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The Information Content of Intraday Implied Volatility for Volatility Forecasting

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ABSTRACT
This study examines the intraday S&P 500 implied volatility index (VIX) to determine when the index contains the most information for volatility forecasting. The findings indicate that, in general, VIX levels around noon are most informative for predicting realized volatility. We posit that the VIX performs better during this time period because trading motivation around noon is less complex, and therefore trades contain more information on the market expectation of future volatility. Further investigation on the 2008 financial crisis period suggests that market participants become more cautious, and thus the forecasting performance is sustained until the market's close.

KEY WORDS implied volatility; VIX; intraday; volatility forecasting; crisis

INTRODUCTION

Forecasts of the future volatility of asset returns are crucial inputs for numerous investment decisions such as derivatives pricing and risk management, and therefore of great interest to many market participants. The literature has explored volatility forecasting extensively. Because option prices reflect market participants' expectations of future movements of the underlying asset prices, research has primarily focused on the volatility implied in option prices. Although some studies argue that implied volatility is a biased forecast of future volatility that contains little incremental information beyond historical volatility (Becker and Clements, 2008; Becker *et al*., 2006, 2007),[1] most prior research finds that implied volatility is a reliable predictor of future volatility (e.g. Becker *et al*., 2009; Blair *et al*., 2001; Christensen and Prabhala, 1998; Fleming, 1998; Taylor *et al*., 2010; Yu *et al*., 2010).

Nearly all previous studies on the information content of implied volatility focus on daily-based implied volatility; that is, the daily closing level is employed as the predictor. However, high-frequency data show that the trading activities of many financial assets present particular intraday patterns. Wood *et al*. (1985), Mclnish and Wood (1990) and Gerety and Mulherin (1992), among others, report a U-shaped pattern for trading volume of many financial assets with trading volume particularly high at the market's open and close. Information accumulation during the non-trading overnight period causes pent-up demand and drives large trading volume at the market's open, and traders' reluctance to carry the risk of holding positions overnight motivates large trading volume at the market's close (Brock and Kleidon, 1992; Gerety and Mulherin, 1992). Because trading at the market's close is motivated by specific information and risk factors that are not present during other times of the trading day, we posit that using the closing level of implied volatility may not be the most informative predictor for future volatility.

To explore whether intraday implied volatility contains more information than the daily closing level commonly used for volatility forecasting, we use the S&P 500 implied volatility index (VIX), recorded at 30-minute intervals. Our empirical results show that the VIX roughly displays a W-shaped intraday pattern and that the intraday VIX does, in fact, contain more information for future volatility than the closing-day VIX. The performance of the intraday VIX in both the volatility model specification and volatility forecasting is worst at the market's open, increases until noon, decreases over the afternoon and then rises slightly toward the end of the trading day. We conjecture that the superior performance of the VIX levels around noon may be driven by less complicated trading motivations and the lower proportion of individual investors during the lunchtime hour. Having already digested the information that occurs overnight when the market is closed and not yet worrying about carrying risk over the next night, traders are more likely to be driven by less complicated motivations in the middle period of the trading day, and therefore trades are more informative. In addition, institutional and more sophisticated investors are more likely to continue to trade throughout the lunch hour, whereas individual investors are more likely to leave their accounts idle while they break

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[1]Becker *et al*. (2007) examine the S&P 500 implied volatility index (VIX) and find that it contains no information relevant to future volatility beyond that available from model-based volatility forecasts.

over the noon hour. As a result, around noon the proportion of individual investors that are usually regarded as noise traders becomes lower, and the VIX levels become more informative for the following realized volatility.

The trading behavior of investors during a crisis period has attracted a significant amount of attention (Ben-David *et al*., 2012; Chiang and Zheng, 2010; Yu and Hsieh, 2010). The information content of the VIX during a crisis period is particularly important (Bates, 2012; Hilal *et al*., 2011) because it provides valuable information to hedge extreme risk and allows us to better understand market sentiment and behavior. We therefore further examine whether the information content of the intraday VIX levels is different during the period of the 2008 global financial crisis. The results suggest that during the crisis period traders are more cautious and that the performance of the intraday VIX level peaks around noon and remains high until the end of the trading day.

This article contributes to the literature in a number of ways. First, this study contributes to literature on using implied volatility for volatility forecasting by examining the value of intraday levels and by providing a guideline for predicting volatility with implied volatility because past studies have examined the information content of the VIX based on the daily VIX in predicting future volatility. Second, with the increasing availability of high-frequency data, we add to a line of prior research that extends daily generalized autoregressive conditional heteroskedasticity (GARCH) models to incorporate intraday information such as daily high–low price range (Taylor, 1987), the number of intraday price changes (Laux and Ng, 1993) and the standard deviation of intraday returns (Taylor and Xu, 1997) as additional regressors. This study provides evidence to support the potential value of the intraday VIX as an information source for volatility forecasting. Finally, a number of studies have tested the intraday pattern of various trading activities, such as return, volatility and trading volume. Contrary to most intraday pattern research, our study adds new empirical evidence that the VIX displays an intraday pattern and that noontime implied volatility levels provide the best prediction of future volatility.

The remainder of the study is organized as follows. The next section describes the data. The third section presents the analysis of intraday patterns of trading volume and the VIX. The fourth and fifth sections provide the analysis of volatility modeling and volatility forecasting, respectively. The sixth section examines the information content of the intraday VIX during the 2008 global financial crisis. Finally, the seventh section provides the conclusions.

DATA

The data consist of the daily and intraday levels of the VIX index, which is calculated from the prices of options on the S&P 500 index and a measure of market expectation of stock return volatility over the following 30 calendar days. The VIX is compiled from a wide range of strike prices with a model-free formula and thus is independent of any option-pricing model. We obtain daily VIX levels from the Chicago Board Options Exchange (CBOE) and minute-by-minute intraday levels from the CQG Data Factory. The sample period is 3 January 2005 to 30 April 2010.

