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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 mixed-frequency insight to the growing literature on the (monthly) economic policy uncertainty-(daily) 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, and whether or not accounting for the signal quality in forecasting models can 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 indeed matters when it comes to the predictive role played by policy uncertainty over subsequent stock market volatility. While high EPU is found to predict 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 helps 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 U.S. and U.K. stock markets in terms of how policy signals are processed by market participants, they highlight the role of the quality of policy signals as a driver of volatility forecasts with significant economic implications.

Keywords: Economic policy uncertainty; Signal quality; Market Volatility; Forecasting.
JEL Codes: C32, C53, D8, E32, G15

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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 as well as labor supply. A number of 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 Pástor and Veronesi (2013, 2016) 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 economic policy uncertainty (EPU) effect on stock market (e.g., Brogaard and Detzel, 2015; Dakhlaoui and Aloui, 2016; You et al., 2017) and institutional investment returns (Ali et al., forthcoming), while others have established a link to volatility and covariance patterns across the stock, bond and commodity markets (Liu and Zhang, 2015; Liu et al., 2017; Badshah et al., 2019).

A number of studies in this strand of the literature including Liu and Zhang (2015), Lie et al., (2016) and Goodell et al. (2020) show that aggregate stock market volatility tends to co-move with EPU, while 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 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, that 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 U.S. and U.K. 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 clearly 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 and Granger, 2003; Rapach and Strauss, 2008; Rapach et al., 2008).

The recent evidence in Bialkowski et al. (2022) suggests that the relationship between policy uncertainty and market volatility is driven by a combination of the quality of political signals as well as 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, while 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, while more recently, Jiang and Sun (2014) show that the dispersion in investors' beliefs positively predicts subsequent stock returns. These findings are further supported by Balcilar et al. (2018) who use the dispersion in equity market exposures of active managers as a proxy for differences in opinion and 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 although 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 economic policy uncertainty 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, i.e. 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 expectations 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 and Massa, 2005), historical income volatility or stock return volatility (Berkman et al., 2009), mutual funds' active holdings (Jiang and Sun, 2014) and more recently, the dispersion in equity market exposures of active managers (Balcilar et al., 2018), none of these studies has 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 to 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.

Since our uncertainty-based predictors are at monthly frequency, while we aim to predict daily returns, we use the generalized autoregressive conditional heteroskedasticity (GARCH) variant of mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model (Engle et al., 2013). The GARCH-MIDAS avoids the loss of information that would have resulted by 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 namely, 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.

Indeed, our findings show that the quality of the policy signal matters when it comes to 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, while the positive relationship between EPU and volatility breaks down when the signal quality is low. Out-of-sample analysis further confirms this 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 to the benchmark model. The improved volatility forecasts obtained from the forecasting models conditioned on signal quality are also found to yield favorable economic gains for investors, captured by the certainty equivalent returns and Sharpe ratios. Our results show that augmenting the forecasting model with a combination of EPU and signal quality predictors not only yields out-of-sample volatility forecasts, but also higher utility gains generated by the portfolios created from these forecasts. Finally, our analysis indicates clear distinctions between the U.S. and U.K. stocks markets in terms of the predictive role played by the quality of political signals and how those signals are processed by market participants. 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 findings from the in- and out-of-sample analysis, while 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 economic policy uncertainty in the economy and the monthly data is obtained from: policyuncertainty.com. The EPU index captures economic policy uncertainty 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 sixteen countries, Baker et al. (2021) show that journalists attribute one third of large stock market fluctuations in the U.S. 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 Bialkowski et al. (2022) is sourced from: qualityofpoliticalsignals.com. Like the EPU index, this index is also constructed via textual analysis of news articles from 10 leading newspapers each in the U.S. and U.K., however, the articles are categorized with regards to the terms they contain pertaining to 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. Since 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 U.S., and (2nd) January, 2001 to (31st) January, 2022 for the U.K.

