Forecasting volatility with the VIX index: is it worthwhile?

Edited by
V. Cantino, P. De Vincentiis, G. Racca

Risk management: perspectives and open issues.

A multi-disciplinary approach

Mc Graw Hill Education

Mc Graw Hill Education

Programme and Portfolio Manager: Natalie Jacobs
Programme Manager B&E: Marta Colnago
Programme Manager Custom: Daniele Bonanno
Production: Donatella Giuliani

ISBN 9780077180171

Forecasting volatility with the VIX index: is it worthwhile?

Authors

- *Alessio Bongiovanni, PhD Student, alessio.bongiovanni@unito.it - University of Torino*
- *Paola De Vincentiis, Full Professor, paola.devincentiis@unito.it - University of Torino*
- *Eleonora Isaia, Associate Professor, eleonora.isaia@unito.it - University of Torino*

This paper explores the information content and the forecasting power of the VIX index, computed by CBOE. As a benchmark, the forecasting performance of VIX is compared to the Garch (1;1) model and historical volatility. The total period of 20 years taken into consideration (January 1995-December 2014) is split into two sub-periods, precisely before and after March 2006. This is when the trading of option contracts having as underlying VIX index began. By comparing the two sub-periods, we can judge if the information content of VIX increased after becoming a negotiable asset.
The results of the analysis are not clear-cut. The VIX index shows strong information content, but is an upward biased forecast of realized performance. When comparing VIX to Garch and historical volatility, the former is dominant, when the outlier period of the subprime crisis is excluded from the sample. The information content of VIX seems unaffected by the event of becoming the underlying of option contracts.

Keywords: VIX, historical volatility, Garch models, forecast ability, information content
JEL Classification: G14, G17

1 Introduction

Estimating volatility is one of the main goals of academicians and practitioners in the financial field. Forecasts of future price variability are needed to make funding or investment decisions, to value financial instruments, and to measure the risk of a portfolio. Not surprisingly a vast empirical and theoretical literature focused on this topic, proposing new methods for estimating volatility or comparing the effectiveness of techniques already in-use. In particular, our work belongs to that stream of literature which explores the merits of implied volatility (IV) measures, i.e. volatility measures derived from option prices. From a theoretical point of view, these measures could be superior to other types of estimates because they reflect market expectations instead of deriving from a statistical model or from historical returns. In fact, IV is often indicated as a forward-looking measure. In the following sections we will briefly review the literature on the topic and explain our incremental contribution to this literature (section 2), describe the methodology adopted by the study and the features of the sample (section 3) and present the results of our empirical investigation (section 4).

2 Literature review

As already mentioned above, the literature concerning volatility measurement is rich and extensive. One stream of literature compares various volatility-forecasting methods by pitting one against the other. Typically the expected volatility estimated through different alternative methods is used as independent variable to explain realized volatility, i.e. the dependent variable. The information content and forecasting power of the expected volatility measure are judged by looking at the significance of the beta coefficient and by testing the null hypothesis that the coefficient is equal to 1 and the intercept is equal to zero. The relative forecasting power of different volatility measures are analyzed by including them concurrently in a regression and by comparing the coefficients of the various independent variables.

Poon and Granger (2005) examined 93 studies structured in this way and published during a 20-year period. Their overall conclusion is that option-implied volatility most frequently provides better forecasts than time-series models. Among the most influential empirical studies dealing with option-implied volatility, it is worth mentioning Jorion (1995). Focusing on the currency market, he finds that implied volatility outperforms statistical time-series, even when these are given the advantage of *ex post* parameter estimates. However, IV appears to be a biased volatility forecast. Similarly, Fleming (1998), Ederington and Guan (2002), Szakmary et al. (2003), Corrado and Miller (2005) find that IV dominates historical volatility despite being an upward biased forecast. Shu and Zhang (2003) reach the same conclusion, using four different measures of realized volatility, characterized by increasing complexity. Day and Lewis (1992) find that implied volatilities derived from S&P100 index options contain incremental information when added as an exogenous variable to Garch and E-Garch models, but they are unable to draw precise conclusions as to the relative predictive power of Garch forecasts and implied volatility to *ex post* volatility.

