Economic policy uncertainty and stock market volatility

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Abstract

This paper investigates the predictability of economic policy uncertainty (EPU) to stock market volatility. Our in-sample evidence suggests that higher EPU leads to significant increases in market volatility. Out-of-sample findings show that incorporating EPU as an additional predictive variable into the existing volatility prediction models significantly improves forecasting ability of these models. The improvement is robust to the model specifications.

Keywords: Economic policy uncertainty; Realized volatility; Predictability

JEL codes: C53; E44; E52; E60

1. Introduction

Economic policy uncertainty (EPU) has been the subject of extensive investigation since the EPU index was constructed by Baker et al. (2013) (see, e.g., Antonakakis et al., 2013; Colombo, 2013; Karnizova and Li, 2014; Klößner and Sekkel, 2014; Wang et al., 2015). Notably, there are many empirical papers that investigate the effects of EPU on stock market return or volatility (see, e.g., Amengual and Xiu, 2015; Antonakakis et al., 2013; Balcilar et al., 2013; Brogaard and Detzel, 2015; Fanta and Sum, 2013; Johnson and Lee, 2013; Kang and Ratti, 2012; Lam and Zhang, 2013). In this study, we contribute to the literature by examining predictability of EPU to stock market volatility. In particular, we investigate whether adding EPU to the existing volatility prediction models can improve forecasting ability. This issue has not been addressed in the existing studies. Moreover, we show *out-of-sample* results whereas existing studies focus on *in-sample* relationships between EPU and volatility only. Therefore, our study provides additional financial implications because out-of-sample volatility forecasts are of great importance for portfolio allocation and financial risk management.

We use the 5-min high-frequency return of the S&P 500 to calculate daily realized market volatility, and eight popular models that capture evolution of daily realized volatility (RV) to examine the role of EPU. Our in-sample evidence indicates that the effects of the past EPU on the current RV are significantly positive, regardless of which model is used. This is consistent with the finding in Antonakakis et al. (2013) that a rise in policy uncertainty increases stock market return uncertainty.

Out-of-sample results also suggest that EPU plays a significant role in predicting market realized volatility. Overall, we find that EPU helps to predict market volatility both in-sample and out-of-sample. Our finding is intrinsically consistent with the work of Karnizova and Li (2014), which indicates that EPU indexes help predict economic recessions. Business-cycle fluctuation is one of the most important driving forces of stock market activity (Rapach and Zhou, 2013). The predictability of EPU to stock volatility can be explained by a general equilibrium model developed by Pastor and Veronesi (2012), hereafter PV. PV find that introducing new policies with an uncertain impact increases the volatility of the stochastic discount factor. The increase in the volatility of the discount factor leads to increases in risk premia which in turn result in high volatility in stock market.

The remainder of this paper is organized as follows. Section 2 briefly describes the realized volatility models. Section 3 presents the data and discusses the main empirical results. Section 4 presents our conclusions.

2. Methodology

2.1 Realized volatility

Andersen and Bollerslev (1998)'s pioneering study proposes using realized volatility (RV) as a proxy for integrated variance. For a specific business day t , the realized volatility can be calculated as the sum of the squared intraday returns $r_{t,j}$:

$$RV_t = \sum_{j=1}^M r_{t,j}^2, t=1,2,\dots,T, \quad (1)$$

where $1/M$ is the given sampling frequency. As we use 5-min intraday data, we have $M=48$.

2.2 Volatility models

The goal of this study is to examine the ability of EPU to predict the realized volatility (RV). As the results may depend on the model specification, we use the following the eight popular volatility models rather than make a single choice.

We first use the heterogeneous autoregressive RV (HAR-RV) of Corsi et al. (2009). This model is simple to implement, as it only contains three explanatory variables: lagged daily realized volatility ($RV_{d,t}$), lagged weekly realized volatility ($RV_{w,t}$) and lagged monthly realized volatility ($RV_{m,t}$). To examine the ability of EPU to predict RV, we add the lagged daily EPU to the volatility equation as a predictor. A modified HAR with EPU can then be written as follows:

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EPU_t + \varepsilon_{t+1}, \quad (2)$$

where $RV_{w,t}$ is the average RV from day t-5 to day t-1, and $RV_{m,t}$ is the average RV from day t-22 to t-1.

Andersen et al. (2007) extend HAR-RV by adding the jump component and introduce the HAR-RV-J model accordingly. The specification of HAR-RV-J with EPU is

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \beta_{j,d} J_t + \theta EPU_t + \varepsilon_{t+1}, \quad (3)$$

where $J_t = \max(RV_t - BPV_t, 0)$, $BPV_t = u_1^{-2} \sum_{j=2}^M |r_{t,j-1}| |r_{t,j}|$ and $u_1 = (2/\pi)^{0.5} = E(|Z|)$ is

the mean of the absolute value of the standard normally distributed random variable Z .