We offer some preliminary analyses (summary statistics and pre-tests) to understand the behaviour 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 while those of the pre-tests (Serial correlation and Conditional Heteroscedasticity tests) are presented in Table 2. The summary statistics are carried out on 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 of political signals. The high quality of political signals (EPU-Quality[High]) denotes values of the actual index for political signals below its median while 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. We find that the mean value of stock returns for the US is higher than that of the UK while 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. In terms of EPU and its variants, the US is observed to record higher values than the UK implying that economic policy uncertainty is more pronounced in the former than the latter and interacting EPU with quality of political signals does not seem to change the outcome. In other words, the values of the interaction terms are larger for the US than the UK. On the pre-tests, we find evidence of serial correlation and heteroscedasticity for the variables of interest (see Table 2) and therefore accounting for these salient features in the estimation process is crucial for robust outcomes. The GARCH-MIDAS indeed comes in handy in this regard 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 modelling 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 economic policy uncertainty (EPU) and signal quality index that are available at 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 are more adequately harnessed. This framework also reduces the likelihood of estimation biases occasioned by aggregation and disaggregation that is often employed by the extant uniform frequency-based methods. Essentially, GARCH-MIDAS uses every piece of information, regardless of how minute, captured by the EPU and quality of signal indexes to improve the predictive performance of the model for daily stock market volatility.

We define daily stock returns $\left(r_{i,t}\right)$ as the log returns of the stock price index. Since we deal with mixed frequency series, note that $i=1,...,N_t$ and $t=1,...,T$ 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 by the following form:

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

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

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 $\text{GARCH}\left(1,1\right)$ based short-run component $\left(g_{i,t}\right)$ that is characterized by a higher frequency and a long-run component that captures the long-run volatility by the parameter $\left(\mu_t\right)$; $e_{i,t}$ 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) as:

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

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 (economic policy uncertainty and quality of signal index) are transformed to daily frequency, without loss of originality of the model. We transform the monthly varying long-term component $\left(\mu_t\right)$ 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 $\left(\mu_i\right)$ for the realized volatility and the exogenous factor:

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

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

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

where m is the intercept for the long-run component; θ is the coefficient of the predictor (whether realized volatility 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) realized volatility (RV) and this is considered as the benchmark (or the conventional GARCH-MIDAS) model; (ii) RV and economic policy uncertainty (EPU); (iii) RV, EPU and low quality of political signal index; and (iv) RV, EPU and high quality of political signal index. Note that for the variants interacted with RV, the principal components analysis (PCA) is employed to combine them into a single factor.

Note further in equations (4) and (5) that the beta polynomial weights $\phi_k\left(w_1, w_2\right) \geq 0,\ \ k = 1,...,K$ are constrained to sum to unity in order to achieve identification of the model's parameters. We filter the secular component of the MIDAS weights using forty $\left(K = 40\right)$ MIDAS months. 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 $\left[\phi_k\left(w_1, w_2\right) = \dfrac{\left[k/\left(K+1\right)\right]^{w_1-1} \times \left[1-k/\left(K+1\right)\right]^{w_2-1}}{\sum_{j=1}^{K}\left[j/\left(K+1\right)\right]^{w_1-1} \times \left[1-j/\left(K+1\right)\right]^{w_2-1}}\right]$ to a one-parameter beta weighting function $\left[\phi_k\left(w\right) = \dfrac{\left[1-k/\left(K+1\right)\right]^{w-1}}{\sum_{j=1}^{K}\left[1-j/\left(K+1\right)\right]^{w-1}}\right]$, by constraining w_1 to unity and setting $w_2 = w$, to ensure that the weighting function will be monotonically decreasing (Engle et al. 2013); where the weights are positive and sum to one. Also, the weights are constrained to be greater than unity $\left(w > 1\right)$ 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 $\left(\theta\right)$ such that a significant estimate would imply 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. Liu and Zhang, 2015; Lie et al., 2016; Goodell et al., 2020), 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.