Canina and Figlewski (1993) sharply confute the papers commented so far. Indeed, they find that implied volatility derived from S&P100 index options has no correlation at all with future volatility. However, a few years later, Christensen and Prahbala (1998) strongly criticize the method of this study, attributing the peculiar results reported to a problem of overlapping data that was not adequately managed. By solving the issue, the authors confirm that implied volatility outperforms historical volatility in forecasting future volatility, even providing stronger evidence compared to previous studies. Further confutations are made by Becker et al. (2007) who find that the VIX index does not contain incremental information, when compared to a combination of model-based volatility forecasts. As in the study conducted by Canina and Figlewski (1993), this empirical study presents a problem of overlapping observations. Moreover, they do not directly compare VIX forecasts against any single model-based forecast but to quite a complicated combination that would be difficult to use in day-by-day practice. Thus, the contribution is merely theoretical.

Among the empirical works described, our study is mostly in line with Christensen and Prahbala (1998) and Shu and Zhang (2003). However, we introduce a few variations that represent our specific contribution to this field of literature:

- we contrast implied volatility not only with historical volatility but also with volatility measured through a Garch (1;1) model;
- we do not derive implied volatility from one or more ATM near-to-maturity options, as commonly done in literature, but we directly use the VIX index calculated by CBOE, which is based on OTM options and is characterized by a constant average time-to-maturity of 22 trading days;
- the long and varied period covered by our time series allows to draw some conclusions about the effectiveness of different volatility measurements in different market conditions;
- we provide evidence of the effect of VIX options trading on the information content and effectiveness of the index;
- we check the effect of multi-collinearity when comparing the information value of different volatility measurements, whereas most studies do not directly address the problem.

3 Methodology and sample

As briefly synthesized before, our paper is aimed to explore the information content and the predictive power of the VIX index. We investigate relations between implied and realized volatility and assess whether the VIX index is a better predictor of future volatility, compared to historical volatility measurements.

In the analyses, we use the daily closing prices directly calculated by the CBOE, which represent, as already said, the implied volatilities of S&P500 over the next 30-day period (22 trading days). The time horizon of our analyses is a twenty-year period, from January 1995 to December 2014, divided into two subperiods, before and after March 2006, which represents the date when the trading of options on the VIX index began. By comparing the two sub-periods, we can judge if the information content of VIX increased after becoming a negotiable asset.

We initially run a univariate regression, considering the realized volatility as dependent variable and the VIX index as independent variable.

$$RV_t = \alpha + \beta\, Vix_{t-1} \qquad (1)$$

With equation (1) we measure the ability of the VIX index, registered in t-1, i.e. 22 trading days before, to forecast the realized volatility at time t.

Now two problems need to be overcome: overlapping data (Canina and Figlesky 1993, and Christensen and Prabhala 1998) and possible errors in the realized volatility measurement. To address the first issue, for each period we consider the VIX price of the day following the measurement of the realized volatility, which will be calculated again after 22 trading days.

To manage the second problem we test four different measurements, gradually more accurate, of realized volatility, namely the standard deviation, the Parkinson extreme value estimator (1980), the Roger and Satchel estimator (1991) and the Yang and Zhang estimator (2000), and we run equation (1) for each of the different measurements of realized volatility, considered in turn as dependent variable.

We then compare the forecasting power of the VIX index with other estimation methods based on historical data, in particular with the simple moving average (SMA), the exponential moving average (EWMA) and the Garch (1;1) model. Therefore, to gauge whether historical volatility measurements are weaker predictors than implied volatility estimates, we run the same univariate regression for each predictor, equations (2) (3) and (4), and compare the relative T-statistics, the size of the coefficients and the power of the models.

$$RV_t = \alpha + \beta\, SMA_{t-1} \qquad (2)$$

$$RV_t = \alpha + \beta\, EWMA_{t-1} \qquad (3)$$

$$RV_t = \alpha + \beta\, GARCH_{t-1} \qquad (4)$$

Later, following the main stream of the literature on this topic, we include both implied and historical volatilities in a multivariate regression, estimating the following equations:

$$RV_t = \alpha + \beta\, Vix_{t-1} + \beta\, SMA_{t-1} \qquad (5)$$

$$RV_t = \alpha + \beta\, Vix_{t-1} + \beta\, EWMA_{t-1} \qquad (6)$$

$$RV_t = \alpha + \beta\, Vix_{t-1} + \beta\, GARCH_{t-1} \qquad (7)$$

All estimates are repeated for each of the four realized volatility measures and over the three time horizons described above.

