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Forecasting stock price volatility: New evidence from the GARCH-MIDAS model

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ABSTRACT

This paper introduces a combination of asymmetry and extreme volatility effects in order to build superior extensions of the GARCH-MIDAS model for modeling and forecasting the stock volatility. Our in-sample results clearly verify that extreme shocks have a significant impact on the stock volatility and that the volatility can be influenced more by the asymmetry effect than by the extreme volatility effect in both the long and short term. Out-of-sample results with several robustness checks demonstrate that our proposed models can achieve better performances in forecasting the volatility. Furthermore, the improvement in predictive ability is attributed more strongly to the introduction of asymmetry and extreme volatility effects for the short-term volatility component.

1. Introduction

Accurate modeling and forecasting of the stock market volatility plays a crucial role in financial regulation, portfolio decisions, risk management, credit derivatives and other fields, which affect financial market participants' decision-making processes. Financial regulatory authorities pay a great deal of attention to the stock market volatility in order to avoid the volatility spillover effect of radical changes in the global financial markets. Market investors even track the stock market volatility in real time so as to optimize portfolio strategy and avoid market risk. Therefore, the issue of forecasting the stock market volatility has attracted the attention of many scholars (see e.g. Andersen, Bollerslev, Diebold, & Labys, 2003; Corsi, 2009; Fuertes, Izzeldin, & Kalotychou, 2009; Patton & Sheppard, 2015; Poon & Granger, 2003).

Traditionally, the stock volatility has been forecast by utilizing the GARCH model and its extensions (see e.g. Bekaert & Hoerova, 2014; Bollerslev & Mikkelsen, 1996; Dueker, 1997; Hansen & Lunde, 2005; Wang & Wu, 2012). However, GARCH-class models are strictly limited to using data at the same frequency, so they are not suitable for investigating the main drivers of long-term financial market volatility (Ghysels, Santa-Clara, & Valkanov, 2006). Recent studies have documented that the GARCH-MIDAS class specifications proposed by Engle, Ghysels, and Sohn (2013) demonstrate superior forecasting abilities for the stock volatility (see e.g. Asgharian, Hou, & Javed, 2013; Girardin & Joyeux, 2013). The notable advantage of this model over the traditional GARCH-class models is that it can decompose the total conditional variance of the conventional GARCH model into two parts: short-term volatility, with a high frequency captured by a GARCH process, and long-term volatility, with a low frequency. Because of this advantage, GARCH-MIDAS is employed widely in empirical studies (see e.g. Asgharian, Christiansen, & Hou, 2015; Fang, Chen, Yu, & Qian, 2018; Pan, Wang, Wu, & Yin, 2017).

The asymmetry effect first examined by Black (1976) implies that asset returns and volatilities respond differently to bad news and good news. Since an asymmetric volatility implies negatively-skewed return distributions,

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i.e., it can help to explain some of the probability of large losses, many studies consider the asymmetry effect in GARCH-class models when forecasting the stock volatility. The related results show that the asymmetric GARCH-class models seem to perform better than the symmetric GARCH models (see e.g. Alberg, Shalit, & Yosef, 2008; Awartani & Corradi, 2005; Byun & Cho, 2013; Pan & Liu, 2018). Nevertheless, to the best of our knowledge, the impact of the asymmetry effect for GARCH-MIDAS class models has not received sufficient attention. Recently, Asgharian, Christiansen, and Hou (2018) extended the GARCH-MIDAS model by incorporating asymmetry in the long-term component of macro variables; however, as a first step in this research, we extend the GARCH-MIDAS model to account for the asymmetry effect both in the long- and short-term volatility components.

One shortcoming of the standard GARCH-MIDAS model is that it does not accommodate extreme market events, which has been considered to provide a complementary understanding of the stock market volatility. In particular, when events occur, people are concerned more with large stock price fluctuations than with mild fluctuations. Various exogenous events, such as regional wars, political affairs and financial crises, have been found to produce violent fluctuations in the stock volatility (see e.g. Chan & Wei, 1996; Ma, Ji and Pan, 2019; Ma, Liao, Zhang and Cao, 2019; Nikkinen, Omran, Sahlström, & Äijö, 2008; Schwert, 2011). For example, Choudhry (2010) notes that the majority of the wartime events in World War II that historians label important resulted in structural breaks in the stock return volatility. Schwert (2011) confirms the existence of high levels of volatility following recent periods of market stress, such as the stock crash of 1987 and the subprime mortgage crisis of 2007, regardless of whether the volatility is measured in monthly returns, daily returns, or 15-minute returns. Hence, extreme events are related closely to extreme volatility, which is generally defined as the potential for significant adverse deviations from the expected prediction results. According to Jacob (2007), the GARCH model's forecasting performance can also be improved by including extreme value estimators. For this reason, we address the effect of the extreme volatility when stock markets face extreme shocks. Furthermore, similarly to existing studies (see, e.g., Andersen, Bollerslev, & Diebold, 2007; Behrens, Lopes, & Gamerman, 2004; Gençay, Selçuk, & Ulugülyağci, 2003), we identify extreme volatility naturally based on thresholds in excess of some critical value for the stock return. Therefore, we usually call this effect the threshold effect instead of the extreme volatility effect. We introduce threshold effect characteristics to the GARCH-MIDAS model and examine whether the GARCH-MIDAS model that contains the threshold effect can forecast better than the standard GARCH-MIDAS model without the threshold effect.

Through the discussion that both the asymmetry and threshold effects have significant impacts on the stock volatility forecasting, this study modifies the GARCH-MIDAS model by adding the two effects in order to capture the leverage effect and the extreme risk phenomenon in stock markets. Our extended model accounts for (a) the influence of extreme events on the stock volatilities of small and large news, (b) the asymmetric responses of the stock return volatility to good versus bad news, and (c) the predictive accuracy of our extended volatility models.

In contrast to previous studies, we contribute to the literature on stock volatility predictability in three dimensions. First, due to many factors, such as extreme weather events, political disputes, and economic policies, the statistical property of volatility undergoes major changes. Because of these factors, we intend to characterize the extreme volatility effect to account for both the short-term and long-term components in GARCH-MIDAS class models. To this end, we adopt the volatility thresholds in GARCH-MIDAS models for extremely negative and positive returns, respectively, and construct new volatility models in order to provide a new perspective on modeling and forecasting the stock volatility. Following Arısoy, Altay-Salih, and Akdeniz (2015) and Huang (2015), the thresholds are determined by the empirical quantile of the return. Furthermore, the proposed models are instrumental, as McNeil and Frey (2000) note that the prediction accuracy can be improved significantly by considering the influence of extreme events, particularly in stock markets, where large volatility shocks are quite common because the stock market volatility is characterized by different dynamics under different market conditions. As far as we know, there have been no studies to date in which the extreme volatility effect is described in a GARCH-MIDAS framework. The present study will fill this gap.

Second, Mele (2007) shows that the asymmetry effect is an important factor that contains information that influences the stock price volatility, and Annaert, De Ceuster, and Verstegen (2013) show that extreme shocks in stock markets increase the future volatility. Therefore, we modify the standard variance equations in the GARCH-MIDAS model by adding dummy variables for the asymmetry and threshold effects together. Based on different combinations of asymmetric and threshold financial asset volatilities in the short-term and long-term components, we develop a total of 15 extensions of the GARCH-MIDAS model. The new models can describe the impact of not only 'good' and 'bad' news (information asymmetries), but also 'small' and 'large' news (the extreme volatility effect) on the stock volatility. Therefore, we can investigate those models in order to gain new insights, and we begin by investigating the simultaneous impacts of asymmetry and threshold effects on forecasting the stock price volatility.

