2022	0.4836	0.1080	0.0488	0.3649	18.1014	0.1249	0.0793
RV + EPU-Quality[High]	0.0765	0.5968	25.2800	0.4874	0.1085	0.0535	0.3680	18.1680	0.1280	0.0798
RV + EPU-Quality[Low]	0.0771	0.5314	23.3407	0.4221	0.0994	0.0501	0.3422	17.4398	0.1027	0.0753

Note: For each model variation, there are four measures—return, volatility, certainty equivalent return (CER), and Sharpe ratio (SR). TO is the average turnover for the out-of-sample period along the lines of Callot et al. (2017). The leverage ratio is denoted by θ with a value of one indicating no leverage. We set the leverage ratio to 6 and 8 and the risk aversion level to 3. This table also considers both 1% and 0.5% transaction costs.

forecasts generated from various GARCH-MIDAS model variations. We observe that all model variations yield positive mean portfolio returns, with a characteristic feat of higher returns associated with higher risk. Compared with the benchmark GARCH-MIDAS model that includes only *RV*, all other model variations incorporating one or more exogenous variables yield higher returns and higher CER and Sharpe ratio values. This suggests that incorporating EPU and signal quality in the predictive models (in combination with the realized stock market volatility) yields better economic gains than the benchmark GARCH-MIDAS-RV model when the leverage ratio is set to 6. The feats of economic gains are similar when the leverage parameter is set to 8; although the returns and economic gains are relatively low for corresponding models when the leverage ratio is 6. Overall, the economic analysis of portfolios constructed based on the volatility forecasts generated from contending GARCH-MIDAS models shows that augmenting the forecasting model with a combination of EPU and signal quality predictors yields not only out-of-sample volatility forecasts but also the utility gains generated by the portfolios created from these forecasts, lending credence to the stance of outperformance revealed in the modified DM statistics. These results also apply to the case of the UK stock market, reported on the right-hand panel of Table 5, with improved CER and Sharpe Ratio estimates obtained from model variations that incorporate EPU singly and combined with high-quality political signals.

In tandem with Fleming et al. (2003), Brown and Smith (2011), Bollerslev et al. (2018), and, more recently, Luo et al. (2022), we set the transaction cost to 1% and 0.5% as a way to ascertain its impact on returns of the risky asset in comparison with the risk-free asset. The results are presented in Table 6, showing the adjusted returns, volatility, CER, and Sharpe ratio. We also report the average portfolio turnover for the out-of-sample period (TO) in the table. The stances remain unchanged when the cost (0.5% transactional cost and 1% transactional cost when the model combines RV and EPU) of implementing a portfolio investment strategy has been factored into the computation of the economic significance of the incorporated predictor variable. We observe that the risk-adjusted returns and CER values become slightly larger even after we consider the transaction cost of 0.5%. Considering that the average portfolio turnover is generally smaller for the forecasting models that incorporate policy uncertainty with high signal quality, the low turnover supported by high-quality informational signals may help mitigate the effect of transaction costs compared to the other forecasting models.

5 | CONCLUSION

The role of EPU as a driver of stock market return and volatility has been examined in quite a number of studies in the literature. Recent evidence, however, suggests that the positive link between policy uncertainty and volatility is more complicated than what the literature generally argues and that the quality of the policy signals plays a significant intermediary role in the effect of EPU on stock market volatility. This paper provides novel insight into the growing literature on the EPU–volatility nexus by examining the out-of-sample predictive ability of the quality of political signals over stock market volatility at various forecast horizons and whether or not accounting for the signal quality in forecasting models can help achieve economic gains for investors. While our in-sample tests confirm the positive association between policy uncertainty and stock market volatility, we also find that the quality of the policy signal indeed matters when it comes to the predictive role of policy uncertainty over subsequent stock market volatility. Our results show that high EPU predicts high volatility, particularly when the signal quality is high, and the positive relationship between EPU and volatility breaks down when the signal quality is low.

Out-of-sample forecasting analysis further confirms the importance of signal quality in the accuracy of stock market volatility forecasts. We find that the out-of-sample predictive performance of EPU over stock market volatility is indeed conditional on the level of signal quality, as failing to consider signal quality in the predictive model does not lead to any improvement in the forecast performance compared with the benchmark model. The improved volatility forecasts obtained from the forecasting models conditioned on signal quality also yield favorable economic gains for investors, captured by the CERs and Sharpe ratios. Our results show that augmenting the forecasting model with a combination of EPU and signal quality predictors yields out-of-sample volatility forecasts and higher utility gains generated by the portfolios created from these forecasts. These findings imply that the quality of policy signals captures valuable information regarding future market fluctuations, and so it is expedient for investors to take cognizance of prevailing signal quality to underscore market uncertainty while making portfolio decisions as a way to better guard themselves against market losses. The findings also underscore the role of ambiguity and divergent beliefs in how information propagates to the market and how it drives future realizations of market volatility. Considering that high-frequency estimates are heavily utilized in the trading and valuing of risky assets, including most derivative contracts, our findings provide a guideline for incorporating divergent beliefs captured by the quality of informational signals in forecasting analysis. Finally, while our findings highlight the role of the quality of policy signals as a driver of volatility forecasts, they also indicate clear distinctions between the US and UK stock markets regarding the predictive role played by the quality of political signals and how market participants process those signals. It will be interesting for future work to examine how the quality of policy signals relates to fund flows across different asset classes and whether or not those signals capture predictable patterns in the cross-section of returns. Another interesting extension of our work would be to examine the predictive role of cross-market information in these markets and explore the marginal benefits of incorporating cross-market information in the performance of volatility forecasts.

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CONFLICT OF INTEREST STATEMENT

The authors do not have any conflict of interest in the subject matter or materials discussed in this manuscript.

DATA AVAILABILITY STATEMENT

The data supporting this study's findings are available on request from the corresponding author. Some data are not publicly available due to privacy or ethical restrictions.

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ENDNOTES

[1] See Engle et al. (2013) for further technical details on constructing the GARCH-MIDAS model.

[2] The PCA factors are recursively generated for the out-of-sample period to ensure that every forecast is based on the newly estimated parameters and the recursively estimated principal component factors.

[3] There is no hard and fast rule to the best approach to determine the optimal number of lags in a GARCH-MIDAS model estimation (Ghysels et al., 2007). However, as the model framework depends on how much historic information would be required to explain the inherent secular component, extant studies tend to use conventional information criteria and log-likelihood statistics (see Borup & Jakobsen, 2019, among others).

[4] The contributions of the incorporated variables (*EPU*, *EPU-Quality[low]*, and *EPU-Quality[High]*) are, respectively, 26.62%, 28.88%, and 48.57% in the case of the United States; and 26.46%, 37.68%, and 41.63%, respectively, in the case of the United Kingdom. The remaining proportion of the total variation in each case is the contribution of the RV in explaining the total variation in the principal component factors generated for the United States and the United Kingdom.

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