Forecasting volatility and computing value-at-risk with the VIX index: is it worthwhile?

This paper explores the information content and the forecasting power of the VIX Index, computed by CBOE, on two different levels. First, the expected 30-day volatility implicit in the index level is compared to the realized volatility over the following 30 days. As a benchmark, the forecasting performance of VIX is compared to the Garch (1;1) model and historical volatility. Then, VIX is used to compute value-at-risk, with a parametric approach, for a hypothetical portfolio replicating Standard and Poor's 500 Index and the measure is backtested against actual losses, using both Kupiec and Lopez statistical tests. At this point the performance of VIX is compared against the Garch (1;1) model and historical volatility once again.

In both tests, 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 an 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. When used to compute value-at-risk, however, the measures based on VIX are less effective than those using Garch models, especially in periods of higher volatility

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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.

The most recent contributions focus on comparing the performance on different models across different asset classes, different financial markets and in different market conditions. Kourtis et al. (2016) compare the forecasting power of implied and GARCH volatility at an international level, taking into consideration 13 equity indices from 10 countries. They find a very similar ranking of the models analysed in the different markets. In particular, the implied volatility corrected for the risk premium is superior over the monthly horizon, whereas the Heterogenous Autoregressive model provides the best forecast at the daily horizon.

Browless et al. (2011) compare a set of models belonging to the ARCH family on a wide array of assets with the aim of comparing not only their forecasting power, but also their ability to cope with a crisis period such as the 2008 turmoil. Surprisingly they find a ranking insensitive to market conditions at the daily horizon. On the contrary, the long-run forecasts are negatively affected by a surge in market volatility.

Charoenwong et al. (2009), focusing on the foreign exchange market, compare the predictive power of implied volatility derived from exchange-traded and over-the-counter options, concluding for a superiority of the latter. Furthermore, they confirm the greater information content of implied volatility compared to time-series based estimates.

A second stream of literature less rich in terms of contributions tests the effectiveness of different volatility forecasts in a risk management framework. In this case, the volatility forecast is not directly compared to realized volatility but is used as an input to estimate the maximum potential loss on a given asset or portfolio with a determined confidence level. The effectiveness of the risk measure is then backtested against actual losses. In these empirical works, focus is not on the capacity to exactly predict the level of volatility but on the ability to adequately

capture the tails of the distribution and, thus, the extreme values. Christoffersen et al. (2001) do not find evidence that value-at-risk estimated using implied volatility is superior to the same indicator based on Garch or historical volatilities. Chong (2004) finds that implied volatility is not effective in estimating VAR because it tends to overestimate volatility in periods of stability, whereas it underestimates risk when the market is more volatile. Conversely, Giot (2005) finds that IV performs quite well as an input to VAR measurement, even in challenging market conditions characterized by bear prices and high volatility. More recently, in a study focused on the Korean market, Kim and Ryu (2015) document quite a poor performance in VAR estimates for the equivalent of VIX on the KOSPI index, when compared to Garch-based volatilities or to implied volatilities directly derived from OTM or ATM options. This poor performance is particularly evident during and after the sub-prime crisis when the models based on ATM implied volatilities outperform alternative estimation methods.

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;
- we value the effectiveness of implied volatility not only as a tool to forecast predict realized volatility, but also as an input in value-at-risk models, thus combining two different streams of literature on the topic;
- 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.

Furthermore, we carry out a specific analysis of the determinants of forecast errors made by VIX. In particular, we explore the dependence of these errors on the level of realized volatility and the trend of prices (bull vs. bear market).

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 sub-periods, 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 Prabhala1998) 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:

$$RV_t = \alpha + \beta\ Vix_{t-1} + \beta\ SMA_{t-1} \quad (5)$$
$$RV_t = \alpha + \beta\ Vix_{t-1} + \beta\ EWMA_{t-1} \quad (6)$$
$$RV_t = \alpha + \beta\ Vix_{t-1} + \beta\ GARCH_{t-1} \quad (7)$$

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 multi-collinearity 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.

To conclude the analysis of the first research question and deeply understand the VIX index's forecasting ability, we compute the forecasting errors of VIX and test their dependence on various market conditions.