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

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

where T is the full length (spanning the in- and out-of-sample periods) of the forecast errors; h denotes the out-of-sample period forecast horizons. The conventional DM test is defined as $DM = \bar{d} \big/ \sqrt{V\left(d\right)/T} \sim N\left(0,1\right)$, where $\bar{d} = 1/T\left[\sum_{t=1}^{T} d_t\right]$ is the average loss differential defined by $d_t \equiv g\left(\varepsilon_{it}\right) - g\left(\varepsilon_{jt}\right)$ with $g\left(\varepsilon_{it}\right)$ and $g\left(\varepsilon_{jt}\right)$ respectively, denoting the loss functions of the forecast errors, ε_{it} and ε_{jt}, corresponding to returns forecasts, $\hat{r}_{it}$ and $\hat{r}_{jt}$ of contending models; and $V\left(d_t\right)$ denotes the unconditional variance of d_t. The null hypothesis $\left(H_0 : E(d_t) = 0\right)$ of equality of contending models' precisions is tested against a mutually exclusive alternative $\left(H_1 : E(d_t) < 0\right)$ that a model variant (with one or more of the exogenous factors) yields more precise forecasts than the specified benchmark model. The forecast performance is evaluated at 30-day, 60-day and 120-day ahead forecast horizons, using 50% of the sample under a rolling window framework.

3. Empirical Results

3.1 In-sample Analysis

Table 3 presents the in-sample predictability results for U.S. stock market volatility based on the alternative models described earlier. The conventional GARCH-MIDAS model that includes realized volatility (*RV*) is considered as 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. The positive slope coefficient captured by θ in the benchmark GARCH-MIDAS model that includes realized volatility (*RV*) is consistent with the evidence in the literature on volatility clustering effects which 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. Liu and Zhang, 2015; Lie et al., 2016; Goodell et al., 2020). These patterns are consistent both for the U.S. and U.K. markets (reported in Table A1 in the Appendix), confirming our prior expectations on the EPU-volatility nexus.

When we examine the model variations that incorporate signal quality, however, we observe a positive and highly significant slope coefficient, consistently in both the full and 50% samples, for the *RV + EPU-Quality[High]* model. This confirms the inferences in Bialkowski et al. (2022) that the positive association between policy uncertainty and market volatility is robust when the signal quality is high. 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, while the coefficient turns even negative in the 50% data sample. These observations show that the quality of the signal indeed matters when it comes to the predictive role of policy uncertainty over subsequent stock market volatility. While high EPU predicts high volatility in all specifications, and in particular when the signal quality is high, we find 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 U.S. are fully in line with the evidence in Bialkowski et al. (2022), we find that this pattern is not as robust for the U.K. reported in Table A1 in the Appendix. In contrast to the evidence for the U.S., find that low quality policy signals in fact contribute to higher stock market volatility in the U.K., indicated by the positive and significant slope coefficients in the *RV + EPU-Quality[Low]* model. In sum, while the results confirm that the quality of the political signal indeed matters in regards to the policy uncertainty effect on stock market volatility, the two markets display some degree of heterogeneity in terms of how policy signals are processed by market participants.

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 labelled 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 labelled augmented model is preferred over the benchmark model under all standard levels of significance.

Examining Panel A in Table 4 where the benchmark model is the conventional GARCH-MIDAS model that includes realized volatility (*RV*), we find that all model variants, with the exception of the variant involving RV and EPU, significantly outperform the benchmark model that uses realized volatility as the only exogenous factor to predict the U.S. 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 significance compared to the benchmark model. This result is consistently observed across all three specified forecast horizons (30-day, 60-day and 120-day). In other words, the model variants that incorporate quality of political signal index, in combination with RV and EPU, offer statistically significant improvements in the out-of-sample forecasts of US stock return volatility, over the benchmark model. However, the model variant that excludes the quality of political signal index (that is, 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 to 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 in Panel B another scenario where the model variant with RV and EPU only is considered as the benchmark model. In essence, under this scenario, we evaluate the forecast performance of the model variants that include 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. These results further highlight the relevance of the quality of political signal for the out-of-sample predictability of stock market volatility across both the short and long forecast horizons. Therefore, our results show that augmenting the RV- and EPU-based GARCH-MIDAS models with quality of 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 U.K., reported in Table A2 in the Appendix, generally support the predictive role of signal quality over and above the EPU index alone, we see that the improvement in the forecasting performance for the U.K. only applies to models when the signal quality is high. Thus, the results further confirm the heterogeneity across the two stock markets, reported in the in-sample analysis in Tables 1 and A1, with respect to how policy signals are processed by market participants.