Following Blair *et al*. (2001) to evaluate the performance of volatility forecasting, we take the sum of squared 5-minute returns of the S&P 500 index levels within a day as the measure of daily realized volatility, which serves as the target of volatility forecasting. Table I presents the summary statistics of annualized realized volatility and the VIX. Consistent with previous studies, we find, first, that the VIX is highly correlated with realized volatility, with a correlation of 0.875. Second, the skewness and kurtosis of both realized volatility and the VIX are positive. Third, both realized volatility and the VIX are highly persistent. However, because the VIX represents an

Table I. Summary statistics of daily realized volatility and VIX

	Realized volatility	VIX
Mean	16.43	21.40
SD	0.14	0.12
Skewness	3.04	1.94
Kurtosis	16.54	7.10
Autocorrelation		
Lag 1	0.85	0.99
Lag 2	0.39	0.15
Lag 3	0.13	0.15
Lag 4	0.13	−0.02
Lag 5	0.12	0.13
Correlation	0.875	

Note: This table shows the summary statistics of daily realized volatility and the VIX for the sample period (3 January 2005 to 30 April 2010). The realized volatility computed by the sum of squared intraday returns and the VIX is the measure of implied volatility compiled by the CBOE using a model-free formula.

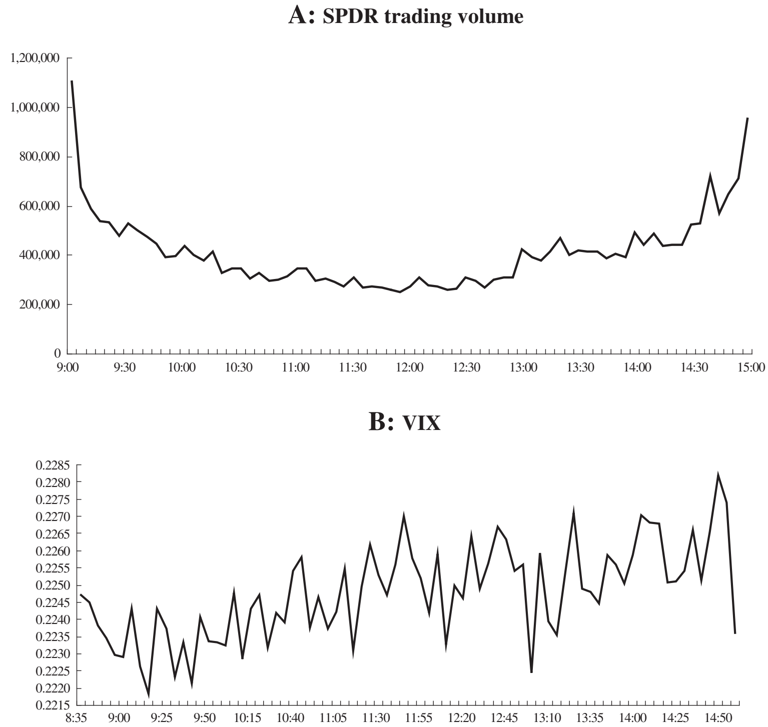

Figure 1. The intraday patterns of trading volume and VIX. The figure shows the intraday patterns of the trading volume of SPDR and VIX for the sample period from 3 January 2005 to 30 April 2010. SPDR is an ETF of S&P 500 index and VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. For each time point, the trading volume of SPDR and VIX levels are averaged across days. (A) SPDR trading volume; (B) VIX

Table II. The model estimation for the daily returns of the S&P500 index

	Model							
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\alpha_0 \times 10^5$	0.1030	0.0779***	1.2100***	−1.7400***	0.0151	0.0134	−1.1600**	−0.2250***
	(1.55)	(6.84)	(2.96)	(−3.07)	(0.29)	(0.27)	(−2.29)	(−4.94)
α_1	0.0718***	−0.0443***	−0.1239**	−0.0611***	−0.0722***	−0.1236***	−0.1438***	−0.1455***
	(4.49)	(−4.30)	(−2.57)	(−2.64)	(−4.08)	(−4.83)	(−6.66)	(−4.67)
α_2		0.1457***			0.2063***	0.1325***		0.1063***
		(8.05)			(7.01)	(4.72)		(2.99)
β	0.9211***	0.9628***			0.9014***	0.8619***		0.7126***
	(59.22)	(92.11)			(36.90)	(35.87)		(10.83)
γ			1.4315***			0.2325***	0.6917***	0.1122***
			(9.02)			(5.31)	(8.61)	(3.19)
δ				0.9313***	0.0486***		0.3984***	0.2977***
				(13.65)	(2.92)		(3.57)	(4.01)
Max. log-likelihood	4012.29	4041.16	3986.12	4043.63	4051.24	4035.09	4058.89	4069.04

Note: This table exhibits the estimation results of GJR GARCH models (Glosten *et al*., 1993) for the daily returns of the S&P 500 index. The sample period is 3 January 2005 to 29 January 2010. The full model is specified as

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t \tilde{} N(0, h_t)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \mathrm{INTRA}_{t-1} + \delta \mathrm{VIX}_{t-1}^2$$

where r_t is the return and h_t is the conditional variance of the S&P 500 index at time t. s_t equals 1 if ε_t is negative, and zero otherwise. INTRA is the realized volatility computed by the sum of squared intraday returns, and VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. With the constraints on various sets of parameters, we estimate eight alternative models. The models are estimated by the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992). t-Statistics are reported in parentheses. Asterisks indicate significance at the ***1%, **5% and *10% level.

average volatility for a 30-calendar-day period, whereas realized volatility is a measure of daily volatility, realized volatility is more volatile than the VIX (Becker and Clements, 2008; Becker *et al*., 2007). Finally, the VIX behaves in a similar dynamic pattern to realized volatility, but the VIX is consistently higher than realized volatility, indicating a negative volatility risk premium (Bakshi and Kapadia, 2003; Bollerslev *et al*., 2011; Bollerslev and Zhou, 2006).