Finally, our third contribution is an empirical comparison of the standard model, the asymmetry model, the threshold model, and the asymmetry-threshold model in the framework of the GARCH-MIDAS model fitted to daily S&P 500 returns. Five loss function criteria are employed for evaluating the forecasting performances of 15 extended GARCH-MIDAS models when large fluctuations occur. Furthermore, by using the model confidence set (MCS) test (Hansen, Lunde, & Nason, 2011), we find consistent evidence that the estimated asymmetry-threshold models are closer to the observed sample than models that incorporate either the asymmetry effect or the extreme volatility effect. Although none of the models emerges as clearly the best in the out-of-sample period, it seems that models that include both asymmetry and extreme volatility effects can improve the predictability of the stock volatility. Moreover, the proposed GARCH-MIDAS models can also be used to forecast the future volatilities of other markets, such as the oil, bond, and exchange markets.

We employ the daily price data of the S&P 500 index from 1993 to 2016 in our forecasting analysis. Fifteen extended GARCH-MIDAS models are used to generate forecasts. The MCS test, using five loss function criteria, is employed for evaluating the models' forecasting performances. We find that models that contain the asymmetry and extreme volatility effects perform best, while the standard model performs worst out-of-sample, which implies that considering both the asymmetry effect and the extreme volatility effect can improve the predictability of the stock volatility. More specifically, we find significant evidence that (a) bad news has a greater influence than good news, (b) negative and positive extreme shocks have significant, somehow differential impacts on the stock volatility, (c) the stock volatility is more likely to be affected by negative extreme shocks than by positive extreme shocks, and (d) both the asymmetry effect and the extreme volatility effect can affect the stock volatility in both the long term and the short term, though the impact of effects in the short term is greater. These conclusions are robust and reliable for different benchmarks and threshold windows.

The remainder of this paper is organized as follows. Section 2 presents the methodology of our asymmetry-threshold GARCH-MIDAS model. Section 3 describes the data. Section 4 shows the in-sample and out-of-sample empirical results. The final section concludes the paper.

2. Methodology

This section provides brief descriptions of the standard GARCH-MIDAS model and of the corresponding models extended by capturing the asymmetry and extreme volatility effects.

2.1. Standard GARCH-MIDAS model

Let $r_{i,t}$ be the log return on day i in month t; then, the GARCH-MIDAS model proposed by Engle et al. (2013) and Engle and Rangel (2008) can be described as the following process:

$$r_{i,t} - E_{i-1,t}\left(r_{i,t}\right) = \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \forall i = 1, 2, \ldots, N_t \tag{1}$$

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

where N_t is the number of trading days in month t; $E_{i-1,t}()$ is the conditional expectation, given information up to time $(i - 1)$; and $\psi_{i-1,t}$ denotes the information set up to day $i - 1$ of period t. Obviously, the volatility has two separate components: $g_{i,t}$ denotes the short-term component, which accounts for daily fluctuations, and τ_t represents the long-term component, which initially is assumed to be fixed for month t.

Assuming that $E_{i-1,t}\left(r_{i,t}\right)$ is equal to μ, Eq. (1) can be written as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \forall i = 1, 2, \ldots, N_t. \tag{3}$$

The short component $g_{i,t}$ is driven by the following standard GARCH (1,1) process:

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}, \tag{4}$$

where $\alpha > 0$, $\beta > 0$, $\alpha + \beta < 1$.

The long component τ_t is captured as the smoothed realized volatility of the MIDAS regression:

$$\tau_t = m + \theta\sum_{k=1}^{K}\varphi_k(\omega_1, \omega_2)RV_{t-k}, \tag{5}$$

where RV_t denotes the fixed time span realized volatility (RV) at time t:

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2, \tag{6}$$

and $\varphi_k(\omega_1, \omega_2)$ is the function that defines the weighting scheme of MIDAS filters. For the weighting function, Engle et al. (2013) propose both the beta and exponentially weighted lag structures. Ghysels, Sinko, and Valkanov (2007) indicate that the beta polynomial is more flexible and used more commonly for accommodating various lag structures. Thus, we consider only the beta function, which is written as follows:

$$\varphi_k\left(\omega_1, \omega_2\right) = \frac{(k/K)^{\omega_1-1}\left(1-k/K\right)^{\omega_2-1}}{\sum_{j=1}^{K}\left(j/K\right)^{\omega_1-1}\left(1-j/K\right)^{\omega_2-1}}, \tag{7}$$

and we set ω_2 equal to one so that φ is a monotonic function of ω_1.

There are two kinds of estimation methods for estimating the GARCH-MIDAS model: fixed-window and rolling-window. As was discussed by Angelidis, Benos, and Degiannakis (2004) and Degiannakis, Livada, and Panas (2008), the use of restricted rolling window samples in out-of-sample forecasting can capture the changes in market activity more effectively. Specifically, the rolling window scheme employs a fixed rolling window that allows the parameters to be re-estimated on a daily basis. It removes the restriction that τ_t is fixed for month t, and we let τ and g both change at a daily frequency. Therefore, we capture the information updated in the long term by considering a rolling window scheme, defined as follows:

$$\tau_i^{(r\omega)} = m_i^{(r\omega)} + \theta_i^{(r\omega)}\sum_{k=1}^{K}\varphi_k(\omega_1, \omega_2)RV_{i-k}^{(r\omega)}, \tag{8}$$

where $RV_i^{(r\omega)} = \sum_{i=1}^{N'} r_{i-j}^2$ is the rolling window $(r\omega)$ realized volatility, while i denotes the day of the period. We set N' equal to 22, which means that we use the monthly realized volatility with the rolling window realized volatility. For simplicity, we drop the superscript "$(r\omega)$" in the equations that follow.

2.2. GARCH-MIDAS with the asymmetry effect

We account for the asymmetry effect by modifying the GARCH-MIDAS models to incorporate the sign asymmetry of the volatility process as an additional explanatory variable. Given studies such as those of Charfeddine (2016), Degiannakis (2004), Lin, Chen, and Gerlach (2012), and Pan and Liu (2018), we find that the GARCH-MIDAS model with an asymmetry term is a suitable model for forecasting the stock price volatility. We therefore extend the GARCH-MIDAS model to account for the asymmetry effect in the short- and long-term volatility components.

For the short-term asymmetry effect, we use the GJR (1,1) specification to model the process of the short-term component as follows:

$$g_{i,t} = (1-\alpha-\beta-0.5\gamma) + \left(\alpha + 1_{\{r_{i-1,t}<0\}}\gamma\right) \times \frac{(r_{i,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}, \tag{9}$$

where $1_{\{\}}$ is an indicator function, which means that the function takes a value of one if the condition is satisfied, and zero otherwise. Obviously, the asymmetry term $1_{\{r_{i-1,t}<0\}}$ is set to differentiate positive returns from negative returns.

For the long-term asymmetry effect, we modify the GARCH-MIDAS model by decomposing the MIDAS regression into the following two parts, inspired by Patton and Sheppard (2015):

$$\tau_i = m + \theta^- \sum_{k=1}^{K} \varphi_k(\omega) RS^-_{i-k} + \theta^+ \sum_{k=1}^{K} \varphi_k(\omega) RS^+_{i-k}, \tag{10}$$

where $RS^-_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{r_{i-j}<0\}}$ and $RS^+_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{r_{i-j}>0\}}$ are the realized semivariance measures that can exhibit variation for positive and negative returns, respectively.