Finally, we further conduct additional comparisons in Panels C and D to formally test whether the asymmetry effect with respect to signal quality indeed exists between high and low quality of political signals. The results for the U.S. stock market do not yield any evidence of asymmetry between low and high quality of 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 signal index. Imperatively, in modelling U.S. stock market volatility using the quality of political signal as a predictor, the aggregate quality of political signal may not necessarily be decomposed as both low and high quality of signal index can be modelled in much the same way. This feat is consistent across the forecast horizons and an indication of the robustness of the result to the forecast horizons. However, when the high and low quality signals are combined with RV and EPU, we find evidence of a weak asymmetry effect for the medium (60-day ahead) forecast horizon. The weak significance and lack of consistency in the outcome of the latter across the forecast horizons seem to diminish the credibility of accounting for asymmetry in the quality of political signal. In other words, the outcome in favor of no asymmetry appears to have greater weight than that with asymmetry. In contrast, the results for the U.K., reported in Panels C and D in Table A2 show that signal quality indeed matters for the U.K. such that high quality of political signals yield improved forecast performance compared to low quality signals across all forecast horizons. These findings highlight clear distinctions between the two markets in terms of 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 that are popularly employed in the literature. Essentially, the interest is in ascertaining the economic gains of incorporating exogenous predictor variable(s) for the prediction of stock market volatility. This provides economic-based confirmation to lend support to the statistical conclusions earlier reached by the modified DM statistics. The economic gains of different GARCH-MIDAS-X model variants that incorporate economic policy uncertainty and the quality of signal index, singly and jointly, are compared with the conventional GARCH-MIDAS that is based on realized volatility.

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

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

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; $\hat{r}_{t+1}$ is the stock market realized volatility forecast at time $t+1$; $\hat{r}_{t+1}^{f}$ is a risk-free asset (3-month Treasury bill rate); and $\hat{\sigma}_{t+1}^2$ is an estimate of return volatility, obtained as a 30-day moving window of daily returns. The certainty equivalent return for the investor's optimal portfolio allocation is defined in equation (8)

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

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

$$U(R_p) = E(R_p) - 0.5(1/\gamma)Var(R_p) = w\theta(r - r^f) + (1-w)r^f - 0.5(1/\gamma)w^2\theta^2\sigma^2 \tag{9}$$

where the variance of the portfolio return is defined as $Var(R_p) = w^2\theta^2\sigma^2$, and σ^2 denotes excess return volatility. The model that yields the highest returns, CER and Sharpe ratio that is defined as $SR = (R_p - r^f)\big/\sqrt{Var(R_p)}$; and minimum volatility (see Liu et al., 2019) is adjudged the model with the most favourable economic gains.

Table 5 presents the mean portfolio returns, volatility, certainty equivalent returns and Sharpe ratios obtained from the volatility forecasts that are 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 to the benchmark GARCH-MIDAS model that includes only realized volatility (RV), however, all other model variations that incorporate one or more exogenous variables are found to yield higher returns as well as higher CER and Sharpe ratio values. This suggests that the incorporation of EPU and signal quality in the predictive models (in combination with the realized stock market volatility) yields improved 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 lower 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 not only yields 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 U.K. stock market, reported in Table A3, with improved CER and Sharpe Ratio estimates obtained from model variations that incorporate EPU in combination with high quality political signals. In sum, we conclude that EPU and the quality of the political signal are indeed good predictors that can improve not only the out-of-sample forecast performance of volatility models, but also offer improved economic outcomes for investors.

