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S&P 500 volatility, volatility regimes, and economic uncertainty

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Abstract

We assess the relationship between regime-dependent volatility in S&P 500, economic policy uncertainty, the S&P 500 bull and bear sentiment spread (bb_sp), as well as the Chicago Board Options Exchange's VIX over the period 2000–2018. Our findings from two-covariate GARCH–MIDAS (GM) methodology, regime switching Markov Chain, and quantile regressions suggest that the association of realized volatility and sentiment varies across high- and low-volatility regimes and depends on investors' sensitivity toward incidents of market uncertainties under these regimes. The findings suggest that these indicators may not be useful in volatility forecasting, especially under high-volatility regimes.

KEYWORDS

economic policy uncertainty, GARCH–MIDAS, quantile regression, regime switching Markov Chain regression, VIX, volatility

JEL CLASSIFICATION

G10, G12, G17

1 | INTRODUCTION

There is long-standing literature on how investor sentiment and economic uncertainty seep into financial markets. For instance, it is well established that equity market volatility (EMV) is affected, sometimes over extended periods of time, by investor beliefs that may or may not transpire. In the behavioral finance literature (e.g., Baker & Wurgler, 2006, 2007), investors are accepted as potentially irrational so that their actions may be driven by unwarranted pessimism or optimism, rather than by fundamental factors. In other words, asset price dynamics may also be explained by investor psychology, contrary to thesis or efficient markets (Fama, 1965). Can investor sentiment or uncertainty explain short-term volatility or the persistence of long-term volatility? To what degree? These are some of the key questions we address in the paper.

It is widely understood that the measurement of stock market volatility is critical in financial modeling (e.g., in portfolio optimization) and the assessment of risk (e.g., in stress testing), and in derivatives pricing. For instance, in futures contracts, volatility is considered a source of contango and backwardation (e.g., Alizadeh & Nomikos, 2011; Beckmann & Czudaj, 2014; Robe & Wallen, 2016). However, there is overwhelming evidence that EMV is not easy to measure. The evidence shows that equity price dynamics follow nonlinear processes (e.g., Adrangi et al., 2001; Eve et al., 1997; Peters, 1994), tend to cluster, and are time-varying (e.g., Bollerslev et al., 1988), and that co-movements across asset classes tend to increase in periods of distress (e.g., Ang & Bekaert, 2015; Ang & Chen, 2002). Our study extends this literature by examining the role that investor sentiment might play in nonlinear volatility dynamics.

We investigate the association of the US EMV, represented by the volatility in the S&P 500 index, with variables that reflect sentiments and uncertainties surrounding markets and economic policies from 2000 to 2018. The sampling period excludes the COVID-19 years of 2019–2021 because this period is characterized by exceptional fear and volatility. Economic uncertainty is captured via the economic policy uncertainty index (EPU, Baker et al., 2012b), which measures uncertainty on economic policy risks, the Chicago Board Options Exchange's VIX (CBOE VIX) (expected volatility measure from S&P 500 options), and the S&P bull–bear spread, which measures investor sentiment. The EPU has been extensively used in the literature to proxy a lack of consensus on economic policy. Therefore, it is also a measure of sentiment relating to economic uncertainty. The VIX is widely known as the "fear index" as it is known to rise at times when stress is indicated and fall when markets are bullish (e.g., Whaley, 2009). It is one of our sentiment indicators for the stock market. Volatility is measured via a generalized autoregressive conditional heteroskedasticity–mixed-data sampling (GARCH–MIDAS [GM]) model, which has been proven superior to other variations of GARCH frameworks in terms of its predictive power as well as its ability to simultaneously deliver the short- and long-term predictions of volatility. Short- and long-term volatilities are examined across regimes. We deploy the Markov switching and quantile regressions (MSR and QR, respectively), suitable to delineate the association of volatility with uncertainty indicators during the low- and high-volatility periods.

We find that the sentiment and uncertainty indicators are important in explaining both short- and long-run volatilities (SRV and LRV), however, only under low-volatility regimes. In other words, these indicators do not play a major role when volatility is abnormally high. Nonetheless, we are able to show an important role for both VIX and EPU for LRV patterns. This is important because volatility clustering/persistence is mostly treated as a statistical (not necessarily intuitive) characteristic of the markets. In finding significance for investor sentiment and uncertainty, our evidence provides an intuitive explanatory variable for these patterns.

The results, in general, are an endorsement of our methodology that takes into account switching volatility regimes in that we do find differences across the economic regime changes. The finding that economic certainty indicators such as EPU and VIX matter less in high-volatility regimes may be disappointing to market observers but is somewhat intuitive. Extreme volatility generally arises very suddenly and without warning, so that sentiment changes would lag the volatility. On the other hand, sentiment changes during periods of calm should be expected to have a greater impact on volatility. For instance, a growth in the sentiment that monetary tightening would take place is more likely to provoke a larger jump in volatility when markets are calm than when they have already been substantially disrupted.

Our paper contributes to the literature in two important ways: (i) We analyze, jointly, how short-term and long-term components of volatility are linked with market sentiment and economic uncertainty; (ii) we improve the Su et al. (2019) model by first deriving the short- and long-term S&P 500 volatility measures from a two-covariate GM model. In the second step, we include three market uncertainty trackers in the MSR and QR, thus avoiding possible specification errors that precious research possibly suffered from. These uncertainty trackers have been shown by researchers to be significantly associated with short- and long-term volatilities in asset returns (see Pan et al., 2021; Su et al., 2017, 2019; Kang et al. 2021, among others).

The remainder of the paper is organized as follows. Section 2 provides a brief look into the literature on the EPU and, separately, the GM methodology that we employ here. Section 3 discusses the data and their sources, and Section 4 offers brief explanations of the methodologies used. The presentation and discussion of the empirical results are the subjects of Section 5, and Section 6 offers a summary and some concluding remarks.

2 | LITERATURE REVIEW OF UNCERTAINTIES AND VOLATILITY

In this section, we provide a succinct overview of the existing literature on the EPU and other relevant uncertainty indicators that have been found to impact asset price volatilities. Additionally, we summarize a selection of studies that utilize the GM framework to derive long- and short-term equity volatilities.

2.1 | Literature on uncertainty, economic policy uncertainty, and asset price volatility

Sentiment and uncertainty indicators have garnered increasing attention in recent years. Manela and Moreira (2017) developed a monthly news-based indicator (NVIX), whereas Baker et al., 2012a, 2012b, 2016, 2019, 2021) created various indices that capture economic or financial uncertainty (FU), Twitter-based measures of economic uncertainty, and other metrics that quantify market uncertainties.

These indicators have gained significant importance, particularly in analyzing the volatility of different asset classes. Notable studies in this field include Altig et al. (2020), Dutta et al. (2021), Jiang et al. (2019), Krol (2014), Pan et al. (2017), Pan et al. (2021), Su et al. (2017, 2018, 2019), Xu et al. (2021), and Lindblad (2017), among others.

The findings of these studies have led to the widely accepted view that economic uncertainty, policy uncertainty, and sentiments significantly contribute to asset price volatilities. In the following section, we provide a brief overview of some of these stylized facts.

Pan et al. (2021) demonstrated that macroeconomic uncertainty plays a significant role in affecting the long-term volatility component of the daily values of the S&P 500. Fang et al. (2018) found that changes in the investor confidence in the United States spill into the G7 equity markets.

Zhu et al. (2019) considered EMV indices based on the text counts of newspaper articles, including several keywords related to the US economy or stock market volatility. They examine the daily volatility in S&P 500, NYSE Composite, NASDAQ Composite, and DJIA. They found that these indices are associated with EMV.

Similarly, Su et al. (2019) investigated the role of uncertainty in short- and long-term volatilities of equities in nine economies. They consider three measures of US market uncertainties, namely, EPU, FU, and NVIX. EPU is constructed from the three types of underlying components. One component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in the next 10 years. The third component uses the disagreement among economic forecasters as a proxy for uncertainty. FU, proposed by Ludvigson et al. (2021), measures a common component in the time-varying volatilities of h-step ahead forecast errors across a large number of financial indicators. NVIX is suggested by Manela and Moreira (2017).