2.3. GARCH-MIDAS with the extreme volatility effect

Recent developments in volatility modeling have been concerned with the influence of extreme events on the volatility and extreme losses (see e.g. Kim, Rachev, Bianchi, Mitov, & Fabozzi, 2011; Piccoli, Chaudhury, Souza, & da Silva, 2017; Zhang, Yu, Wang, & Lai, 2009). These studies show that it has become essential to build a volatility model that incorporates the abnormal volatility of extreme returns under the effect of extreme events. We account for the impacts of extreme shocks on volatility forecasting using the following threshold GARCH-MIDAS model:

$$g_{i,t} = \left(1-\alpha-\beta-1_{\{r_{i,t}<q_1\}}\gamma^{-*} - 1_{\{r_{i,t}>q_2\}}\gamma^{+*}\right) + \left(\alpha + 1_{\{r_{i,t}<q_1\}}\gamma^{-*} + 1_{\{r_{i,t}>q_2\}}\gamma^{+*}\right) \times \frac{(r_{i,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}, \tag{11}$$

where $\beta > 0$, $\alpha+\beta+1_{\{r_{i,t}<q_1\}}\gamma^{-*}+1_{\{r_{i,t}>q_2\}}\gamma^{+*} < 1$, $1_{\{\}}$ is an indicator function, and q_1 and q_2 are the volatility thresholds for extremely negative returns and extremely positive returns, respectively. Specifically, $1_{\{\}} = 1$ indicates a high stock volatility, while $1_{\{\}} = 0$ denotes the existence of low volatility.

The general specification of the volatility threshold dummies $1_{\{\}}$ depends on the hypothesis to be tested, whether$r_{i,t} < q_1$ and $r_{i,t} > q_2$. We suggest defining the volatility threshold as $q_i = Q_i(\delta_i)$, $i = 1, 2$, where δ_i is the quantile level (namely, a parameter assuming values between zero and one) and $Q_i(\delta_i)$ denotes the empirical δ_i quantile of the return $r_{i,t}$. Obviously, the parameters γ^{-*} and γ^{+*} in Eq. (11) include information on the threshold effect when extreme negative shocks and extreme positive shocks occur, respectively.

Similarly to the short-term case, we also model a threshold structure based on the long-term volatility levels as follows:

$$\tau_i = m + \theta^{-*} \sum_{k=1}^{K} \varphi_k(\omega) RS^{-*}_{i-k} + \theta^{+*} \sum_{k=1}^{K} \varphi_k(\omega) RS^{+*}_{i-k} + \theta^{*} \sum_{k=1}^{K} \varphi_k(\omega) RS^{*}_{i-k}, \tag{12}$$

where $RS^{-*}_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{r_{i-j}<q_1\}}$ and $RS^{+*}_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{r_{i-j}>q_2\}}$ are the realized variance, which can capture the variation caused by extreme returns, and $RS^{*}_{i-k} = \sum_{j=1}^{N'} r^2_{i-j} 1_{\{q_1 \le r_{i-j} \le q_2\}}$ denotes the regular realized volatility. Obviously, the realized variance in Eq. (12) is decomposed into three components – a regular component, an extreme negative component and an extreme positive component – by utilizing the thresholds that are in excess of some critical value for the stock return.

2.4. GARCH-MIDAS with asymmetry and extreme volatility effects

We have considered the asymmetry and extreme volatility effects separately in Sections 2.2 and 2.3, respectively. This step enables us to examine the impacts of both the asymmetry and extreme volatility effects on the volatility of stock price returns through the residual term of the return equation of the GARCH-MIDAS model. This subsection therefore develops a set of models with both the asymmetry effect and the extreme volatility effect in the processes of both the short-term and long-term volatility components. At the same time, we also investigate whether those new models are more powerful for forecasting the volatility.

Mathematically, this modified GARCH-MIDAS model is expressed by Eqs. (9)–(12) as follows:

$$\begin{aligned} g_{i,t} = & \left(1-\alpha-\beta-0.5\gamma^- - 1_{\{r_{i,t}<q_1\}}\gamma^{-*} -0.5\gamma^+ - 1_{\{r_{i,t}>q_2\}}\gamma^{+*}\right) \\ & + \left(\alpha + 1_{\{r_{i,t}<0\}}\gamma^- + 1_{\{r_{i,t}<q_1\}}\gamma^{-*} + 1_{\{r_{i,t}>0\}}\gamma^+ + 1_{\{r_{i,t}>q_2\}}\gamma^{+*}\right) \times \frac{(r_{i,t}-\mu)^2}{\tau_t} \\ & + \beta g_{i-1,t} \end{aligned} \tag{13}$$

$$\tau_i = m + \theta^- \sum_{k=1}^{K} \varphi_k(\omega) RS^-_{i-k} + \theta^{-*} \sum_{k=1}^{K} \varphi_k(\omega) RS^{-*}_{i-k} + \theta^+ \sum_{k=1}^{K} \varphi_k(\omega) RS^+_{i-k} + \theta^{+*} \sum_{k=1}^{K} \varphi_k(\omega) RS^{+*}_{i-k}. \quad (14)$$

Eqs. (13) and (14) describe the short-term and long-term volatility components for measuring the impacts of both asymmetry and extreme volatility effects on the stock volatility. The asymmetry-threshold model refers to the impacts of bad and good news based on the asymmetry effect, as well as the impacts of small and large news based on the extreme volatility effect.

In summary, we use these new variance equations discussed in Sections 2.2–2.4 to replace the existing short-term and long-term volatility components in the standard GARCH-MIDAS model discussed above. Specifically, we consider four types of effects for inclusion in the GARCH-MIDAS model: asymmetry effects in the short-term volatility, asymmetry effects in the long-term volatility, including extreme effects in the short-term volatility, and including extreme effects in the long-term volatility. Including or excluding each effect enables us to specify 2^4 (=16) extensions. Thus, we have a total of 16 models, including the basic GARCH-MIDAS model with none of the effects. A typology of these models is given in Table 1. Three of these models take into account only the asymmetry effect in the short- or long-term, three merely consider the extreme volatility effect, and the remaining nine account for both asymmetry and extreme volatility effects in the short or long term.

3. Data

Following Becker and Clements (2008), we consider the S&P500 index, one of the best single gauges of large-cap U.S. equities, which are employed widely in stock volatility forecasting. Daily stock price data are available from the Federal Reserve Economic Data (FRED), maintained by the Federal Reserve Bank of St. Louis. Our sample spans the period from January 1991 to December 2016.[1]

4. Estimation results

This section begins by providing the parameter estimation results of the 16 models described in Table 1. In addition, we also evaluate the out-of-sample forecasting performances of those models under different criteria in order to explore whether introducing asymmetry and extreme volatility effects can improve the forecasting ability. Moreover, extreme volatility in stock returns is related to events for which the probability is small. Following Herrera and Clements (2018), we choose the quantile levels $\delta_1 = 0.1$ and $\delta_2 = 0.9$ in Eqs. (11)–(14), respectively. Thus, this study defines an "extreme event" as one that belongs to the most negative 10% of returns in stock markets or the most positive 10% of log-changes.