5. Conclusion

The role of economic policy uncertainty 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 to 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, while 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 not taking into account signal quality in the predictive model does not yield any difference in the forecast performance as compared to the benchmark model. The improved volatility forecasts obtained from the forecasting models conditioned on signal quality are also found to yield favorable economic gains for investors, captured by the certainty equivalent returns and Sharpe ratios. Our results show that augmenting the forecasting model with a combination of EPU and signal quality predictors not only yields out-of-sample volatility forecasts, but also higher utility gains generated by the portfolios created from these forecasts. 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 U.S. and U.K. stocks markets in terms of the predictive role played by the quality of political signals and how those signals are processed by market participants. 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.

References

Ajinkya, B., and M.J. Gift, 1985, Dispersion of Financial Analyst's Earnings Forecasts and the (Option Model) Implied Standard Deviations of Stock Returns, Journal of Finance 40, 1353-1365.

Ali, S, Badshah, I., Demirer, R., Hegde, P. (forthcoming). Economic Policy Uncertainty and Institutional Investment Returns: The Case of New Zealand. Pacific-Basin Finance Journal.

Anderson, E. W., Ghysels, E, and J.L. Juergens, 2005, Do Heterogeneous Beliefs Mater for Asset Pricing? Review of Financial Studies 18, 875-924.

Badshah, I., Demirer, R., Suleman, M., T. (2019). The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging. *Energy Economics* 84, 104553.

Balcılar, M., R. Demirer, R. Gupta, M. Wohar (2018). Differences of Opinion and Stock Market Volatility: Evidence from a Nonparametric Causality-in-Quantiles Approach. Journal of Economics and Finance, 42 (2), 339–351.

Bali, T. G., Brown, S. J., & Tang, Y. (2017). Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics*, *126*(3), 471-489.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*(4), 1593-1636.

Baker, S., Bloom, N., Davis, S. J., & Sammon, M. (2021). What triggers stock market jumps? NBER working paper 28687 (April 2021).

Berkman, H., Dimitrov, V., Jain P. C., Koch, P. D., Tice, S. 2009. Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. Journal of Financial Economics 92, 376–399.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The quarterly journal of economics*, *98*(1), 85-106.

Białkowski, J., Dang, H. D., & Wei, X. (2022). High policy uncertainty and low implied market volatility: An academic puzzle? *Journal of Financial Economics* 143 (3), 1185-1208.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, *77*(3), 623-685.

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, *61*(1), 3-18.

Chen, J., Hong, H., Stein, J., 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66, 171–205.

Colacito, R., Engle, R.F., and Ghysels, E. (2011). A component model for dynamic correlations. Journal of Econometrics, 164(1), 45-59.

Dakhlaoui, I., Aloui, C., 2016. The interactive relationship between the US economic policy uncertainty and BRIC stock markets. Int. Econ. 146, 141–157.

Das, S., Demirer, R., Gupta, R., and Mangisa, S. (2019). The effect of global crises on stock market correlations: Evidence from scalar regressions via functional data analysis. Structural Change and Economic Dynamics, 50, 132–147.

Diebold, F.X., and Mariano, R.S. (1995). Comparing Predictive Accuracy. Journal of Business and Economic Statistics, 13(3), 253-263.

Diether, K., Malloy, C., Scherbina, A., 2002.Differences of opinion and the cross-section of stock returns. Journal of Finance 57, 2113–2142.

Dixit, A. K., & Pindyck, R. S. (1995). The options approach to capital investment. *Real Options and Investment under Uncertainty-classical Readings and Recent Contributions. MIT Press, Cambridge*, *6*.

Drechsler, I. (2013). Uncertainty, time□varying fear, and asset prices. *The Journal of Finance*, *68*(5), 1843-1889.

Engle, R.F., Ghysels, E., and Sohn, B. (2013). Stock Market Volatility and Macroeconomic Fundamentals. The Review of Economics and Statistics, 95(3), 776-797.