Now, considering the second research question, we plan on testing the feasible use of VIX to estimate the maximum potential loss in a Value-At-Risk (VAR) model and its supposed greater ability with respect to the Garch, SMA and EWMA historical measurements. We thus compute the VAR, on a daily basis, of a hypothetical portfolio replicating Standard and Poor's 500 index, considering the four volatility estimators one after the other. Backtesting procedures are used to compare the different models. In particular, we contrast two periods, namely January 2008-December 2009 (504 observations) and March 2013-February 2015 (499 observations). The former is the length of time during which the VIX index reached its peak, whereas the latter is the time-frame when the market volatility was extremely low, rarely above 20 per cent. We then assess the accuracy of the models by carefully analysing the exception rate, using Kupiec's unconditional coverage test (1995), Christoffersen's conditional coverage test (1998) and Lopez's loss function test (1999).

Table 1 provides some descriptive statistics for the volatility estimation methodologies used in the following analysis. Despite the critical market phase during the years 2008-2009, mean and median valuesu do not present significant 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 (2006-2014) are the larger standard deviation of each estimation method, the maximum values, which

are considerably higher, and the higher root mean square errors (RMSE) that indicate more difficulties, compared to the previous period, in predicting the realized volatility.

The higher mean and median values registered by the Volatility Index in all period analysed seem to suggest an upward bias of VIX index that might incorporate a greater weight given by investors to the occurrence of low frequency – high impact losses. It is also worth noting – at this preliminary descriptive level – the higher RMSE associated to the VIX in the second sub-period (2006-2014) which contains the subprime crisis and which is consequently characterised by higher peak values of volatility.

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	Mean square error
VIX	20,54%	19,61%	10,05%	80,06%	8,41%	0,5421%
GARCH	16,24%	14,08%	7,72%	58,65%	7,68%	0,5076%
SMA	16,56%	14,48%	5,39%	80,76%	9,74%	0,5143%
EWMA	16,67%	14,52%	6,09%	74,43%	9,46%	0,4731%
Volatility estimators for the period 01/1995-02/2006						
	Mean	Median	Minimum	Maximum	Standard deviation	Mean square error
VIX	20,29%	20,18%	10,77%	37,52%	6,31%	0,4353%
GARCH	11,66%	10,95%	8,59%	21,75%	2,78%	0,5562%
SMA	15,94%	14,64%	5,84%	44,92%	7,35%	0,4055%
EWMA	16,16%	15,02%	6,14%	40,27%	7,17%	0,3808%
Volatility estimators for the period 03/2006-12/2014						
	Mean	Median	Minimum	Maximum	Standard deviation	Mean square error
VIX	20,76%	17,66%	10,05%	80,06%	10,51%	0,6935%
GARCH	16,51%	13,50%	8,26%	61,28%	9,54%	0,6039%
SMA	17,33%	14,24%	5,39%	80,76%	12,06%	0,6981%
EWMA	17,30%	14,27%	6,40%	74,64%	11,67%	0,6036%

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

Table 2 presents the descriptive statistics of the different volatility estimators when these are used as input in a Var model. The differences between the two periods in terms of market conditions are evident in this case: the comparison between averages, the larger gap between maximum and minimum—essentially due

to the peaks reached—and the higher standard deviation that concern the first sub-period immediately point out the significantly more volatile phase experienced by the market in the years 2008-09.

Consistently with what was described above, once again the average VIX level indicates its tendency to provide a volatility estimate that is higher than other methods, suggesting that its use as market risk parameter might lead to a more conservative estimate.

Table 2 Descriptive statistics for the periods on which the Var models are backtested

Volatility estimators for the period 2008-09					
	Mean	Median	Minimum	Maximum	Standard deviation
SMA	30,73%	23,02%	10,08%	89,95%	18,21%
EWMA	30,25%	22,61%	10,84%	83,55%	17,36%
GARCH	26,97%	20,54%	11,70%	71,14%	14,33%
VIX	32,09%	26,01%	16,30%	80,86%	13,25%
Volatility estimators for the period 2013-15					
	Mean	Median	Minimum	Maximum	Standard deviation
SMA	11,40%	10,74%	5,45%	18,94%	3,26%
EWMA	11,18%	10,56%	6,27%	17,99%	2,82%
GARCH	12,84%	11,99%	8,95%	22,50%	2,75%
VIX	14,50%	13,89%	10,32%	26,25%	2,48%

4 Results

In order to clearly present our findings, this section is organized in six 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 three stages provide some innovations to the previous studies dealing with collinearity problems and the corresponding identification of outliers, the factors bearing the forecast errors of VIX and the performance test of the various estimation methods as input in Var models.