4.1. In-sample estimation

We plot the estimated secular components of the total conditional volatility obtained from the various GARCH-MIDAS extensions given in Table 1. As a concise, readable example, Fig. 1 shows the estimated secular volatility of Models 0, 7, and 15.[2]

The estimates of the GARCH-MIDAS parameters are presented in Table 2.[3] The parameters of the basic GARCH-MIDAS model are all positive and significant, indicating that the GARCH-MIDAS model fits the stock return and can be used to forecast the stock volatility. The sums of α and β are noticeably close to one, confirming the existence of a strong volatility persistence effect. Meanwhile, most of the parameters of the remaining extensions based on the GARCH-MIDAS model are also significant, implying that these extensions fit the stock return very well.

First, we analyze the parameters of models 1, 2, 5, 6, 7, 8, 9, 11, 12, 14, and 15 that considered the asymmetry effect. The asymmetry parameter γ of these models for the short-term volatility maintains a significant negative impact on the stock volatility, which is strong evidence that bad news has a greater short-term impact on the stock volatility than good news. This result is consistent with the findings of Veronesi (1999). Furthermore, the significance of θ^+ and θ^- for the long-term volatility is mixed across various models. Specifically, in general, the significant coefficient of θ^+ is negative, which implies that this component leads to a lower long-term volatility. However, the estimated results in Table 2 indicate that the negative realized semi-variances can result in high long-term volatilities, because the coefficient is significantly positive.

Second, we analyze the parameters of models 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, and 15 that considered the extreme effect. It can be found that most of the parameters γ^{+*}, γ^{-*}, θ^{+*} and θ^{-*} are significant, implying the existence of a strong "extreme volatility effect". In addition, the estimation results given in Table 2 for the short- and long-term components demonstrate that higher negative extreme effects can lead to higher volatilities for both the short term and the long term, whereas the impact of a positive extreme effect is minor. This evidence implies that the extreme effect is a potential source of stock volatility persistence, which is consistent with Aboura and Wagner's (2016) argument that large stock market declines can be seen, at least in part, as a consequence of volatility feedback at extreme levels.

Third, we analyze the special case of model 15, which includes both asymmetry and extreme volatility effects in both the short- and long-term components. It is clear that all of the parameters of these newly-considered effects are significant. We find that the asymmetry coefficients of the new model are larger than the coefficients that describe the extreme volatility effect ($|\gamma^+| > |\gamma^{+*}|$, $|\gamma^-|$

1 The descriptive statistics of the S&P 500, along with its daily returns and volatility, are reported and displayed in the online appendix (Table A1 and Figure A1).

2 The secular volatilities for all GARCH-MIDAS models are provided in the online appendix (Figure D1).

3 We estimate and forecast all models using the Python software (version 3.7).

Table 1
The typology of GARCH-MIDAS and its extensions.

Model number	Asymmetry effect in short-term	Asymmetry effect in long-term	Extreme volatility effect in short-term	Extreme volatility effect in long-term	Eq. number for short-term component	Eq. number for long-term component	Model description
Model 0					(4)	(5)	The basic GARCH-MIDAS model
Model 1	✓				(9)	(5)	Including asymmetry in short-term volatility
Model 2		✓			(4)	(10)	Including asymmetry in long-term volatility
Model 3			✓		(11)	(5)	Including threshold in short-term volatility
Model 4				✓	(4)	(12)	Including threshold in long-term volatility
Model 5	✓		✓		(13)	(5)	Including asymmetry and threshold in short-term volatility
Model 6		✓		✓	(4)	(14)	Including asymmetry and threshold in long-term volatility
Model 7	✓	✓			(9)	(10)	Including asymmetry in both short- and long-term volatility
Model 8	✓			✓	(9)	(12)	Including asymmetry in short-term volatility and threshold in long-term volatility
Model 9	✓	✓		✓	(9)	(14)	Including asymmetry in both short- and long-term volatility and extreme in long-term volatility
Model 10			✓	✓	(11)	(12)	Including extreme in both short- and long-term volatility
Model 11		✓	✓		(11)	(10)	Including asymmetry in long-term volatility and extreme in short-term volatility
Model 12		✓	✓	✓	(11)	(14)	Including asymmetry in long-term volatility and extreme in both short- and long-term volatility
Model 13	✓	✓	✓		(13)	(10)	Including asymmetry in both short- and long-term volatility and extreme in short-term volatility
Model 14	✓		✓	✓	(13)	(12)	Including asymmetry in short-term volatility and extreme in both short- and long-term volatility
Model 15	✓	✓	✓	✓	(13)	(14)	Including asymmetry and extreme in both short- and long-term volatility

Notes: The extensions are constructed by considering the four kinds of effects listed in columns 2–5, where the effects that are included are labeled "✓". For clarity, each model is described in the last column.

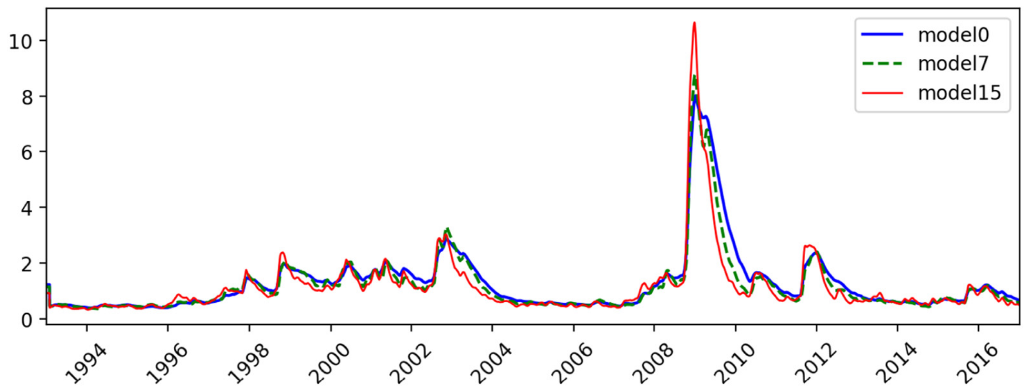

Fig. 1. The estimated secular volatilities of Models 0, 7, and 15.

$> |\gamma^{-*}|$, $|\theta^{+}| > |\theta^{+*}|$, and $|\theta^{-}| > |\theta^{-*}|$), which implies that the asymmetry effect has a greater impact on the stock volatility. In addition, all of the negative parameters (γ^{-*}, γ^{-}, θ^{-}, θ^{-*}) have significant impacts on the stock volatility at the 1% significance level, whereas some of the positive parameters (γ^{+}, θ^{+}) have no influence on the stock volatility. Furthermore, the rankings of the absolute coefficient values ($|\gamma^{-*}| > |\gamma^{+*}|$, $|\gamma^{-}| > |\gamma^{+}|$, $|\theta^{-*}| >$

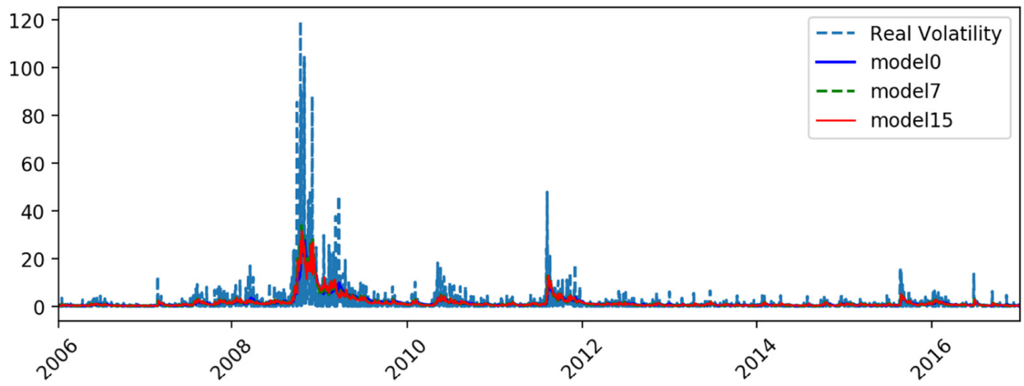

Fig. 2. Volatility forecasts from Models 0, 7, and 15.