Gilchrist, S., Sim, J. W., & Zakrajšek, E. (2014). *Uncertainty, financial frictions, and investment dynamics* (No. w20038). National Bureau of Economic Research.

Goetzmann, W., Massa, M., 2005. Dispersion of opinion and stock returns. Journal of Financial Markets 8, 325–350.

Goodell, J.W. , McGee, R.J. , McGroarty, F. , 2020. Election uncertainty, eco- nomic policy uncertainty and financial market uncertainty: A prediction market analysis. J. Bank. Financ. 110, 105684 .

Harvey, D., Leybourne, S. and Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13(2),* 281–291.

Jiang, H., Sun, Z. 2014. Dispersion in beliefs among active mutual funds and the cross-section of stock returns. Journal of Financial Economics 114 (2014) 341–365

Johnson, T.C., 2004. Forecast dispersion and the cross section of expected returns. Journal of Finance 59, 1957–1978.

Kelly, B., Pástor, Ľ., & Veronesi, P. (2016). The price of political uncertainty: Theory and evidence from the option market. *The Journal of Finance*, *71*(5), 2417-2480.

Li, X. , Balcilar, M. , Gupta, R. , Chang, T. , 2016. The causal relationship between economic policy uncertainty and stock returns in China and India: evidence from a bootstrap rolling window approach. Emerg. Mark. Finance Trade 52, 674–689 .

Liu, L. , Zhang, T. , 2015. Economic policy uncertainty and stock market volatility. Finance Res. Lett. 15, 99–105 .

Liu, Z., Ye, Y., Ma, F., & Liu, J. 2017. Can economic policy uncertainty help to forecast the volatility: A multifractal perspective. Physica A-Statistical Mechanics and Its Applications 482, 181-188.

Liu, J., Ma, F., Tang, Y. & Zhang, Y. (2019). Geopolitical risk and oil volatility: A new insight. *Energy Economics*, *84*, 104548.

Pastor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The journal of Finance*, *67*(4), 1219-1264.

Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of financial Economics*, *110*(3), 520-545.

Poon, S-H, and Granger, C. W. J. (2003). Forecasting Volatility in Financial Markets: A Review. Journal of Economic Literature, 41(2), 478-539.

Rapach, D.E., and Strauss, J.K. (2008). Structural Breaks and GARCH Models of Exchange Rate Volatility. Journal of Applied Econometrics, 23(1), 65-90.

Rapach, D.E., Strauss, J.K., and Wohar, M.E. (2008). Forecasting stock return volatility in the presence of structural breaks, in Forecasting in the Presence of Structural Breaks and Model Uncertainty, in David E. Rapach and Mark E. Wohar (Eds.), Vol. 3 of Frontiers of Economics and Globalization, Bingley, United Kingdom: Emerald (May 2008), pp. 381–416.

You, W., Guo, Y., Zhu, H., & Tang, Y. 2017. Oil price shocks, economic policy uncertainty and industry stock returns in China: Asymmetric effects with quantile regression. *Energy Economics 68*, 1-18.

Table 1: Summary statistics

	Mean	Std. Dev.	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 [US]					
EPU	137.16	66.24	1.97	9.09	0.48	265	Monthly	Jan-2000	Jan-2022
EPU-Quality[Low]	9468.60	12354.4	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	11798.93	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 of political signals. The high quality of political signals (EPU-Quality[High]) denotes values of the actual index for political signals below its median while those above it are for the low quality (EPU-Quality[Low]). In other words, the higher the value the index, the lower the quality of political signals. Std. Dev. 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 [US]								
	$ARCH(1)$	$ARCH(2)$	$ARCH(3)$	$Q(1)$	$Q(2)$	$Q(3)$	$Q^2(1)$	$Q^2(2)$	$Q^2(3)$
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. ***, ** and * indicate significance of tests at 1%, 5% and 10% levels, respectively. 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.