Though the majority of the studies on this topic does not deal with the multicollinearity problem that might arise when the VIX index and a measure of historical volatility are entered in the same model, we prefer to face this issue by computing and evaluating the Variance Inflation Factors. In fact, a potential imperfect collinearity between these two variables cannot be excluded *a priori*. In this regard, it has to be mentioned that few abnormal observations registered in the heart of the financial crisis—from September 2008 to April 2009—and identified both with the leverage measure and Cook's distance, have been excluded from the regressions in order to reduce the multi-collinearity effect.

Table 1 provides some descriptive statistics for the volatility estimation methodologies used in the following analysis.

Table 1 Descriptive statistics for the entire period 01/1995-12/2014 and for the two sub-period 01/1995-02/2006 and 03/2006-12/2014.

Volatility estimators for the period 01/1995-12/2014					
	Mean	Median	Minimum	Maximum	Standard deviation
VIX	20,54%	19,61%	10,05%	80,06%	8,41%
GARCH	16,24%	14,08%	7,72%	58,65%	7,68%
SMA	16,56%	14,48%	5,39%	80,76%	9,74%
EWMA	16,67%	14,52%	6,09%	74,43%	9,46%
Volatility estimators for the period 01/1995-02/2006					
	Mean	Median	Minimum	Maximum	Standard deviation
VIX	20,29%	20,18%	10,77%	37,52%	6,31%
GARCH	11,66%	10,95%	8,59%	21,75%	2,78%
SMA	15,94%	14,64%	5,84%	44,92%	7,35%
EWMA	16,16%	15,02%	6,14%	40,27%	7,17%
Volatility estimators for the period 03/2006-12/2014					
	Mean	Median	Minimum	Maximum	Standard deviation
VIX	20,76%	17,66%	10,05%	80,06%	10,51%
GARCH	16,51%	13,50%	8,26%	61,28%	9,54%
SMA	17,33%	14,24%	5,39%	80,76%	12,06%
EWMA	17,30%	14,27%	6,40%	74,64%	11,67%

For the methodologies based in historical data the volatility is computed on daily observations and expressed in annualized terms

Despite the critical market phase during the years 2008-2009, mean and median values do not present important differences among the periods analysed, remaining quite similar even when the entire sample is split into two sub-samples. Indeed, the only elements that prove the stressed conditions characterizing the second sub-period are the larger variability of each estimation method and the maximum values, which are considerably higher. This indicates the abnormal volatility peaks reached by the market.

Furthermore, the higher mean and median values taken by the Volatility Index seem to suggest its tendency to provide a higher measure of market risk, compared to historical volatilities. This evidence could be interpreted in two different ways, precisely, on the one hand, its higher values could indicate better information content in predicting realized volatility than the historical methods but, on the other hand, this could also suggest an overestimation error made by VIX that might incorporate a greater weight given by investors to the occurrence of significant losses, which lead them to quantify a higher measure of future volatility.

4 Results

In order to clearly present our findings, this section is organized in four steps. Starting by using univariate regressions for a comparative study of dominant literature on the topic, we later examine the possible differences in terms of forecasting ability in various market phases, and compare the information content of both VIX and the historical methods by entering them as independent variables in the same regression. The last stage provide some innovations to the previous studies dealing with collinearity problems and the corresponding identification of outliers.

4.1 Comparison with previous literature

We have tested for evidence provided by mainstream literature on the topic. To this end, we first analysed the predictive power of VIX by using different alternative measurement methods for *ex-post* volatility, characterized by increasing levels of complexity. Using the same method, we also analysed the forecasting power of EWMA and Garch-model based volatility. In particular, the following tables only report the results obtained using EWMA but an unreported robustness check made by substituting EWMA with SMA confirms the evidence.

Table 3, 4, and 5, first section, detail the result of this analysis. Basically we find evidence that is consistent with previous literature. First of all, the results indicate positive and statistically significant relations between VIX and realized volatility, proving that it actually contains information about *ex post* volatility. Despite this, with the sole exception of Garch models, when realized volatility is computed by standard deviation, all the estimation methods are biased indicators of the *ex post* measured.

The remarkable values of R^2 in the various regressions in which VIX is used as independent variable indicate its ability to explain a significant part of realized volatility and, compared with the values calculated on the regression based on historical methods, it seems to have a better predictive power. And yet, no clear relations can be observed between said capacity and the precision of the realized volatility measure as previously supposed.