$|\theta^{+*}|$, and $|\theta^-| > |\theta^+|$) show that the stock volatility is related more strongly to past bad news and large news than to good news or small news. The reason for this may be that extreme bad events drive investors to pay more attention to information related to the future uncertainty. Meanwhile, the stock volatility is influenced more strongly by the asymmetry effect than by the threshold effect. The results indicate that the asymmetry effect is more efficient at predicting the stock market volatility.

4.2. Out-of-sample forecasting

The out-of-sample performance of the predictive ability is more important than its in-sample performance because market participants are more concerned about the model's ability to predict the future than about its ability to analyze the past (e.g., Ma, Ji et al., 2019; Ma, Liao et al., 2019; Wang, Wei, Wu, & Yin, 2018). This subsection explores whether incorporating the asymmetry and threshold effects can improve the predictive ability of the stock volatility by using out-of-sample predictions to make direct comparisons of the performances of the extended GARCH-MIDAS models.

In particular, we divide the sample data into two subgroups: (1) in-sample data for volatility modeling, from January 1991 to January 2006; and (2) out-of-sample data for model evaluation, from February 2006 to December 2016. At each step, we discuss the forecasting performances of the various models for the remainder of the sample and then shift the estimation window by one period. Fig. 2 plots the volatility forecasts and the true volatilities generated by Models 0, 7, and 15 in Table 1.[4] Initially, the forecasting accuracy of the volatility models is gauged using loss functions. According to Diebold and Lopez (1996) and Wang and Wu (2012), it is difficult to decide which loss function is the best at evaluating the accuracy of volatility forecasting, and therefore we select five loss functions as the forecasting error benchmark:

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2 \tag{15}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|\sigma_t^2 - \hat{\sigma}_t^2\right| \tag{16}$$

$$\mathrm{HMSE} = \frac{1}{n}\sum_{t=1}^{n}(1 - \sigma_t^2/\hat{\sigma}_t^2)^2 \tag{17}$$

$$\mathrm{HMAE} = \frac{1}{n}\sum_{t=1}^{n}\left|1 - \sigma_t^2/\hat{\sigma}_t^2\right| \tag{18}$$

$$\mathrm{QLIKE} = \frac{1}{n}\sum_{t=1}^{n}(\ln(\hat{\sigma}_t^2) - \sigma_t^2/\hat{\sigma}_t^2)^2, \tag{19}$$

where n is the total number of volatility forecasts, and σ_t^2 and $\hat{\sigma}_t^2$ are the actual value and forecast value of the volatility, respectively. Specifically, σ_t^2 is the squared daily return, which is taken as a proxy for the actual volatility during the out-of-sample period.[5] $\hat{\sigma}_t^2$ denotes the out-sample volatility forecasts obtained from each of the abovementioned models (Models 0–15). MSE and MAE are the mean squared error and mean absolute error, while HMSE and HMAE are the heteroscedasticity-adjusted versions of MSE and MAE, respectively, which are non-linear loss measurements. In particular, the findings of Patton (2011) show that the QLIKE loss functions provide consistent rankings because of the lower impact of the most extreme observations in the sample.

Following Ma, Ji et al. (2019), Ma, Liao et al. (2019) and Ma, Wei, Liu, and Huang (2018), the loss functions provide no information on whether the differences in forecasting losses among models are statistically significant. We therefore employ the MCS approach developed by Hansen et al. (2011). Unlike the SPA test (Hansen, 2005), the MCS test does not require a benchmark in order to be specified, which makes it very useful in applications without an obvious benchmark. The MCS test sequentially eliminates the models with the worst performances from the full set of models M until the null hypothesis of equal forecast accuracy (EPA) is no longer rejected at the α significance level; then, the set of models that survives forms the MCS.

[4] The corresponding graphs for the remaining models in Table 1 are given in the online appendix (Figure D2).

[5] The squared daily returns are taken as a proxy for the actual volatilities, following many studies, such as those of Asgharian et al. (2013), Pan et al. (2017), Wang, Wu, and Yang (2016) and Wei, Wang, and Huang (2010).

Table 2
Estimation results of GARCH-MIDAS and its extensions.

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
μ	0.056***	0.025***	0.055***	0.041***	0.056***	0.020**	0.056***	0.026***	0.077***	0.027***	0.041**	0.033***	0.041***	0.020***	0.019**	0.017***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.001)	(0.011)	(0.010)	(0.005)	(0.010)	(0.003)
α	0.102***	0.001	0.101***	0.099***	0.099***	0.065	0.097***	0.001	0.101***	0.001	0.096***	0.050***	0.095***	0.070***	0.002	0.002
	(0.006)	(0.016)	(0.009)	(0.000)	(0.008)	(0.072)	(0.010)	(0.014)	(0.009)	(0.015)	(0.017)	(0.014)	(0.016)	(0.040)	(0.015)	(0.013)
β	0.851***	0.840***	0.847***	0.869***	0.857***	0.848***	0.852***	0.851***	0.834***	0.849***	0.877***	0.889***	0.882***	0.859***	0.839***	0.870***
	(0.011)	(0.009)	(0.018)	(0.012)	(0.016)	(0.011)	(0.018)	(0.029)	(0.015)	(0.027)	(0.015)	(0.010)	(0.011)	(0.031)	(0.015)	(0.038)
ω	6.483***	7.4013***	7.223***	8.151***	6.717***	10.121***	6.227***	7.153***	5.792***	6.906***	7.633***	7.606***	7.478***	9.377***	11.677***	8.046***
	(1.670)	(1.439)	(2.079)	(1.670)	(2.034)	(1.832)	(1.819)	(1.769)	(2.193)	(1.500)	(1.721)	(1.478)	(1.472)	(1.621)	(2.650)	(1.467)
m	0.614***	0.340***	0.381***	0.536***	0.721***	0.384***	−0.192	0.321***	0.699***	−0.020	0.711***	−0.495***	0.521***	0.618***	−0.020	−0.031
	(0.041)	(0.051)	(0.070)	(0.064)	(0.049)	(0.066)	(0.233)	(0.055)	(0.040)		(0.065)	(0.035)	(0.076)	(0.102)		(0.212)
θ	0.166***	0.027***		0.208***		0.186***										
	(0.008)	(0.002)		(0.033)		(0.012)										
θ^*					0.296***				0.252***		0.198***				0.199***	
					(0.077)				(0.068)		(0.030)				(0.019)	
θ^+			0.006				0.025	−0.007		0.003		−0.215***	−0.308***	−0.093**		0.011
			(0.017)				(0.059)	(0.022)		(0.021)		(0.021)	(0.062)	(0.039)		(0.019)
θ^-			0.049***				0.227***	0.062***		−0.057		0.001	0.001	0.251***		0.323***
			(0.016)				(0.085)	(0.021)		(0.045)		(0.113)	(0.182)	(0.032)		(0.089)
θ^{+*}					−0.001		−0.011		−0.001	0.049**	0.177***		−0.000017		−0.106**	0.063***
					(0.478)		(0.019)		(0.120)	(0.021)	(0.048)		(0.148)		(0.051)	(0.023)
θ^{-*}					0.234***		0.059*		0.248***	0.219***	0.127**		−0.000011		0.204***	0.106**
					(0.017)		(0.017)		(0.017)	(0.062)	(0.071)		(0.283)		(0.030)	(0.056)
γ		0.199***						0.195***	0.121***	0.1925***						
		(0.015)						(0.022)	(0.017)	(0.020)						
γ^+						−0.097*								−0.134***	−0.083***	−0.086
						(0.071)								(0.028)	(0.010)	(0.026)
γ^-						0.211***								0.193***	0.222***	0.278***
						(0.072)								(0.039)	(0.023)	(0.032)
γ^{+*}				−0.129***		0.047***					−0.091***	−0.081***	−0.125***	0.038*	−0.027**	0.059***
				(0.017)		(0.016)					(0.014)	(0.015)	(0.016)	(0.026)	(0.018)	(0.015)
γ^{-*}				0.066***		−0.096***					0.096***	0.106***	0.067***	−0.084***	−0.118***	−0.112***
				(0.019)		(0.012)					(0.018)	(0.019)	(0.018)	(0.027)	(0.033)	(0.021)