The estimation results of Su et al. (2019) show that EPU is positively associated with the industrialized countries' EMV. Their results, though mixed, add to the literature regarding the crucial role of the uncertainty indices in the volatility of equity markets.

Baker et al. (2012b) developed the EPU to capture uncertainty about fiscal and monetary policies.

Baker et al. (2012a) examined the EPU in the context of the 2009 recession and isolated the reasons behind a slow recovery in the post-recession years. They find the EPU index fluctuates over time and shows extraordinarily high levels of EPU over the period of 2008–2012, reaching its maximum in August 2011. Furthermore, they document that policy uncertainties account for the large fraction of the overall economic uncertainty during the study period. They found that rising EPU foreshadows slows output, employment, and investment. They conclude with some confidence that high levels of policy uncertainty are associated with weaker economic growth.

Al-Thaqeb and Algharabali (2019) reviewed the findings of some research regarding EPU's associations with financial markets and firms' behavior. Overall, the results from previous studies indicate that firms turn conservative at times of high EPU (Colak et al., 2017; Jens, 2017; Kelly et al., 2016). Therefore, firms reduce capital investment (Gulen & Ion, 2015), launch fewer initial public offerings (Colak et al., 2017), curtail mergers and acquisitions (Bonaime et al., 2018; Nguyen & Phan, 2017), reduce dividend payments (Panousi & Papanikolaou, 2012; Walkup, 2016), and retain cash (Demir & Ersan, 2017; Im et al., 2017; Phan et al., 2019).

Liu and Zhang (2015) investigated the association of EPU with realized stock market volatility. Using 5-min high-frequency data for realized volatility, they show that lagging EPU is significantly related to contemporaneous volatility. These findings support those in Antonakakis et al. (2013) that a rise in policy uncertainty increases equity market return uncertainty and that including EPU in volatility models improves their predictive power regardless of the model specification. Arouri et al. (2016) studied the effect of EPU on the US stock market. Their regression findings reveal that a rise in EPU reduces stock returns, especially during extreme volatility periods.

Many papers also study EPU with the possibility that it captures international contagion risks. Tsai (2017) explored the role of the EPU in China, Japan, Europe, and the United States on the contagion risk of investments in 22 equity markets worldwide. The results show that EPUs in Europe and China influence volatility in Asian and European markets, respectively. They attribute the association of various EPU indices with the interdependence of equity markets. Choi and Hammoudeh (2010) estimated conditional correlations (DCCs) among several assets, including crude oil and S&P 500 in a regime switching context.

Chang (2022) deployed MSRs to analyze synchronous and asynchronous volatility associations between the US and Japanese stock markets by including the EPU index. The results show that this association switches from synchronous to asynchronous patterns, and the EPU contagion to equity volatility is mainly happening in the US markets.

Wen et al. (2019) investigated the association of macroeconomic variables in China with the US EPU index. Their study shows that the EPU in the United States is associated with fluctuations in macroeconomic variables in China. Other scholars have been interested in the contagion from EPU to crude oil prices (Sharif et al., 2020), exchange rates (Krol, 2014), real-time economic uncertainty indices (Altig et al., 2020), and bond markets (Liow et al., 2018), to name a few.

The summary of various studies that utilize indicators of uncertainty and policy uncertainty to measure asset price volatility indicates that there is ample support for the positive association between asset price volatility and uncertainty indices.

2.2 | Literature on GARCH–MIDAS, quantile regressions, Markov switching, and related applications

In this section, we summarize some of the literature on methods that we deploy in the current study—namely, GM, QRs, and MSRs. Most of our review is focused on applications, though the main intention is also to show the continued development and repurposing of the GARCH framework to the GM frameworks. The studies most pertinent to our paper are Sue (2017) and Pan et al. (2021), both of which we build upon.

The aim of the current research is to examine the association of the volatility in S&P 500 with a set of uncertainty and policy uncertainty indices. Building on the existing methodologies, we hope to derive volatility measurements that are superior to the existing ones.

Efforts to improve volatility measurement and forecasts by enhancing existing GARCH and other econometric models are ongoing. Among the pioneering work is that of Ding and Granger (1996) and Engle and Lee (1999). Inspired by their seminal work, researchers have taken steps that show improvements in the volatility estimation of GARCH models.

For instance, Javaheri et al. (2004) proposed a GARCH (1,1) model combined with a convexity condition to investigate the hedging of volatility swaps. Awartani and Corradi (2005) estimated the out-of-sample volatility predictive ability of several GARCH model variations and found that, for one-step-ahead and longer horizon forecasts, the asymmetric GARCH models are superior to GARCH (1,1). Liu and Hung (2010) conducted superior performance ability tests to compare various GARCH formulations. They found that the GJR-GARCH model achieves the most accurate volatility forecasts for the S&P 500, closely followed by the EGARCH model. Hajizadeh et al. (2012) proposed hybrid models based on EGARCH and artificial neural networks to enhance the performance of the EGARCH model in forecasting the volatility of the S&P 500 index. Their hybrid model opens the door to other innovative approaches for estimating volatility forecasts of various financial assets. Carnero et al. (2012) suggested robust methodology alternatives to improve GARCH volatility estimates and possibly correct for the upward estimation bias. Adrangi et al. (2015) estimated bivariate vector autoregressive EGARCH models to estimate volatility and examine volatility spillovers across crude oil and equity markets.

The latest approach to improve the performance of GARCH models in the past decade has been tapping into data with varying frequencies. The pioneering effort in this direction by Engle et al. (2013) gave rise to a mixed-frequency data sampling method combined with GM modeling. Following Amendola et al. (2017, 2019), Asgharian et al. (2013), Conrad and Loch (2015), Conrad et al. (2018), Engle et al. (2013), Lindblad (2019), Pan et al. (2017, 2021), and Borup and Jakobsen (2019) have employed the model in their research. These researchers show that including the available low-frequency macroeconomic variables in forecasting the volatility of financial assets in high frequencies improves volatility estimates and forecasts. A recent work by Amado et al. (2019) provides a survey on multiplicative component GM model performance and applications.

Pan et al. (2017) deployed a regime switching univariate GM model to investigate the association between WTI and Brent crude oil spot price volatility and market fundamentals. Importantly, regime switching GM models produce superior forecasts of crude oil volatility. Fang et al. (2018) employed a two-covariate GM model and found that changes in the investor confidence in the United States spill into the G7 equity markets. Zhu et al. (2019) considered EMV indices based on the text counts of newspaper articles, including several keywords related to the US economy or stock market volatility. They deploy unicovariate GM to examine the daily volatility in S&P 500, NYSE Composite, NASDAQ Composite, and DJIA. Conrad et al. (2018) deployed a GM approach to derive the long- and short-term volatility components of cryptocurrencies.

Of particular interest to this study, Su et al. (2019) investigated the role of uncertainty in short- and long-term volatilities of equities in nine economies. They deploy a two-variable GM model, decomposing the conditional variance into short-term and long-term components. The short-term component corresponds to daily volatility. For the long-term component, they estimate a linear function for low-frequency measures of uncertainty. They consider three measures of US market uncertainties, namely, EPU, FU, and NVIX. EPU is constructed from the three types of underlying components. One component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in the next 10 years. The third component uses the disagreement among economic forecasters as a proxy for uncertainty. FU, proposed by Ludvigson et al. (2021), measures a common component in the time-varying volatilities of h-step ahead forecast errors across a large number of financial indicators.

The estimation results of Su et al. (2019) show that EPU is positively associated with the industrialized countries' EMV. Considering forecasting power, higher NVIX surprisingly leads to lower volatility. FU fails to add to and predictive power of the model, especially for the long-term stock market volatility. Their results, though mixed, add to the literature regarding the crucial role of the uncertainty indices in the volatility of equity markets. Su et al. (2019) did not include all three indicators of uncertainty in their two-covariate GM models possibly to avoid complex estimation problems. However, their GM model may also suffer from misspecification as it is limited to two out of three uncertainty trackers. The possible misspecification may also jeopardize the accuracy of the model predictive power, resulting in spurious findings.