Andersen et al. (2007) further decompose RV into a continuous sample path and jumps. Based on this decomposition, the following HAR-RV-CJ model is proposed:

$$RV_{t+1} = \beta_0 + \beta_{c,d} CSP_t + \beta_{c,w} CSP_{w,t} + \beta_{c,m} CSP_{m,t} + \beta_{j,d} CJ_t + \beta_{j,w} CJ_{w,t} + \beta_{j,m} CJ_{m,t} + \theta EPU_t + \varepsilon_{t+1}, \quad (4)$$

where $CJ_t = I(Z_t > \Phi_\alpha) \cdot [RV_t - BPV_t]$, $CSP_t = I(Z_t \leq \Phi_\alpha) \cdot RV_t + I(Z_t > \Phi_\alpha) \cdot BPV_t$ and $I(\cdot)$ is the indicator function. $CSP_{w,t}$ ($CJ_{w,t}$) and $CSP_{m,t}$ ($CJ_{m,t}$) are the weekly and monthly averages of the continuous sample path and jump, respectively.

Corsi et al. (2010) modify the jump statistic in Equation (4) and propose following the HAR-RV-TCJ model accordingly:

$$RV_{t+1} = \beta_0 + \beta_{c,d} TC_t + \beta_{c,w} TC_{w,t} + \beta_{c,m} TC_{m,t} + \beta_{j,d} TJ_t + \theta EPU_t + \varepsilon_t. \quad (5)$$

The aforementioned volatility models do not capture the role of the “leverage effect” in volatility dynamics. For this reason, Patton and Sheppard (2013) develop a series of models using signed realized measures. The first model is the extension of the standard HAR-RV by decomposing the daily RV into two semi-variances (HAR-RV-RS-I),

$$RV_{t+1} = \beta_0 + \beta_d^+ RS_t^+ + \beta_d^- RS_t^- + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EPU_t + \varepsilon_{t+1}, \quad (6)$$

where $RS_t^- = \sum_{j=1}^M r_{t,j}^2 I(r_{t,j} < 0)$ and $RS_t^+ = \sum_{j=1}^M r_{t,j}^2 I(r_{t,j} > 0)$.

The second model (HAR-RV-RS-II) adds a term that interacts the lagged realized variance with an indicator for negative daily returns $RV_t I(r_t < 0)$. The equation of this model is

$$RV_{t+1} = \beta_0 + \beta_d^+ RS_t^+ + \beta_d^- RS_t^- + \gamma RV_{d,t} I(r_t < 0) + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EPU_t + \varepsilon_{t+1}, \quad (7)$$

The third model for capturing the “leverage effect” contains the signed jump variation and an estimator of the variation due to the continuous part (bipower variation) (HAR-RV-SJ-I):

$$RV_{t+1} = \beta_0 + \beta_{j,d} SJ_t + \beta_{bv,d} BV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EPU_t + \varepsilon_{t+1}, \quad (8)$$

where $SJ_t = RS_t^+ - RS_t^-$.

The final model for “leverage effect” disentangles the role of positive and negative jumps, respectively (HAR-RV-SJ- II):

$$RV_{t+1} = \beta_0 + \beta_{j,d}^+ SJ_t^+ + \beta_{j,d}^- SJ_t^- + \beta_{bv,d} BV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta EPU_t + \varepsilon_{t+1}, \quad (9)$$

where $SJ_t^+ = SJ_t I(SJ_t > 0)$ and $SJ_t^- = SJ_t I(SJ_t < 0)$.

Overall, we use a total of eight HAR-type volatility equations to model and forecast the realized volatility.

3. Data and Empirical Results

3.1 Data description and summary statistics

We use 5-min high frequency data from the Standard and Poor’s 500 (S&P 500) index collected from Datastream. Our sample data are for the trading time in each business day between 9:30:00 and 16:00:00 and cover the period from January 2, 1996 to June 24, 2013. After removing the data for days with too few transactions, we finally obtain 4280 trading days. We calculate RV using percent returns of closing prices. Baker et al.’s (2013) index of EPU is downloaded from the Economic Policy Uncertainty website (<http://www.policyuncertainty.com/>). We use the EPU index divided by 100 in empirical analysis. The summary statistics of RV and EPU are given in Table 1.