INTRADAY PATTERNS OF TRADING VOLUME AND THE VIX

Because trading volume has a varying intraday pattern and different intervals of intraday volume convey different information, we begin our analysis by exploring the intraday patterns of the S&P 500 index. As the index is not a tradable asset, we analyze the trading volume of SPDR, an exchange-traded fund (ETF) of the S&P 500 index. Figure 1(A) shows that SPDR's trading volume displays a U-shaped pattern across the trading hours within a day, which is consistent with the common findings of previous studies (e.g. Gerety and Mulherin, 1992; Mclnish and Wood, 1990; Wood *et al*., 1985).

To investigate the information content of intraday VIX levels, we further explore whether the VIX also has a particular intraday pattern and, if so, whether it is similar to the pattern for trading volume as it may be a signal for the differences of information contents of alternative intraday VIX levels. Figure 1(B) plots the averaged intraday variations of the VIX. The graph indicates a rough W-shaped pattern for the VIX from market open to close. Namely, the

Table III. Model estimation with alternative intraday VIX levels

	Time of alternative intraday VIX												
	9:00	9:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Model 4	4039.40	4040.19	4041.88	4042.79	4043.46	4044.42	4047.07	4047.00	4047.97	4048.11	4046.58	4045.94	4043.63
Model 7	4055.92	4055.91	4056.74	4057.07	4056.95	4057.00	4058.58	4058.79	4059.31	4059.84	4059.13	4059.67	4058.89
Model 8	4068.56	4068.72	4068.96	4069.15	4069.00	4069.03	4069.55	4069.71	4069.92	4069.71	4069.57	4069.37	4069.04

Note: This table shows the estimation results of models 4, 7 and 8 specified in Table II with alternative intraday VIX levels. The sample period is from 3 January 2005 to 29 January 2010. The specifications of the three alternative models in conditional variance are

$$\begin{aligned}
&\text{Model 4}: \ h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \delta \mathrm{VIX}_{t-1}^2 \\
&\text{Model 7}: \ h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma \mathrm{INTRA}_{t-1} + \delta \mathrm{VIX}_{t-1}^2 \\
&\text{Model 8}: \ h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2 s_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \mathrm{INTRA}_{t-1} + \delta \mathrm{VIX}_{t-1}^2
\end{aligned}$$

where h_t is the conditional variance of the S&P 500 index at time t. s_t equals 1 if ε_t is negative and zero otherwise. INTRA is the realized volatility computed by the sum of squared intraday returns, and VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. The models are estimated by the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992). Because the patterns of the estimates of coefficients are similar across the models with alternative intraday VIX levels, only the maximum log-likelihood values are reported.

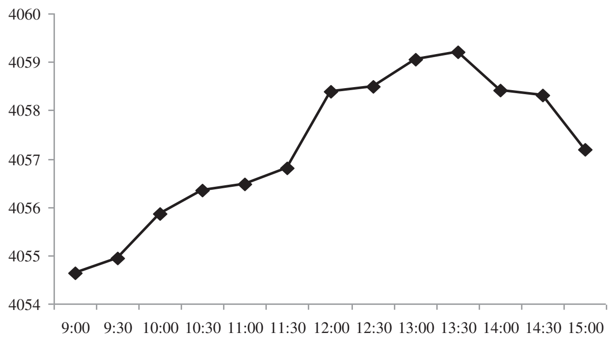

Figure 2. Maximum log-likelihood values of the models with alternative intraday VIX levels. The figure shows the averaged maximum log-likelihood values of models 4, 7 and 8 specified in Table II with alternative intraday VIX levels. For each time point, the maximum log-likelihood values of the three models are averaged. The sample period is from 3 January 2005 to 29 January 2010. The specifications of the three alternative models in conditional variance are

$$\begin{aligned}
&\text{Model 4}: \ h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \delta \mathrm{VIX}_{t-1}^2 \\
&\text{Model 7}: \ h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma \mathrm{INTRA}_{t-1} + \delta \mathrm{VIX}_{t-1}^2 \\
&\text{Model 8}: \ h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2 s_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \mathrm{INTRA}_{t-1} + \delta \mathrm{VIX}_{t-1}^2
\end{aligned}$$

where h_t is the conditional variance of the S&P 500 index at time t. s_t equals 1 if ε_t is negative and zero otherwise. INTRA is the realized volatility computed by the sum of squared intraday returns, and VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. The models are estimated by the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992)

VIX is higher at the open, middle and near the close of trading hours but, interestingly, has an obvious drop at the market's close. Different from the intraday patterns of some price dynamics and trading activities such as returns, volatility and trading volume, the VIX exhibits special properties not only at the open and close of the market but also in the middle period. Although the pattern is rough, this up-and-down movement of the VIX may signal the possibility that intraday VIX levels contain more information than—and therefore outperform—closing VIX levels in predicting volatility.