Pan et al. (2021) proposed a set of univariate GM models for value-at-risk (VaR) and expected shortfall. They obtain the parameters of the proposed models by minimizing the loss function suggested by Fissler and Ziegel (2016). Their data sets consist of daily returns of S&P 500, monthly values of industrial production (IP), and producer price index. Their proposed GM models show that macroeconomic uncertainty plays an important role in affecting the long-term volatility component. The main shortcoming of the Pan et al. (2021) model maybe that proposed GM models are univariate. They only account for each volatility measure one at a time, which raises the risk of models being misspecified. They do not show how their models may perform relative to bivariate or other GM models.

Several studies have used QRs to estimate the link between volatility and sentiment indicators. Dutta et al. (2021) used QRs to examine the association between news-based EMV and crude oil *volatility*. Their QRs on monthly data indicate a significant but asymmetric effect of EMV trackers on the oil market volatility during periods of high oil volatility but not when the oil market is less volatile. Xu et al. (2021) deployed a QR-based univariate GM (QR-GM) model to predict the VaR of daily spot and futures returns for crude oil. Their findings suggest that GM and QR-GM models are powerful tools to study the impact of the low-frequency variables on the quantile of high-frequency-dependent variables. The main drawback of this research is that it includes a single covariate, GEPU in its GM.

Conrad and Kleen (2020) demonstrated that the multiplicative GM outperforms the heterogeneous autoregression of Corsi (2009), the realized GARCH of Hansen et al. (2012), the high-frequency-based volatility of Shephard and Sheppard (2010); and the MS-GARCH. They conclude that the multiplicative component structure of the GM model may be the source of its superior performance over other GARCH model variations. The indications of the superior performance of the GM method motivate its deployment in the current study.

The extensive literature on the subject of volatility estimation and methodologies to investigate volatility drivers points to interest among investors, policy makers, fund managers, and speculators regarding the subject.

Our paper is a continuation of the previous stream of papers on the subject. Prior to this paper, Fang et al. (2018) and Su et al. (2019) also deployed a two-variable GM model to investigate the association of market uncertainties with EMV. However, as suggested by Conrad and Kleen (2020), "GARCH-MIDAS models that include more than two variables in the long-term component are difficult to estimate because the likelihood is relatively insensitive with respect to changes in the weighting parameters." Based on our experience, GM models that include more than two covariates to model the long-term volatility are impossible to estimate. That is the main reason that almost all GM models estimated in previous research are univariate and, therefore, misspecified. Su et al. (2017) resorted to including permutations of the pairs of measures of uncertainty in their GM models. This approach, while making estimation possible, is incomplete as several uncertainty measures are needed. Our paper adds to the literature by including economic fundamentals in the GM model, and uncertainty measures in QR and MSR in a complementary second step. This methodology allows us to investigate the association of several variables with market volatility in a two-step manner.

3 | DATA

We sample data between January 3, 2000 and April 30, 2018 to derive volatility estimates through August 2020. Monthly data on the national financial confidence index (NFCI) and US IP are taken from the Federal Reserve Bank of St. Louis (FRED). The daily data on S&P 500 index values adjusted for dividends for the same time frame come from Yahoo Finance. The daily index values of the VIX and the EPU in the United States are taken from the Bloomberg and the FRED (St. Louis) databases, respectively.

The weekly data on the bull and bear sentiment spread index (bb_sp) are taken from the American Association of Individual Investors (AAII). Since 1987, AAII has published the results of the weekly survey of its members' sentiment as the AAII Investor Sentiment Survey (AAIISS). The AAIISS results are published by Bloomberg and Barron's, among other financial publications. Analysts and financial professionals have used the AAIISS as an indicator of investor sentiment. Historically, the average AAIISS results for the bulls and the bears are 38% and 30.5%, respectively. The values for the bulls and bears reflect the sentiment of investors regarding the direction of the equity markets over the next 6 months. We include the bb_sp to capture the association between investor sentiment and EMV. For instance, higher than expected values of bullish and bearish sentiments would be significantly associated with market volatility. We enter this variable in absolute values in our tests. Weekly values are converted to daily values using a third-degree polynomial to simulate their daily fluctuations because MIDAS estimation of QR and regime MSR is not available at this time. Various frequency conversion methodologies are suggested in the literature. For instance, Chow and Lin (1971), Denton (1971), Litterman (1983), and Di Fonzo (1990), among others, offered alternative univariate and multivariate methodologies for dealing with this issue. Based on the authors' experience, the outputs from these methodologies are understandably highly correlated and do not qualitatively alter the final estimation results. For instance, the daily series bb_sp that we converted shows a strong correlation coefficient of 0.995 with those obtained through the methods suggested by Denton (1971) and Litterman (1983).

The daily news-based EPU index is constructed using the archives of Access World News's News Bank service. This global database stores archives of thousands of newspapers and other news sources. The EPU index is based on more than a thousand US newspapers, ranging from large national papers, such as *USA Today*, to small local ones. The index is computed by determining the number of newspaper articles that contain the words *economy*, *uncertainty*, *legislation*, *deficit*, *regulation*, *Federal Reserve*, or *White House*. This number is then normalized by the total number of newspaper articles. The EPU index is updated daily for the current and past months.

We also include the daily index of the leading indicator of implied market volatility, the VIX. The CBOE introduced the first volatility index in 1993, which was known as the VXO. It was based on implied volatilities from at-the-money options on the S&P 100 index, using a methodology proposed by Whaley (1993). The CBOE used an alternative methodology in 2003 to calculate the VIX as a weighted sum of out-of-money option prices for all S&P 500 strikes in real time. Whaley (2009) discussed the public and media interest in the value of the VIX as a measure of volatility and explains the origin and purpose of creating the VIX and its role in explaining the state of the economy and equity markets.

The VIX is intended to measure the expected price fluctuations in the S&P 500 index options over the next 30 days. Market participants have used the VIX and its predecessor, the VOX, to gauge the market sentiment in the United States and around the world. We use the VIX as an indicator of the future financial market risk because the financial press quotes the VIX volatility index as a gauge of investor fear. Governmental agencies and central banks use the VIX to assess risk in financial markets. Previous research has shown that, though far from perfect, the VIX does have some forecasting power. Moreover, a strong association exists between the VIX and contemporaneous price dynamics: Positive shocks to the VIX are associated with declining markets and vice versa. It follows, therefore, that an elevated VIX portends weaker prices in the future. In that sense, the VIX captures both, fear and price dynamics—a high VIX indicates fear associated with market declines (e.g., Whaley, 2009).

4 | METHODOLOGY

Applying the multiplicative GM methodology, we drive short- and long-term volatility estimates. Daily S&P 500 return series and monthly NCFI and IP are the high- and low-frequency series included in the GM estimation of SRV and LRV in the S&P 500, respectively. Similarly, Engle et al. (2013) used monthly IP growth and monthly inflation as explanatory variables.

Having obtained estimates for SRV and LRV, we estimate a set of regressions that summarizes the relationship between the dependent variable (i.e., SRV or LRV) and the explanatory variables (i.e., the bb_sp, the EPU index, and the VIX). The following equation is the implicit regression model:

$$\text{S\&P volatility} = f\,(\text{bb\_}sp,\ \text{EPU},\ \text{VIX})\,. \tag{1}$$

Before testing the association of S&P 500 volatility with the potential explanatory variables, we examine the bb_sp, the VIX, and the EPU for possible structural breaks. If we find breaks in the series, we interpret them as a period of regime change. Volatility in S&P 500 in the short and long term will plausibly vary during these regime changes. The Markov switching and QR are well equipped to capture changes in the state of volatility. For instance, QRs appropriately examine the association of uncertainty indices with volatility at low-to-high quantiles of the volatility of S&P 500. Similarly, Markov switching regressions show the manner of transition of these relationships from one regime to another. Appropriate methodologies will be deployed to capture in the data their effects on the relationship among the variables. Furthermore, it is necessary to test each time series for stationarity. Visual inspection shows that the bb_sp appears stationary, and its graph shows no visible structural breaks, whereas the VIX and others exhibit structural breaks and appear not to be stationary. These issues are taken up next.