Insert Table 1 here

3.2 The marginal effects of EPU

Table 2 reports the in-sample estimation results of the eight volatility models with the additional predictor of EPU. We can see that the parameter of EPU is significantly positive at the 5% level, regardless of the volatility model that is used.

The regression coefficients are also relatively stable when the volatility model changes. This finding suggests the strong ability of EPU to predict RV. We calculate the effects of one standard deviation increase in policy uncertainty in terms the percent change in volatility, as well as the two standard error upper and lower bands, using the regression coefficients of EPU. The results in Table 3 suggest that the marginal effect of EPU is about 0.03-0.04 percent, depending on the model specification. The significant impacts of EPU are consistent with the findings in recent studies that macroeconomic news can affect stock volatility (see, e.g., [Asgharian et al., 2015](#); [Onan et al., 2014](#)).

Insert Table 2 and Table 3 here

Stock market volatility is of course an important source of economic uncertainty. Therefore, it may be argued that the significant marginal effect of EPU is caused by the fact that policy uncertainty variable and S&P volatility are endogenous. Actually, a larger fraction of policy uncertainty is due to the uncertainty about policy-related macroeconomic variables such as Consumer Price Index, Government Budget and Federal Expenditure. These variables are exogenous to stock market volatility at least in the short-term. Another considerable part of policy uncertainty comes from events that are exogenous to stock market volatility such as Gulf Wars and the Clinton and Obama Election. From above analysis, we can conclude that our policy uncertainty variable is exogenous to S&P volatility to a large extent. Baker et al.(2013) also argue that their policy uncertainty index have substantial independent variation to VIX.

3.3 Is EPU helpful for predicting RV?

Compared with the in-sample results, market participants may be more concerned about out-of-sample performance because they would like to know how well they can use the model in the future. For this reason, we examine whether adding EPU to a volatility model can improve its predictive ability for out-of-sample data.

We use the rolling window method in our forecasting procedure. Specifically, we divide the whole sample data into two subsamples: in-sample data covering the first 2000 trading days for parameter estimation, and out-of-sample data covering the remaining 2280 days for evaluating the forecasting performance. The estimation period is then rolled forward by adding a new day and dropping the most distant day. In this way, the sample size employed to estimate the model parameters is fixed, and we re-estimate the parameters of these models each day to obtain volatility forecasts.

We obtain volatility forecasts for the horizons of 1 day and 20 days. To measure the forecasting accuracy, we use the following two heteroscedasticity-adjusted loss functions suggested by Bollerslev and Ghysels (1996):

$$\text{HMSE} = n^{-1} \sum_{t=1}^n (1 - RV_t / h_t)^2, \quad (10)$$

$$\text{HMAE} = n^{-1} \sum_{t=1}^n |1 - RV_t / h_t|, \quad (11)$$

where n is the number of volatility forecasts ($n=2280$), RV_t is the actual realized volatility and h_t is the volatility forecast. In addition, we use the Diebold and Mariano (1995) (DM) test to examine whether the differences in the loss functions between the two models are significant.

We compare the forecasting accuracy between the volatility model with EPU and

that without EPU and display the results in Table 4. For a forecasting horizon of 1 day, the forecasting loss of a model with EPU is smaller than that without EPU, regardless of the model employed. Moreover, the p-values of the DM test indicate that after adding EPU as one more predictor, the improvement in predictive ability is significant at the 5% level for each of eight volatility models. For the 20-day horizon, the gains in predictability are relatively weak but still significant at the 10% level. This result suggests that EPU has the ability to predict RV for out-of-sample data.

Insert Table 4 here

4. Concluding Remarks

In a recent paper, Pastor and Veronesi (2012) explain theoretically how policy uncertainty affects stock market volatility. This paper improves on their work by empirically examining whether economic policy uncertainty (EPU) can predict future market volatility. Our in-sample as well as out-of-sample evidence suggests that EPU exhibits significantly predictive power of market volatility which is robust to the specifications of the volatility prediction models considered. Overall, our findings indicate that EPU has predictive ability to stock market volatility.

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Tables

Table 1 Descriptive statistics of Realized volatility and policy uncertainty index

	Mean	Max.	Min.	Std.Dev.	Skewness	Kurtosis
RV	1.035	18.62	0.046	1.480	5.033	35.78
EPU	0.982	7.191	0.047	0.706	2.019	7.477

Notes: RV is the realized volatility calculated for the percent returns. EPU is the economic policy uncertainty index divided by 100.