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 3, 4 and 5, 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 3 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 4 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 5 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 6 and 7 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 6 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 7 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, Table 8 reports the Variance Inflation Factors (VIF) for the three different estimation methods during the analysed periods, distinguishing for each one the relative VIF with the VIX. First of all, it is important to underscore the fact that all VIFs are lower than the critical value usually accepted, which is ten. In detail, considering the entire period and the first sub-period, despite their rather high values, they seem to indicate the absence of a serious problem of collinearity, thus proving the stability of the previous analysis.

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 these particular observations might have been sampled when market volatility reached its peaks to have a significant influence on the tested relations between the different estimation methods.

The last row of **Errore. L'origine riferimento non è stata trovata.** shows the VIF values obtained for a new regression series, which refers to a different sub-sample derived by excluding observations 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.

Table 8 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

	$VIF_{VIX,SMA}$	$VIF_{VIX,EWMA}$	$VIF_{VIX,GARCH}$
01/1995-12/2014	5,195	5,713	4,897
01/1995-02/2006	2,992	3,251	2,465
03/2006-12/2014	8,239	9,384	8,646
03/2006-12/2014*	3,481	5,287	5,316

Sample obtained with the exclusion of observations from 09/2008 to 04/2009

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 9 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 9 Regression models for the different measurements of realized volatility for the sub-period 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

4.5 Factors bearing of VIX forecast errors

The lower predictive power of VIX during the most turbulent market phases, as stated in the previous section, seems to indicate a bias in its forecast ability that is more pronounced in the market downturns. In order to assess the behaviour of its predictive errors, Tables 10 and 11 report the regressions results in which their dependence on the different market conditions is analysed. It can be noticed by the realized volatility and by the S&P500 return, both calculated on 22 trading days.

The first two columns of the tables show the regression in which the realized volatility is used as explanatory variable. As hypothesized, the forecast errors are

greater when the realized volatility is higher, suggesting that the investors' expectations might provide an error of over/underestimation related to their possible disproportionate reactions in particularly turbulent market phases.

It is more interesting to observe the regression in which the past realized volatility is added as independent variable, since it significantly increases the coefficients of determination. Taking into account the fact that the realized volatility at time *t* maintains the greatest weight in determining the predictive errors of VIX, the minus sign acquired by the coefficients of lagged volatility seems to indicate that they are higher when the previous volatility is lower, which could mean that VIX already incorporates the past volatility with positive relations.

The next two columns report the regression results in which the impact of the stock index return size on predictive errors was tested. All the periods studied present significant negative relations between the magnitude of errors and the return size, suggesting that in the particular bear phases, such as the years 2008-09, the loss in the predictive power of VIX is considerable, thus justifying the divergence that characterizes the sub-period 03/2006-12/2014 in the two samples.

In order to assess the joint effect of these variables in greater detail, the last column includes the interaction between standard deviation and index return.

Consistently with the above results, with the sole exception of the first sub-period, its slope coefficients indicate negative relations between the latter and the forecast error. The error made by VIX seems to be more pronounced in market phases characterized by high volatility accompanied by market downturns, highlighting a difference in its forecast ability that is directly linked to market dynamics. It is a valid element especially in the sub-period 03/2006-12/2014 where, indeed, the size of the coefficient of this variable is greater, confirming once again the singularity of the results obtained for the period 2006-2014 on the full sample.