4.1 | Structural breaks and stationarity

We apply Bai and Perron's (2003) test of structural breaks and examine the stationarity of the series under study by deploying the augmented Dickey–Fuller (ADF; Dickey & Fuller, 1979) and the Phillips–Perron (PP; Perron & Phillips, 1987) tests. Tests of structural breaks and stationarity are well covered by the literature; in the interest of brevity, we do not pursue them here.

4.2 | GARCH–MIDAS

Bollerslev (1986) proposed the GARCH model to better capture the volatility clustering evidenced in financial markets. In a conventional autoregressive conditional heteroskedasticity (ARCH) time series model, a dependent variable is assumed to be homoscedastic. However, in financial markets, volatility demonstrates temporal heteroscedasticity. Volatility clustering exists for prices and rates of return. Periods of low volatility can follow periods of high volatility and vice versa. Heteroskedasticity in financial markets may be due to an irregular pattern of variation in market variables. For instance, markets exhibit higher volatility during periods of actual or perceived financial crises and remain calm during steady economic growth periods.

In this study, we use a class of component GARCH based on MIDAS regression models, which were introduced by Ghysels et al. (2004, 2016). MIDAS methodology offers a framework to incorporate variables of different frequencies to obtain multi-horizon volatility. We estimate that the GM model will generate the short- and long-term real volatilities in the daily returns of the S&P 500. The GM model includes monthly values of the NFCI and IP in the United States. The MIDAS regression model is expressed as

$$y_{t+k} = \alpha_0 + \alpha_1 x_t^m + \varepsilon_t^m, \tag{2}$$

where y_{t+k} is the k step-ahead value of the dependent variable at time t with the highest frequency, x_t^m may be a vector of independent variables at time t and m is the frequency matching that of y, ε_t^m is the random innovation at time t with m frequency, and α_0, α_1 are the intercept and a conformable vector of model coefficients. The expressions for ε_t and its variance in GARCH (1,1) specification are as follows:

$$\varepsilon_t = (\varepsilon_{t-j})\sqrt{\sigma_{\varepsilon,t}{}^2}$$

and

$\sigma^2_{\varepsilon,t} = f(\varepsilon_{t-1}, \sigma^2_{t-1})$, for GARCH (1,1) specification.

Following Engle et al. (2013), Ghysels et al. (2016), and Conrad and Kleen (2020), we combine the high-frequency daily data with low-frequency monthly data in the GM model. The conditional variance of innovations is decomposed into short- and long-term volatility components multiplicatively as

$$\sigma^2_{\varepsilon,t} = h_{i,t}\tau_t, \tag{3}$$

where h and τ capture the short-term volatility of the high-frequency data and the long-term volatility, respectively, given by Equations (4) and (6).

The short-term component of GM in Equation (3) is taken from Engle et al. (2013), which uses the GARCH process of Bollerslev (1986):

$$h_{i,t} = a_0 + a_1 \frac{\varepsilon^2_{t-1}}{\tau_t} + a_2 h_{i-1,t}. \tag{4}$$

The short-term volatility component h_{it} varies daily within period t that signifies the lower frequency. The short-term component of GM in this paper is taken from Engle et al. (2013), which uses the GARCH process of Bollerslev (1986). It is designed to capture daily volatility clustering and is a mean-reverting unit-variance GJR-GARCH (1,1) process. We rewrite Equation (4) to break down each coefficient into its estimated components as

$$h_{i,t} = (1 - \alpha - \gamma/2 - \beta) + (\alpha + \gamma|_{\varepsilon_{i-1,t}<0}) \frac{\varepsilon^2_{t-1}}{\tau_t} + \beta h_{i-1,t}. \tag{5}$$

Equation (6) is the basis for the long-term volatility for which the realized volatility is smoothed over K periods and will be expanded by adding low-frequency covariates:

$$\tau_t = m + \theta \sum_{k=1}^{K} \phi_k(w_1, w_2) x_{t-k}. \tag{6}$$

The short-term component accounts for the well-recorded volatility clustering in the daily S&P 500 returns. The long-term component is constant across days and changes at lower frequency, consistent with low-frequency series in the GM model, which in this paper is bimonthly, similar to the Conrad and Kleen (2020) specification. Equation (6) may be further enhanced to include other variables and their variances.

The weighting scheme in Equation (6) is given by

$$\phi_k(w_1, w_2) = \frac{(k/K)^{w_1-1}(1-k/K)^{w_2-1}}{\sum_{j=1}^{K}(j/K)^{w_1-1}\sum_{j=1}^{K}(1-j/K)^{w_2-1}}, \tag{7}$$

where
$\sum_k^K \phi_k(w_1, w_2) = 1.$

The weighting scheme in (7) generates hump-shaped or convex weights. As w_1 is restricted to 1 (see Conrad & Kleen, 2020; Su et al., 2017; Fang et al., 2018), the weighting scheme guarantees a decay pattern where the rate of decaying is determined by parameter w_2. The restricted weighting scheme boils down to
$\phi_k(w_2) = \frac{(1-k/K)^{w_2-1}}{\sum_{j=1}^{K}(1-j/K)^{w_2-1}}.$

4.3 | Regime switching Markov regression

In a regime switching framework, a random variable y may depend on a discrete state variable that is not observable. This regression model is appropriate when we believe that there are multiple regimes present in the data-generating process. At any time t, the process could be in state s_t. The switching model allows for a different regression model for each regime. The conditional mean of y_t in regime m, given a vector of switching regressors x and coefficients β_m and nonswitching vectors of regressors z_t and coefficients ϕ, is given by

$$\mu_t^{(m)} = x_t'\beta_m + z_t'\phi. \tag{8}$$

Assuming that the regression error ε_t is independently and identically distributed and its variance may be regime dependent, the regime switching regression model may be expressed by

$$y_t = x_t'\beta_m + z_t'\phi + \sigma_m\varepsilon_t. \tag{9}$$

Regime probabilities may be assumed to be a function of a vector of exogenous variables and parameters. The multinomial logit expression of the regime probabilities is given by

$$P(s_t = m|\Omega_{t-1}, \psi) = p_m(E_{t-1}, \psi) = \frac{\exp(E'_{t-1}, \psi_m)}{\sum_{j=1}^{M}\exp(E'_{t-1}, \psi_j)}. \tag{10}$$

where m is a given regime, p_m is the regime probabilities, Ω_{t-1} is the information set at time $t-1$, E_{t-1} is the vector of exogenous observable variables, and ψ represents model coefficients.

The model parameters are estimated through the iterative optimization of the log of the likelihood function, based on Equations (9) and (10), and given as

$$l(\beta, \phi, \sigma, \psi) = \sum_t^T \log\left\{\sum_{m=1}^{m}\frac{1}{\sigma_m}\varpi\left[\frac{(y_t-\mu_t(m))}{\sigma_m}\right]\cdot P(s_t = m|\Omega_{t-1}, \psi)\right\}. \tag{11}$$

The likelihood function in Equation (10) is maximized with respect to the parameters $\beta, \phi, \sigma, \psi$ using iterative nonlinear optimization methods. The regime probabilities are derived by filtering while optimizing Equation (11).