Table 2 Estimation results of volatility models

	HAR-RV	HAR-RV-J	HAR-RV-CJ	HAR-RV-TCJ	HAR-RV-RS-I	HAR-RV-RS-II	HAR-RV-SJ-I	HAR-RV-SJ-II
β_0	0.025 (1.198)	0.028 (1.336)	0.032 (1.472)	0.073*** (3.459)	0.025 (1.224)	0.022 (0.289)	0.033 (1.612)	0.019 (0.927)
β_d	0.481*** (27.67)	0.483*** (27.76)						
β_w	0.304*** (11.65)	0.302*** (11.59)			0.358*** (14.04)	0.353*** (13.88)	0.388*** (15.39)	0.386*** (15.41)
β_m	0.147*** (7.019)	0.148*** (7.090)			0.141*** (6.927)	0.151*** (7.452)	0.156*** (7.626)	0.148*** (7.265)
$\beta_{c,d}$			0.480*** (27.61)	0.487*** (28.02)				
$\beta_{c,w}$			0.304*** (11.62)	0.294*** (11.42)				
$\beta_{c,m}$			0.150*** (7.148)	0.160*** (7.718)				
$\beta_{j,d}$		-0.453*** (-2.715)	0.225 (1.196)	0.226*** (4.815)				
$\beta_{j,w}$			-0.680 (-1.534)					
$\beta_{j,m}$			0.491 (0.615)				-0.401*** (-16.34)	
β_d^+					0.836*** (30.78)	0.658*** (16.00)		
β_d^-					0.024 (0.460)	0.084** (2.494)		
γ						0.099*** (2.732)		
β_{bv}							0.400*** (24.00)	0.342*** (19.12)
$\beta_{j,d}^+$								-0.065 (-1.393)
$\beta_{j,d}^-$								-0.742*** (-15.88)
EPU	0.047** (2.522)	0.046** (2.517)	0.046** (2.476)	0.061*** (3.315)	0.052*** (2.912)	0.055*** (3.112)	0.057*** (3.174)	0.050*** (2.804)

Notes: This table provides the parameter estimation results for the realized volatility models. The numbers in the parentheses are the t-statistics. The asterisks *, ** and *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

Table 3 Marginal effect of economic policy uncertainty on daily volatility

	HAR-RV	HAR-RV-J	HAR-RV-CJ	HAR-RV-TCJ	HAR-RV-RS-I	HAR-RV-RS-II	HAR-RV-SJ-I	HAR-RV-SJ-II
Average effect	0.033	0.032	0.032	0.043	0.037	0.039	0.040	0.035
Upper band	0.060	0.058	0.059	0.069	0.062	0.064	0.066	0.061
Lower band	0.007	0.007	0.006	0.017	0.012	0.014	0.015	0.010

Notes: This table provides the effects of one standard deviation increase in policy uncertainty index in terms of the percentage change in volatility. We also give the upper and lower bands of two standard errors.

Table 4 Forecasting results of volatility models

HMSE				HMAE		
Horizon=1						
	Model with EPU	Model without EPU	p-values of DM statistics	Model with EPU	Model without EPU	p-values of DM statistics
HAR-RV	0.346	0.373	0.007	0.413	0.418	0.001
HAR-RV-J	0.345	0.370	0.007	0.412	0.418	0.001
HAR-RV-CJ	0.343	0.367	0.008	0.412	0.417	0.001
HAR-RV-TCJ	0.331	0.356	0.011	0.411	0.417	0.001
HAR-RV-RS-I	0.337	0.366	0.007	0.403	0.407	0.007
HAR-RV-RS-II	0.338	0.366	0.008	0.403	0.408	0.006
HAR-RV-SJ-I	0.327	0.354	0.013	0.401	0.406	0.016
HAR-RV-SJ-II	0.356	0.388	0.013	0.410	0.416	0.001
Horizon=20						
HAR-RV	1.248	1.337	0.053	0.658	0.663	0.074
HAR-RV-J	1.265	1.355	0.052	0.659	0.665	0.056
HAR-RV-CJ	1.371	1.453	0.073	0.664	0.670	0.055
HAR-RV-TCJ	1.294	1.437	0.035	0.659	0.667	0.056
HAR-RV-RS-I	1.244	1.322	0.065	0.658	0.663	0.073
HAR-RV-RS-II	1.211	1.299	0.055	0.656	0.662	0.052
HAR-RV-SJ-I	1.238	1.318	0.063	0.657	0.663	0.075
HAR-RV-SJ-II	1.242	1.327	0.055	0.657	0.663	0.063

Notes: This table provides the loss functions of different volatility models with economic policy uncertainty (EPU) and those without EPU. The p-values of Diebold and Mariano (1995) test are also given.