Focusing on method based on historical data, Garch models have a lower information content than the EWMA, although they should theoretically provide a more accurate estimate as a result of the explicit consideration of the volatility clustering phenomenon. However, it should be considered that the Garch parameters are assumed to be constant for the entire period examined, and this could, therefore, be the principal cause of its lower information content.

4.2 Analysis of predictive power in various market conditions

In order to test for the predictive power of different *ex ante* volatility measurements, we split the 20-year period into two sub-periods characterized by different market climates, and precisely a quiet first one (1995-2006), and a turbulent second one (2006-2015), as specified in comments to the descriptive statistics. The two sub-periods also allow to evaluate the effect of option trading with VIX underlying on its information content.

Some interesting elements can be highlighted by considering Tables 2, 3 and 4, second and third section. First, no significant differences can be observed between the coefficients of determination, although the second sub-period presents a market fall, followed by an explosion of volatility levels that, however, seems to be well captured by VIX. Furthermore, this lack of differences indicates the absence of substantial changes in the market participant's behaviour towards the expected volatility, suggesting that the introduction of VIX option contracts has not actually triggered important changes in relations between implied and realized volatility.

With regard to historical volatilities, both methods are characterized by significant losses in terms of forecasting ability in the first sub-period while, instead, in the second one they are affected by a growth in their forecasting ability that makes the corresponding R^2 more consistent with the VIX one.

The above evidence seems to point out the absence of a predictive method that significantly dominates the others in estimating future realized volatility during the period 03/2006-12/2014 because of the very small differences in R^2 regressions.

Moreover, the dynamics described above suggest that the extreme market conditions could likely have a direct impact on the forecasting ability, with all the historical methods seemingly gaining predictive power, compared to the previous period and to VIX that, instead, shows the same explanatory power across the different periods.

Table 2 Regression models for the different measures of realized volatility, assuming as independent variables the VIX level.

Dependent variables for the period 1995-2014				
	$\sigma_{Dev.std}$	σ_{Park}	$\sigma_{R\&S}$	$\sigma_{Y\&Z}$
Intercept	-0,02343**	-0,0018	0,004458	-0,0007093
	(0,0108)	(0,0086)	(0,0081)	(0,0084)
VIX_{t-1}	0,9202**	0,6701**	0,6231**	0,6799**
	(0,0487)	(0,0387)	(0,0366)	(0,0377)
N	228	227	227	227
R^2	0,6120	0,5708	0,5631	0,5909
F(2,225)	48,57	264,17	334,06	255,36
Dependent variables for the period 01/1995-02/2006				
Intercept	-0,01961	-0,008285	-0,001676	-0,005197
	(0,0146)	(0,0117)	(0,0110)	(0,0113)
VIX_{t-1}	0,8765**	0,7010**	0,6584**	0,7007**
	(0,0687)	(0,0550)	(0,0516)	(0,0531)
N	127	126	126	126
R^2	0,5658	0,5670	0,5680	0,5843
F(2,125)	55,8444	215,998	265,12	213,67
Dependent variables for the period 03/2006-12/2014				
Intercept	-0,01189	0,001873	0,008018	0,002822
	(0,01670)	(0,01325)	(0,01257)	(0,01298)
VIX_{t-1}	0,8913**	0,6533**	0,5989**	0,6639**
	(0,07170)	(0,05690)	(0,05398)	(0,05573)
N	101	101	101	101
R^2	0,6095	0,5711	0,5542	0,5891
F(2,100)	11,64	87,64	116,07	83,88

*Standard errors in parentheses, * indicates significance at the 10 percent level, ** indicates significance a 95 percent level, *** indicates significance at the 1 percent level*

Table 3 Regression models for the different measures of realized volatility, assuming as independent variable the exponential weighted moving average (EWMA).

