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# Leverage effect, economic policy uncertainty and realized volatility with regime switching

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## HIGHLIGHTS

- Investigate the impacts of leverage effect and EPU on future volatility with regime switching.
- The leverage effect and EPU with regimes can achieve higher forecast accuracy.
- Our proposed models outperform HAR-RV-type and GARCH-class models in forecasting volatility.
- Our findings are robust.

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## ABSTRACT

In this study, we first investigate the impacts of leverage effect and economic policy uncertainty (EPU) on future volatility in the framework of regime switching. Out-of-sample results show that the HAR-RV including the leverage effect and economic policy uncertainty with regimes can achieve higher forecast accuracy than RV-type and GARCH-class models. Our robustness results further imply that these factors in the framework of regime switching can substantially improve the HAR-RV's forecast performance.


## 1. Introduction

Volatility plays a central role in asset pricing, hedging, asset allocation and risk measurement. Using the intraday data to model and forecast volatility is always a hot topic in academia and practice fields. Many scholars have found that the high-frequency volatility models outperform GARCH-class models [1–3]. Corsi [4] proposes a simple heterogeneous autoregressive RV (HAR-RV), which can powerfully capture "stylized facts" in financial market volatility such as long memory and multi-scaling behavior. For this reason, it has received much attention in financial econometrics (see, e.g., [5–11]). Considered the above advantages of this model, and inspired by Corsi and Renò [12], Liu and Zhang [13], Liu et al. [14]

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and Ma et al. [15,16], we use the HAR-RV model as our benchmark model to investigate the impacts of leverage effect and economic policy uncertainty (EPU) on future volatility and further combine the switching regime model to explore whether those improvements can increase the models forecasting performance.

To the best of our knowledge, some studies [12–14] have related to our research, but those works are all based on the framework of the linear models. Goldman et al. [17], Raggi and Bordignon [18], Ma et al. [15,16] and Wang et al. [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, we fill the gap to first investigate the effects of leverage effect and EPU on future realized volatility in the framework of the regime switching.

Out-of-sample results show that the HAR-RV model including the leverage effect and EPU and combining the regimes significantly outperform other RV-type and GARCH-class models. Furthermore, we use the RK to replace RV as the dependent variable and find that add the leverage effect and EPU to HAR-RK model with regime switching also have better performance than other RK-type and GARCH-class models'. Our findings are very helpful to the researchers, market participants, and policymakers to make their decisions.

The remainder of the paper is organized as follows. The next section introduces the volatility models, for example, HAR-RV and extended models. Section 3 describes the empirical data. In-sample estimation, out-of-sample evaluation, and robustness check are discussed in Section 4. Section 5 provides the conclusions.

## 2. Methodology

### 2.1. Realized volatility

In this study, we use the intraday returns of the S&P 500 and construct the daily realized variance (RV). RV is proposed by Andersen and Bollerslev [20]. For a given day $t$, we divide the time interval [0, 1] into $n$ subintervals of length, where $M = 1/\Delta$ and $\Delta$ is the sampling frequency. Consequently, the realized volatility or variance[1] (RV) can be defined as the sum of all available intraday high-frequency squared returns and defined as:

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

where $r_{t,j}$ represents the day $t$ of $j$th intraday return. Based on the theory of Barndorff-Nielsen and Shephard [21], RV can be satisfied as when $\Delta \to 0$:

$$\mathrm{RV}_t \to \int_0^t \sigma^2(s)ds + \sum_{0<s\leq t} \kappa^2(s). \tag{2}$$

where $\int_0^t \sigma^2(s)ds$ is the continuous component. When $\Delta \to 0$, this part is approximately equal to the realized bi-power variation (BPV). BPV can be calculated by:

$$\mathrm{BPV}_t = u_1^{-2} \sum_{j=2}^{1/\Delta} \left|r_{t,j}\right| \left|r_{t,j-1}\right|. \tag{3}$$

where $u_1 \sim 0.7979.\sum_{0<s\leq t} \kappa^2(s)$ is the discontinuous part of the quadratic variation process, which is the jump component.

### 2.2. HAR-RV and its extended models

In this research, we use an attractive high-frequency model to predict volatility, the heterogeneous autoregressive model of realized volatility (HAR-RV) proposed by Corsi [4]. The standard HAR-RV model contains only three independent variables: the one-day ($RV_t$), one-week ($RVW_t$) and one-month ($RVM_t$) lagged averaged realized variances. The model is,

$$RV_{t+1} = c + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \varepsilon_{t+1}. \tag{4}$$

We consider another popular extended model, which include the "leverage effect" that volatility is correlated with lagged negative returns, named the LHAR-RV,

$$RV_{t+1} = c + \beta_d RV_t + \beta_w RVW_t + \beta_m RVM_t + \gamma_d r_t^- + \gamma_w rw_t^- + \gamma_m rm_t^- + \varepsilon_{t+1}. \tag{5}$$

which $r_t^- = r_t I(r_t < 0)$, $rw_t^-$ and $rm_t^-$ are the average weekly and monthly negative daily returns, respectively.

[1] We will use the terms realized volatility and realized variation (variance) interchangeably, which is similar to the work of Andersen et al. [5].