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The information content of option-implied information for volatility forecasting with investor sentiment

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ABSTRACT

This study explores the effect of investor sentiment on the volatility forecasting power of option-implied information. We find that the risk-neutral skewness has the explanatory power regarding future volatility only during high sentiment periods. Furthermore, the implied volatility has varying volatility forecasting ability depending on the level of investor sentiment. Our findings suggest that the effectiveness of volatility forecasting models based on option-implied information varies over time with the level of investor sentiment. We confirm the important role of investor sentiment in volatility forecasting models exploiting option-implied information with strong evidence from in-sample and out-of-sample analyses. We also present improvements in the accuracy of volatility forecasts from volatility forecasting models derived by incorporating investor sentiment in these models.

1. Introduction

Volatility forecasting is one of the most important issues in the asset pricing literature. In particular, financial assets are priced based on risk-return tradeoffs;[2] therefore, estimating the appropriate level of volatility has a large impact on determining the price of financial assets such as stocks and options.[3] Volatility forecasting also plays a critical role in financial risk management.[4] Firms can prepare well for upcoming risk if they can predict increases in future volatility, a common measure of risk. Over the past two decades, several volatility forecasting models based on various factors have been developed. Some of studies point out that option-implied information such as the risk-neutral skewness and the implied volatility, is effective at predicting future stock return volatility (Latane and Rendleman, 1976; Jiang and Tian, 2005; and Byun and Kim, 2013). In the line of the literature, we examine whether investor sentiment affects the relationship between the future volatility and the option-implied information.

Our study investigates the impact of investor sentiment on the validity of volatility forecasting models based on option-implied information. Fundamental issues such as whether the option market leads the stock market or vice versa are discussed in the financial literature (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; Xing et al., 2010; An et al., 2013; Bali and Murray, 2013). Some research papers that support the informativeness of the option market find that option-implied information has the predictive power regarding stock market movements at high frequencies, such as daily or intra-day frequencies (Manaster and Rendleman, 1982; Bhattacharya, 1987; and Anthony, 1988). In contrast, An et al. (2013) find that the predictability of information in an option market regarding stock market movements lasts for more than a month. The factors driving the persistence and magnitude of predictability have not been determined. We suggest that investor sentiment is an important factor that determines the persistence and magnitude of the option market predictability of stock market movements. Byun and Kim (2013) show that the risk-neutral

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[2] See, e.g., Merton (1980), Ghysels et al. (2005), Bali and Peng (2006), Christensen and Nielsen (2007), Bandi and Perron (2008), and Bollerslev et al. (2009).

[3] See, e.g., Heston and Nandi (2000), Christoffersen et al. (2008), Goyal and Saretto (2009), Christoffersen et al. (2012), and Corsi et al. (2013).

[4] See, e.g., Christoffersen and Diebold (2000), Clements et al. (2008), and Maheu and McCurdy (2011).

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skewness has the stock return volatility forecasting power at only daily and weekly frequencies. According to their findings, the risk-neutral skewness does not anticipate future monthly stock return volatility. Along the same lines, we report that the risk-neutral skewness derived from option prices has significantly stronger predictive power regarding future stock return volatility during high sentiment periods than low sentiment periods. In addition, its predictive power lasts for a long horizon (a month) during high sentiment periods. We also find that investor sentiment affects the relationship between the implied volatility and the future stock return volatility.

We expect investor sentiment to strengthen the predictive power of the risk-neutral skewness on monthly stock return volatility for the following two reasons. First, sentiment investors help informed traders disguise their informed tradings during high sentiment periods. According to An et al. (2013), information from an option market can be used to predict stock market movements for a relatively long period (one month) due to the presence of uninformed noise traders in the stock and option markets. These findings imply that it takes a significant amount of time to determine efficient prices in the presence of uninformed traders. Trading by uninformed noise traders conceals informed trading initiated by informed traders. Therefore, the ability of the risk-neutral skewness to forecast future volatility is significantly stronger during periods where noise traders are actively involved in the stock market. During high sentiment periods, a larger number of individual investors participate aggressively in the stock market, and their trading has a strong influence on market prices (Barber and Odean, 2008; Karlsson et al., 2009; and Yuan, 2012). Because most individual investors are uninformed, stock prices do not respond immediately to informed trading during high sentiment periods. Accordingly, the risk-neutral skewness has the stronger predictive power regarding stock return volatility during high sentiment periods than low sentiment periods. In addition, the risk-neutral skewness anticipates future stock return volatility for a long period (one month) during high sentiment periods.

Second, the skewness is a common measure of the risk of future potential negative stock returns, including downward stock return jumps (Dennis and Mayhew, 2002; Doran et al., 2007; Bali and Hovakimian, 2009; and Conrad et al., 2013). We find that the forecasting power of the risk-neutral skewness, a forward-looking measure of the skewness, is stronger during high sentiment periods, suggesting that during high sentiment periods, information in the risk-neutral skewness is not reflected quickly in stock market movements through realizing downward jumps. It also indicates that pessimistic opinions about the stock market are not fully incorporated into stock prices during high sentiment periods. There are three reasons why pessimistic opinions are not reflected instantly in the stock market during high sentiment periods (Yu and Yuan, 2011 and Stambaugh et al., 2012). The first reason is that during high sentiment periods, the stock market is influenced primarily by individual investors who rarely take short positions. Barber and Odean (2008) show that only 0.29% of individual investors utilize short selling, as they are limited by knowledge or behavior biases. The second reason is that to take a short position, investors are required to have supplies of stock loans, which are usually offered by institutional investors. Stocks are more likely to be overpriced during high sentiment periods (Baker and Wurgler, 2007). Thus, informed institutional investors are not willing to loan stocks during high sentiment periods, because many of them are aware of overvaluation during those periods (D'Avolio, 2002). The decreased number of stock loans makes taking short positions costly. The last reason is that pessimistic investors hesitate to sell their stocks or to take short positions due to arbitrage risk during high sentiment periods (Shleifer and Vishny, 1997). Stock prices may keep increasing over the short-term before eventually decreasing to fair prices during high sentiment periods because irrational and inexperienced investors trade in unpredictable ways. As mentioned before, during high sentiment periods, these irrational and inexperienced sentiment investors are strongly involved in the stock market and make the arbitrage risk higher than usual (Yu and Yuan, 2011). The three reasons listed above provide another explanation of why we expect the risk-neutral skewness to have the stronger forecasting ability regarding future stock return volatility during high sentiment periods than low sentiment periods.

This research also focuses on the effect of investor sentiment on the ability of the implied volatility to forecast future volatility. Latane and Rendleman (1976) report that the weighted average of the Black and Scholes call option-implied volatilities outperforms historical return volatility in future volatility forecasting. Furthermore, the option-implied volatility is affected by the behavioral biases of investors (Stein, 1989 and Poteshman, 2001). We therefore expect and find that overreaction in the stock market during high sentiment periods leads to misestimation of the option-implied volatility and weakens the volatility forecasting power of the option-implied volatility. Our findings provide empirical evidence consistent with Barberis and Huang (2001)'s theoretical expectation that overreaction in current stock returns results in misestimation of future stock return volatility. They investigate irrational investors who are loss averse and trade financial assets based on mental accounting. When past performance is good, loss-averse investors are less concerned about future losses, because past good performance acts as a cushion for future potential losses (Goyal and Saretto, 2009). Therefore, investors underestimate the risk of the stock market in the future. According to Baker and Wurgler (2007), the stock market is likely to be overvalued during high sentiment periods. Our prediction is that this overreaction exacerbates the misestimation of the implied volatility, which contributes to the weaker volatility predicting power of the implied volatility during high sentiment periods than low sentiment periods. Similarly, Goyal and Saretto (2009) report the results based on cross-sectional analysis that the option-implied volatility of individual stocks are misestimated after overreaction to stock returns. The results are consistent with ours. However, our results have different implications, because we investigate time-series volatility forecasting of the stock market.

This study contributes to the financial literature by providing evidence that investor sentiment plays a key role in the relationship between the option-implied information and the future stock return volatility. Investor sentiment can explain irrational phenomena in the stock market. Sometimes, existing rational asset pricing models are not able to perfectly explain anomalies in the stock market. However, numerous studies demonstrate the relationship between the investor sentiment and the stock market movement[5] and successfully explain irrational phenomena by considering investor sentiment.[6] Yu and Yuan (2011) suggest that an unstable mean–variance relationship is induced by investor sentiment in the stock market. Stambaugh et al. (2012) suggest that market anomalies are more significant during high sentiment periods than low sentiment periods. Another area of literature focuses on the effect of investor sentiment in the stock market on option prices.[7] Mahani and

[5] See, e.g., De Long et al. (1990), Lee et al. (1991), Kamstra et al. (2000), Hirshleifer and Shumway (2003), Brown and Cliff (2004, 2005), Dowling and Lucey (2005), Baker and Wurgler (2006, 2007), Lemmon and Portniaguina (2006), Edmans et al. (2007), Palomino et al. (2009), Kaplanski and Levy (2010), Baker et al. (2012), and Białkowski et al. (2012).

[6] See, e.g., Shleifer and Vishny (1997), Baele et al. (2010), Yu and Yuan (2011), Baker and Wurgler (2012), Stambaugh et al. (2012), Shen and Yu (2013), and Kim et al. (2014).

[7] See, e.g., Cao et al. (2005), Han (2008), Mahani and Poteshman (2008), and Bauer et al. (2009).

Poteshman (2008) provide empirical evidence that unsophisticated investors also participate in the option market. Additionally, Han (2008) supplies empirical evidence that index option prices and the option volatility smile are affected by investor sentiment in the stock market. To the best of our knowledge, our study is the first to examine the effect of investor sentiment on the relationship between the option-implied information and the future stock return volatility.

We adopt two option-implied information measures to forecast future volatility: the implied volatility and the risk-neutral skewness. Byun and Kim (2013) derive a linear relationship between the physical variance and the risk-neutral moments, such as the risk-neutral variance and the risk-neutral skewness. If return innovation is normally distributed, the physical variance is identical to the risk-neutral variance. However, for non-normal return innovation, the risk-neutral skewness plays an important role in forecasting future volatility. We employ the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV model) of Corsi (2009) to exploit information in historical records. To present the time-varying relationship between the option-implied information and the future stock return volatility with investor sentiment, we evaluate the volatility forecasting power of option-implied information during high sentiment and low sentiment periods after controlling for historical information. In the in-sample analysis, the coefficient estimate on the risk-neutral skewness is positive and highly significant only during high sentiment periods. Furthermore, the addition of a sentiment variable to volatility forecasting models with option-implied information improves their explanatory power for future monthly volatility from 1.6% to 2.2%. Consistent with the significant results of the in-sample analysis, we also observe significant improvements in the out-of-sample analysis. Our findings indicate that investor sentiment plays a key role in volatility forecasting models that consider option-implied information.

