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Volatility forecasting: Global economic policy uncertainty and regime switching

Miao Yu *, Jinguo Song

China University of Political Science and Law, Beijing, China

HIGHLIGHTS

- I explore the impacts of global economic policy uncertainty on future aggregate monthly volatility.
- Introducing the regime switching in forecasting models, and explore the predictive ability.
- In-sample results show that the GEPU index has a significant impact on one-ahead-step volatility of US stock market.
- The GEPU performs much bigger role on future RV in high volatility regime period than during low volatility regime.
- The GEPU index can increase the forecasts accuracy, especially considering the regime switching.

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ABSTRACT

In this study, I explore the impacts of global economic policy uncertainty on futures aggregate monthly volatility and introduce the regime switching in forecasting models, and analyze the predictive ability. In-sample empirical results show that the GEPU index has a significant impact on one-ahead-step volatility of US stock market. Additionally, the GEPU performs much bigger role on future RV in high volatility regime period than during low volatility regime. The out-of-sample results indicate that the GEPU index can indeed increase the forecasts accuracy, especially introducing the regime switching to the forecasting model. Importantly, the robust test is consistent with the conclusions.

1. Introduction

As we are known, volatility plays an important role in asset pricing, hedging, portfolio selection and risk measurement [e.g., 1–8]. The volatility of stock market not only has a significant influence on the market itself, but also the real economy [e.g., 9–11]. Thus, modeling and forecasting the volatility of stock market is critical for researchers, market participants, and policymakers.

However, accurately forecasting volatility is still difficult. In this study, I explore the impacts of uncertainty on future volatility, and use the global economic and policy uncertainty index (henceforth GEPU) to represent the uncertainty, and seek to find new evidence to increase the forecasts accuracy. The base of GEPU is EPU index, which is first proposed by Baker et al. [12]. EPU is based on newspaper coverage frequency. Baker et al. [12] use this new measure to investigate the effects of policy uncertainty on stock price volatility and find that policy uncertainty raises stock price volatility. In technical details, GEPU is a GDP-weighted average of national EPU indices for 19 countries that accounting over 50% of total world GDP, for example, US, China, Japan and EU. Each national EPU index reflects the relative frequency of own-country newspaper articles that contain terms pertaining to the economy (E), policy (P) and uncertainty (U). In real world, the sudden change of GEPU

* Corresponding author.
E-mail addresses: miaoy@cupl.edu.cn (M. Yu), 1601060631@cupl.edu.cn (J. Song).

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is also consistent with major events like 9/11, Global Financial Crisis and Trump election, etc. Comparing to EPU, the GEPU covers more information around the world and tracks global uncertainty trend that helps more in forecasting volatility [13]. To best of my knowledge, several studies relate to my study. For example, Liu and Zhang [14] investigate the predictability of economic policy uncertainty (EPU) to stock market volatility, and find that incorporating EPU as an additional predictive variable into the existing volatility prediction models significantly improves forecasting ability of these models. Liu et al. [15] investigate whether economic policy uncertainty (EPU) can affect future volatility based on the multifractal insight, and also find that adding EPU as explanatory variable to volatility models can indeed improve the forecasting performance. Ma et al. [16] also investigate whether economic policy uncertainty (EPU) index can increase the HAR-RV-type models' forecast accuracy with considering the threshold of EPU index, and indicate that the HAR-RV models including above-threshold EPU can further improve the forecast accuracy and yield higher economic values by setting specific thresholds for a range of horizons.

Compared to these existed studies, my paper has three remarkable differences. First, my paper focus on the aggregate stock volatility based on monthly data. Compared to the realized and multifractal volatility using the high-frequency data, the monthly data are more convenient to acquire and apply in real practices. Hence, the monthly aggregate volatility has received more attentions by scholars and investors, who are interested in the asset pricing and return predictability. Second, this paper has paid its attention on GEPU, and explores whether the GEPU has impacts on future volatility of the stock market. To the best of author's knowledge, there are few papers on doing this related research. This is because the GEPU index can be freely used in recent two years. Of course, limited scholars [e.g., 13,17] have just utilized this index to do some research on other markets. However, my paper is in the first group to fill this linkage between the GEPU and volatility forecasting in US market, the most important market. Third, these aforementioned works are all based on the framework of linear models. Previous studies [e.g., 8,18,19] have evidenced that high level of persistence when volatility is low, implying the presence of nonlinearities. Moreover, due to many factors such as business cycle, major events and economic policy, the statistical property of volatility (e.g., volatility persistence) always undergoes structural breaks or switches between different regimes. Therefore, in this study, I explore the impacts of global economic policy uncertainty on futures aggregate monthly volatility and introduce the regime switching in forecasting models, and analyze the predictive ability.

The conclusions of this paper are as below. In-sample empirical results show that the GEPU index has a significant impact on one-ahead-step volatility in the US stock market. The normality test of residuals in each model significantly rejects the null hypothesis that residual meets the normal distribution as the important assumption of linear model. The normality test results indicate that linear model may be not suitable to estimate future RV with these variables. In out-of-sample section, GEPU improves the forecasting power of traditional autoregressive model of volatility. Additionally, the GEPU performs much bigger role on future RV in high volatility regime period than during low volatility regime. The out-of-sample results indicate that the GEPU index can indeed increase the forecasts accuracy, especially introducing the regime switching to the forecasting model. That means the combination of GEPU and regime switching can improve the forecasting accuracy of volatility, which is important in asset pricing, hedging, portfolio selection and risk measurement. Importantly, my robust test is consistent with the conclusions.

The rest of the paper is organized as follows: Section 2 describes the volatility measures and models. The methodology of out-of-sample forecasting and the Model Confidence Set (MCS) test are discussed in Section 3. Section 4 provides the data and some preliminary analysis. The empirical forecasting results are presented in Section 5. Section 6 concludes the paper.

2. Volatility measure and models

2.1. Realized Variance

The primary interest is to measure the monthly variance of stock market, which will be estimated from Realized Variance (RV). RV can measure the actual market volatility more accurate with less trading noise that achieves a balance [20]. In US market, RV is applied in many studies to represent the real volatility [e.g. 21,22]. The monthly RV is calculated by

$$\mathrm{RV}_t = \sum_{j=1}^{N} r_{t,j}^2 \tag{1}$$

where $r_{t,j}$ is the return in month t, day j.

2.2. Forecasting model

As far as I know, the autoregression of RV itself in one lag, AR(1)-RV model, has been used in many studies focusing on forecasting the RV [8]. The AR(1) model of RV archives a balance on model complexity and forecasting accuracy. The AR(1) model of RV is termed as AR(1)-RV and given by

$$RV_{t+1} = a + \beta_1 \times RV_t + \omega_{t+1} \tag{2}$$

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