A variation of Equation (9) is a first-order Markov process where the probability of being in a regime depends on the previous state. Therefore, the transition probabilities are given by

$$p(s_t = j|s_{t-1} = i) = p_{ij}^t. \tag{12}$$

The transition matrix for M regimes may be written as

$$p(t) = \begin{pmatrix} p_{11}^t & \dots & a^t{}_{1M} \\ \vdots & \ddots & \vdots \\ a^t{}_{M1} & \cdots & a^t{}_{Mn} \end{pmatrix}. \tag{13}$$

Each row of the transition matrix in Equation (13) is defined by a distinct multinomial logit, as in Equation (9). By computing the one-step-ahead predictions of the regime probabilities and the Markov transition matrix, one may arrive at the one-step-ahead joint densities of the data and regimes in period t. The likelihood function for period t is the marginal probability distribution of the observed data, which is derived by summing the joint probabilities across unobserved states. The likelihood function is given in the following equation:

$$l(\beta, \phi, \sigma, \psi) = \sum_{j=1}^{M} f(x'_t\beta_m + z'_t\phi + \sigma_m\varepsilon_t, s_t|\Omega_{t-1}, \psi), \tag{14}$$

and is maximized by nonlinear methods to obtain the optimum values of the model parameters.

4.4 | Quantile regression

The extreme movements and structural breaks in the VIX and EPU series potentially have asymmetric effects on S&P volatility in the short and long term. Market participants and investors are not only sensitive to the smoothed association of the VIX and EPU with S&P volatility, but they are also interested in the impact of extreme up-and-down movements of the VIX and EPU and their association with S&P volatility. Structural breaks may be one source of extreme fluctuations in volatility.

QRs are well suited to accommodate the asymmetric dependence between dependent and explanatory variables. QR models are nonlinear (see, e.g., Galvao et al., 2020) and robust in the presence of extreme events and asymmetric dependence when the assumption of linearity may not be appropriate (see Geraci, 2019; Yu et al., 2003). They are superior to Ordinary Least Squares (OLS) estimates because they allow coefficient estimates to vary with the distribution of the dependent variable, thus accurately modeling the relationship between the explanatory variables and the dependent variable. Following is a brief explanation of QR.

Suppose that we have a random variable Y (S&P volatility) with a probability distribution function

$$F(y) = \text{Prob}(Y \leq y)$$

so that, for $0 < \tau < 1$, the τth quantile of Y may be defined as the smallest y satisfying

$$F(y) \geq \tau :$$

$$Q(\tau) = \inf\{y : F(y) \geq \tau\}.$$

The empirical distribution function is given by

$$F_n(y) = \sum_{s} l(Y_i \leq y),$$

where $l(.)$ is a binary function that takes the value 1 if $Y_i \leq y$ is true and 0 otherwise. The resulting empirical quantile is given by

$$Q_n(\tau) = \inf\{y : F(y) \geq \tau\}.$$

Alternatively, the empirical quantile may be expressed as an optimization problem as

$$Q_n(\tau) = \arg\min\left\{\sum_i \rho_\tau(Y_i - \omega)\right\},$$

where $\rho_\tau(w) = w(\tau - 1(w < 0))$, which asymmetrically assigns weights to positive and negative values in the estimation process.

The extension of this methodology that allows for regressors X is the QR. We assume a linear specification for the conditional quantile of the dependent variable SPRB was given values for the vector of explanatory variables X such that:

$$Q(\tau|X_i, \beta(\tau)) = X_i'\beta(\tau), \tag{15}$$

where in Equation (15) $\beta(\tau)$ is the vector of coefficients associated with the τth quantile.

Then, the conditional QR estimator can be shown to be

$$\beta_n(\tau) = \arg\, min_{\beta(\tau)}\left\{\sum_i \rho_\tau(Y_i - X_i'\beta(\tau)\right\}.$$

The QR estimator is derived as the solution to a linear programming problem. We use a modified version of the Koenker and D'Orey (1987) version of the Barrodale and Roberts (1973) simplex algorithm.

Under mild regularity conditions, QR coefficients may be shown to be asymptotically normally distributed (see Koenker & Ng, 2005) with the asymptotic covariance matrix, depending on the model assumptions. The coefficient covariance matrices in QR analysis are obtained from estimated nuisance quantities.

In this paper, we relax the assumption that the quantile density function does not depend on X. The asymptotic distribution of $\sqrt{n(\hat{\beta}(\tau) - \beta(\tau)}$, under the identically and not independently distributed assumption, is expressed in the Huber sandwich form (see, among others, Hendricks & Koenker, 1992),

$\tau(1-\tau)H(\tau)^{-1}JH(\tau)^{-1}$, where $J = \lim_{n\to\infty}(\sum_i X_i X_i'/n)$,

$H(\tau) = \lim_{n\to\infty}(\sum_i X_i X_i' f_i(q_i(\tau))/n)$,

where $f_i(q_i(\tau))$ is the conditional density function of the response, evaluated at the τth conditional quantile for individual i. We deploy the Powell (1986) kernel method based on residuals of the estimated model.

The Powell (1986) kernel approach computes a kernel density estimator, using the residuals of the original fitted model,

$$\hat{H} = 1/n \sum b_n^{-1} K(\vartheta(\tau)/b_n X_i X_i',$$

where K is a kernel function that integrates to 1, and b_n is a kernel bandwidth. For bandwidth specification, we employ a method suggested by Hall and Sheather (1988) and a kernel bandwidth suggested by Koenker and Ng (2005). Koenker and Machado (1999) defined a pseudo R-squared for the goodness-of-fit statistic for QR that is analogous to the R-squared from conventional regression analysis.

5 | EMPIRICAL FINDINGS

5.1 | Structural breaks and stationarity

The Bai–Perron test signals four structural breaks in the VIX that occurred around April 2003, September 2008, January 2012, and July 2017. The break dates in the EPU roughly coincide with those of the VIX and could be due to the same events. The first break appears to coincide with several notable events in the world. The most significant of these events was the invasion of Iraq by the US and UK coalition that was not authorized by the United Nations, which unleashed political and economic uncertainty that was significant. Furthermore, 2003 was the year of numerous politically motivated attacks in Saudi Arabia and Turkey, among other places. The most significant economic jolt of September 2008 was the onset of a financial crisis that began in the US mortgage-backed bond market and rapidly spread to the global financial network. The third break in the data coincides with several important events in the United States and around the world. Hurricane Sandy inflicted huge costs on the US economy and temporarily disrupted the supply chain while threatening economic growth in the United States. Political crises in Iraq and Syria were sources of uncertainty in the Middle East and spanned global economies. Among other geopolitical events, North Korean missile tests and territorial disputes between China and its neighbors added fuel to uncertainty around the globe. The final break could have been caused by Britain's triggering its departure proceedings from the European Union, which required Britain to invoke Article 50 of the Lisbon Treaty. Upon news of this event, markets dropped, and the British pound weakened.

Examining the graphs of the short- and long-term S&P 500 volatilities and the three series, bull and bear spread, VIX, and EPU, suggests possible mean and covariance stationarity. To confirm the graphic evidence (not presented, for the purpose of brevity), we conducted formal statistical tests. Table 1, Panel B presents the statistical evidence of the behavior of these series. As shown, all variables under study are found to be stationary, employing the ADF, PP, and unit root test with break points test statistics.

TABLE 1 Break points, diagnostics, and summary (1/03/2000–4/30/2018).

Panel A: Bai–Perron test of structural breaks					
	VIX	**EPU**		**VIX**	**EPU**
Break test	***F*-Statistic**	***F*-Statistic**	**Critical value**[a]	**Dates**	**Dates**
0 vs. 1[b]	622.61	269.77	8.58	4/22/2003	5/1/2003
1 vs. 2[b]	732.93	211.39	10.13	9/09/2008	9/14/2007
2 vs. 3[b]	854.50	288.92	11.14	1/20/2012	10/04/2012
3 vs. 4	85.36	194.06	11.83	7/14/2017	4/04/2016
Unit root tests 1/03/2000–30/2018					
Panel B: Levels					
	_bb_sp	**EPU**	**VIX**	**SRV**	**LRV**
ADF	−7.007[b]	−29.114[b]	−9.331[b]	−12.876[b]	−7.707[b]
PP	−6.290[b]	−54.604[b]	−6.962[b]	−6.310[b]	−5.273[b]
With structural break	−7.006[b]	−29.110[b]	−8.743[b]	−13.351[b]	−4.593[b]
DWH exogeneity test (difference *J*-statistic)				4.542	5.737
Null hypothesis: regressors are exogenous					
Panel C: Summary descriptive statistics for model variables. All variables are in level					
Mean	0.067	105.542	19.854	1.070	1.068
Stand Dev	0.117	80.769	8.963	1.109	0.985
Skewness	0.153	2.683	2.214	5.883	5.084
Kurtosis	2.901	14.112	10.592	58.931	93.880
Jarque-Bera test (J–B)	23.365[b]	32,935.15[b]	16,753.02[b]	708,325.400[b]	383,751.000[b]

Note: Bai and Perron (2003) (Econometric Journal), critical values. The null hypothesis for ADF and PP tests is that a series is nonstationary. Intercepts were included in the PP tests. The ADF test is performed with break point possibility and includes both a trend and an intercept. Unit root tests with break points tests include a trend and intercept in regressions. Break selection is based on the Dickey–Fuller t statistic minimization. DWH tests the null of exogeneity by comparing the difference in J-statistics from restricted and unrestricted models based on critical values of chi-squared distribution. Insignificant test statistic means that the null hypothesis is not rejected.