The rest of the paper is organized as follows. Section 2 introduces volatility measurement. Section 3 describes data and reports our main empirical results. Section 4 investigates the robustness of our empirical results. Section 5 concludes the paper.

2. Volatility measurement

The stock return volatility, the variable of our interest, is a latent variable in the asset price process. Thus, the description for the measurement of the realized volatility is important for volatility forecasting. The realized volatility is utilized as the estimator of the stock return volatility. In this section, we explain about our volatility measurement.

We assume that the process of a logarithmic asset price at time t (X_t) is a standard jump diffusion process:

$$dX_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t, \tag{1}$$

where μ_t is the drift term at time t with a continuous and locally finite variable sample path, σ_t is the volatility process at time t, W_t is a standard Brownian motion, κ_t is a jump size at time t, and a counting process q_t equals 1 if a jump occurs at time t.

Given a fixed time window T, the quantity of variance during the time window T is approximated by the quadratic variation of above process over the time window T. The quadratic variation is as follows:

$$[X]_t^{t+T} := X_{t+T}^2 - X_t^2 - 2\int_t^{t+T} X_{s-} dX_s, \tag{2}$$

where t is a specific time (e.g., day). A popular estimator of the quadratic variation based the log asset price process is the realized variance. For simplicity, we assume that time window T is one day. We define the intraday return over the day t as

$$r_{t,i}^{\delta} \equiv X_{t+i\times\delta} - X_{t+(i-1)\times\delta}, \tag{3}$$

where $i = 1, \ldots, N(= 1/\delta)$, and δ is the length of subintervals over the time $[t, t+1]$. In addition, we define the realized volatility as the square root of the realized variance, and the realized volatility during one day $[t, t+1]$ is defined as

$$RV_{t,t+1}^{\delta} = \sqrt{\sum_{i=1}^{N} (r_{t,i}^{\delta})^2}, \tag{4}$$

where $r_{t,i}^{\delta}$ is the i-th intraday return over the day t with the length of subintervals, δ. The square of the realized volatility (i.e., the realized variance) converges in probability to the quadratic variation, as $\delta \to 0$.[8] We omit the superscript δ in the realized volatility for simplicity. Based on the daily realized volatility, let the multi-period realized volatilities be denoted as

$$RV_{t,t+h} = \sqrt{[RV_{t,t+1}^2 + RV_{t+1,t+2}^2 + \cdots + RV_{t+h-1,t+h}^2]/h}, \tag{5}$$

where $h = 1, 2, \ldots$. We denote the multi-period realized volatilities for $h = 22$ as the monthly realized volatility.

3. Data and empirical analysis

We analyze the ability of the forecasting models to forecast future volatility of S&P 500 index with investor sentiment. First, we describe the dataset used for constructing the realized volatility, the implied volatility, and the risk-neutral skewness. In addition, we introduce Baker and Wurgler's investor sentiment index to capture varying investor sentiment in the stock market. After that, we evaluate the effect of investor sentiment on the volatility forecasting ability of the risk-neutral skewness and the implied volatility.

3.1. Data

Our dataset consists of high frequency data for S&P 500 index, daily VIX, daily option prices of S&P 500 index, and investor sentiment index. For the high frequency data of S&P 500 index, the intraday data is provided by Chicago Mercantile Exchange (CME). The intraday data of S&P 500 index includes the period from 9:35 a.m. to 4:00 p.m. Eastern Standard Time (EST). To construct the realized volatility, we sample the intraday data of S&P 500 index at the five-minute frequency and have 77 observations for a day. For the VIX, the implied volatility of S&P 500 index, the daily data is obtained from Chicago Board of Options Exchange (CBOE). Treasury bill rates from the Federal Reserve Bank of St. Louis are used as a measure of the risk-free rate.

Daily option prices of S&P 500 index are obtained from OptionMetrics. The data of S&P 500 index option covers the period from 4 January 1996 to 30 August 2010, for a total of 3681 daily observations. The daily price of option is defined as the mid-price of the bid and ask prices at each day's close. The index option data are filtered by the following filtering rules. First, any options with a zero bid price are excluded from our sample. In addition, the option prices below 3/8 are removed from the sample. These options may not have reliable information due to the error caused by the minimum tick size or the lack of liquidity. Second, options under the violation of no-arbitrage condition are removed. Third, we use only *OTM* call and put options. Following Bakshi et al. (2003), the call (put) option

[8] In our empirical analysis, we use the intraday returns with the five-minute sampling frequency. If the frequently sampled returns are utilized for the construction of the realized volatility, microstructure noises are induced by the bid-ask bounce, the infrequent trading, and other factors. Thus, previous literature (e.g., Andersen and Bollerslev, 1998; Andersen et al., 2011; Chen and Ghysels, 2011; and Golosnoy et al., 2014) suggest the five-minute sampling frequency to keep the balance between the accuracy of the realized volatility and the influence of the microstructure noise.

Table 1
Summary statistics.

Statistics	Realized volatility	VIX	Risk-neutral skewness	Sentiment index
Panel A: Whole sample period				
Mean	0.90%	1.40%	−0.093	0.192
Standard deviation	0.48%	0.55%	0.027	0.595
Skewness	2.79	1.90	−0.383	1.577
Kurtosis	11.81	6.44	0.389	3.019
Min	0.39%	0.62%	−0.240	−0.902
Max	4.12%	5.09%	−0.021	2.497
LB_{10}	34,409	32,338	21,726	1,036
Panel B: High sentiment periods				
Mean	0.96%	1.44%	−0.088	0.578
Standard deviation	0.56%	0.54%	0.027	0.598
Skewness	2.84	2.56	−0.394	1.554
Kurtosis	10.58	10.89	0.065	1.393
Min	0.39%	0.62%	−0.240	0.069
Max	4.12%	5.09%	−0.021	2.497
Panel C: Low sentiment periods				
Mean	0.83%	1.36%	−0.098	−0.195
Standard deviation	0.37%	0.56%	0.025	0.232
Skewness	1.54	1.34	−0.510	−1.165
Kurtosis	2.25	2.32	0.852	0.732
Min	0.41%	0.62%	−0.226	−0.902
Max	2.19%	4.32%	−0.031	0.068

The table reports summary statistics of S&P 500 index monthly realized volatility, VIX, risk-neutral skewness, and sentiment index. The row labeled LB_{10} gives the Ljung-Box test statistics for up to tenth-order serial correlation. Risk-neutral skewness is estimated using S&P 500 index options based on Bakshi et al. (2003), and sentiment index is obtained from Baker and Wurgler (2007). Panel A reports summary statistics during the whole sample period. Panel B reports summary statistics during high sentiment periods (i.e., above the median value of the sentiment index), and Panel C reports summary statistics during low sentiment periods (i.e., below the median value of the sentiment index). Summary statistics for all variables except sentiment index are reported based on daily frequency, and summary statistics of sentiment index are reported based on monthly frequency. The sample period is from 4 January 1996 to 30 August 2010.

is *OTM* if $K/S > 1$ ($K/S < 1$), where S denotes the contemporaneous stock price, and K is the strike price of the options. Finally, we remove the options whose time to maturity is less than nine calendar days, because these options may have market microstructure concerns. Since S&P 500 index options are European, we do not consider the early exercise premium of S&P 500 index options.

Based on the above filtered option data, we estimate the risk-neutral skewness. We employ the risk-neutral skewness derived from the model-free approach of Bakshi et al. (2003). To eliminate the effect of the maturity difference on the comparison of the risk-neutral skewness with the implied volatility, we linearly interpolate to construct 30 calendar day constant maturity series of the risk-neutral skewness.

To measure time-varying investor sentiment in the stock market, we use the market-based sentiment measure suggested by Baker and Wurgler (2007). Baker and Wurgler (2007) construct a sentiment index based on the principal component analysis. Their sentiment index is defined as the first principal component of residuals from the regression in which six investor sentiment proxies (closed-end fund discount, NYSE share turnover, number of IPOs, average first-day return of IPOs, equity share in new issues, and dividend premium) are regressed on a set of macroeconomic variables to remove the effects of macroeconomic variables. The monthly time-series of the sentiment index is obtained from the website of Jeffrey Wurgler.[9] The monthly frequency in the sentiment index is appropriate to forecast monthly realized volatility.

Table 1 presents the summary statistics of the S&P 500 index monthly realized volatility, VIX, the risk-neutral skewness, and the sentiment index. The summary statistics of the monthly realized volatility, VIX, and the risk-neutral skewness are reported based on daily frequency, and those of the sentiment index are reported based on monthly frequency. The mean values of the monthly realized volatility and VIX are 0.90% and 1.40%, and the standard deviations of those are 0.48% and 0.55%, respectively. During high sentiment periods, the mean values of the monthly realized volatility and VIX are larger than those during low sentiment periods. The monthly realized volatility is more positively skewed than VIX during the whole sample period, high sentiment periods, and low sentiment periods. While the distributions of the monthly realized volatility and VIX during the whole sample period and high sentiment periods are leptokurtic, the distributions of those during low sentiment periods are platykurtic. Since the Ljung-Box statistics of the monthly realized volatility and VIX during the whole sample period are very high, the time-series of the monthly realized volatility and VIX exhibit a high degree of autocorrelation. The risk-neutral skewness of the S&P 500 index is always negative, and these results are consistent with Bakshi et al. (2003). The risk-neutral skewness is more negative during low sentiment periods than high sentiment periods. The distribution of the risk-neutral skewness is always platykurtic, and the time-series of the risk-neutral skewness have high auto-correlation due to high value of the Ljung-Box statistics.[10]

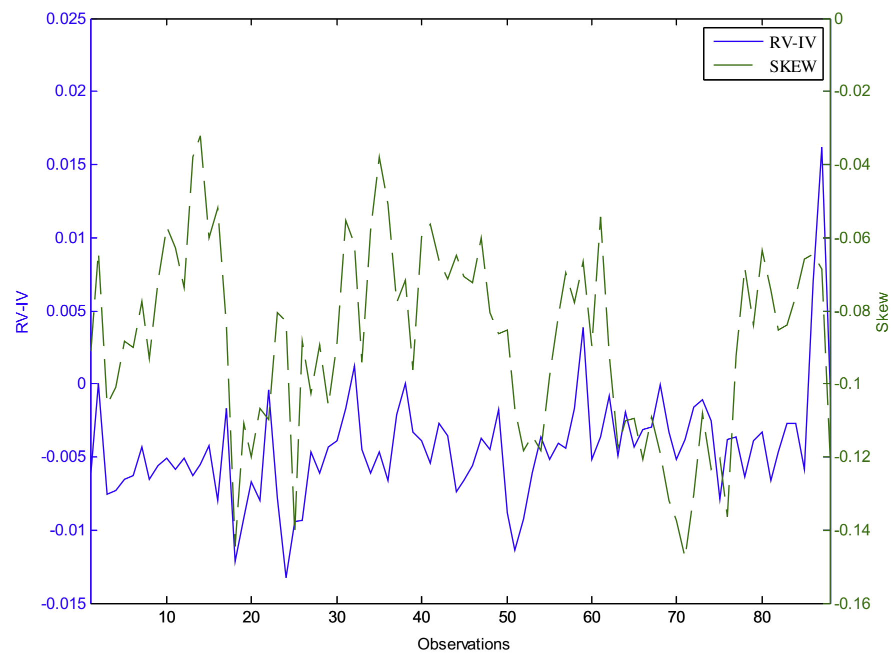
3.2. Option-implied information and investor sentiment

We first select the volatility forecasting models to analyze the effect of investor sentiment on the forecasting ability of option-implied information. Among the recent volatility forecasting models, the HAR-RV model shows that historical information of

[9] http://people.stern.nyu.edu/jwurgler.