Notes: The table gives the estimation results of GARCH-MIDAS and its extensions from Table 1. Standard errors are reported in parentheses.
*Indicate rejections of the null hypothesis at the 10% significance level.
**Indicate rejections of the null hypothesis at the 5% significance level.
***Indicate rejections of the null hypothesis at the 1% significance level.

Table 3
The MCS test results for the S&P 500 index using the GARCH-MIDAS models.

	MSE	MAE	HMSE	HMAE	QLIKE
Model 0	**0.627**	0.007	0.025	0.000	0.000
Model 1	**0.655**	0.008	**0.207**	0.001	0.001
Model 2	**0.633**	0.007	0.083	0.000	0.000
Model 3	**0.885**	0.007	**0.207**	**0.342**	0.001
Model 4	**0.595**	0.012	**0.178**	0.006	0.000
Model 5	**0.962**	0.007	**0.221**	**0.342**	**0.224**
Model 6	**0.627**	0.007	**0.178**	0.034	0.000
Model 7	**0.773**	0.008	0.004	0.000	0.003
Model 8	**0.655**	0.007	0.099	0.006	0.000
Model 9	**0.775**	0.007	**0.207**	0.006	0.012
Model 10	**0.773**	0.008	**0.207**	**0.342**	0.005
Model 11	**0.609**	0.008	**0.207**	0.031	0.004
Model 12	**0.773**	**1.000**	0.000	0.000	0.004
Model 13	**0.837**	0.008	0.141	0.000	**0.737**
Model 14	**0.775**	0.008	**0.588**	**1.000**	**0.737**
Model 15	**1.000**	0.008	**1.000**	**0.342**	**1.000**

Notes: The typology of the models is given in Table 1. The numbers in the table are the p-values. Numbers larger than 0.10 are indicated in bold and underlined, and suggest that the corresponding model performs significantly better among the model set.

We employ the range statistics $T_R = max_{i,j\in M} \frac{|\bar{d}_{ij}|}{\sqrt{\widehat{var}\bar{d}_{ij}}}$ and the semi-quadratic statistics $T_{SQ} = \sum_{i,j\in M} \frac{(\bar{d}_{ij})^2}{\widehat{var}\bar{d}_{ij}}$ to test the null hypothesis of EPA, where d_{ij} is the loss differential between two extended GARCH-MIDAS models in M and $\widehat{var}\bar{d}_{ij}$ is an estimate of $var(\bar{d}_{ij})$ that is obtained using the stationary block bootstrap. Furthermore, we choose a threshold value of 0.10 for selecting superior forecasting models. In summary, if the MCS p-value is larger than 0.10, the corresponding model can achieve a greater forecasting accuracy. The p-values are determined from 10,000 block bootstraps.

The MCS test results are presented in Table 3. First, under the MSE loss function, we find that the MCS p-values of all models are greater than 0.10, which shows that those models can generate better forecasts, while Model 15, which considers both the asymmetry effect and the extreme volatility effect in both the short and long term, is the best forecasting model relative to other new models. Furthermore, Model 15 also significantly outperforms other models under the HMSE and QLIKE loss function. Second, based on the MAE loss functions, Model 12 is the only model that passes the MCS test, which indicates that this model exhibits a statistically higher forecasting accuracy than the other models. Third, from the empirical results of the HMAE loss function, we determine that Model 14 is capable of achieving a greater forecasting accuracy than the other models.

In general, combining the results from all of the loss functions, we find that Models 12, 14, and 15 outperform than the benchmark model (GARCH-MIDAS) and the other models for forecasting. The main reason why the three newly-proposed models deliver the best forecasting performance may be because the models contain as potential predictors not only information regarding asymmetry but also information reflecting the huge fluctuations caused by extreme events. Overall, the evidence suggests that the use of the extended GARCH-MIDAS model offers a substantial improvement in forecasting accuracy.

We examine whether including asymmetry and extreme effects can help to improve the forecast accuracy of the stock volatility by also employing the DM test (Harvey, Leybourne, & Whitehouse, 2017; Miao, Ramchander, Wang, & Yang, 2017) to compare the forecasting performances of our extended models and the standard GARCH-MIDAS model directly. The DM test supposes that a forecaster has an identical loss function $g(A, B)$, so that two different forecasts, A and B, lead to similar losses due to errors. The two forecasts have equal accuracies if and only if the loss differential has zero expectations for all t. The DM statistics can be derived as

$$\mathrm{DM} = \frac{\frac{1}{T}\sum_1^t \{g(e_{A,t+h}) - g(e_{B,t+h})\}}{\hat{\sigma}_{g(e_{A,t+h})-g(e_{B,t+h})}}, \tag{20}$$

where $g(e_{A,t+h})$ and $g(e_{B,t+h})$ denote the losses from forecast errors that evolve from prediction models A and B, with $\hat{\sigma}$ denoting a consistent estimate of the standard deviation of the difference in losses. Here, the loss function is set to the mean square error. The null hypothesis is that $g\left(e_{A,t+h}\right) = g(e_{B,t+h})$ for all t, and DM is distributed simply as N (0, 1) under this null (Diebold & Mariano, 1995). The null hypothesis of the DM test is that the two predictive models have the same level of accuracy. Thus, we reject the null hypothesis if the p-value is less than 0.05; that is, we can conclude that the predictive accuracies of the two competing models are significantly different.