Table 3: In-Sample Predictability Results

Response Variable	μ	α	β	θ	w	m
			Full Data Sample			
RV	0.0680***	0.1380***	0.8074***	0.0186***	11.3640***	0.5038***
	[0.0113]	[0.0094]	[0.0132]	[0.0024]	[2.6541]	[0.0555]
RV + EPU	0.0658***	0.1253***	0.8457***	0.0380***	49.9910**	0.0333
	[0.0114]	[0.0086]	[0.0095]	[0.0054]	[21.7120]	[0.1123]
RV + EPU-Quality[High]	0.0671***	0.1304***	0.8401***	0.0389***	31.5190	0.0385
	[0.0111]	[0.0084]	[0.0094]	[0.0086]	[21.1540]	[0.1069]
RV + EPU-Quality[Low]	0.0669***	0.1319***	0.8422***	0.0552	1.0031	0.0943
	[0.0112]	[0.0083]	[0.0091]	[0.0532]	[1.8408]	[0.1237]
			50% Data Sample			
RV	0.0523***	0.0772***	0.8827***	0.0230***	20.2690	0.4075***
	[0.0194]	[0.0119]	[0.0316]	[0.0075]	[13.2830]	[0.1429]
RV + EPU	0.0504***	0.0633***	0.9195***	0.1145***	49.9960*	0.3921**
	[0.0191]	[0.0089]	[0.0116]	[0.0239]	[26.2600]	[0.1612]
RV + EPU-Quality[High]	0.0504***	0.0669***	0.9201***	0.0875***	49.9960*	-0.0547
	[0.0191]	[0.0091]	[0.0107]	[0.0258]	[27.0050]	[0.1933]
RV + EPU-Quality[Low]	0.0532***	0.0766***	0.9139***	-1.0020***	1.0010**	-0.2187
	[0.0192]	[0.0092]	[0.0106]	[0.3375]	[0.4157]	[0.2751]

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

Table 4: Diebold and Mariano Out-of-Sample Forecast Evaluation

Model	Volatility		
	$h = 30$	$h = 60$	$h = 120$
Panel A: *Benchmark Model: GARCH-MIDAS[RV]*			
RV + EPU	0.3124	0.3103	0.2470
RV + EPU-Quality[High]	-2.0382**	-2.1800**	-1.9185*
RV + EPU-Quality[Low]	-2.7438***	-2.4720**	-2.2035**
Panel B: *Benchmark Model: GARCH-MIDAS [RV + EPU]*			
RV + EPU-Quality[High]	-3.4754***	-2.5429**	-1.7827*
RV + EPU-Quality[Low]	-2.9725***	-2.3552**	-1.6138
Panel C: *Benchmark Model: GARCH-MIDAS[RV + Quality[Low]]*			
RV + Quality[High]	0.9325	0.7676	0.6555
Panel D: *Benchmark Model: GARCH-MIDAS – [RV+EPU-Quality[Low]]*			
RV+EPU-Quality[High]	1.3487	1.6958*	0.9934

Note: The table presents the modified Diebold and Mariano test statistics which compares the row labelled 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 labelled model is preferred over the benchmark model, under all the standard levels of significance.

Table 5: Economic Significance

Model	**Returns**	**Volatility**	**CER**	**SR**
		Panel A: $\gamma = 3$ *and* $\theta = 6$		
RV	0.5383	23.1850	0.4291	0.1012
RV + EPU	0.6089	25.2613	0.4993	**0.1110**
RV + EPU-Quality[High]	0.6124	25.3398	0.5030	**0.1115**
RV + EPU-Quality[Low]	0.5467	23.3970	0.4374	**0.1025**
		Panel B: $\gamma = 3$ *and* $\theta = 8$		
RV	0.5362	23.1292	0.4270	0.1009
RV + EPU	0.6067	25.2022	0.4971	**0.1107**
RV + EPU-Quality[High]	0.6102	25.2800	0.5008	**0.1112**
RV + EPU-Quality[Low]	0.5446	23.3407	0.4353	**0.1022**

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.