[10] In unreported results, the stock market return innovation during high sentiment periods diverges even further from the normal distribution, as compared to that during low sentiment periods. The Jarque–Bera test has the null hypothesis that the distribution of the series is normal. Even though the Jarque–Bera test rejects that the distribution of the monthly log stock market return during high sentiment periods and low sentiment periods is normal, the Jarque–Bera statistics of the monthly log stock market return are 1310.60 and 505.46 during high sentiment periods and low sentiment periods, respectively. By definition of the Jarque–Bera statistic, larger deviation of the distribution of the series from the normal distribution increases the Jarque–Bera statistic.

(a) High sentiment periods



(b) Low sentiment periods

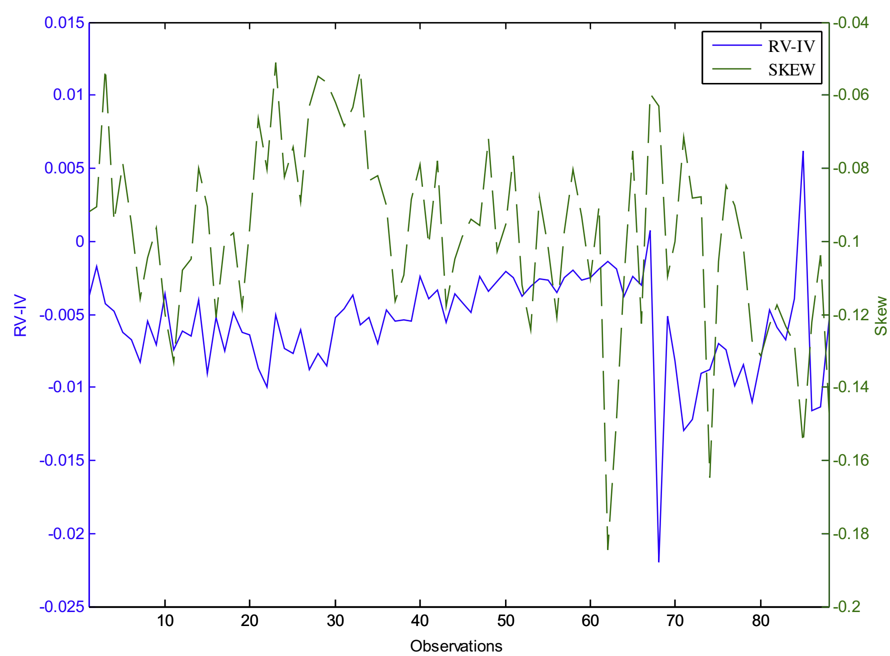


Fig. 1. Difference between realized volatility and implied volatility and risk-neutral skewness. The figure plots the difference between the monthly realized volatility and the implied volatility (left scale) and the risk-neutral skewness (right scale). (a) plots the difference between the monthly realized volatility and the implied volatility and the risk-neutral skewness during high sentiment periods (i.e., above the median value of the sentiment index), and (b) plots the difference between the monthly realized volatility and the implied volatility and the risk-neutral skewness during low sentiment periods (i.e., below the median value of the sentiment index). The solid line represents the difference between the monthly realized volatility and the implied volatility, and the dashed line represents the monthly risk-neutral skewness. The sample period is from January 1996 to August 2010, for a total of 176 monthly observations.

underlying asset movements can help to forecast future volatility. The HAR-RV model, proposed by Corsi (2009), utilizes a linear form of past realized volatilities sampled at different frequencies to capture the empirical memory persistence of volatility. The main motivation of the HAR-RV model is that investors with different time horizons perceive, react to, and cause different types of volatility components. Three past realized volatilities over different horizons are able to identify three primary volatility components: the short-term investors with daily or higher trading frequency (i.e., past daily realized volatility), the medium-term investors who rebalance their positions weekly (i.e., past weekly realized volatility), and the long-term investors with a characteristic time of one or more months (i.e., past monthly realized volatility). Although the HAR-RV model is not included in the class of long memory models, the

HAR-RV model successfully achieves the purpose of modeling the long memory behavior of volatility in a simple and parsimonious way and shows good performance in volatility forecasting. Thus, we choose the volatility forecasting models stemming from the HAR-RV model to control for historical information on volatility forecasting. The HAR-RV model is given by

$$RV_{t,t+22} = \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} + \varepsilon_{t,t+22}. \tag{6}$$

The HAR-RV model with investor sentiment (HAR-RV (S) model) can be expressed as:

$$\begin{aligned} RV_{t,t+22} = {} & \beta_0 + \beta_0^S \times D_t + \beta_D RV_{t-1,t} + \beta_D^S D_t \times RV_{t-1,t} + \beta_W RV_{t-5,t} \\ & + \beta_W^S D_t \times RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_M^S D_t \times RV_{t-22,t} + \varepsilon_{t,t+22}, \end{aligned} \tag{7}$$

where D_t is a sentiment dummy variable, the value of which equals 1 if month t is included in high sentiment periods. Following Yu and Yuan (2011) and Stambaugh et al. (2012), a high sentiment month is defined as a month in which the sentiment index is higher than the median of the monthly sentiment index over the whole sample period.[11] Based on empirical results in Jiang and Tian (2005) and Byun and Kim (2013), we employ the implied volatility calculated by the model-free approach and the risk-neutral skewness to investigate the effect of investor sentiment on the ability of option-implied information to forecast future volatility.

Fig. 1 displays the time-series of the risk-neutral skewness and the difference between the monthly realized volatility and implied volatility.[12] Fig. 1a) shows the time-series movements of these two variables during high sentiment periods, and Fig. 1b) plots the movements of those during low sentiment periods. During high sentiment periods, the difference between the monthly realized volatility and implied volatility tends to co-move with the risk-neutral skewness. The correlation between them during high sentiment periods is 0.15. On the other hand, during low sentiment periods, the difference between the monthly realized volatility and implied volatility tends to move in the opposite direction to the movements of the risk-neutral skewness. The correlation between them during low sentiment periods is −0.19. The different volatility patterns during high and low sentiment periods suggest that the forecasting power of the implied volatility and the risk-neutral skewness for future volatility is affected by the level of investor sentiment.

Based on the HAR-RV model, earlier studies propose the combination of historical information and option-implied information. Fradkin (2008) and Busch et al. (2011) suggest the way of involving both past realized volatilities and the implied volatility to improve the volatility forecasting power. Also, they design the Heterogeneous Autoregressive model of Realized Volatility and Implied Volatility (HAR-RV-IV model). In addition, Byun and Kim (2013) propose the Heterogeneous Autoregressive model of Realized Volatility, Implied Volatility, and Skewness (HAR-RV-IV-SK model) to consider information of the risk-neutral skewness in volatility forecasting.

To check the robustness in the monthly volatility forecasting power of option-implied information during high sentiment periods, we employ the HAR-RV-IV model and the HAR-RV-IV-SK model. The HAR-RV-IV model and the HAR-RV-IV-SK model can be written as:

$$RV_{t,t+22} = \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_{IV} IV_t + \varepsilon_{t,t+22}, \tag{8}$$

$$\begin{aligned} RV_{t,t+22} = {} & \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_{IV} IV_t \\ & + \beta_{SK} SKEW_t + \varepsilon_{t,t+22}. \end{aligned} \tag{9}$$

The combinations of the above two models with investor sentiment (the HAR-RV-IV (S) model and the HAR-RV-IV-SK (S) model) can be expressed as:

$$\begin{aligned} RV_{t,t+22} = {} & \beta_0 + \beta_0^S \times D_t + \beta_D RV_{t-1,t} + \beta_D^S D_t \times RV_{t-1,t} + \beta_W RV_{t-5,t} \\ & + \beta_W^S D_t \times RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_M^S D_t \times RV_{t-22,t} \\ & + \beta_{IV} IV_t + \beta_{IV}^S D_t \times IV_t + \varepsilon_{t,t+22}, \end{aligned} \tag{10}$$

$$\begin{aligned} RV_{t,t+22} = {} & \beta_0 + \beta_0^S \times D_t + \beta_D RV_{t-1,t} + \beta_D^S D_t \times RV_{t-1,t} \\ & + \beta_W RV_{t-5,t} + \beta_W^S D_t \times RV_{t-5,t} + \beta_M RV_{t-22,t} + \beta_M^S D_t \\ & \times RV_{t-22,t} + \beta_{IV} IV_t + \beta_{IV}^S D_t \times IV_t + \beta_{SK} SKEW_t \\ & + \beta_{SK}^S D_t \times SKEW_t + \varepsilon_{t,t+22}, \end{aligned} \tag{11}$$

where D_t is a sentiment dummy variable, the value of which equals 1 if day t is included in high sentiment months.