VOLATILITY MODELING

We use the asymmetric GJR GARCH(1,1) model proposed by Glosten *et al.* (1993) as our basic volatility model and incorporate realized volatility and the VIX in the conditional variance equation of the model. The specification is essentially similar to Blair *et al.* (2001), who provide an excellent volatility forecast specification from which the information content of the VIX can be inferred. The general specification is

$$r_t = u + \varepsilon_t, \quad \varepsilon_t \tilde{} N(0, h_t) \tag{1}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \mathrm{INTRA}_{t-1} + \delta \mathrm{VIX}_{t-1}^2 \tag{2}$$

where r_t is the return and h_t is the conditional variance of the S&P 500 index at time t. s_t equals 1 if ε_t is negative and zero otherwise. INTRA is the realized variance computed by the sum of squared intraday returns, and VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. With the constraints on various sets of parameters, we estimate eight alternative models. For example, if we set $\alpha_1 = \alpha_2 = \beta = \gamma = 0$ ($\alpha_1 = \alpha_2 = \beta = \delta = 0$), the model predicts volatility by the previous squared VIX (realized variance) alone. We

Table IV. Evaluation of in-sample volatility forecasting for alternative intraday VIX levels

	Time of alternative intraday VIX												
Horizon	9:00	9:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Panel A: RMSE × 10^5													
1	31.51	31.51	31.50	31.48	31.41	31.45	31.37	**31.31**	**31.31**	31.57	31.68	31.81	31.42
5	121.55	121.23	121.05	120.90	120.40	120.10	**119.87**	120.06	120.17	121.66	121.28	121.68	120.59
10	237.16	237.10	235.26	234.61	**234.05**	234.49	234.56	235.18	234.85	238.56	238.11	238.90	237.79
20	497.18	498.07	495.67	494.40	**492.38**	492.58	492.86	494.45	493.58	500.51	500.67	501.64	498.35
Panel B: MAE × 10^5													
1	10.35	10.37	10.27	10.24	**10.18**	10.19	10.25	10.23	**10.18**	10.23	10.30	10.40	10.20
5	45.90	46.16	45.99	45.62	45.46	45.32	45.43	45.39	**45.22**	45.49	45.64	46.12	45.77
10	95.28	95.58	94.97	94.21	**93.79**	93.86	94.41	94.62	94.34	95.38	95.55	96.17	95.48
20	202.65	204.64	204.07	202.60	**201.75**	202.27	203.22	203.82	202.65	204.07	205.06	205.28	204.55
Panel C: MAPE													
1	0.8839	0.8826	0.8751	0.8701	0.8663	0.8639	0.8604	0.8589	**0.8556**	0.8566	0.8616	0.8648	0.8618
5	0.5922	0.5937	0.5881	0.5849	0.5833	0.5817	0.5802	0.5789	**0.5766**	0.5821	0.5874	0.5924	0.5890
10	0.5603	0.5621	0.5567	0.5533	0.5515	0.5508	0.5510	0.5496	**0.5472**	0.5538	0.5592	0.5629	0.5599
20	0.5513	0.5544	0.5493	0.5458	0.5436	0.5441	0.5460	0.5450	**0.5414**	0.5457	0.5514	0.5537	0.5529
Panel D: P measure													
1	0.5032	0.5034	0.5037	0.5043	0.5065	0.5054	0.5077	0.5095	**0.5098**	0.5013	0.4981	0.4939	0.5062
5	0.6009	0.6030	0.6041	0.6051	0.6084	0.6103	**0.6118**	0.6106	0.6099	0.6002	0.6026	0.6000	0.6071
10	0.5750	0.5752	0.5818	0.5841	**0.5861**	0.5845	0.5843	0.5820	0.5832	0.5700	0.5716	0.5687	0.5727
20	0.4831	0.4813	0.4863	0.4889	**0.4931**	0.4927	0.4921	0.4888	0.4906	0.4762	0.4759	0.4738	0.4807
Panel E: Adjusted R^2 from the regression of log (realized variance) on the log (variance forecast)													
1	0.7448	0.7447	0.7463	0.7481	0.7501	0.7509	0.7510	0.7515	0.7514	0.7502	0.7507	0.7488	**0.7532**
5	0.8052	0.8043	0.8063	0.8073	0.8083	0.8088	0.8082	**0.8092**	0.8086	0.8045	0.8050	0.8026	0.8064
10	0.7955	0.7944	0.7967	0.7976	**0.7983**	0.7982	0.7974	0.7982	0.7982	0.7932	0.7925	0.7906	0.7935
20	0.7646	0.7635	0.7657	0.7673	**0.7679**	**0.7679**	0.7672	0.7676	0.7677	0.7630	0.7619	0.7603	0.7623

This table shows the in-sample (3 January 2005 to 29 January 2010) results of volatility forecasting for alternative intraday VIX levels. The model —Model 4—uses VIX as the only predictor considered. The dynamic process of conditional variance is specified as

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \delta \mathrm{VIX}_{t-1}^2$$

where h_t is the conditional variance of the S&P 500 index at time t. VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. The model is estimated by the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992). The model performance is evaluated by the following seven measures that have been commonly used in the literature: (a) root mean square error (RMSE); (b) mean absolute error (MAE); (c) mean absolute percentage error (MAPE); (d) proportion of explained variability, P (Blair *et al.*, 2001); and (e) adjusted R^2 from the regression of log (realized variance) on log (variance forecast). The forecasts of four different horizons (1, 5, 10 and 20 days) are explored. Bold entries indicate the superiority of the corresponding VIX among alternative intraday VIX levels.