Table 4 shows the results of the DM test. The numbers in the table are the ratios of the loss functions of the new GARCH-MIDAS models in Table 1 to that of the standard model. We find that the loss ratios are lower than one in most cases (64 cases out of 75), indicating that our extended models exhibit lower loss functions than the benchmark model, and thus generate more accurate forecasts under the pre-specified loss criterion. Model 15 performs best under all of the loss functions, which shows that incorporating both the asymmetry and extreme volatility effects in both the short and long term offers the most substantial improvement in forecasting accuracy among all the extended models. Moreover, the p-values of the DM tests show that a comparison of our new models' out-of-sample forecasts is statistically significant. Furthermore, we compare all models in pairs by using the DM test, which can exhibit different predictive accuracies between each model in Table 1. Our DM tests suggest that Model 15 can achieve more accurate volatility forecasts than the other extended GARCH-MIDAS models.[6]

5. Conclusions

This study proposes 15 extensions of the GARCH-MIDAS model introduced by Engle et al. (2013), which can accommodate both the asymmetry effect and the extreme volatility effect caused by extreme shocks in the short-term and/or long-term volatility components. We forecast

[6] The detailed results comparing the 16 forecasting models are given in the online appendix (Tables B1–B15). More importantly, we perform several robustness checks, such as using FTSE data, different volatility thresholds, out-of-sample analyses conditional on dynamic thresholds, empirical studies for S&P 500 futures, and empirical studies of individual stocks, the results of which support our main findings. We show these empirical results in the online appendix (Tables C1–C9).

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Table 4
Results of the Diebold–Mariano test between Model 0 and Models 1–15.

	MSE	MAE	HMSE	HMAE	QLIKE
Model 1	0.950* (−1.38)	0.976*** (−2.570)	0.900*** (−2.813)	0.960*** (−5.139)	0.942*** (−7.774)
Model 2	1.001 (0.426)	0.997*** (−6.576)	1.001 (0.361)	1.002 (7.171)	1.000 (0.100)
Model 3	0.946* (−1.46)	0.982** (−1.996)	0.869*** (−2.989)	0.953*** (−6.306)	0.950*** (−6.842)
Model 4	0.997 (−0.150)	1.001 (1.847)	0.998 (−0.998)	0.999 (−1.130)	0.999 (−0.645)
Model 5	0.944* (−1.403)	0.976*** (−2.448)	0.869*** (−3.201)	0.951*** (−5.933)	0.935*** (−8.014)
Model 6	0.999 (−0.313)	0.994*** (−6.945)	0.975 (−0.992)	0.999 (−0.072)	0.997* (−1.492)
Model 7	0.953* (−1.455)	0.971*** (−3.12)	0.922** (−2.252)	0.970*** (−3.898)	0.941*** (−7.909)
Model 8	1.001 (0.027)	0.999 (−0.035)	1.034 (1.105)	1.013 (1.894)	0.994 (−0.822)
Model 9	0.951* (−1.500)	0.966*** (−3.931)	0.881** (−2.266)	0.969*** (−3.912)	0.939*** (−7.976)
Model 10	0.951* (−1.343)	0.981** (−2.137)	0.907*** (−2.648)	0.962*** (−5.011)	0.950*** (−6.798)
Model 11	0.952* (−1.406)	0.980*** (−2.332)	0.883** (−2.201)	0.963*** (−4.963)	0.950*** (−6.846)
Model 12	0.984 (−0.392)	0.860*** (−9.406)	2.265 (6.777)	1.357 (12.912)	1.076 (2.755)
Model 13	0.946* (−1.612)	0.964*** (−4.299)	0.885*** (−2.746)	0.962*** (−4.737)	0.932*** (−8.534)
Model 14	0.950 (−1.249)	0.978** (−2.198)	0.853** (−2.160)	0.959*** (−4.595)	0.933*** (−7.733)
Model 15	0.943** (−1.605)	0.961*** (−4.421)	0.832** (−2.120)	0.959*** (−4.675)	0.927*** (−8.426)

Notes: The table presents the results of a Diebold–Mariano forecast evaluation between the benchmark of the standard GARCH-MIDAS model (Model 0) and Models 1–15 given in Table 1. A ratio lower than 1 indicates that the model forecasts volatility better than the benchmark model. The DM test statistics are shown in parentheses.

*Denote rejections of the null hypothesis at the 10% significance level.

**Denote rejections of the null hypothesis at the 5% significance level.

***Denote rejections of the null hypothesis at the 1% significance level.

the volatility of the S&P 500 index in order to investigate whether our proposed models can attain a higher forecasting accuracy. First, the in-sample results show that the asymmetry and extreme volatility effects in our GARCH-MIDAS model frameworks have significant impacts on the stock price volatility. Moreover, we find that the asymmetry effect has a more significantly negative impact than the extreme volatility effect, indicating that the asymmetry effect contributes more to the predictability of the stock volatility. In summary, the asymmetry effect and the extreme volatility effect are two important factors in the high persistence of the stock volatility. Second, the out-of-sample findings based on five loss function criteria suggest that the asymmetry-threshold GARCH-MIDAS model can outperform the standard existing model significantly. Moreover, the improvement in the predictive ability of volatility models is attributed more strongly to the introduction of short-term asymmetry and extreme volatility effects than to the long-term effects. Third, according to a robustness check, these conclusions are robust to different stock markets, forecasting evaluation criteria, and volatility thresholds. The contribution of this paper is that it further expands and enriches the traditional GARCH-MIDAS models and introduces asymmetry and threshold terms for building superior extensions of the GARCH-MIDAS model in order to model and forecast the volatility.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2019.08.005.

References

Aboura, S., & Wagner, N. (2016). Extreme asymmetric volatility: stress and aggregate asset prices. *Journal of International Financial Markets, Institutions and Money*, *41*, 47–59.

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics*, *18*(15), 1201–1208.

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *Review of Economics and Statistics*, *89*(4), 701–720.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, *71*(2), 579–625.

Angelidis, T., Benos, A., & Degiannakis, S. (2004). The use of GARCH models in VaR estimation. *Statistical Methodology*, *1*(1–2), 105–128.

Annaert, J., De Ceuster, M., & Verstegen, K. (2013). Are extreme returns priced in the stock market? European evidence. *Journal of Banking & Finance*, *37*(9), 3401–3411.

Arısoy, Y. E., Altay-Salih, A., & Akdeniz, L. (2015). Aggregate volatility expectations and threshold CAPM. *The North American Journal of Economics and Finance*, *34*, 231–253.

Asgharian, H., Christiansen, C., & Hou, A. J. (2015). Macro-finance determinants of the long-run stock–bond correlation: The DCC-MIDAS specification. *Journal of Financial Economic*, *14*(3), 617–642.

Asgharian, H., Christiansen, C., & Hou, A. J. (2018). Economic policy uncertainty and long-run stock market volatility and correlation. Available at SSRN 3146924.

Asgharian, H., Hou, A. J., & Javed, F. (2013). The importance of the macroeconomic variables in forecasting stock return variance: A GARCH-MIDAS approach. *Journal of Forecasting*, *32*(7), 600–612.

Awartani, B. M., & Corradi, V. (2005). Predicting the volatility of the S & P-500 stock index via GARCH models: the role of asymmetries. *International Journal of Forecasting*, *21*(1), 167–183.

Becker, R., & Clements, A. E. (2008). Are combination forecasts of S & P 500 volatility statistically superior? *International Journal of Forecasting*, *24*(1), 122–133.

Behrens, C. N., Lopes, H. F., & Gamerman, D. (2004). Bayesian analysis of extreme events with threshold estimation. *Statistical Modelling*, *4*(3), 227–244.