Abbreviations: ADF, augmented Dickey–Fuller; DWH, Durbin–Wu–Hausman; Patrick (2021) EPU, economic policy uncertainty; LRV, long-run volatility; PP, Phillips–Perron; SRV, short-run volatility.

[a]Bai–Perron (Econometric Journal, 2003) critical values.

[b]Represents significance at 1% level.

5.2 | Markov switching regression results

Table 2 shows the coefficient estimates of the GM model that produces the short-term and long-term volatility components of the realized volatility in S&P 500. The estimated β is 0.861 and statistically significant, suggesting strong persistence in the short-term volatility component. Su et al. (2017) found similar results in their research. The α and Υ coefficients are also statistically significant in Equation (4). The θ coefficients represent the changes in the long-term volatility stemming from the lagged effects of the IP and NFCI. The coefficient θ is positive and statistically significant; therefore, the long-term volatility is directly associated with IP. The rise in NCFI and the long-term volatility are negatively associated as shown by the negative and

TABLE 2 Generalized autoregressive conditional heteroskedasticity–mixed-data sampling (GARCH–MIDAS) with two covariates, change in industrial production and national financial confidence index (NFCI).

μ	2.176[a]
	(0.011)
α	1.2e − 8
	(0.012)
β	0.861[a]
	(0.017)
Υ	0.189[a]
	(0.024)
m	0.306[a]
	(0.104)
θ	1.007[a]
	(0.094)
w_2	172.1[a]
	(16.045)
θ_2	−1.385[a]
	(0.062)
w2_2	53.898[a]
	(15.520)

[a]Significant at 1% level.

statistically significant θ_2, which is plausible. A rise in the financial confidence index represents growing investor confidence and thus could lead to a fall in the long-term volatility component of S&P 500.

Before estimating the MSR estimation of Equation 1, it is essential to determine if there is any endogeneity in the equation. We address this concern by testing the endogeneity among SRV, LRV, and the explanatory variables in Equation (1) using the Durbin–Wu–Hausman test.

Our analysis, presented in Table 1, confirms that the null hypothesis of exogeneity of the uncertainty variables is statistically supported, indicating that endogeneity is not an issue in our model.

Table 3 presents the estimation results of the MSR. The results show that, for the periods of high volatility (regime 1), the EPU and the VIX are not salient in the minds of market participants. The association between both indicators of uncertainty and the short- and long-term volatilities is either statistically insignificant or has the wrong sign. The rationale may be that the marginal uncertainty introduced into the market by these two measures of uncertainty is not considerable. However, under the regime of low volatility and calmness in the market, the association of the volatility with the EPU and the VIX is positive and statistically significant. This suggests sensitivity among market participants to the EPU and the VIX. Therefore, we can conclude that the attitude of market participants regarding the VIX and the EPU is dependent on the volatility regime in the marketplace. Lin and Zhang (2015), Su et al. (2019), Tsai (2017), and Chang (2022) also found a positive association between EPU and volatility in equity markets. The variable bullish and bearish sentiment spread on S&P 500 (sbb_sp) is associated with the LRV under both regimes, but

TABLE 3 Markov switching estimation of Equation (1).

	Regime	C	_bb_sp	EPU	VIX	LN(σ)
SRV	Regime 1	3.034[a]	0.045	8.97×10^{-5}	−0.046[a]	0.507[a]
		(0.169)	(0.334)	(0.0007)	(0.008)	
SRV	Regime 2	0.579[a]	0.252[a]	0.0004[a]	0.002[a]	−1.238[a]
		(0.018)	(0.032)	(6.53×10^{-5})	(0.0006)	
LRV	Regime 1	3.304[a]	0.018[a]	−0.0009	−0.056[a]	0.373[a]
		(0.152)	(0.035)	(0.0006)	(0.008)	
LRV	Regime 2	0.635[a]	0.415[a]	0.0004[a]	0.001[b]	−1.158[a]
		(0.015)	(0.035)	(6.5×10^{-5})	(0.0006)	

Note: Significance indicates nonstationary. Numbers in parentheses are root mean squared errors (RMSE). SRV and LRV represent short- and long-run volatilities in S&P 500 from GARCH–MIDAS model (1/03/2000–8/20/2020).
Abbreviations: EPU, economic policy uncertainty; LRV, long-run volatility; SRV, short-run volatility.
[a]Represents significance at 1% level.
[b]Represents significance at 10% level.

TABLE 4 Short-term volatility transition summary: constant Markov transition probabilities and expected durations.

	SRV		LRV	
	Low volatility	High volatility	Low volatility	High volatility
Low volatility	0.987	0.012	0.993	0.006
High volatility	0.038	0.961	0.020	0.979
Constant expected durations	77.550	26.279	165.415	48.282

Note: SRV and LRV represent short- and long-run volatilities in S&P 500 from GARCH–MIDAS model (1/03/2000–8/20/2020).

not with the SRV. It is indicating that it takes some time for market participants to form their sentiment toward volatility on the basis of the _bb_sp.

Table 4 summarizes the transition probabilities from low and high volatilities for both short- and long-term volatilities in the S&P 500. It appears that the probability of transitioning from low to high volatility or in reverse is quite low. However, the S&P 500 experiences longer periods of low volatility compared to those of high volatility. Therefore, as we said, and as supported by anecdotal observations, during a long period of a low-volatility regime, market participants are expected to be sensitive to uncertainties in economic policy and the VIX. Incidents of cataclysmic events that significantly roil markets are not common. Our volatility forecasts are based on data that do not include the period of extreme shock and volatility, in this case, COVID-19. Thus, forecasts are for normal levels of volatility that equity markets exhibit. In the past, equity markets shrugged off shocks such as the Avian influenza (H5N1) and the severe acute respiratory syndrome coronavirus.

Figures 1 and 2 plot the predicted one-step transition probabilities of being in low- and high-volatility regimes for the short- and long-term volatilities. These probabilities are derived from the MSR estimations of Equation (1). The constant transition probabilities and the expected duration of each regime for both volatility measures are presented in Table 4. It is evident that the low-volatility regimes are expected to last longer than the high-volatility regime. Therefore, policy uncertainties and the VIX will be critical more often than not, which is plausible and indicates that equity markets do not favorably perceive uncertainties stemming from policy decisions or financial turbulence.