Table V. Evaluation of out-of-sample volatility forecasting for alternative intraday VIX levels

	Time of alternative intraday VIX												
Horizon	9:00	9:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00
Panel A: RMSE × 10^5													
1	7.16	7.06	7.09	7.12	7.10	7.02	7.07	7.09	7.13	7.14	7.19	7.05	**6.98**
5	37.12	37.35	37.30	36.98	36.76	**36.34**	36.77	36.93	37.00	36.99	37.28	37.01	36.67
10	126.16	127.07	126.82	125.33	124.18	**123.48**	124.45	125.82	126.33	126.52	126.21	125.62	123.54
20	292.61	294.70	293.42	289.85	288.08	**286.76**	288.98	291.50	292.36	293.16	293.20	291.96	289.20
Panel B: MAE×10^5													
1	6.50	6.39	6.40	6.41	6.43	6.39	6.40	6.37	6.36	**6.35**	6.44	6.37	6.37
5	27.80	27.69	27.54	27.35	27.18	**26.98**	27.25	27.44	27.53	27.48	27.88	27.63	27.22
10	83.10	83.29	82.79	82.31	82.07	**81.72**	82.35	82.76	82.82	82.71	83.38	83.01	82.14
20	227.07	228.13	226.20	224.09	223.37	**222.20**	223.91	225.21	225.25	226.05	227.76	226.73	225.16
Panel C: MAPE													
1	1.4552	1.4302	1.4251	1.4261	1.4300	1.4268	1.4233	1.4119	**1.4070**	1.4090	1.4272	1.4238	1.4165
5	1.0429	1.0317	1.0250	1.0210	1.0159	1.0113	1.0139	1.0144	**1.0056**	1.0093	1.0288	1.0293	1.0141
10	1.0339	1.0321	1.0219	1.0204	1.0171	1.0152	1.0201	1.0215	**1.0124**	1.0181	1.0355	1.0338	1.0259
20	1.1288	1.1324	1.1164	1.1082	1.1055	**1.0980**	1.1065	1.1093	1.1020	1.1077	1.1258	1.1197	1.1125
Panel D: P measure													
1	−0.2539	−0.2176	−0.2285	−0.2378	−0.2330	−0.2048	−0.2233	−0.2299	−0.2420	−0.2464	−0.2651	−0.2142	**−0.1909**
5	−0.2559	−0.2714	−0.2678	−0.2460	−0.2315	**−0.2034**	−0.2323	−0.2428	−0.2473	−0.2471	−0.2667	−0.2482	−0.2255
10	−0.1086	−0.1246	−0.1202	−0.0940	−0.0739	**−0.0619**	−0.0787	−0.1026	−0.1114	−0.1148	−0.1093	−0.0990	−0.0630
20	−0.3091	−0.3279	−0.3164	−0.2845	−0.2689	**−0.2572**	−0.2768	−0.2992	−0.3069	−0.3140	−0.3143	−0.3032	−0.2788
Panel E: Adjusted R^2 from the regression of log (realized variance) on the log (variance forecast)													
1	0.2693	0.2913	0.2839	0.3040	0.3107	0.3106	0.3090	0.3020	0.3039	0.3049	0.3161	0.3294	**0.3503**
5	0.2081	0.2024	0.1995	0.2259	0.2412	0.2414	0.2328	0.2184	0.2301	0.2194	0.2196	0.2158	**0.2452**
10	0.0258	0.0181	0.0180	0.0335	**0.0452**	0.0449	0.0380	0.0247	0.0266	0.0201	0.0243	0.0242	0.0443
20	0.0456	**0.0579**	0.0536	0.0328	0.0241	0.0252	0.0309	0.0427	0.0384	0.0510	0.0511	0.0518	0.0350

This table shows the out-sample (February 1, 2010–April 30, 2010) results of volatility forecasting for alternative intraday VIX levels. The model, Model 4, uses VIX as the only one predictor considered. The dynamic process of conditional variance is specified as

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \delta \mathrm{VIX}_{t-1}^2$$

where h_t is the conditional variance of the S&P 500 index at time t. VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. The model is estimated by the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992). The model performance is evaluated by the following seven measures that have been commonly used in the literature: (a) root mean square error (RMSE); (b) mean absolute error (MAE); (c) mean absolute percentage error (MAPE); (d) proportion of explained variability, P (Blair *et al*., 2001); (e) adjusted R^2 from the regression of realized variance on the variance forecast; (f) adjusted R^2 from the regression of log (realized variance) on log (variance forecast); and (g) adjusted R^2 from the regression of square root (realized variance) on square root (variance forecast). The forecasts of four different horizons (1, 5, 10, and 20 days) are explored. Bold entries indicate the superiority of the corresponding VIX among alternative intraday VIX levels.

use the quasi-maximum likelihood estimation method proposed by Bollerslev and Wooldridge (1992) to estimate the models.

Table II presents the parameter estimates, t-statistics and log-likelihood values for the eight models for the in-sample period of 3 January 2005 to 29 January 2010 using the daily closing VIX level. The first and second models are the GARCH(1,1) and GJR models, respectively. The estimates of α_2 are significant at the 1% level, indicating a substantial asymmetric effect of news impact.

Models 3 and 4 use INTRA based on 5-minute returns and the VIX, respectively, to describe conditional variances. Although models 3 and 4 have the same number of parameters, model 4's log-likelihood value is higher by 57.51. In other words, the VIX is more informative than 5-minute returns. The comparison of models 5–8, which consider the interaction of daily historical information, high-frequency returns and implied volatility, respectively, also supports the finding that the VIX provides more relevant information than high-frequency index returns and daily historical information. In other words, the results in Table II are consistent with Blair *et al.* (2001).

Given the superior information content of the VIX, we now turn our attention to explore whether one or more intraday VIX levels are more informative than the daily closing level of the VIX for volatility forecasting. Table III presents the estimation results of models 4, 7 and 8 in Table II with alternative intraday VIX levels recorded every 30 minutes.[2] Because the patterns of the estimates of coefficients are similar across

[2]We also use each minute interval for the VIX level and find similar results. To save space we do not report these results, but they are available upon request.

the models with alternative intraday VIX levels, we only report the maximum log-likelihood values. The results show that the highest log-likelihood values do not appear at the market's close (15:00), a finding that is fairly consistent across the different models (models 4, 7 and 8). Specifically, the highest log-likelihood values appear at 13:30 for models 4 and 7 and at 13:00 for model 8. In other words, for daily volatility forecasting, the VIX levels recorded around noon may be more informative than the daily closing level.