Table 2 presents the results for option-implied information considering investor sentiment.[13] Before showing the time-varying volatility forecasting power of option-implied information with investor sentiment, we report the results of past realized volatilities from the HAR-RV model and the HAR-RV (S) model to check whether investor sentiment has a significant effect on the volatility forecasting power of past realized volatilities. All coefficient estimates on past realized volatilities in the HAR-RV model are positive and significant at the 1% level, which is consistent with empirical results in Corsi et al. (2010). However, the coefficient estimates on the interaction terms between the past realized volatilities and sentiment dummy variables are all insignificant in the HAR-RV (S) model. Thus, these results suggest that the forecasting ability of historical information reflected in past realized volatilities is not influenced by investor sentiment in the stock market.

In the HAR-RV-IV (S) model only considering the implied volatility, β_{IV} is positively significant at the 1% level. The coefficient estimate on the interaction term between the implied volatility and sentiment dummy variable (β_{IV}^S) is negatively significant at the 5% level, also suggesting consistent evidence with our expectation that the implied volatility has the weaker volatility forecasting power during high sentiment periods.[14] By the introduction of investor sentiment, the adjusted R^2 in the HAR-RV-IV (S) model is improved by 1.6%, as compared with the HAR-RV-IV model. These results support our expectation that the volatility forecasting power of option-implied information time-varies depending on investor sentiment.

In the HAR-RV-IV-SK (S) model incorporating the risk-neutral skewness, β_{SK} is not significant, which indicates that the risk-neutral skewness does not have an impact on future volatility during low sentiment periods. Furthermore, β_{SK}^S in the HAR-RV-IV-SK (S) model is positively significant at the 5% level, pointing out that the risk-neutral skewness has the significant volatility forecasting

[11] The number of daily observation during high sentiment periods and low sentiment periods are 1840 observations and 1841 observations, respectively.

[12] The proposition in Byun and Kim (2013) states the following equation: $\sigma_t^2 \approx \sigma_t^{*2} + \beta \times SKEW_t^*$ where $\sigma_t^2(\sigma_t^{*2})$ is the conditional variance under the physical (risk-neutral) measure, and $SKEW_t^*$ is the conditional risk-neutral skewness. The difference between the monthly realized volatility and the implied volatility presents the informativeness of the implied volatility in volatility forecasting, and the co-movement in the risk-neutral skewness and the difference between the monthly realized volatility and the implied volatility shows the explanatory power of the risk-neutral skewness for the part of future volatility induced by the non-normality of the return innovation.

[13] Similar to Byun and Kim (2013), the realized volatilities and the implied volatilities in the regressions are 100 times the original value of them to clearly report the coefficient estimate on each forecasting variable.

[14] Without past realized volatilities in the regression, the coefficient estimates on the implied volatility and the risk-neutral skewness during high sentiment periods are significant at the 10% and the 5% level, respectively. During high sentiment periods, while the coefficient estimate on the risk-neutral skewness is positive, that on the implied volatility is positive (but weakly significant), contrary to the result shown in Table 2. We conjecture that the steady effect of past realized volatilities interferes in the relationship between the future volatility and the implied volatility during high sentiment periods. The unreported results for the regression without past realized volatilities are available upon request.

Table 2
Option-implied information with investor sentiment.

Model specification	HAR-RV	HAR-RV (S)	HAR-RV-IV	HAR-RV-IV (S)	HAR-RV-IV-SK	HAR-RV-IV-SK (S)
β_0	0.199***(4.617)	0.236***(4.441)	0.114***(2.846)	0.088*(1.824)	0.190**(2.323)	−0.010(−0.088)
β_0^S		−0.046(−0.686)		0.055(0.650)		0.319**(2.045)
β_D	0.178***(7.504)	0.158***(5.645)	0.136***(4.275)	0.051**(2.046)	0.132***(4.627)	0.054**(2.194)
β_D^S		0.032(0.759)		0.120**(2.431)		0.102**(2.271)
β_W	0.338***(3.531)	0.233***(4.709)	0.311***(2.906)	0.121**(2.316)	0.307***(2.900)	0.121**(2.402)
β_W^S		0.117(0.841)		0.215(1.527)		0.195(1.415)
β_M	0.278***(3.679)	0.323***(5.479)	0.142*(1.772)	0.027(0.360)	0.143*(1.737)	0.029(0.381)
β_M^S		−0.030(−0.211)		0.208(1.323)		0.216(1.320)
β_{IV}			0.190**(2.400)	0.423***(6.296)	0.193**(2.474)	0.425***(6.143)
β_{IV}^S				−0.330**(−2.574)		−0.313**(−2.562)
β_{SK}					0.786(1.071)	−0.925(−0.931)
β_{SK}^S						2.872**(2.123)
Adj. R^2	0.642	0.649	0.649	0.665	0.650	0.672

The table shows the significance of the implied volatility and the risk-neutral skewness for forecasting future monthly volatility with the sentiment dummy variables. The HAR-RV model is the Heterogeneous Autoregressive model of Realized Volatility. The HAR-RV (S) model adds the sentiment dummy variables to the HAR-RV model. The HAR-RV-IV model is the Heterogeneous Autoregressive model of Realized Volatility and Implied Volatility. The HAR-RV-IV (S) model incorporates the sentiment dummy variables into the HAR-RV-IV model. The HAR-RV-IV-SK model is the Heterogeneous Autoregressive model of Realized Volatility, Implied Volatility, and Skewness. The HAR-RV-IV-SK (S) model adds the sentiment dummy variables to the HAR-RV-IV-SK model. Robust t-statistics following Newey and West (1987) corrected t-statistics with 44 lags are reported in parentheses. Adjusted R^2 for each model is reported in last row. The sample period is from 4 January 1996 to 30 August 2010, for a total of 3681 daily observations. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

power only during high sentiment periods. Other coefficient estimates are similar to those in the HAR-RV-IV (S) model, and we are able to achieve the increment of 2.2% in the adjusted R^2 by incorporating investor sentiment into HAR-RV-IV-SK model. These results are consistent with our conjecture that the volatility forecasting power of the risk-neutral skewness time-varies with the level of investor sentiment, and the increased forecasting power of the risk-neutral skewness by investor sentiment is not associated with the forecasting power of past realized volatilities and the implied volatility during high sentiment periods.[15]

3.3. Out-of-sample performance

In Section 3.2, we report the results of the in-sample analysis with the time-varying forecasting performance of option-implied information depending on the level of investor sentiment. In this section, we evaluate the out-of-sample forecasting performance with statistical tools. We re-estimate the coefficient estimates in the forecasting models.

The detailed procedure of estimation of the volatility forecast is as follows: First, we use the first 1404 daily observations, from January 1996 to July 2001, to initialize the volatility forecasting models. Then, we construct the volatility forecast at day t with a recursive parameter estimation of the coefficient estimates in the volatility forecasting models at each day t on a cumulative window of all daily observations available up to day $t-1$. In addition, we specify the sentiment dummy variables for the volatility forecast at day t in the forecasting models based on the time-series of the sentiment index from the first month to the month which includes the sentiment index for day t. For example, the volatility forecast on August 1, 2001 is estimated by the sentiment dummy variable constructed based on the monthly time-series of the sentiment index from December 1995 to July 2001.

To measure the accuracy of the volatility forecast, we employ three loss functions in Patton (2011). Three loss functions are MSE, MAE, and QLIKE, and these functions are the measures of the forecast accuracy to be invariant to noise in the proxy for the out-of-sample analysis. Three loss functions are expressed:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(\widehat{RV}^2_{t,t+22} - RV^2_{t,t+22}\right)^2, \tag{12}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|\widehat{RV}^2_{t,t+22} - RV^2_{t,t+22}|, \tag{13}$$

$$QLIKE = \frac{1}{N}\sum_{t=1}^{N}\left(\log(RV^2_{t,t+22}) + \frac{\widehat{RV}^2_{t,t+22}}{RV^2_{t,t+22}}\right), \tag{14}$$

where $\widehat{RV}_{t,t+22}$ is the forecast for future monthly volatility at day t, $RV_{t,t+22}$ is the true future monthly volatility at day t, and N is the number of the volatility forecasts.

To statistically compare the results of the volatility forecasting models in the out-of-sample analysis, we utilize two statistical tests in the comparison of the volatility forecasting models. Two statistical tests are the model confidence set test in Hansen et al. (2011) and the Diebold-Mariano test in Diebold and Mariano (1995). The model confidence set test has the null hypothesis that there is no difference in the expectation of the difference in the loss function among the various forecasting models and shows p-value for the null hypothesis. If the model is rejected at the significance level α, this model is worse than other models in the set. Thus, the model with $p = 1$ survives to the last in the set and is the best among the multiple forecasting models. The Diebold-Mariano test has the null hypothesis that there is no difference in the accuracy of the volatility forecasts estimated by two competing forecasting models and shows the t-statistic to measure the significance of the difference of the loss function between two volatility forecasts. If the t-statistic in the Diebold-Mariano test is negative (positive), the forecasting error of former (latter) forecasting model is smaller than that of latter (former) forecasting model.

The results of the out-of-sample analysis are reported in Table 3. Overall, we observe the significant improvements in the effectiveness of the volatility forecasting models after incorporating investor sentiment. The model confidence set test shows that the HAR-RV-IV-SK (S) model achieves the best performance, because this model has the smallest value of the loss function among other forecasting models. The p-values of the HAR-RV-IV-SK (S) model in three loss functions are equal to one. The Diebold-Mariano test

[15] To address the small sample property of the Newey and West (1987) corrected t-statistics due to overlapping observations, we employ the monthly non-overlapping regressions method and the bootstrapping method suggested by Efron (1979). A description of those is provided in Appendix A. As a result, we confirm that our results are not driven by the small sample property. The unreported results are available upon request.

confirms the outperformance of the volatility forecasting models when the volatility forecasting models incorporate investor sentiment. In the first column of Panel B in Table 3, the HAR-RV (S) model also has smaller forecasting error than the HAR-RV model. The negative *t*-statistic of MSE (MAE or QLIKE) means that the investors are able to achieve the smaller forecasting errors if considering investor sentiment. Although the *t*-statistic of MSE is not statistically significant, the *t*-statistic of MSE is negative. The *t*-statistics of MAE and QLIKE are also negative, and the HAR-RV (S) model is statistically superior to the HAR-RV model at the 5% (1%) significance level based on MAE (QLIKE). In the second (third) column, the improvements in the HAR-RV-IV (S) model (the HAR-RV-IV-SK (S) model) in MAE and QLIKE are statistically significant at the 5% and 1% level as compared the HAR-RV-IV model (the HAR-RV-IV-SK model), respectively.