Dependent variables for the period 01/1995-12/2014				
	$\sigma_{Dev.std}$	σ_{Park}	$\sigma_{R\&S}$	$\sigma_{Y\&Z}$
Intercept	0,03543**	0,03950**	0,04142**	0,04041**
	(0,0089)	(0,0069)	(0,0064)	(0,0066)
$EWMA_{t-1}$	0,7832**	0,5788**	0,5468**	0,5920**
	(0,0463)	(0,0358)	(0,0332)	(0,0347)
N	227	227	227	227
R^2	0,5600	0,5369	0,5467	0,5648
F(2,225)	10,99	110,22	152,39	104,88
Dependent variables for the period 01/1995-02/2006				
Intercept	0,05470**	0,04742**	0,04821**	0,04907**
	(0,0125)	(0,0098)	(0,0089)	(0,0094)
$EWMA_{t-1}$	0,6481**	0,5397**	0,5219**	0,5482**
	(0,0708)	(0,0552)	(0,0505)	(0,0530)
N	126	126	126	126
R^2	0,4033	0,4355	0,4627	0,4636
F(2,124)	12,45	58,23	77,25	56,43
Dependent variables for the period 03/2006-12/2014				
Intercept	0,03294**	0,03395**	0,03610**	0,03493**
	(0,01322)	(0,01041)	(0,009701)	(0,01010)
$EWMA_{t-1}$	0,8115**	0,5993**	0,5570**	0,6118**
	(0,06331)	(0,04984)	(0,04646)	(0,04835)
N	101	101	101	101
R^2	0,6240	0,5936	0,5921	0,6179
F(2,99)	4,43	50,88	73,50	48,59

Table 4 Regression models for the different measures of realized volatility, assuming as independent variable the historical volatility computed by a GARCH(1.1) models

Dependent variables for the period 01/1995-12/2014				
	$\sigma_{Dev.std}$	σ_{Park}	$\sigma_{R\&S}$	$\sigma_{Y\&Z}$
Intercept	0,01952*	0,02872**	0,03231**	0,02999**
	(0,0111)	(0,0086)	(0,0080)	(0,0084)
$GARCH_{t-1}$	0,9016**	0,6603**	0,6172**	0,6716**
	(0,0615)	(0,0477)	(0,0447)	(0,0467)
N	227	227	227	227
R^2	0,4889	0,4602	0,4588	0,4788
F(2,225)	1,56	51,61	74,69	45,96
Dependent variables for the period 01/1995-02/2006				
Intercept	-0,01936	-0,01542	-0,01423	-0,01586
	(0,0230)	(0,0180)	(0,0164)	(0,0173)
$GARCH_{t-1}$	1,533**	1,287**	1,259**	1,317**
	(0,1920)	(0,1500)	(0,1371)	(0,1441)
N	126	126	126	126
R^2	0,3396	0,3725	0,4048	0,4022
F(2,124)	36,25	11,23	10,59	37,25
Dependent variables for the period 03/2006-12/2014				
Intercept	0,01338	0,01999	0,02355**	0,02090*
	(0,01538)	(0,01212)	(0,01135)	(0,01183)
$GARCH_{t-1}$	0,9682**	0,7120**	0,6592**	0,7256**
	(0,08058)	(0,06348)	(0,05945)	(0,06200)
N	101	101	101	101
R^2	0,5932	0,5596	0,5540	0,5805
F(2,99)	0,63	20,70	33,15	18,35

4.3 Comparison between the predictive power of the various estimation methods

As third step of our analysis, we placed the Volatility Index against historical and Garch-based volatility to test for a supposed superiority of implied volatility.

Tables 5 and 6 present the results of this analysis. Focusing on the entire period, the values of the VIX_{t-1} coefficients, which range from 0,3739 to 0,9113, are higher than the historical methodology ones, and indicate a better forecasting ability for volatility derived from option prices. This evidence is validated by two additional elements, first, the coefficient for historical volatility decreases considerably in all measurement methods studied and, furthermore, the effect of R^2 regressions is not such as to justify their inclusion, because they remain substantially unchanged.

These results are also confirmed during the first sub-period 01/1995-02/2006 where the higher forecasting ability of VIX surfaces once again. In particular, this period differs from the entire one only for the slope coefficients of the historical estimation techniques that are not statistically different from zero, thus confirming the superiority of VIX.

The analysis of the second sub-period, instead, provides evidence that differs from the above, with slight differences between Garch and EWMA volatilities. Indeed, for the latter method, the differences in slope coefficients against VIX ones are more notable and are surprisingly higher in all the measurement methods considered, such as produce VIX coefficients that are not significantly different from zero.

The Garch estimates too, in this specific sub-period, retrieve predictive power, although the clear superiority of one estimation method cannot be observed. Order relations are variable and depend on the measuring techniques analysed; moreover, the differences between coefficients is not adequate to argue which presents the better performance.