APPENDIX

Table A1: In-Sample Predictability Result for the UK

Response Variable	μ	α	β	θ	w	m
Full Data Sample						
RV	0.0402***	0.1269***	0.7945***	0.0297***	14.1510***	0.3133***
	[0.0119]	[0.0095]	[0.0172]	[0.0029]	[2.8279]	[0.0466]
RV + EPU	0.0384***	0.1015***	0.8800***	0.0237***	49.9970	0.1117
	[0.0119]	[0.0067]	[0.0077]	[0.0078]	[34.9900]	[0.1277]
RV + EPU-Quality[High]	0.0392***	0.1045***	0.8773***	-0.0069	13.7180	0.1285
	[0.0117]	[0.0067]	[0.0076]	[0.0157]	[70.3410]	[0.1309]
RV + EPU-Quality[Low]	0.0392***	0.1073***	0.8723***	0.1080**	11.6420	0.1120
	[0.0118]	[0.0071]	[0.0080]	[0.0449]	[14.1860]	[0.1235]
50% Data Sample						
RV	0.0604***	0.1250***	0.8224***	0.0368***	13.4430**	0.2613***
	[0.0194]	[0.0177]	[0.0292]	[0.0059]	[5.2836]	[0.0955]
RV + EPU	0.0572***	0.0921***	0.8854***	0.1337***	49.9990**	0.5661***
	[0.0193]	[0.0137]	[0.0169]	[0.0186]	[24.1410]	[0.1710]
RV + EPU-Quality[High]	0.0590***	0.1058***	0.8792***	0.2466***	3.4469**	-0.0376
	[0.0192]	[0.0119]	[0.0131]	[0.0933]	[1.6117]	[0.2883]
RV + EPU-Quality[Low]	0.0600***	0.1114***	0.8669***	0.6661***	9.1116	0.6435***
	[0.0196]	[0.0134]	[0.0173]	[0.1426]	[6.3561]	[0.2094]

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

Table A2: Diebold and Mariano Out-of-Sample Forecast Evaluation for the UK

Model	**Volatility**		
	$h = 30$	$h = 60$	$h = 120$
Panel A: *Benchmark Model: GARCH-MIDAS – [RV]*			
RV + EPU	1.5512	1.1712	0.9119
RV + EPU-Quality[High]	-4.1692***	-3.3072***	-2.2888**
RV + EPU-Quality[Low]	3.5861***	2.6357***	1.8864*
Panel B: *Benchmark Model: GARCH-MIDAS – [RV + EPU]*			
RV + EPU-Quality[High]	-3.5649***	-2.7552***	-2.0249**
RV + EPU-Quality[Low]	1.6819*	1.4919	1.2065
Panel C: *Benchmark Model: GARCH-MIDAS - [RV + Quality[Low]]*			
RV + Quality[High]	4.3908***	3.0926***	2.1691**
Panel D: *Benchmark Model: GARCH-MIDAS – [RV + EPU-Quality[Low]]*			
RV+EPU-Quality[High]	-4.5749***	-3.3055***	-2.3268**

Note: The table presents the modified Diebold and Mariano test statistics which compares the row labelled 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 labelled model is preferred over the benchmark model, under all the standard levels of significance.

Table A3: Economic Significance for the UK

Model	Returns	Volatility	CER	SR
Panel A: $\gamma = 3$ *and* $\theta = 6$				
RV	0.6941	71.4839	0.4541	0.0778
RV + EPU	0.7316	73.2156	0.4916	**0.0813**
RV + EPU-Quality[High]	0.7465	74.7506	0.5065	**0.0821**
RV + EPU-Quality[Low]	0.6816	71.1291	0.4421	0.0765
Panel B: $\gamma = 3$ *and* $\theta = 8$				
RV	0.6920	71.3029	0.4520	0.0777
RV + EPU	0.7294	73.0313	0.4894	**0.0811**
RV + EPU-Quality[High]	0.7443	74.5627	0.5043	**0.0820**
RV + EPU-Quality[Low]	0.6795	70.9486	0.4400	0.0764

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.