Table 10 Regression model for the forecast errors made by the VIX, assuming as independent variables the standard deviation and the return of S&P500 for the entire period 01/1995-12/2014

Dependent variables for the period 01/1995-12/2014					
	(1)	(2)	(3)	(4)	(5)
Intecept	-0,09533**	-0,06901**	-0,03505**	-0,03431**	-0,07269**
	(0,0068)	(0,0048)	(0,0033)	(0,0033)	(0,0060)
σ_t	0,3349**	0,7547**			0,2030**
	(0,0352)	(0,0339)			(0,0313)
σ_{t-1}		-0,5789**			
		(0,0338)			
$Return_t$			-0,7182**	-0,7205**	-0,2275**
			(0,0624)	(0,0624)	(0,0960)
$Return_{t-1}$				-0,08457	
				(0,0624)	
σ_t*$Return_t$					-1,041**
					(0,2351)
N	228	227	228	227	228
Adjusted R^2	0,2826	0,6874	0,3667	0,3692	0,5228

Table 11 Regression model for the forecast errors made by the VIX, assuming as independent variables the standard deviation and the return of S&P500 for the two sub-periods 01/1995-02/2006 and 03/2006-12/2014

Dependent variables for the period 01/1995-02/2006					
Intercept	-0,1011**	-0,07097**	-0,04108**	-0,03937**	-0,09270**
	(0,009)	(0,007)	(0,004)	(0,004)	(0,009)
σ_t	0,3544**	0,6507**			0,3144**
	(0,051)	(0,048)			-(0,049)
σ_{t-1}		-0,4847**			
		(0,048)			
$Return_t$			-0,4608**	-0,4808**	-0,237
			(0,085)	(0,085)	(0,231)
$Return_{t-1}$				-0,1567*	
				(0,085)	
σ_t*$Return_t$					-0,5905
					(1,100)
N	127	126	126	125	126
Adjusted R^2	0,2763	0,6008	0,1841	0,1994	0,3807
Dependent variables for the period 03/2006-12/2014					
Intercept	-0,08933**	-0,06119**	-0,03020**	-0,03052**	-0,05373**
	(0,01160)	(0,006801)	(0,005289)	(0,005357)	(0,009313)
σ_t	0,3162**	0,8524**			0,1033**
	(0,05501)	(0,04791)			(0,04604)
σ_{t-1}		-0,7008**			
		(0,04781)			
$Return_t$			-0,9196**	-0,9230**	-0,3041*
			(0,08869)	(0,08921)	(0,1660)
$Return_{t-1}$				0,08797	
				(0,08922)	
σ_t*$Return_t$					-1,154**
					(0,3286)
N	101	101	101	100	101
Adjusted R^2	0,2426	0,7604	0,5158	0,5156	0,5978

4.6 Volatility Index performance as estimate of the market risk in a Value-at-Risk model

The last step of this paper aims at examining the option of using VIX in a Value-at-Risk model to quantify the maximum potential loss of a hypothetical position on the S&P500 index, comparing its performance with those of the other methods based on historical data.

Table 12 briefly shows the key variables required to assess the performance of the various volatility parameters. The first two columns present the number of exceptions (X) and the corresponding failure rate (π), respectively.

An early study of these variables immediately shows a significant difference between the two periods in terms of exceptions observed. With the sole exception of simple moving averages at 95% confidence level, in all other cases estimation methods are significantly worse in the first period of work than in the second one. Said evidence is also confirmed by the corresponding failure rate, which is always greater than the theoretically established one, both at 95% and 99% confidence level.

The situation is partly different if we consider the one calculated only in the second period, precisely, while the rate obtained for the moving averages is higher at both confidence levels, those derived from the Var based on Garch and VIX are lower than the expected 5%, and are slightly higher considering a 1% level.

In order to obtain clearer evidence of these differences, the third column reports the statistics associated with Kupiec's unconditional coverage test (LR_{pof}), which refers to the null hypothesis of model adequacy. Its application further validates the above data for the two different periods. In the first one, only the Var computed by simple moving averages can be considered adequate at 95% confidence level, although it must be said that even just one additional exception would make the model inadequate. In all the other cases the failure rates are statistically higher, denoting the inability to accurately quantify the market risk.

The results based on the second period studied are completely different. Only in the case of moving averages with a 99% confidence level can the null hypothesis be rejected, indicating a strong discrepancy in the performance of the estimation methods across the different periods, with the simple moving averages providing better quantification of the market risk during the most volatile phases. On the other hand, despite the worse performance during the above period, the Garch models (1.1) and VIX present a significantly better performance in the quieter market phase.

In order to also take into account the temporal distribution of Var violations, the following two columns present the statistics that refer to the independence of the exceptions test (LR_{ind}) and the conditional coverage test (LR_{cc}), which allow to jointly evaluate the independence and the frequency of exceptions.