Hence, the above evidence seems to contradict the evidence that characterizes the entire period and the first sub-period, with results that contrast considerably with those referring to said time intervals. Generally, in this period, which is characterized by extreme volatility values caused by the financial crisis originated by the Lehman Brothers' bankruptcy, the forecasting ability of VIX closely resembles that of the various historical estimation methods and, therefore, it is not possible to judge which of them possesses better predictive power. Only the exponential moving averages seem to dominate the implied volatility.

Finally, it is interesting to underscore the differences between EWMAs and Garch models; although the latter methods take in account volatility clustering and the EWMA can be seen as a particular case presented by them, the achieved results suggest the superiority of the latter methods, indicating that the greater weight given to the lagged index return and failure to consider long-term average variance might allow them to obtain better performance in a more variable market phase.

Table 5 Regression models for the different measures of realized volatility, assuming as independent variable the VIX level and the historical volatility computed by the exponential weighted moving average (EWMA)

Dependent variables for the period 01/1995-12/2014				
	$\sigma_{Dev.std}$	σ_{Park}	$\sigma_{R\&S}$	$\sigma_{Y\&Z}$
Intercept	-0,01323	0,00722	0,01496*	0,009609
	(0,0116)	(0,0092)	(0,0086)	(0,0089)
VIX_{t-1}	0,6876**	0,4561**	0,3739**	0,4351**
	(0,1157)	(0,0915)	(0,0857)	(0,0886)
$EWMA_{t-1}$	0,2269**	0,2099**	0,2444**	0,2401**
	(0,1030)	(0,0815)	(0,0764)	(0,0789)
N	227	227	227	227
Adjusted R^2	0,62	0,5832	0,5822	0,6071
$F(3, 224)$	34,07	182,74	235,27	179,58
Dependent variables for the period 01/1995-02/2006				
Intercept	-0,01757	-0,005486	0,002497	-0,001501
	(0,0151)	(0,0121)	(0,0112)	(0,0116)
VIX_{t-1}	0,8427**	0,6169**	0,5330**	0,5897**
	(0,1246)	(0,0992)	(0,0924)	(0,0953)
$EWMA_{t-1}$	0,03215	0,08877	0,1323	0,1172
	(0,1094)	(0,0871)	(0,0811)	(0,0837)
N	126	126	126	126
Adjusted R^2	0,5651	0,5706	0,5772	0,5908
$F(3; 123)$	36,21	144,39	180	144,2
Dependent variables for the period 03/2006-12/2014				
Intercept	0,01080	0,02042	0,02826**	0,02287
	(0,01842)	(0,01458)	(0,01367)	(0,01417)
VIX_{t-1}	0,3649*	0,2231	0,1291	0,1988
	(0,2135)	(0,1690)	(0,1584)	(0,1642)
$EWMA_{t-1}$	0,5011**	0,4096**	0,4472**	0,4427**
	(0,1921)	(0,1521)	(0,1426)	(0,1478)
N	101	101	101	101
Adjusted R^2	0,6273	0,5925	0,5865	0,6158
$F(3, 98)$	10,48	64,56	87,57	63,42

Table 6 Regression models for the different measures of realized volatility, assuming as independent variable the VIX level and the historical volatility computed by a GARCH(1,1) model

Dependent variables for the period 01/1995-12/2014				
	$\sigma_{Dev.std}$	σ_{Park}	$\sigma_{R\&S}$	$\sigma_{Y\&Z}$
Intercept	-0,02294**	-0,001702	0,004625	-0,0005701
	(0,0109)	(0,0086)	(0,0082)	(0,0084)
VIX_{t-1}	0,9113**	0,6530**	0,5942**	0,6558**
	(0,1083)	(0,0859)	(0,0811)	(0,0836)
$GARCH_{t-1}$	0,009463	0,02104	0,03561	0,02969
	(0,1188)	(0,0943)	(0,0890)	(0,0918)
N	227	227	227	227
Adjusted R^2	0,6117	0,5709	0,5634	0,5911
F(3, 224)	31,76	175,38	221,93	169,6
Dependent variables for the period 01/1995-02/2006				
Intercept	-0,01961	-0,01561	-0,0144	-0,01605
	(0,0188)	(0,0150)	(0,0139)	(0,0144)
VIX_{t-1}	0,8657**	0,6482**	0,5667**	0,6225**
	(0,1085)	(0,0865)	(0,0806)	(0,0832)
$GARCH_{t-1}$	0,02177	0,1552	0,2694	0,2298
	(0,2457)	(0,1959)	(0,1824)	(0,1883)
N	126	126	126	126
Adjusted R^2	0,5648	0,5692	0,5756	0,5893
F(3,123)	36,16	143,77	179,15	143,5
Dependent variables for the period 03/2006-12/2014				
Intercept	-0,007084	0,005648	0,01217	0,006873
	(0,01678)	(0,01332)	(0,01258)	(0,01301)
VIX_{t-1}	0,5568**	0,3904**	0,3096*	0,3818**
	(0,2088)	(0,1658)	(0,1565)	(0,1619)
$GARCH_{t-1}$	0,3916*	0,3078*	0,3386*	0,3303*
	(0,2299)	(0,1825)	(0,1723)	(0,1782)
N	101	101	101	101
Adjusted R^2	0,6129	0,5747	0,5623	0,5949
F(3, 98)	8,87	60,46	56,23	58,43