Based on empirical results in Tables 2 and 3, we confirm that investor sentiment plays a crucial role in exploiting information of the option prices to forecast future volatility, and the volatility forecasting models considering investor sentiment present better performance than those not considering investor sentiment. Furthermore, the empirical results show that the improvements in the forecasting ability of option-implied information (i.e., the implied volatility and the risk-neutral skewness) with investor sentiment are larger than those in the forecasting power of historical information (i.e., past realized volatilities) with investor sentiment.

4. Robustness check

To strengthen our findings, we suggest some robustness checks in this section. Firstly, we check whether investor sentiment still have a significant impact on the forecasting ability of option-implied information in the various forecasting models. In Section 4.1, we employ the sum of absolute intra-daily returns abbreviated to the realized absolute value instead of the realized volatility in the forecasting models. In Section 4.2, we include past negative returns in three different time horizons (daily, weekly, and monthly frequencies) to reflect the leverage effect on the volatility forecasting models. In Section 4.3, we replace past realized volatilities in the volatility forecasting models with the continuous component and the jump component of past realized volatilities. Secondly, we investigate whether any other macroeconomic variables improve the forecasting ability of option-implied information in the volatility forecasting models, similar to investor sentiment in Section 4.4. Finally, we evaluate the performance of the volatility forecasting models incorporating investor sentiment during the financial crisis in Section 4.5.

4.1. Realized absolute value with investor sentiment

We show that our significant results with past realized volatilities are not driven by the definition of volatility in this section. To do so, we introduce the realized absolute value (i.e., the sum of absolute intra-daily returns). Ghysels et al. (2006) find empirical evidence that the Mixed Data Sampling (MIDAS) volatility forecasting model using the realized absolute value has the better performance in the forecasting future conditional variance than the MIDAS volatility forecasting model using the realized volatility. Forsberg and Ghysels (2007) suggest the incorporation of the realized absolute value into the HAR-RV model and also obtain empirical results consistent with the results in Ghysels et al. (2006). They show that the outperformance of the realized absolute value in the HAR-RV model stems from the robustness of the realized absolute value to the sampling error. The sampling error of the realized absolute value depends on the second power of volatility, while that of the realized volatility is determined by the fourth power of volatility. Thus, the process of the sampling error for the realized absolute value is more stable and better behaved than that for the realized volatility. In addition, the realized absolute value is not affected by the jumps asymptotically, whereas the jumps affect the realized volatility.

Using the replacement of past realized volatilities with past realized absolute values in the volatility forecasting models, we check whether the forecasting ability of the implied volatility and the risk-neutral skewness to future volatility is affected by investor sentiment. The realized absolute value is defined as follows:

$$RAV_{t,t+1} = \mu_1^{-1}\Delta^{1/2}\sum_{i=1}^{N}|r_{t,i}|, \tag{15}$$

where $\mu_1 \equiv \sqrt{2/\pi} = E(|Z|)$ is the mean of absolute value of the random variable which is standard normally distributed, Δ is the sampling frequency, and N is the number of intra-daily returns in day t. The Heterogeneous Autoregressive model of Realized Volatility and Realized Absolute Value (HAR-RV-RAV model) suggested by Forsberg and Ghysels (2007) and the HAR-RV-RAV model with

Table 3
Out-of-sample performance.

Panel A: Model confidence set test

Model specification	HAR-RV	HAR-RV (S)	HAR-RV-IV	HAR-RV-IV (S)	HAR-RV-IV-SK	HAR-RV-IV-SK (S)
MSE	1.8308(0.241)	1.8288(0.241)	1.8201(0.350)	1.7795(0.414)	1.8100(0.414)	1.7493(1.000)
MAE	0.5068(0.002)	0.4927(0.003)	0.4900(0.053)	0.4686(0.109)	0.4840(0.109)	0.4630(1.000)
QLIKE	0.7915(0.000)	0.7515(0.000)	0.7199(0.000)	0.6570(0.020)	0.6785(0.014)	0.6226(1.000)

Panel B: Diebold-Mariano test

Model comparison	HAR-RV (S) vs. HAR-RV	HAR-RV-IV (S) vs. HAR-RV-IV	HAR-RV-IV-SK (S) vs. HAR-RV-IV-SK
MSE	−0.044	−0.643	−1.031
MAE	−1.987**	−2.070**	−2.068**
QLIKE	−5.059***	−2.973***	−3.402***

The table shows comparison of the out-of-sample performance of the 1-month-ahead volatility forecasts for S&P 500 index. The HAR-RV model is the Heterogeneous Autoregressive model of Realized Volatility. The HAR-RV (S) model adds the sentiment dummy variables to the HAR-RV model. The HAR-RV-IV model is the Heterogeneous Autoregressive model of Realized Volatility and Implied Volatility. The HAR-RV-IV (S) model incorporates the sentiment dummy variables into the HAR-RV-IV model. The HAR-RV-IV-SK model is the Heterogeneous Autoregressive model of Realized Volatility, Implied Volatility, and Skewness. The HAR-RV-IV-SK (S) model adds the sentiment dummy variables to the HAR-RV-IV-SK model. In Panel A, the values of criteria measures are reported, and the *p*-values of the model confidence set test are given in parentheses. The model with *p*=1 is the best, and the true value of QLIKE is 0.5687. In Panel B, the *t*-statistic of the Diebold-Mariano test based on each criteria measure is reported.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

investor sentiment, abbreviated to the HAR-RV-RAV (S) model, can be expressed as:

$$RV_{t,t+22} = \beta_0 + \beta_D RAV_{t-1,t} + \beta_W RAV_{t-5,t} + \beta_M RAV_{t-22,t} + \varepsilon_{t,t+22}, \quad (16)$$

$$\begin{aligned} RV_{t,t+22} = {} & \beta_0 + \beta_0^S \times D_t + \beta_D RAV_{t-1,t} + \beta_D^S D_t \times RAV_{t-1,t} + \beta_W RAV_{t-5,t} \\ & + \beta_W^S D_t \times RAV_{t-5,t} + \beta_M RAV_{t-22,t} + \beta_M^S D_t \times RAV_{t-22,t} + \varepsilon_{t,t+22}. \end{aligned} \quad (17)$$

Similar to the volatility forecasting models in Section 3.2, we add the implied volatility, the risk-neutral skewness, and the sentiment dummy variables to the HAR-RV-RAV model.

Table 4 shows the results of the volatility forecasting models with the realized absolute values in the in-sample and out-of-sample analyses. In Panel A, all coefficient estimates present analogous results with Table 2. β_{SK}^S is positive and significant at the 5% level. In addition, β_{IV}^S is negatively significant at the 1% level in both the HAR-RV-RAV-IV (S) model and the HAR-RV-RAV-IV-SK (S) model. These two coefficient estimates are not affected by the replacement of past realized volatilities. The improvements in the adjusted R^2 induced by investor sentiment are 0.7%, 1.5%, and 2.1% in the HAR-RV-RAV (S) model, the HAR-RV-RAV-IV (S) model, and the HAR-RV-RAV-IV-SK (S) model, respectively. These improvements are very similar to the results in Table 2.

In Panel B of Table 4, the t-statistics of Diebold-Mariano test for MAE are more prominent than those in Table 3, and the model confidence set test and the Diebold-Mariano test show similar results to the results in Table 3. The empirical results in this section confirm that the forecasting ability of option-implied information with investor sentiment is still sustained with past realized absolute values.

4.2. Leverage effect with investor sentiment

Corsi and Reno (2012) point out the persistent leverage effect with a long-range dependence in the volatility. To address the leverage effect issue on the models of HAR specification, they use past negative returns as additional explanatory variables to the models of HAR specification. The leverage effect captures a negative correlation between the past negative returns and the volatility in a discrete time. Corsi and Reno (2012) provide empirical evidence that the addition of past negative returns improves the performance in volatility forecasting. The Leverage Heterogeneous Autoregressive model of Realized Volatility (LHAR-RV model), which is the HAR-RV model with the addition of past negative returns, is as follows:

$$\begin{aligned} RV_{t,t+22} = {} & \beta_0 + \beta_D RV_{t-1,t} + \beta_W RV_{t-5,t} + \beta_M RV_{t-22,t} \\ & + \beta_{r(1)^-} r^-_{t-1,t} + \beta_{r(5)^-} r^-_{t-5,t} + \beta_{r(22)^-} r^-_{t-22,t} + \varepsilon_{t,t+22}, \end{aligned} \quad (18)$$

where $r^-_{t-i,t} = \min(r_{t-i,t}, 0)$, and $r_{t-i,t}$ is past simple return during i days. Similar to the volatility forecasting models in the previous sections, the LHAR-RV model with investor sentiment is abbreviated to the LHAR-RV (S) model. Additionally, we add the implied volatility, the risk-neutral skewness, and the sentiment dummy variables to the LHAR-RV model to check the forecasting power of option-implied information with past negative returns for future volatility depending on the level of investor sentiment.

The results of the volatility forecasting models with past negative returns in the in-sample and out-of-sample analyses are presented in Table 5. We also find the similar results in Table 5 with regard to the results in Tables 2 and 3 suggesting that our results are not affected by the leverage effect of past negative returns. In the LHAR-RV-IV-SK (S) model, β_{SK}^S is positive and significant at

Table 4
Realized absolute value with investor sentiment.