To further observe the information content of intraday VIX levels, we average the maximum log-likelihood values of models 4, 7 and 8 with alternative intraday VIX levels. Specifically, for each time point, we average the maximum log-likelihood values of the three models. Figure 2 shows that the maximum log-likelihood value is highest around midday. These results are consistent with our conjecture that the market has a lower degree of noise and trading motivations are less complicated around the noon hour, and thus the VIX levels around noon time contain more information for future volatility.

VOLATILITY FORECASTING

The results thus far show that using intraday VIX levels can enhance volatility modeling. In this section, we examine both the in-sample and out-of-sample volatility forecasting performance of various VIX levels recorded every 30 minutes using the GJR GARCH model. We generate various (1-, 5-, 10- and 20-day) horizons of volatility forecasts from the models with alternative intraday VIX levels and compare them with their corresponding

Table VI. Test of out-of-sample volatility forecasting

Horizon	Mean	t Value
Panel A: RMSE×10^5		
1	0.1217	8.64***
5	0.6733	10.65***
10	2.1980	6.89***
20	4.8250	8.02***
Panel B: MAE×10^5		
1	0.053	4.62**
5	0.519	7.97***
10	1.010	8.05***
20	3.544	8.08***
Panel C: MAPE		
1	0.0184	5.51***
5	0.0159	5.41***
10	0.0122	5.78***
20	0.0166	5.74***
Panel D: P Measure		
1	−0.0421	−8.48***
5	−0.0451	−10.57***
10	−0.0381	−6.86***
20	−0.0428	−7.99***
Panel E:Adjusted R^2 from the regression of log (realized variance) on the log (variance forecast)		
1	−0.0474	−10.54***
5	−0.0240	−6.04***
10	−0.0167	−6.10***
20	−0.0177	−5.78***

This table shows the out-of-sample (1 February 2010 to 30 April 2010) tests of the volatility forecasting differences between the superiority VIX and alternative intraday VIX levels for each performance measure. The model—Model 4—uses VIX as the only predictor considered. The dynamic process of conditional variance is specified as

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \delta \mathrm{VIX}_{t-1}^2$$

where h_t is the conditional variance of the S&P 500 index at time t. VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. The model is estimated by the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992). The model performance is evaluated by the following seven measures that have been commonly used in the literature: (a) root mean square error (RMSE); (b) mean absolute error (MAE); (c) mean absolute percentage error (MAPE); (d) proportion of explained variability, P (Blair *et al*., 2001); (e) adjusted R^2 from the regression of realized variance on the variance forecast; (f) adjusted R^2 from the regression of log(realized variance) on log (variance forecast); and (g) adjusted R^2 from the regression of square root (realized variance) on square root (variance forecast). The forecasts of four different horizons (1, 5, 10 and 20 days) are explored. Asterisks indicate significance at the
***1% level.

forecasted targets proxied by the realized volatilities computed as the sums of the squared intraday 5-minute returns (Andersen *et al*., 2001).[3]

No universally accepted best measure exists for the evaluation of volatility forecasting. Hence we adopt seven measures that are commonly used in the literature: (a) root mean square error (RMSE); (b) mean absolute error (MAE); (c) mean absolute percentage error (MAPE); (d) proportion of explained variability, P (Blair *et al*., 2001); and (e) adjusted R^2 from the regression of logarithmic realized variance on the logarithmic variance forecast. We use the log and square root transformations as variance-stabilizing functions in the regressions because the realized variance is very heteroskedastic (Deo *et al*., 2006).

RMSE, MAE, and MAPE are defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(\widehat{\sigma}_{\mathrm{t}}^{2} - \mathrm{RV}_t\right)^2} \tag{3}$$

$$\mathrm{MAE} = \frac{1}{T}\sum_{i=1}^{T}\left|\widehat{\sigma}_t^2 - \mathrm{RV}_t\right| \tag{4}$$

$$\mathrm{MAPE} = 100\frac{1}{T}\sum_{i=1}^{T}\left|\frac{\widehat{\sigma}_t^2 - \mathrm{RV}_t}{\mathrm{RV}_t}\right| \tag{5}$$

where $\widehat{\sigma}_t^2$ and RV_t denote the variance forecast and realized variance at time t, respectively. A better forecast has a lower error measure. We follow Blair *et al*. (2001) to capture the proportion of variance of realized volatility explained by volatility forecasts as P, defined as

$$P = 1 - \frac{\sum_{i=1}^{T}\left(\widehat{\sigma}_t^2 - \mathrm{RV}_t\right)^2}{\sum_{i=1}^{T}\left(\widehat{\sigma}_t^2 - \overline{\sigma}^2\right)^2} \tag{6}$$

The three regression-based evaluation methods are defined as

$$\log(\mathrm{RV}_t) = \alpha_2 + \beta_2 \log\left(\widehat{\sigma}_t^2\right) + \varepsilon_t \tag{7}$$

Our in-sample window for the parameter estimation covers the period from 3 January 2005 to 29 January 2010. To focus clearly on the comparison between alternative intraday VIX levels, we employ model 4, which uses only the VIX to generate volatility forecasts.[4] Table IV presents the in-sample performance of alternative horizons and intraday VIX levels in volatility forecasting. Data in bold indicate the superiority of intraday VIX levels at the corresponding time. Although the results derived from different evaluation measures are entirely consistent, we find that, in general, the volatility forecasts generated using the intraday VIX levels perform best between 11:00 and 13:00. The results are not dependent on performance measures and forecasting horizons (except the adjusted R^2 from the regression of logarithmic variables for the 1-day horizon). In general, volatility forecasts obtained from the intraday VIX at 13:00 outperform all other volatility forecasts.

For our out-of-sample forecasting, we take the last 3 months, 1 February 2010 to 30 April 2010, as our out-of-sample period. By rolling over day by day, we obtain the four horizons of the out-of-sample forecasts. Table V provides the evaluations of the out-of-sample forecasting using the same model (model 4) as our previous evaluations. According to these results, the intraday VIX levels around noon still have superior forecasting performance based on most of the error-based performance measures.