Bekaert, G., & Hoerova, M. (2014). The vix, the variance premium and stock market volatility. *Journal of Econometrics*, *183*(2), 181–192.
Black, F. (1976). Studies of stock price volatility changes. In *Proceedings of the 1976 meetings of the american statistical association, business and economic statistics section* (pp. 177–181).
Bollerslev, T., & Mikkelsen, H. O. (1996). Modeling and pricing long memory in stock market volatility. *Journal of Econometrics*, *73*(1), 151–184.
Byun, S. J., & Cho, H. (2013). Forecasting carbon futures volatility using GARCH models with energy volatilities. *Energy Economics*, *40*, 207–221.
Chan, Y. C., & Wei, K. J. (1996). Political risk and stock price volatility: the case of Hong Kong. *Pacific-Basin Finance Journal*, *4*(2–3), 259–275.
Charfeddine, L. (2016). Breaks or long range dependence in the energy futures volatility: Out-of-sample forecasting and VaR analysis. *Economic Modelling*, *53*, 354–374.
Choudhry, T. (2010). World War II events and the Dow Jones industrial index. *Journal of Banking & Finance*, *34*(5), 1022–1031.
Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Economic*, *7*(2), 174–196.
Degiannakis, S. (2004). Volatility forecasting: evidence from a fractional integrated asymmetric power ARCH skewed- t model. *Applied Financial Economics*, *14*(18), 1333–1342.
Degiannakis, S., Livada, A., & Panas, E. (2008). Rolling-sampled parameters of ARCH and Levy-Stable models. *Applied Economics*, *40*(23), 3051–3067.
Diebold, F. X., & Lopez, J. A. (1996). Forecast evaluation and combination. In G. S. Maddala, & C. R. Rao (Eds.), *Handbook of Statistics*: *vol. 14*, (pp. 241–268). Amsterdam: North-Holland.
Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, *13*, 253–263.
Dueker, M. J. (1997). Markov switching in GARCH processes and mean-reverting stock-market volatility. *Journal of Business & Economic Statistics*, *15*(1), 26–34.
Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics*, *95*(3), 776–797.
Engle, R. F., & Rangel, J. G. (2008). The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies*, *21*(3), 1187–1222.
Fang, L., Chen, B., Yu, H., & Qian, Y. (2018). The importance of global economic policy uncertainty in predicting gold futures market volatility: A GARCH-MIDAS approach. *Journal of Futures Markets*, *38*(3), 413–422.
Fuertes, A. M., Izzeldin, M., & Kalotychou, E. (2009). On forecasting daily stock volatility: The role of intraday information and market conditions. *International Journal of Forecasting*, *25*(2), 259–281.
Gençay, R., Selçuk, F., & Ulugülyağci, A. (2003). High volatility, thick tails and extreme value theory in value-at-risk estimation. *Insurance: Mathematics and Economics*, *33*(2), 337–356.
Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, *131*(1–2), 59–95.
Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews*, *26*(1), 53–90.
Girardin, E., & Joyeux, R. (2013). Macro fundamentals as a source of stock market volatility in China: A GARCH-MIDAS approach. *Economic Modelling*, *34*, 59–68.
Hansen, P. R. (2005). A test for superior predictive ability. *Journal of Business & Economic Statistics*, *23*(4), 365–380.
Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: does anything beat a GARCH (1, 1)?. *Journal of Applied Econometrics*, *20*(7), 873–889.
Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica*, *79*(2), 453–497.
Harvey, D. I., Leybourne, S. J., & Whitehouse, E. J. (2017). Forecast evaluation tests and negative long-run variance estimates in small samples. *International Journal of Forecasting*, *33*(4), 833–847.
Herrera, R., & Clements, A. E. (2018). Point process models for extreme returns: Harnessing implied volatility. *Journal of Banking & Finance*, *88*, 161–175.
Huang, A. Y. (2015). Value at risk estimation by threshold stochastic volatility model. *Applied Economics*, *47*(45), 4884–4900.
Jacob, J. (2007). Forecasting performance of extreme-value volatility estimators. *Journal of Futures Markets*, *27*(11), 1085–1105.
Kim, Y. S., Rachev, S. T., Bianchi, M. L., Mitov, I., & Fabozzi, F. J. (2011). Time series analysis for financial market meltdowns. *Journal of Banking & Finance*, *35*(8), 1879–1891.
Lin, E. M., Chen, C. W., & Gerlach, R. (2012). Forecasting volatility with asymmetric smooth transition dynamic range models. *International Journal of Forecasting*, *28*(2), 384–399.
Ma, Y. R., Ji, Q., & Pan, J. (2019). Oil financialization and volatility forecast: Evidence from multidimensional predictors. *Journal of Forecasting*, *38*(6), 564–581.
Ma, F., Liao, Y., Zhang, Y., & Cao, Y. (2019). Harnessing jump component for crude oil volatility forecasting in the presence of extreme shocks. *Journal of Empirical Finance*, *52*, 40–55.
Ma, F., Wei, Y., Liu, L., & Huang, D. (2018). Forecasting realized volatility of oil futures market: A new insight. *Journal of Forecasting*, *37*(4), 419–436.
McNeil, A. J., & Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *Journal of Empirical Finance*, *7*(3–4), 271–300.
Mele, A. (2007). Asymmetric stock market volatility and the cyclical behavior of expected returns. *Journal of Financial Economic*, *86*(2), 446–478.
Miao, H., Ramchander, S., Wang, T., & Yang, D. (2017). Influential factors in crude oil price forecasting. *Energy Economics*, *68*, 77–88.
Nikkinen, J., Omran, M. M., Sahlström, P., & Äijö, J. (2008). Stock returns and volatility following the September 11 attacks: Evidence from 53 equity markets. *International Review of Financial Analysis*, *17*(1), 27–46.
Pan, Z., & Liu, L. (2018). Forecasting stock return volatility: A comparison between the roles of short-term and long-term leverage effects. *Physica A: Statistical Mechanics and its Applications*, *492*, 168–180.
Pan, Z., Wang, Y., Wu, C., & Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model. *Journal of Empirical Finance*, *43*, 130–142.
Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics*, *160*(1), 246–256.
Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, *97*(3), 683–697.
Piccoli, P., Chaudhury, M., Souza, A., & da Silva, W. V. (2017). Stock overreaction to extreme market events. *The North American Journal of Economics and Finance*, *41*, 97–111.
Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature*, *41*(2), 478–539.
Schwert, G. W. (2011). Stock volatility during the recent financial crisis. *European Financial Management*, *17*(5), 789–805.
Veronesi, P. (1999). Stock market overreactions to bad news in good times: a rational expectations equilibrium model. *Review of Financial Studies*, *12*(5), 975–1007.
Wang, Y., Wei, Y., Wu, C., & Yin, L. (2018). Oil and the short-term predictability of stock return volatility. *Journal of Empirical Finance*, *47*, 90–104.
Wang, Y., & Wu, C. (2012). Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models?. *Energy Economics*, *34*(6), 2167–2181.
Wang, Y., Wu, C., & Yang, L. (2016). Forecasting crude oil market volatility: A Markov switching multifractal volatility approach. *International Journal of Forecasting*, *32*(1), 1–9.
Wei, Y., Wang, Y., & Huang, D. (2010). Forecasting crude oil market volatility: Further evidence using GARCH-class models. *Energy Economics*, *32*(6), 1477–1484.
Zhang, X., Yu, L., Wang, S., & Lai, K. K. (2009). Estimating the impact of extreme events on crude oil price: An EMD-based event analysis method. *Energy Economics*, *31*(5), 768–778.

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