Model specification	HAR-RV-RAV	HAR-RV-RAV (S)	HAR-RV-RAV-IV	HAR-RV-RAV-IV (S)	HAR-RV-RAV-IV-SK	HAR-RV-RAV-IV-SK (S)
Panel A: In-sample performance						
β_0	0.219***(5.298)	0.252***(5.511)	0.138***(3.336)	0.100**(2.109)	0.200**(2.453)	−0.006(−0.055)
β_0^S		−0.042(−0.723)		0.068(0.795)		0.332**(2.169)
β_D	0.318***(7.876)	0.304***(6.960)	0.254***(4.752)	0.121***(2.689)	0.247***(5.059)	0.125***(2.719)
β_D^S		0.018(0.266)		0.174**(2.126)		0.148*(1.919)
β_W	0.587***(3.308)	0.395***(4.323)	0.538***(2.749)	0.179*(1.710)	0.531***(2.738)	0.186*(1.829)
β_W^S		0.207(0.808)		0.401(1.541)		0.367(1.433)
β_M	0.410***(2.819)	0.483***(4.165)	0.214(1.538)	0.071(0.590)	0.208(1.460)	0.092(0.804)
β_M^S		−0.022(−0.085)		0.308(1.123)		0.293(1.032)
β_{IV}			0.172**(2.327)	0.402***(5.826)	0.178**(2.506)	0.395***(5.742)
β_{IV}^S				−0.323***(−2.647)		−0.293***(−2.586)
β_{SK}					0.656(0.874)	−1.026(−1.008)
β_{SK}^S						2.906**(2.139)
Adj. R^2	0.647	0.654	0.653	0.668	0.654	0.675
Panel B: Out-of-sample performance						
MSE	1.8460(0.237)	1.8345(0.237)	1.8374(0.237)	1.7971(0.374)	1.8314(0.374)	1.7699(1.000)
MAE	0.5103(0.001)	0.4934(0.001)	0.4967(0.001)	0.4702(0.074)	0.4907(0.034)	0.4648(1.000)
QLIKE	0.8141(0.000)	0.7758(0.000)	0.7465(0.000)	0.6772(0.017)	0.7063(0.003)	0.6436(1.000)

Model comparison	HAR-RV-RAV (S) vs. HAR-RV-RAV	HAR-RV-RAV-IV (S) vs. HAR-RV-RAV-IV	HAR-RV-RAV-IV-SK (S) vs. HAR-RV-RAV-IV-SK
MSE	−0.248	−0.644	−1.001
MAE	−2.290**	−2.653***	−2.583***
QLIKE	−5.223***	−3.711***	−4.224***

The table shows the significance of the combination of past realized absolute values, the implied volatility, and the risk-neutral skewness for forecasting future monthly volatility with the sentiment dummy variables. Panel A reports the result of the in-sample analysis. Robust t-statistics following Newey and West (1987) corrected t-statistics with 44 lags are reported in parentheses. The sample period is from 4 January 1996 to 30 August 2010, for a total of 3681 daily observations. Panel B reports the result of the out-of-sample analysis. The results of the model confidence set tests are reported in the first table of Panel B, and the results of the Diebold-Mariano tests are reported in the second table of Panel B. The HAR-RV model is the Heterogeneous Autoregressive model of Realized Volatility. The HAR-RV (S) model adds the sentiment dummy variables to the HAR-RV model. The HAR-RV-IV model is the Heterogeneous Autoregressive model of Realized Volatility and Implied Volatility. The HAR-RV-IV (S) model incorporates the sentiment dummy variables into the HAR-RV-IV model. The HAR-RV-IV-SK model is the Heterogeneous Autoregressive model of Realized Volatility, Implied Volatility, and Skewness. The HAR-RV-IV-SK (S) model adds the sentiment dummy variables to the HAR-RV-IV-SK model.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 5
Leverage effect with investor sentiment.

Model specification	LHAR-RV	LHAR-RV (S)	LHAR-RV-IV	LHAR-RV-IV (S)	LHAR-RV-IV-SK	LHAR-RV-IV-SK (S)
Panel A: In-sample performance						
β_0	0.220***(5.044)	0.235***(4.764)	0.161***(3.673)	0.084*(1.866)	0.226***(2.746)	−0.013(−0.111)
β_0^S		−0.010(−0.150)		0.149*(1.736)		0.394**(2.568)
β_D	0.106***(3.811)	0.105***(5.562)	0.092***(3.029)	0.050***(2.864)	0.090***(3.126)	0.053***(3.001)
β_D^S		0.005(0.123)		0.062(1.405)		0.053(1.260)
β_W	0.306***(2.852)	0.228***(4.819)	0.288**(2.437)	0.132**(2.346)	0.282**(2.431)	0.133**(2.468)
β_W^S		0.083(0.502)		0.181(1.072)		0.156(0.945)
β_M	0.305***(3.622)	0.353***(5.777)	0.203**(2.129)	0.028(0.320)	0.202**(2.071)	0.029(0.320)
β_M^S		−0.048(−0.315)		0.289(1.620)		0.288(1.541)
$\beta_{r(1)^-}$	−0.046***(−3.186)	−0.020**(−2.234)	−0.041**(−2.294)	−0.002(−0.165)	−0.039**(−2.291)	−0.004(−0.363)
$\beta_{r(1)^-}^S$		−0.043*(−1.906)		−0.062**(−2.452)		−0.056**(−2.302)
$\beta_{r(5)^-}$	−0.011(−1.347)	−0.024***(−2.623)	−0.005(−0.616)	−0.003(−0.341)	−0.005(−0.564)	−0.002(−0.220)
$\beta_{r(5)^-}^S$		0.022(1.577)		2.4×10^{-4}(0.017)		0.003(0.177)
$\beta_{r(22)^-}$	−0.008(−1.490)	0.005(0.758)	−0.009(−1.554)	0.004(0.607)	−0.009(−1.583)	0.003(0.549)
$\beta_{r(22)^-}^S$		−0.018(−1.501)		−0.017(−1.434)		−0.018(−1.514)
β_{IV}			0.133(1.371)	0.420***(5.713)	0.138(1.453)	0.422***(5.484)
β_{IV}^S				−0.436***(−2.937)		−0.409***(−2.868)
β_{SK}					0.686(0.973)	−0.922(−0.925)
β_{SK}^S						2.711**(2.097)
Adj. R^2	0.654	0.662	0.656	0.675	0.658	0.680
Panel B: Out-of-sample performance						
MSE	1.7111(0.374)	1.7052(0.259)	1.7360(0.259)	1.6739(0.426)	1.7335(0.259)	1.6612(1.000)
MAE	0.4928(0.006)	0.4812(0.006)	0.4827(0.066)	0.4614(0.288)	0.4774(0.118)	0.4583(1.000)
QLIKE	0.7961(0.000)	0.7579(0.000)	0.7346(0.000)	0.6659(0.049)	0.6933(0.049)	0.6313(1.000)

Model comparison	LHAR-RV (S) vs. LHAR-RV	LHAR-RV-IV (S) vs. LHAR-RV-IV	LHAR-RV-IV-SK (S) vs. LHAR-RV-IV-SK
MSE	−0.160	−1.207	−1.462
MAE	−1.685*	−2.219**	−2.079**
QLIKE	−4.299***	−2.530**	−2.853***

The table shows the significance of the combination of the historical realized volatilities, historical negative returns, the implied volatility, and the risk-neutral skewness for forecasting future monthly volatility with the sentiment dummy variables. LHAR-model stands for the Leverage Heterogeneous Autoregressive model. Panel A reports the result of the in-sample analysis. Robust t-statistics following Newey and West (1987) corrected t-statistics with 44 lags are reported in parentheses. The sample period is from 4 January 1996 to 30 August 2010, for a total of 3681 daily observations. Panel B reports the result of the out-of-sample analysis. The results of the model confidence set tests are reported in the first table of Panel B, and the results of the Diebold-Mariano tests are reported in the second table of Panel B.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

the 5% level. In the LHAR-RV-IV model, the coefficient estimate on the implied volatility is insignificant. However, the coefficient estimates on the implied volatility during high sentiment periods in the LHAR-RV-IV (S) model and the LHAR-RV-IV-SK (S) model are negatively significant at the 1% level. Similar to the results in Table 2, the adjusted R^2s in the LHAR-RV (S) model, the LHAR-RV-IV (S) model, and the LHAR-RV-IV-SK (S) model are increased by 0.8%, 1.9%, and 2.2% due to the addition of the sentiment dummy variables, respectively. In Panel A of the in-sample analysis, the coefficient estimate on the daily negative return is significant only in the LHAR-RV model. In the LHAR-RV (S) model, the coefficient estimate on the weekly negative return is negatively significant at the 5% level during low sentiment periods, while it is positive and insignificant during high sentiment periods. The negative sign and significance of $\beta_{r(5)^-}$ are consistent with empirical results in Corsi and Reno (2012).

In Panel B, the model confidence set test and the Diebold-Mariano test also show the improvement by the addition of the sentiment dummy variables in the out-of-sample analysis. The LHAR-RV-IV-SK (S) model is chosen as the best forecasting model, and the forecasting errors in MAE and QLIKE are significantly decreasing with investor sentiment, respectively. The results in this section support that the forecasting ability of option-implied information with investor sentiment is still significant after considering the leverage effect.

4.3. Decomposition of volatility with investor sentiment

Andersen et al. (2007) suggest the volatility forecasting model with the decomposition of volatility into the continuous volatility and the jump, the Heterogeneous Autoregressive model of Realized Volatility, Continuous volatility, and Jumps (HAR-RV-CJ model). They suggest that the HAR-RV-CJ model shows better forecasting performance, because the jump component of volatility is highly important and less persistent than the continuous component of volatility, and thus the decomposition of volatility helps to distinguish between the effects of the continuous component and the jump component of past realized volatilities on future volatility. The HAR-RV-CJ model reads:

$$RV_{t,t+22} = \beta_0 + \beta_{CD}C_{t-1,t} + \beta_{CW}C_{t-5,t} + \beta_{CM}C_{t-22,t} + \beta_{JD}J_{t-1,t} + \beta_{JW}J_{t-5,t} + \beta_{JM}J_{t-22,t} + \varepsilon_{t,t+22}, \quad (19)$$

where $C_{t-i,t}$ is past continuous component of realized volatility during i days, and $J_{t-i,t}$ is past jump component of realized volatility during i days. We employ the jump detection test of Corsi et al. (2010) to decompose past realized volatility into the continuous component and the jump component.[16] The jump detection test proposed by Corsi et al. (2010) provides a more robust estimator of the jump component of the realized volatility to the finite sample bias than that based on standard multi-power variation as described in Huang and Tauchen (2005) and Andersen et al. (2007). The HAR-RV-CJ model with investor sentiment is abbreviated to the HAR-RV-CJ (S) model, and the HAR-RV-CJ-IV model (the

[16] The detailed procedure for decomposition of the continuous component and the jump component of past realized volatility is described in Section 3 of Byun and Kim (2013).

Table 6
Decomposition of volatility with investor sentiment.