4.4 Analysis of collinearity problems and identification of outliers

In order to conduct a detailed analysis of these singular results that differentiate the second sub-period from the others, we deemed it necessary to study a potential problem of multi-collinearity that could affect the variables when they are jointly analysed in the same regression. To this end, we have examined the Variance Inflation Factors (VIF) for the two different estimation methods during the analysed periods, distinguishing for each one the related VIF with the VIX; the results of which, for brevity, have not been reported. First of all, it is important to underscore the fact that all VIFs are lower than the critical value usually accepted, which is ten.

Only the sub-period 03/2006-12/2014 is concerned by VIFs closer to their critical value, which could point out the presence of a misinterpretation in evaluating the forecasting ability based on the above regression. The evident difference from values recorded in the previous sub-period could likely be related to the existence of some extreme observations that characterize this period, suggesting that they might have a significant influence on the tested relations between the different estimation methods.

In order to reduce the collinearity problem, we have ran a new regression series, which refers to a different sub-sample derived by excluding the outliers identified through the use of the leverage influence measure and Cook's distance applied to the original regressions. Their importance is evident by comparing the VIFs of the same period based on the full samples. Indeed, for all the variables studied, the new sub-samples present considerable reductions in the VIF that halve their values and make them lower than the critical one.

The reductions in VIFs, excluding the volatility peak reached during the years 2008-09, confirm the initial theory that these observations have a significant impact on the relations examined. Table 7 refers only to this last sub-period, showing the results of the new regression run based on the above sub-sample. The new regressions highlight remarkably better performances for VIX than those accomplished in the same sub-period with the full sample. This allows them to dominate both Garch and EWMA volatilities in terms of predictive power, and their contribution becomes statistically non-significant as reported by their considerably low coefficients.

In particular, the latter is the method that presents the larger decrease in its coefficients, underscoring the effect of these extreme observations, especially considering the superiority that surfaced for the EWMA in the full sample, which is completely reversed, excluding the outliers.

These results, which are more consistent with the previous literature, indicate that the volatility implied in the option prices, which directly reflects market expectations, seems to better approximate the actual market movements. This could point out the excellent efficiency of market options considering the greater incidence of institutional investors in it, which should access a wider and better information base and, hence, improve the market forecast, subsequently increasing the predictive power of implied volatility.

Table 7 Regression models for the different measurements of realized volatility for the subperiod 03/2006-12/2014, excluding the outliers

Dependent variables for the period 03/2006-12/2014				
	$\sigma_{Dev.std}$	σ_{Park}	$\sigma_{R\&S}$	$\sigma_{Y\&Z}$
Intercept	0,01214	0,02702*	0,02993**	0,02752**
	(0,01891)	(0,01425)	(0,01273)	(0,01343)
VIX_{t-1}	0,7045**	0,4147**	0,3782**	0,4357**
	(0,2068)	(0,1558)	(0,1392)	(0,1469)
$EWMA_{t-1}$	0,04052	0,1042	0,1035	0,09344
	(0,1938)	(0,1461)	(0,1305)	(0,1377)
N	95	95	95	95
Adjusted R^2	0,4139	0,3742	0,3931	0,4129
F(3,90)	16,40	95,75	135,64	99,61
Dependent variables for the period 03/2006-12/2014				
Intercept	0,01093	0,02366*	0,02666**	0,02457*
	(0,01798)	(0,01356)	(0,01213)	(0,01279)
VIX_{t-1}	0,7498**	0,4486**	0,4343**	0,4892**
	(0,2074)	(0,1565)	(0,1399)	(0,1476)
$GARCH_{t-1}$	-0,008319	0,08642	0,05656	0,04738
	(0,2440)	(0,1841)	(0,1646)	(0,1736)
N	95	95	95	95
Adjusted R^2	0,4136	0,3722	0,3897	0,4104
F(3,90)	16,38	95,35	134,72	99,07