Regarding the independence test, it must be underscored that its functional form prevents the calculation of relative statistics for models without consecutive exceptions. However, in order to evaluate this property and to have a measure of the conditional coverage for each estimation method examined, a dummy infinitesimal empirical probability was also given to models that lacked consecutive exceptions in order to distinguish it from zero even if, in fact, this value is almost negligible.

Despite the possibility of having a value for all the Vars, this procedure, in the specific case of the simple and exponential moving averages in the first sub period, provides misleading results due to the comparison between the infinitesimal rate given and the empirical one observed, only considering the violations following a

non-violation day. Except for this singular case, in all other cases and for both periods, the Var models adequately consider the changes in market conditions and, in most cases, present an LR_{ind} value that is considerably lower than the critical one.

Indeed, combining the results obtained by this test and Kupiec's one, it is evident that the most significant component in determining the inadequacy of models is the high empirical failure rate, especially in the first period characterized by more extreme market movements. This allows to observe that even in the more volatile phases, all the methods used to quantify the maximum potential loss provide a measure that, despite its high number of exceptions, seems to adequately face the volatility clustering that could be particularly pronounced in the bear phases.

In order to have a complete representation of predictive performance, the last columns of the table report the key values of the Lopez loss function test. As with the previous one, this test too recorded the worst performances in the period 2008-09, with substantial differences for losses resulting from the VIX and Garch estimates, compared to the ones of the moving averages that show the best performance. These results are relatively surprising since volatility clustering was taken into account by the Garch model, and especially the role of fear gauge awarded to the Volatility index based on the market expectations.

The evidence described is, however, completely reversed in the second period in which the size of losses of these two methods are significantly lower than the moving averages ones.

Very similar evidence is achieved when the number of violations on the variable just described is isolated by the use of the average size of losses. Noteworthy, in this sense, is the average size of violations made by VIX in the first period, which is more than twice the Garch one. Anyhow, in a broad sense, the smaller average size of losses calculated by the Garch model, when compared with VIX ones, seems to indicate that even if VIX provides a better measure in terms of failure rate, they lead to consistent losses when exceptions occur.

Concluding, the analysis of these different methods in predicting the market risk shows, and this is in part surprising, the better performance of the simple moving averages during the most critical period, probably due to the short timeframe in which they are calculated that allows them to react faster to new market shocks and to contain the losses fraction that is exceeded by the Var.

The use of VIX and Garch volatiles, instead, seems to be inadequate in such a context, both for the number of exceptions and the amount of losses. Conversely, their performance is significantly better when the market is in more normal conditions, where the lower volatility allows them to reduce the corresponding failure rate and the average losses that occur.

Table 12 Summary of the tests run to evaluate the performance of the different volatility estimators in VaR calculation

Period 2008-2009								
		X	π	LR_{pof}	LR_{ind}	LR_{cc}	C_M	$\overline{C_M}$
Confidence level 95%	VAR_{SMA}	35	6,93%	3,60	5,22**	8,82**	-35,22%	-1,01%
	VAR_{EWMA}	38	7,40%	5,96**	6,20**	12,16**	-36,25%	-0,95%
	VAR_{GARCH}	44	8,71%	12,19**	3,40	15,59**	-48,27%	-1,10%
	VAR_{VIX}	46	9,11%	14,68**	0,45	15,13**	-51,10%	-1,11%
Confidence level 99%	VAR_{SMA}	14	2,77%	10,85***	0,80	11,65***	-8,75%	-0,62%
	VAR_{EWMA}	14	2,77%	10,85***	0,80	11,65***	-7,93%	-0,57%
	VAR_{GARCH}	21	4,16%	28,53***	1,82	30,35***	-13,97%	-0,67%
	VAR_{VIX}	12	2,38%	7,00***	0,58	7,58***	-16,80%	-1,40%
Period 2013-2015								
		X	π	LR_{pof}	LR_{ind}	LR_{cc}	C_M	$\overline{C_M}$
Confidence level 95%	VAR_{SMA}	35	7,00%	3,81	0,10	3,91	-16,25%	-0,46%
	VAR_{EWMA}	27	5,41%	0,17	3,09	3,26	-14,79%	-0,55%
	VAR_{GARCH}	22	4,40%	0,38	2,03	2,41	-9,21%	-0,42%
	VAR_{VIX}	20	4,00%	1,11	1,67	2,78	-9,78%	-0,49%
Confidence level 99%	VAR_{SMA}	13	2,60%	9,01***	0,70	9,71***	-6,96%	-0,54%
	VAR_{EWMA}	13	2,60%	9,01***	0,70	9,71***	-5,66%	-0,44%
	VAR_{GARCH}	7	1,40%	0,73	0,19	0,92	-1,93%	-0,28%
	VAR_{VIX}	8	1,60%	1,55	0,26	1,81	-2,93%	-0,37%