Model specification	HAR-RV-CJ	HAR-RV-CJ (S)	HAR-RV-CJ-IV	HAR-RV-CJ-IV (S)	HAR-RV-CJ-IV-SK	HAR-RV-CJ-IV-SK (S)
Panel A: In-sample performance						
β_0	0.170***(2.683)	0.213***(3.773)	0.098**(2.005)	0.087*(1.739)	0.164**(2.095)	−0.012(−0.117)
β_0^S		−0.062(−0.625)		0.014(0.124)		0.262*(1.683)
β_{CD}	0.179***(7.706)	0.155***(6.156)	0.141***(4.514)	0.055**(2.087)	0.137***(4.818)	0.058**(2.242)
β_{CD}^S		0.036(0.914)		0.116**(2.431)		0.100**(2.248)
β_{CW}	0.342***(3.734)	0.224***(4.883)	0.319***(3.099)	0.123**(2.342)	0.315***(3.079)	0.123**(2.414)
β_{CW}^S		0.134(1.003)		0.221(1.637)		0.206(1.530)
β_{CM}	0.260***(3.123)	0.314***(5.670)	0.140(1.584)	0.028(0.354)	0.141(1.563)	0.031(0.401)
β_{CM}^S		−0.042(−0.273)		0.181(1.007)		0.190(1.041)
β_{JD}	0.052**(1.983)	0.018(1.324)	0.044(1.583)	−0.011(−0.846)	0.044(1.608)	−0.009(−0.735)
β_{JD}^S		0.066(1.306)		0.094*(1.868)		0.094**(1.970)
β_{JW}	−0.019(−0.260)	0.032(0.581)	−0.021(−0.280)	0.039(0.860)	−0.018(−0.245)	0.035(0.762)
β_{JW}^S		−0.096(−0.772)		−0.104(−0.858)		−0.094(−0.763)
β_{JM}	0.380(1.321)	0.320**(2.049)	0.330(1.071)	0.044(0.251)	0.311(1.034)	0.062(0.407)
β_{JM}^S		0.176(0.369)		0.451(0.937)		0.374(0.805)
β_{IV}			0.169*(1.934)	0.415***(5.724)	0.172**(1.996)	0.415***(5.599)
β_{IV}^S				−0.317***(−2.610)		−0.304***(−2.598)
β_{SK}					0.666(0.984)	−0.934(−0.962)
β_{SK}^S						2.605**(2.130)
Adj. R^2	0.649	0.657	0.654	0.672	0.655	0.677
Panel B: Out-of-sample performance						
MSE	1.7794(0.613)	1.7991(0.230)	1.7743(0.682)	1.7457(0.682)	1.7746(0.682)	1.7339(1.000)
MAE	0.5122(0.002)	0.4933(0.002)	0.4974(0.002)	0.4707(0.222)	0.4924(0.060)	0.4670(1.000)
QLIKE	0.8056(0.000)	0.7483(0.000)	0.7377(0.000)	0.6657(0.015)	0.6985(0.005)	0.6303(1.000)

Model comparison	HAR-RV-CJ (S) vs. HAR-RV-CJ	HAR-RV-CJ-IV (S) vs. HAR-RV-CJ-IV	HAR-RV-CJ-IV-SK (S) vs. HAR-RV-CJ-IV-SK
MSE	0.330	−0.394	−0.626
MAE	−2.377**	−2.494**	−2.413**
QLIKE	−5.577***	−3.293***	−4.096***

The table shows the significance of the combination of the decomposition of past realized volatilities, the implied volatility, and the risk-neutral skewness for forecasting future monthly volatility with the sentiment dummy variables. The -CJ- model stands for the Continuous volatility, and Jumps. Panel A reports the result of the in-sample analysis. Robust *t*-statistics following Newey and West (1987) corrected *t*-statistics with 44 lags are reported in parentheses. The sample period is from 4 January 1996 to 30 August 2010, for a total of 3681 daily observations. Panel B reports the result of the out-of-sample analysis. The results of the model confidence set tests are reported in the first table of Panel B, and the results of the Diebold-Mariano tests are reported in the second table of Panel B.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

HAR-RV-CJ-IV-SK model) with investor sentiment is denoted by the HAR-RV-CJ-IV (S) model (the HAR-RV-CJ-IV-SK (S) model).

We also find the qualitatively same results with the decomposition of volatility in Table 6 as the previous ones. Therefore, our main findings are robust to incorporating the decomposition of volatility into the volatility forecasting model. In Panel A, the coefficient estimates on the continuous components and the daily jump component are positive and significant in the HAR-RV-CJ model. These are consistent with the results of Table 5 in Corsi et al. (2010). In the HAR-RV-CJ (S) model, although the coefficient estimates on the daily jump component during high sentiment periods and low sentiment periods are insignificant, the coefficient estimate on the monthly jump component during low sentiment periods is positive and significant at the 5% level. Similar to the results in Tables 2, 4 and 5, the coefficient estimates on the implied volatility and the risk-neutral skewness during high sentiment periods in the HAR-RV-CJ-IV (S) model and the HAR-RV-CJ-IV-SK (S) model are significant at the 1% and 5% level, respectively. The improvements of the adjusted R^2 in the HAR-RV-CJ (S) model, the HAR-RV-CJ-IV (S) model, and the HAR-RV-CJ-IV-SK (S) model are 0.8%, 1.8%, and 2.2%, respectively.

In Panel B, the model confidence set test and the Diebold-Mariano test confirm the improvement with the sentiment dummy variables in the out-of-sample analysis, and the results in the out-of-sample analysis are similar to the results in Tables 3–5. Taken together with Tables 4–6, empirical evidence supports the improvement in the forecasting ability of option-implied information with investor sentiment.

4.4. Comparing investor sentiment and macroeconomic variables

Ghysels and Wang (2014) show that physical volatility is explained by higher cumulants of risk-neutral density. They also find that the relationship between the physical volatility and the higher cumulants of risk-neutral density (e.g., the risk neutral skewness) is affected by the risk aversion of investors, which varies with business cycle. In addition, Bekaert et al. (2013) decompose the implied volatility into two components: a proxy for risk aversion and expected stock market return volatility. They show that risk aversion and expected stock market return volatility are affected by monetary policy, and a lax monetary policy decreases risk aversion steadily. Accordingly, the implied volatility can be overestimated or underestimated as a measure of future stock return volatility depending on business cycle, because business cycle is related to investors' risk aversion. Thus, the misestimation of the implied volatility induced by the varying risk aversion of investors may influence the volatility forecasting power of it. Overall, it is worth to check whether the volatility forecasting power derived from the implied volatility and the risk-neutral skewness varies with business cycle.

In Section 3, we find that investor sentiment determines two regimes based on the forecasting power of option-implied information for future volatility. Even though Baker and Wurgler (2007) attempt to construct a precise investor sentiment measure, there is some possibility that investor sentiment is contaminated by macroeconomic variables. In this section, we argue that investor sentiment is the unique factor that affects the volatility forecasting

Table 7
Significance of macroeconomic variables.

Panel A: In-sample performance

Macroeconomic variable Model specification	Short rate HAR-RV-IV-SK (M)	Term spread HAR-RV-IV-SK (M)	Default spread HAR-RV-IV-SK (M)	Dividend yield HAR-RV-IV-SK (M)	CAY HAR-RV-IV-SK (M)	Consumption surplus HAR-RV-IV-SK (M)
β_0	0.184(1.212)	0.349***(2.662)	0.253**(2.325)	0.300**(2.519)	0.194(1.328)	0.034(0.288)
β_0^M	0.085(0.444)	−0.216(−1.144)	−0.054(−0.286)	−0.166(−0.845)	0.044(0.241)	0.240*(1.648)
β_D	0.139***(3.556)	0.097***(4.829)	0.108***(5.303)	0.120***(4.873)	0.132***(3.576)	0.082***(3.038)
β_D^M	−0.034(−0.773)	0.048(1.006)	0.025(0.578)	0.011(0.212)	−0.033(−0.770)	0.068(1.411)
β_W	0.367**(2.518)	0.169***(2.914)	0.188***(2.893)	0.234***(3.391)	0.359***(2.616)	0.121(1.454)
β_W^M	−0.181(−1.154)	0.205(1.311)	0.173(1.080)	0.110(0.647)	−0.190(−1.245)	0.309*(1.861)
β_M	0.084(0.721)	0.159(1.564)	0.218**(2.036)	0.165*(1.649)	0.060(0.431)	0.180(1.462)
β_M^M	0.098(0.622)	−0.070(−0.461)	−0.153(−0.965)	−0.071(−0.475)	0.132(0.821)	−0.078(−0.470)
β_{IV}	0.205*(1.838)	0.223***(2.691)	0.177**(2.101)	0.176**(2.107)	0.254**(2.276)	0.305***(3.371)
β_{IV}^M	−0.018(−0.083)	−0.026(−0.177)	0.047(0.332)	0.048(0.311)	−0.027(−0.192)	−0.143(−1.084)
β_{SK}	0.849(0.570)	1.528*(1.812)	0.905(1.197)	1.163(1.161)	1.145(0.810)	−0.816(−0.669)
β_{SK}^M	0.014(0.008)	−1.069(−0.665)	−0.028(−0.018)	−0.651(−0.394)	−0.265(−0.158)	2.781*(1.885)
Adj. R^2	0.655	0.656	0.656	0.652	0.657	0.670

Panel B: Out-of-sample performance

Macroeconomic variable Model comparison	Short rate HAR-RV-IV-SK (M) vs. HAR-RV-IV-SK	Term spread HAR-RV-IV-SK (M) vs. HAR-RV-IV-SK	Default spread HAR-RV-IV-SK (M) vs. HAR-RV-IV-SK
MSE	0.853	0.931	0.909
MAE	1.760*	1.984**	1.737*
QLIKE	2.752***	2.350**	3.119***
Macroeconomic variable	Dividend yield	CAY	Consumption surplus
Model comparison	HAR-RV-IV-SK (M) vs. HAR-RV-IV-SK	HAR-RV-IV-SK (M) vs. HAR-RV-IV-SK	HAR-RV-IV-SK (M) vs. HAR-RV-IV-SK
MSE	1.012	0.745	−0.646
MAE	1.373	2.859***	0.003
QLIKE	−2.061**	7.534***	3.117***

The table shows the significance of the combination of the historical realized volatilities, the implied volatility, and the risk-neutral skewness for forecasting future monthly volatility with the macroeconomic dummy variables. The HAR-RV-IV-SK model is the Heterogeneous Autoregressive model of Realized Volatility, Implied Volatility, and Skewness. The HAR-RV-IV-SK (M) model adds macroeconomic dummy variables to the HAR-RV-IV-SK model. *Short rate* is defined as the three-month T-bill yield. *Term spread* is defined as the difference between the 10-year T-bond and the three-month T-bill yields, and *Default spread* is defined as the difference between Moody's BAA and AAA corporate bond yields. *Dividend yield* is constructed based on data from Robert Shiller's website. *CAY* is the consumption-wealth ratio, and *Consumer surplus* denotes the consumer surplus ratio, which is from Campbell and Cochrane (1999). The consumer surplus ratio and CAY are defined by the most recent quarterly observations available. Panel A reports the result of the in-sample analysis. Robust *t*-statistics following Newey and West (1987) corrected *t*-statistics with 44 lags are reported in parentheses. The sample period is from 4 January 1996 to 30 August 2010, for a total of 3681 daily observations. Panel B reports the result of the Diebold-Mariano tests.
*Significant at 10%. **Significant at 5%. ***Significant at 1%.

power of option-implied information, in contrast to various macroeconomic variables related to business cycle. Furthermore, we suggest that our findings regarding investor sentiment are not driven by macroeconomic variables. To do so, we examine whether any macroeconomic variable does not show the ability to distinguish two regimes in the forecasting power of option-implied information for future volatility. We find that none of the macroeconomic variables have any significant effects.