5 Conclusion

The main aim of this study is to investigate whether the Volatility index is able to predict future realized volatility and what the corresponding information content is. Consistently with mainstream literature, our results point out that VIX is a biased estimator of realized volatility, although its ability to explain a considerable portion of realized performance allows it to dominate the other methods based on historical data. This evidence is partly true even when the entire 20-year period is split into two sub-periods in which VIX maintains a high and comparable predictive power in each of these. Moreover, despite the option of taking a direct stand in terms of expected volatility by introducing options contracts drawn up based on VIX, the above-mentioned gap points out that the information content has not changed significantly, thus proving the absence of incremental information about future volatility in the expectations of investors. By directly analysing the predictive power of VIX against that of the methods based on historical data, the superiority of VIX is confirmed in the entire period and the first sub-period, while the second one is characterized by results that are not as clear. These differences between the two sub-periods prompted us to deepen our analysis in an attempt to explain them. In particular, we found collinearity issues that affect the results in the period 2006-2015, and are basically caused by the presence of some abnormal observations during the most volatile market phase that started in September 2008. Leaving out these outliers, indeed, the relations between implied and historical volatilities returns consistent with the previous studies, showing the better predictive power of VIX.

References

BECKER R., CLEMENTS A.E., WHITE S.I. (2007). *Does implied volatility provide any information beyond that captured in model-based volatility forecasts?, Journal of Banking and Finance*, Vol. 31, pp. 2535-2549.

BOLLERSEV T., 1986. *Generalized autoregressive conditional heteroschedasticity, Journal of Econometrics* 31, 307-327.

CANINA L., FIGLEWSKI S. (1993). *The informational content of implied volatility, The Review of Financial Studies*, Vol. 6, N. 3, pp. 659-681.

CHRISTENSEN B.J., PRABHALA N.R., (1998). *The relation between implied and realized volatility, Journal of Empirical Finance*, Vol. 50, pp. 125-150.

CORRADO, C. J., & MILLER JR, T. W. (2005). *The forecast quality of CBOE implied volatility indexes. Journal of Futures Markets, 25*(4), 339-373.

DAY T.E, LEWIS C.M., 1992. *Stock market volatility and the information content of stock index options, Journal of Econometrics*, 52, pp. 267-287.

EDERINGTON, L., & GUAN, W. (2002). *Is implied volatility an informationally efficient and effective predictor of future volatility?. Journal of Risk, 4*, 29-46.

FLEMING J. 1998. *The quality of market volatility forecasts implied by S&P 100 index option prices, Journal of Empirical Finance*, Vol. 5, pp. 317-345.

JORION P. 1995. *Predicting volatility in the foreign exchange market, The Journal of Finance*, Vol. 50, pp. 507-528.

PARKINSON, M. (1980). *The extreme value method for estimating the variance of the rate of return. Journal of Business*, 61-65.

POON S.H., GRANGER C. 2005. *Practical issues in forecasting volatility, Financial Analyst Journal*, Vol. 61, N.1, pp. 45-71.

ROGERS L.C.G, SATCHELL S.E., *"Estimating variance from high, low and closing price"*, (1991), *The Annals of Applied Volatility* Vol. 1 n.4, 504-512.

SHU, J., & ZHANG, J. E. (2003). *The relationship between implied and realized volatility of S&P 500 index. Wilmott magazine, 4*, 83-91.

SZAKMARY, A., ORS, E., KIM, J. K., & DAVIDSON, W. N. (2003). *The predictive power of implied volatility: Evidence from 35 futures markets. Journal of Banking & Finance, 27*(11), 2151-2175.

YANG D., ZHANG Q., *"Drift-Independent volatility estimation based on high, low, open and close prices"*, *The Journal of Business Vol. 3 n.73 (2000)*, 477-492.