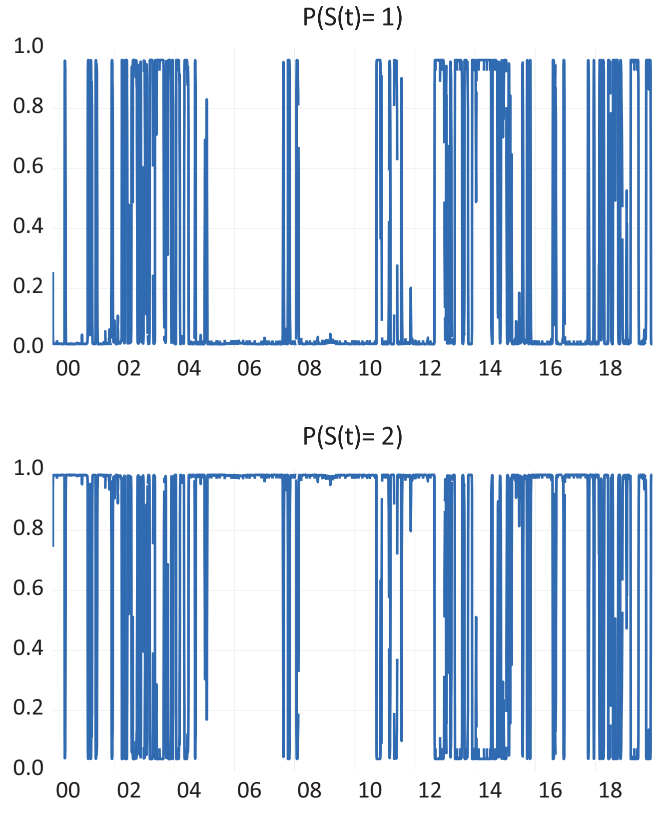

FIGURE 1 Markov switching transition probabilities for short-run S&P500 volatility (1/03/2000–8/20/2020). [Colour figure can be viewed at wileyonlinelibrary.com]

5.3 | Quantile regression results

The QR estimation results are presented in Tables 5 and 6 for the short- and long-term volatility estimates of the S&P 500. The QR estimates the coefficients at various quantiles of the distribution of the S&P 500 volatility and, thus, is better suited to capture the relationship among the variables in the presence of heteroscedasticity and at extreme levels of the distribution as well as the conditional median. The Lagrange Multiplier test for ARCH effects shows the presence of ARCH effects in the SRV but not LRV. The QR estimates remain robust and reliable in the presence of ARCH effects.

Consistent with the MSR findings, the association of the EPU and the VIX with the short- and long-term volatilities of the S&P 500 depends on the quantile under study. For instance, in the first quantile, the associations of the SRV and the LRV with the two measures of uncertainty are virtually identical, statistically significant, and have the expected positive sign. Therefore, under calm conditions in the market, market participants are sensitive to variations in the information content of the VIX and the EPU. However, the same observation is not supported at the last quantile, when markets may be turbulent and the effect of marginal news content in the EPU and the VIX is not as noticeable. We conclude that, during periods of high volatility, the EPU and the VIX may not be the salient factors for market participants. However, that may change during periods of calm in financial markets. There is research in support of this phenomenon. Edwards et al. (1995) analyzed media coverage of issues in the context of elections. They estimate logit models of public opinion polls and time series regression of the relationship between salient issues and presidential approval. They confirm that the public perception of salient issues varies over time.

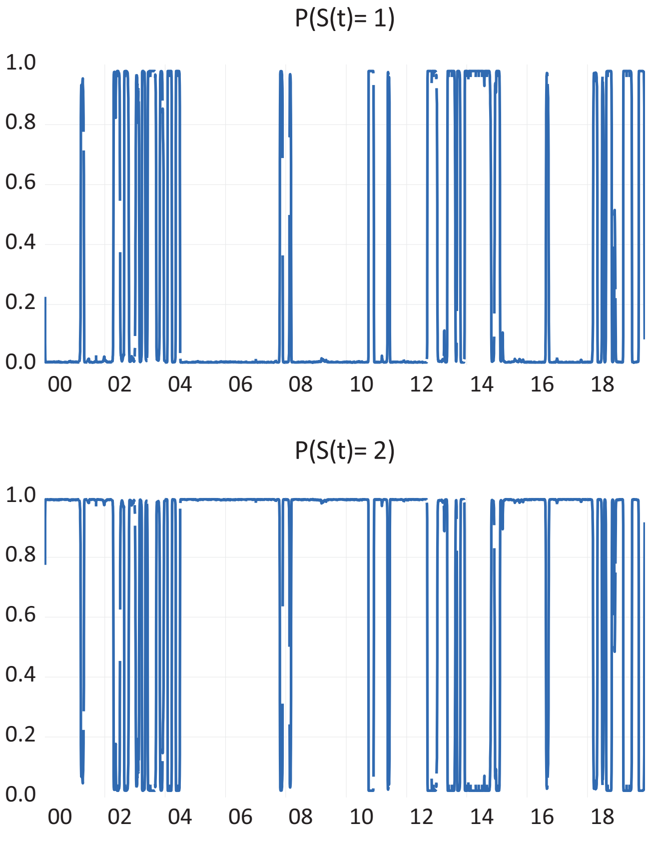

FIGURE 2 Markov switching transition probabilities for long-run S&P500 volatility (1/03/2000–8/20/2020). [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Quantile regression estimation of Equation (1), short-term volatility of S&P 500.

SRV	First Q	*C*	sp_bb_sp	EPU	VIX	Ps_R2	Quasi_LR
		0.239[a]	0.249[a]	0.005[a]	0.001[a]	0.017	131.084
		(0.011)	(0.029)	(5.8×10^{-5})	(0.005)		
SRV	Fifth Q						
		0.786[a]	0.456[a]	0.0001	−0.0009	0.0009	69.516
		(0.026)	(0.048)	(0.001)	(0.0009)		
SRV	Ninth Q						
		2.352[a]	1.866[a]	−0.0002	−0.022[a]	0.034	103.312
		(0.086)	(0.372)	(0.0004)	(0.022)		
SRV	OLS						
		1.240[a]	0.512[a]	7.50×10^{-5}[a]	−0.011[a]	0.016	−7664.342
		(0.045)	(0.092)	(0.0002)	(0.002)		

Note: The values of *R*-squared and likelihood ratio functions for the OLS estimates and pseudo *R*-squared and quasi-likelihood ratio functions are in the last two columns. Huber sandwich standard errors and covariances. Method of Epanechnikov kernel, and Hall–Sheather residuals bandwidth (bw = 0.025648). SRV and LRV represent short- and long-run volatilities in S&P 500 from GARCH–MIDAS model (1/03/2000–8/20/2020).

Abbreviation: EPU, economic policy uncertainty.

[a]Represents significance at 1% level.

TABLE 6 Quantile regression estimation of Equation (1), long-term volatility of S&P 500.

LRV	First Q	*C*	bb_sp	EPU	VIX	Ps_R2	Quasi_LR
		0.257[a]	0.239[a]	0.0006[a]	0.001[a]	0.026	197.322
		(0.010)	(0.028)	(5.07×10^{-5})	(0.0004)		
LRV	Fifth Q						
		0.875[a]	0.474[a]	9.39×10^{-5}	−0.003[a]	0.014	106.786
		(0.026)	(0.048)	(0.001)	(0.001)		
LRV	Ninth Q						
		2.470[a]	0.913[a]	−0.0006[a]	−0.027[a]	0.051	201.706
		(0.086)	(0.372)	(0.0003)	(0.002)		
LRV	OLS						
		1.275[a]	0.425[a]	1.52×10^{-5}	−0.012[a]	0.019	−700.502
		(0.040)	(0.083)	(0.0002)	(0.002)		

Note: The values of *R*-squared and likelihood ratio functions for the OLS estimates and pseudo *R*-squared and quasi-likelihood ratio functions are in the last two columns. Huber sandwich standard errors and covariances. Method of Epanechnikov kernel, and Hall–Sheather residuals bandwidth (bw = 0.025648). SRV and LRV represent short- and long-run volatilities in S&P 500 from GARCH–MIDAS model (1/03/2000–8/20/2020).

Abbreviation: EPU, economic policy uncertainty.

[a]Represents significance at 1% level.

These OLS estimation results, which predict the association of the variables based on the conditional mean of the S&P 500 volatility for both the SRV and the LRV, would be misleading. For instance, Tables 5 and 6 show that OLS estimation results cannot distinguish between periods of high and low volatilities because they are averaging the estimates for both periods.