We divide the whole sample period into two sub-sample periods based on the median of the macroeconomic variables during the whole sample period. We utilize the short rate, the term spread, the default spread, the dividend yield, the consumption-wealth ratio (CAY), and the consumer surplus ratio as the macroeconomic variables. The short rate is defined as the three-month T-bill yield,[17] and the default spread is the difference between Moody's BAA and AAA corporate bond yields. The term spread is the difference between the 10-year T-bond and the three-month T-bill yields. The above three variables are obtained from the Federal Reserve Bank of St. Louis. Monthly dividend yield is taken from Robert Shiller's website. CAY[18] is defined in Lettau and Ludvigson (2001) and obtained from Martin Lettau's website. The consumption surplus ratio is defined in Campbell and Cochrane (1999).[19]

Similar to the in-sample analysis in Section 3.2 and the out-of-sample analysis in Section 3.3, we perform the in-sample and out-of-sample analyses based on the macroeconomic variables.[20] The results of these analyses based on the macroeconomic variables are reported in Table 7. Owing to the limitation of space, we report only the results based on the HAR-RV-IV-SK model with the macroeconomic dummy variables, abbreviated to the HAR-RV-IV-SK (M) model.[21] In Panel A of the in-sample analysis, the HAR-RV-IV-SK (M) model including any macroeconomic dummy variable does not show the significant forecasting power of the implied volatility in contrast to the HAR-RV-IV-SK (S) model. Even though the coefficient estimate on the risk-neutral skewness during high consumption surplus ratio periods is slightly significant, its significance level is only 10%. The improvements of the adjusted R^2 are also relatively small (0.5% (short rate), 0.6% (term spread), 0.6% (default spread), 0.2% (dividend yield), 0.7% (CAY), and 2.0% (consumption surplus ratio), respectively).

In Panel B, we report the results of the model confidence set test.[22] QLIKE in the HAR-RV-IV-SK (M) model with the dividend yield outperform the HAR-RV-IV-SK model. Except for QLIKE with the dividend yield and MSE with the consumption surplus ratio, the *t*-statistics with the macroeconomic variables are positive. Positive *t*-statistics mean that the forecasting error in the HAR-RV-IV-SK

[17] To remove the time-trend of the three month T-bill yield, we also utilize the three month T-bill yield minus its trailing 12-month moving average as the short rate. The results are similar to the results of the three month T-bill yield.

[18] A monthly CAY series is defined as the observation in the most recent quarter.

[19] Similar to Yu and Yuan (2011), the consumption surplus ratio is approximated by a smoothed average of the past 40-quarter consumption growth as in Wachter (2006).

[20] In the in-sample and out-of-sample analyses with the macroeconomic variables, the superscript of the coefficient estimates with the macroeconomic dummy variables is changed from S to M.

[21] M stands for the volatility forecasting model with the macroeconomic variables.

[22] The results of the Diebold-Mariano test are available upon request.

(M) model is larger than that in the HAR-RV-IV-SK model. The coefficient estimate on the risk-neutral skewness during high consumption surplus ratio periods shows the 10% significance level in the in-sample analysis; and however, the HAR-RV-IV-SK (M) model that considers the consumption surplus ratio presents worse performance in predicting volatility in the out-of-sample analysis than the HAR-RV-IV-SK model not considering the consumption surplus ratio. As a result, the in-sample and out-of-sample results in Table 7 indicate that no other macroeconomic variables distinguish two regimes with the improvement in the forecasting power of option-implied information for future volatility. Hence, we confirm that only investor sentiment improves the forecasting power of option-implied information for future volatility.

4.5. Financial crisis

It is very meaningful if the volatility forecasting model incorporating investor sentiment is valid during the crisis periods. Thus, we check the forecasting power of option-implied information with investor sentiment during the financial crisis. Based on the level of the monthly realized volatility, we determine that the financial crisis is from November 2007 to June 2009,[23] and reexamine the in-sample and out-of-sample analyses during the financial crisis.[24] In the in-sample analysis, we divide two regimes based the sentiment index during the financial crisis. While the coefficient estimates on the implied volatility are insignificant in the HAR-RV-IV model and the HAR-RV-IV-SK model, those during low sentiment periods are significant at the 1% level and positive in the HAR-RV-IV (S) model and the HAR-RV-IV-SK (S) model. Even though β_{IV}^{S} is not significant, β_{IV}^{S} is negative in the HAR-RV-IV (S) model and the HAR-RV-IV-SK (S) model. These results are similar to the results in Section 3.2. In addition, β_{SK}^{S} is positive and insignificant. The adjusted R^2s are improved by 4.4% and 5.2% in the HAR-RV-IV (S) model and the HAR-RV-IV-SK (S) model as compared to the HAR-RV-IV model and the HAR-RV-IV-SK model, respectively. These improvements of the adjusted R^2 are larger than those during the whole sample period shown in Table 2.

In the out-of-sample analysis, the model confidence set test confirms that the HAR-RV-IV-SK (S) model is the best model based on MSE and MAE. For QLIKE, the best model is the HAR-RV-IV (S) model, and the second best model is the HAR-RV-IV-SK (S) model. In the Diebold-Mariano test, the *t*-statistics in the comparison between the HAR-RV-IV-SK (S) model and the HAR-RV-IV-SK model are negative although those are not significant. Except for the *t*-statistic of MSE in the comparison between the HAR-RV (S) model and the HAR-RV model, other *t*-statistics are negative. These results in the in-sample and out-of-sample analyses support that investor sentiment still plays an important role in the volatility forecasting power of option-implied information during the financial crisis.

5. Conclusion

In this paper, we clarify the time-varying forecasting power of option-implied information for future volatility during high and low sentiment periods. It is well documented in the literature that the implied volatility and the risk-neutral skewness have the forecasting ability regarding future stock return volatility. Some research papers report that option-implied information provides vital clues about future stock market return volatility only for short-term forecast horizon (i.e., daily and weekly horizons). There is also evidence that the prediction power of option-implied information for future stock returns lasts for more than one month. To address these issues, we provide various types of evidence that investor sentiment is a key factor determining the magnitude and persistence of the forecasting power on future stock return volatility. We expect and find that option-implied information has the time-varying forecasting power depending on the level of investor sentiment.

Our research contributes to an important area in finance by developing a valid long-term (i.e., monthly horizon) volatility forecasting model that incorporates investor sentiment. We incorporate investor sentiment in volatility forecasting models based on the HAR-RV model of Corsi (2009), including past volatility components sampled at different frequencies (i.e., daily, weekly, and monthly frequencies) in addition to option-implied information, such as the implied volatility of Fradkin (2008) and Busch et al. (2011) and the risk-neutral skewness of Byun and Kim (2013). We find that volatility forecasting models that take investor sentiment into account improve the forecasting ability in the in-sample and out-of-sample analyses. Consistent with our conjecture, our findings show that the coefficient estimate on the risk-neutral skewness is positively significant only during high sentiment periods and that the coefficient estimate on the implied volatility varies significantly with the level of investor sentiment. Our research has important implications for practitioners in that they have to be aware of the level of investor sentiment when they use volatility forecasting models with option-implied information for derivative pricing, financial risk management, optimal portfolio selection, and so on. Furthermore, the improvement obtained from considering investor sentiment is robust to various forecasting models stemming from the HAR-RV model, and investor sentiment has the unique ability to distinguish two regimes in the volatility forecasting power of option-implied information, in contrast to the macroeconomic variables. These results support the usefulness of incorporating investor sentiment in the volatility forecasting models utilizing option-implied information.

This study also extends the growing literature related to investor sentiment. Earlier studies of investor sentiment focus on the time-varying mean–variance relationship (Yu and Yuan, 2011), explaining market anomalies (Stambaugh et al., 2012), time-varying economic risk-return relationship (Shen and Yu, 2013), and time-varying predictability of disagreement (Kim et al., 2014)) depending on the level of investor sentiment. We show that option-implied information has the time-varying forecasting power regarding future volatility when investor sentiment is taken into account. Thus, we suggest that investor sentiment in the stock market plays an important role in utilizing information in the option market to anticipate future stock market movements.

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Appendix A

In Appendix A, we address the potential issues of using overlapping stock return volatilities in our regression. To check the robustness of our findings, we use two methods: the non-overlapping monthly volatility method and the bootstrapping method proposed by Efron (1979).

First, we construct monthly non-overlapping stock return volatilities based on the calendar month (total of 176 monthly

[23] The detailed specification for the financial crisis is described in Byun and Kim (2013).

[24] The results during the financial crisis are similar to the results in Section 3 and are omitted for brevity. Those are available upon request.

observations). Then, we perform the in-sample analysis, similar to that in Section 3. The results obtained with non-overlapping stock return volatilities have the same quantitative implications as the results shown in Section 3; investor sentiment influences the relationship between the option-implied information and the future volatility. For brevity, detailed results are not reported here, but are available upon request.

Second, to further address concerns regarding the use of overlapping periods in regression analysis, we adopt a bootstrapping method to estimate the statistical significance of the coefficients described in Efron (1979). To conduct regression analysis based on the bootstrapping method, we draw N observations from the N-observation dataset with replacement. Using the re-sampled dataset, we estimate the coefficients of option-implied information. This process is repeated 10,000 times to get accurate results, because 1,000 replications are generally required produce good estimates.[25] Using these coefficient estimators, standard errors are recalculated as follows:

$$\widehat{se} = \sqrt{\sum_i \frac{\left(\widehat{\theta}_i - \bar{\theta}\right)^2}{k-1}} \tag{A1}$$

where $\widehat{\theta}_i$ is the coefficient estimated using the i th bootstrap sample, and $\bar{\theta}$ is the mean of $\widehat{\theta}_i$. k is the number of replications, which in our case is 10,000. The above equation shows the standard error estimator of the coefficient, constructed based on Hall and Wilson (1991). The results from the bootstrapping method are also consistent with our main findings. Those results are also available upon request.

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