[3]The sampling frequency can be chosen optimally to balance the bias/variance trade-off. The 5-minute frequency is the most frequently adopted frequency for equity assets in the literature.

[4]Because realized variance and VIX are highly correlated, it is difficult to clearly observe the effect of alternative intraday VIX levels on volatility forecasting when both realized variance and VIX are included in the model. Therefore, we focus on model 4 for the following analysis. However, we also use models 7 and 8 to generate volatility forecasts and find similar results. To save space, we do not report them, but they are available upon request.

To further test whether the differences in the performance measures of Table V are statistically significant, we calculate the differences between the superior VIX and alternative intraday VIX levels for each performance measures. Table VI reports the test results of the differences between the superior VIX and alternative intraday VIX levels for each performance measure. From Table VI we find that the differences are statistically significantly positive (negative) in panels A, B, and C (panels D and E). The results again support that intraday VIX levels around noon have superior forecasting performance based on most of the error-based performance measures.

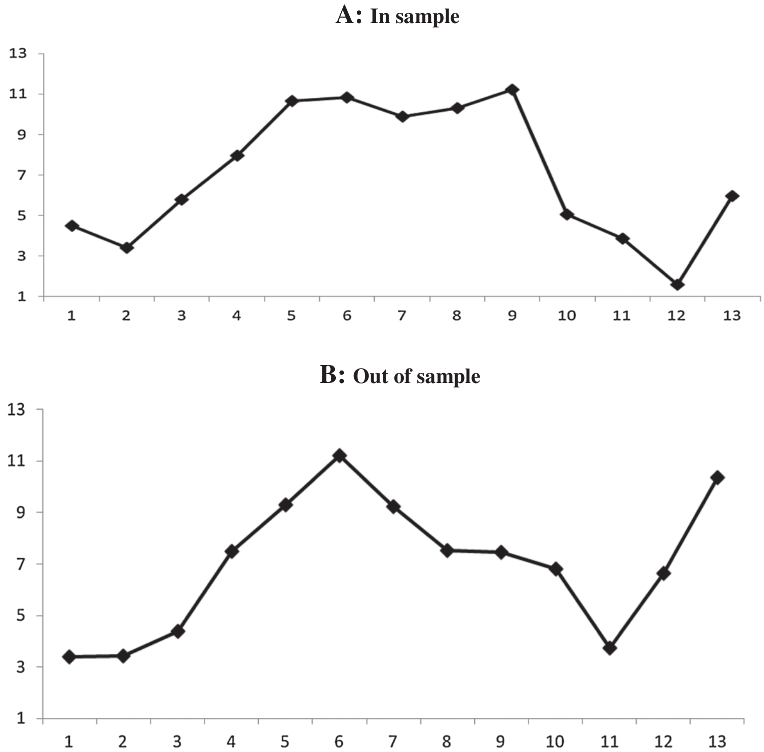

Figure 3. Performance of volatility forecasting across alternative intraday VIX levels. The figure shows the evaluation on the performance of volatility forecasting generated by model 4 for alternative intraday VIX levels. The dynamic process of conditional variance is specified as

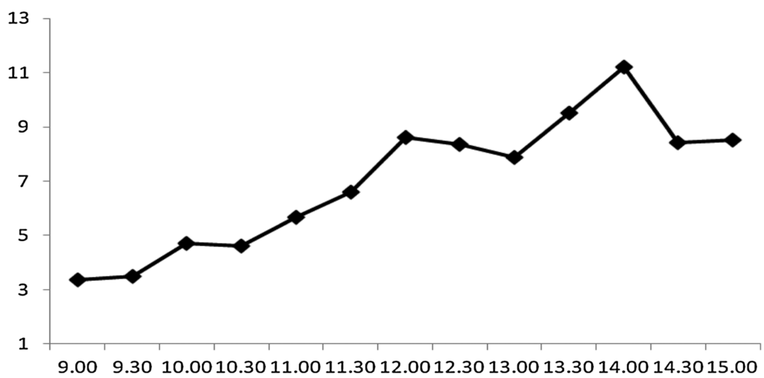

Figure 4. Performance of volatility forecasting for alternative intraday VIX levels during the crisis period. The figure shows the evaluation of the performance of volatility forecasting generated by model 4 for alternative intraday VIX levels during the crisis period (2007–2008). The dynamic process of conditional variance is specified as

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \delta \mathrm{VIX}_{t-1}^2$$

where h_t is the conditional variance of the S&P 500 index at time t. VIX is the measure of implied volatility compiled by the CBOE using a model-free formula. The model is estimated by the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992): (a) root mean square error (RMSE); (b) mean absolute error (MAE); (c) mean absolute percentage error (MAPE); (d) proportion of explained variability, P (Blair *et al.*, 2001); and (e) adjusted R^2 from the regression of log (realized variance) on log (variance forecast). The forecasts of four different horizons (1, 5, 10 and 20 days) are explored. For the results of each measure–horizon category for in-sample out-of-sample volatility forecasting, the values of the performance measure are ranked from 1 to 13 for the 13 alternative intraday VIX levels, with the superior one having a higher rank. Then, for each time point, the ranking values are averaged across measures, horizons and forecasting types (in-sample and out-of-sample).

To observe more clearly the comparison of forecasting performance, we transform the statistics reported in Tables IV and V into score plots in Figure 3. For the results of each measure–horizon category reported in Tables IV (in-sample) and V (out-of-sample), we rank the values of the performance measure from 1 to 13 for the 13 alternative intraday VIX levels with the superior one having a higher rank. Then, for each time point, we average the ranking values across measures and horizons.