Figure 3 shows the coefficient evolution process through quantiles for the SRV. It shows the responses of the short-term volatility in every quantile to each measure of market volatility holding all else constant. The VIX and the EPU show a decreasing association with short-term volatility in the S&P 500. This observation supports the findings of the MSR estimates and shows that these associations are dynamic and that coefficient signs and statistical significance are regime dependent. The coefficients of thesbb_sp remain positive; however, their statistical significance may change, as evidenced by the results in Table 3. Figure 4 is qualitatively almost identical to Figure 1.

6 | SUMMARY AND IMPLICATIONS

This paper investigates the association of the US EMV, represented by the volatility in the S&P 500 index, with economic and financial fundamentals as well as variables that reflect uncertainties in the market and government policies. Importantly, we study the role that these uncertainties play jointly, in long- and short-term volatility patterns. Our sample data cover the time period from 2000 to 2018. To estimate the EMV, we deploy a two-covariate GM model. This model has been proven superior to other variations of GARCH models in terms of its predictive power as well as its ability to simultaneously deliver the short- and long-term predictions of volatility. The short- and long-term S&P 500 volatility estimates are further examined to assess their reaction to uncertainties in economic policies, the bull and bear sentiment spread, and the implied risk measured by the CBOE VIX across market regime changes. Markov switching and QRs are suitable to

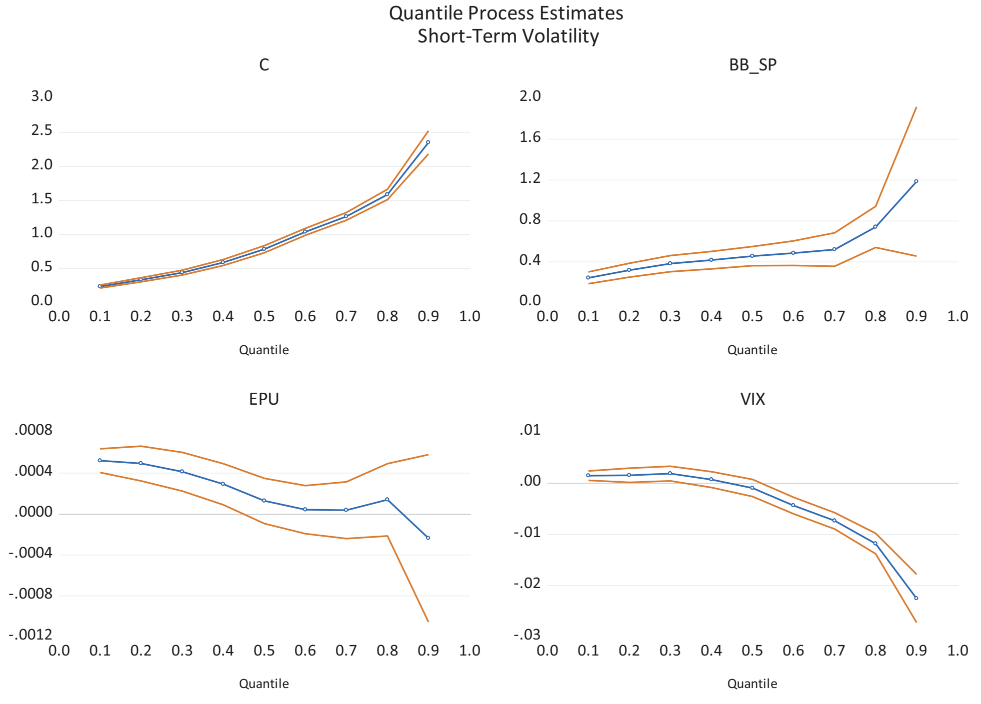

FIGURE 3 Coefficient estimate process for SRV regressions through quantiles (1/03/2000–8/20/2020). [Colour figure can be viewed at wileyonlinelibrary.com]

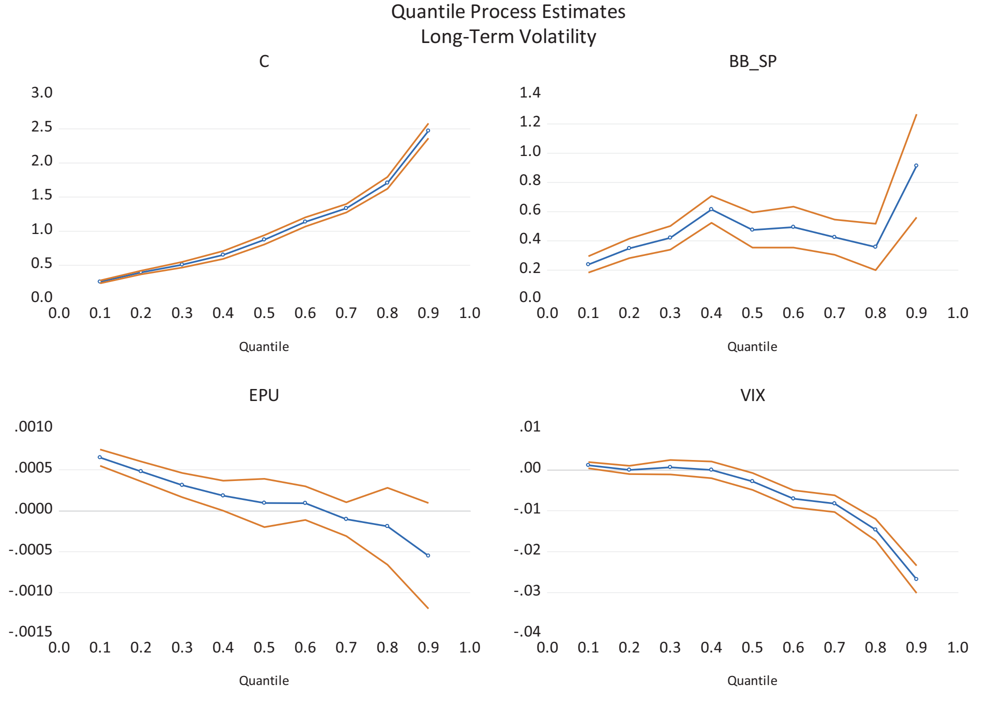

FIGURE 4 Coefficient estimate process for LRV regressions through quantiles (1/03/2000–8/20/2020). [Colour figure can be viewed at wileyonlinelibrary.com]

delineate the association of volatility with uncertainty indicators during the low- and high-volatility periods.

Our findings from MSR and QR suggest that this association varies across high- and low-volatility regimes in the market. Specifically, only under a low-volatility regime is S&P 500 volatility sensitive to uncertainties stemming from government policies and other measures of market risk. The results, in general, are an endorsement of the MSR and QR because we find differences in the S&P 500 volatilities across the economic regime changes. The finding that economic certainty indicators such as EPU and VIX matter less in high-volatility regimes is somewhat intuitive. Major volatility events are often unrelated to prevailing sentiment regarding markets or the economy. Sentiment or uncertainty indicators will be weakly associated with the sharp rise in volatility in such cases. On the other hand, sentiment and uncertainty change when volatility is low (markets are calm) and can be expected to provoke large investor responses.

Volatility plays a central role in all options and derivative pricing frameworks. Volatility in the underlying asset's returns is also a source of contango and backwardation in futures contract prices. Findings of our paper provide valuable information to investors, speculators, and other equity market participants regarding the behavior and volatility of S&P 500. Market participants may be able to devise hedging strategies by taking defensive positions using options and futures contracts. Our findings confirm that movements in bb_sp and VIX would be informative for planning such hedging strategies in the US equity markets. Moreover, as we show, short- and long-term volatilities, VIX,_bb_sp, and EPU are stationary over time showing that their association with volatility in S&P 500 is expected to remain stable and informative in the future.

We make two contributions to literature. First, we confirm that sentiment and uncertainties do matter to LRV. Statistical modeling of volatility should consider the association of such behavioral finance metrics in explaining volatility patterns such as volatility clustering/persistence. Second, we use a more robust form of GM combined with the Markov switching and QRs. In doing so, we show the importance of the framework in effectively capturing the regime-related behavior of volatilities in S&P 500.

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