Panel A of Figure 3 clearly shows that the in-sample forecasting performance is low at the market's open, increases until around noon where it plateaus, decreases over the afternoon to reach its lowest point at 14:30, and then rises slightly at the end of the trading day. The pattern of the out-of-sample performance in Figure 4(B) is similar to the in-sample pattern, except that the apex of the out-of-sample pattern does not plateau at noon before beginning to decline and the performance of the closing VIX also reaches a much higher level.

To enhance the robustness of our results, we further test whether the VIX levels around noon are more informative than non-noon periods. We calculate the absolute forecasting errors for noon periods and non-noon periods. Noon periods are from 11:00 to 13:30 and non-noon periods are otherwise. We generate various (1-, 5-, 10- and 20-day) horizons of volatility forecasts from model 4 with alternative intraday VIX levels and compare them with their corresponding forecasted targets proxied by the realized volatilities.

Table VII reports the absolute forecasting errors for noon periods and non-noon periods, with panel A reporting in-sample and panel B reporting out-of-sample. The results show that the absolute forecasting errors of VIX levels from noon periods are significantly smaller than those from non-noon periods, which are fairly consistent across different horizons (1-, 5-, 10- and 20-day) and samples (in and out). These findings again support our conjecture that VIX levels around noon are more informative than non-noon periods.

In sum, the in-sample and out-of-sample performance in volatility forecasting jointly provide evidence of the superior information content of the VIX levels around noon. These findings support our conjecture that the trading motivation around noon is less complex (noisy), and therefore trading during this timeframe contains more informative market expectations of future volatility. Conversely, trading at the market's open reflects market participants' perception of the overnight information and trading at the market's close contains market participants' reluctance to carry overnight risk. As a result, trading motivations at the market's open and close are more complex than midday and therefore contain more noise about the market expectation of future volatility.

2008 GLOBAL FINANCIAL CRISIS

Because our dataset covers the period of the 2008 global financial crisis, we explore the performance of volatility forecasting for alternative intraday VIX levels during the crisis period to examine whether and, if so, how the performance pattern of intraday VIX levels changes during the crisis period. We follow the same forecasting procedure as before but limit the sample period to 3 January 2007 through 31 December 2008. We define the in-sample period as 3 January 2007 to 30 September 2008 and the out-of-sample from 1 October 2008 to 31 December 2008.

Figure 4 presents the average of ranking values across measures, horizons and forecasting types (in-sample and out-of-sample). During the crisis period the intraday VIX levels around noon still outperform other time periods. If we compare Figures 3 and 4 more closely, we find that the afternoon forecasting performance of Figure 4 is much higher than that in Figure 3. For example, the ranking value at 14:00 is about 9 in Figure 4, compared to about 4

Table VII. Tests of the absolute forecasting errors for noon periods and non-noon periods

Horizon	Noon periods ($\times 10^4$)	Non-noon periods ($\times 10^4$)	Difference ($\times 10^4$)	*t*-Test
Panel A: In-sample				
1	1.0211	1.0309	−0.0098	−1.92*
5	4.5387	4.5884	−0.0496	−2.14**
10	9.4400	9.5321	−0.0921	−1.87*
20	20.2960	20.4120	−0.1158	−2.43**
Panel B: Out-of-sample				
1	0.6384	0.6410	−0.0027	−1.68*
5	0.4169	0.6727	−0.2558	−4.92***
10	0.8338	1.7383	−0.9044	−5.05***
20	1.6677	4.3460	−2.6784	−7.78***

Note: This table reports the absolute forecasting errors for noon periods and non-noon periods. Noon periods are from 11:00 to 13:30, and non-noon periods are otherwise. We generate various (1-, 5-, 10- and 20-day) horizons of volatility forecasts from model 4 with alternative intraday VIX levels and compare them with their corresponding forecasted targets proxied by the realized volatilities. We test the mean difference between noon periods and non-noon periods. Asterisks indicate significance at the ***1%, **5% and *10% level.

in Figure 3. In other words, the results indicate that during the crisis period traders become more cautious. After adjusting positions for the overnight information, the forecasting performance reaches its peak position around noon and remains high until the end of the trading day. The results are consistent with the prior finding (Yu and Hsieh, 2010) that trading behavior of investors is less emotional during a financial crisis period.

CONCLUSION

Forecasts of the future volatility of asset returns are crucial inputs for numerous investment decisions such as derivatives pricing and risk management, and therefore of great interest to many market participants. The literature widely suggests that the implied volatility derived from option prices is the best predictor of future volatility. Given that numerous studies, using high-frequency data, have reported that trading activities display an intraday pattern that conveys different information over the trading day, we first examine whether implied volatility also has a particular intraday pattern. We then investigate whether intraday implied volatility contains more information than the daily closing level, which is commonly used to predict future volatility.

Specifically, we examine the information content of the intraday S&P 500 VIX to determine which, if any, intraday VIX levels offer more information than the daily closing VIX level for volatility forecasting. We find that the VIX roughly displays a W-shaped intraday pattern; it is highest at trading's open, midday and close. In regard to the forecasting performance of intraday VIX levels, it is low at the market's open, increases until noon, decreases over the afternoon and rises toward the end of the trading day. The results indicate that the implied volatility levels around noon contain more useful information on future volatility than implied volatility levels at the market's closing, as commonly used in the literature. The high forecasting performance around noon supports our conjecture that the trading motivation around noon is less complex and noisy and therefore contains more informative market expectations of future volatility.

Finally, we examine the information content of the intraday VIX during the period of the 2008 global financial crisis. The results indicate that during the crisis period traders become more cautious. As a result, the forecasting performance of the intraday VIX reaches its peak around noon and remains high until the end of the trading day. The results can provide valuable information to hedge extreme risk and allow us to better understand market sentiment and investors' trading behavior.

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