*Where X is the number of exceptions, π is the empirical exception rate, LR_{pof}, LR_{ind} and LR_{cc} are respectively the key statistics for the Kupiec's test, independence test and the conditional coverage test. ** and *** indicate the rejection of the null hypothesis with confidence level of 95 and 99% and thus the inadequacy of the VAR model. C_M is the value taken by the loss function and $\overline{C_M}$ is the average size of this function.*

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.

Moreover, our results show that the loss in predictive power of VIX is related to market conditions. Its predictive errors are generally bigger when a bear phase is accompanied by high volatility, suggesting that a volatility measure based only on investor expectations could be driven by unbiased reactions to market shocks.

The second research question concerns the ability of VIX to quantify the maximum potential loss. According to the previous sections, the backtests performed for the Var model indicate the poor performance of VIX during the most turbulent market phase, thus causing the inadequacy of this model both for the failure rate and the size of losses, while the preferable performance of simple moving averages can be noticed. In the second period, which is, instead, characterized by remarkably lower VIX levels, its performance significantly improves, considerably limiting the number of violations and the magnitude of losses.

Despite the very similar performance of VIX and Garch models, the latter method seems to be preferable, as proved by the closer failure rate to the theoretical one and by minimization of Var losses, although in the period 2008-09 with a 99% confidence level it shows a higher exception rate than the VIX one but is associated with a much lower value of the average entity of losses.

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.

Brownless C., Engle R., Kelly B. (2011), A practical guide to forecasting through calm and storm, The Journal of Risk, Vol. 14, N. 2, Winter 2011, pp. 3-22.

Canina L., Figlewski S. 1993. The informational content of implied volatility, The Review of Financial Studies, Vol. 6, N. 3, pp. 659-681.

Charoenwong C., Jenwittayaroje N., Sin Low B. (2009), Who knows more about future currency volatility?, The Journal of Futures Markets, Vol. 29, n. 3, pp. 270-295.

Chicago Board Options Exchange, 2014. The CBOE Volatility Index – VIX. The powerful and flexible trading and risk management tool from the Chicago Board Options Exchange, pp. 1-23.

Chong J., 2004. Value at Risk from econometric models and implied from currency options, Journal of Forecasting 23, pp. 603-620.

Christensen B.J., Prabhala N.R., 1998. The relation between implied and realized volatility, Journal of Empirical Finance, Vol. 50, pp. 125-150.

Christensen, B. J., & Hansen, C. S. (2002). New evidence on the implied-realized volatility relation. The European Journal of Finance, 8(2), 187-205.

Christoffersen P., Hahn J., Inoue A., 2001. Testing and comparing Value-at-Risk measures, Journal of Empirical Finance, pp. 325-342.

Christoffersen, P. F. (1998). Evaluating interval forecasts. International economic review, 841-862.

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.

Giot, P. (2005). Implied volatility indexes and daily Value at Risk models. The Journal of derivatives, 12(4), 54-64.

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

Kim, J. S., & Ryu, D. (2015). Are the KOSPI 200 implied volatilities useful in value-at-risk models?. Emerging Markets Review, 22, 43-64.

Kourtis A., Markellos R.N., Symeonidis L., (2016), An international comparison of implied, realised and GARCH volatility forecasts, The Journal of Futures Markets, Vol. 00, N. 0, pp. 1-30.

Kupiec P., 1995. Techniques for verifying the accuracy of risk measurement models, Journal of Derivatives 2, 173-184.

Lopez, J. A. (1999). Methods for evaluating value-at-risk estimates. Economic review, 2, 3-17.

Martens, M., & Zein, J. (2004). Predicting financial volatility: High-frequency time-series forecasts vis-à-vis implied volatility. Journal of Futures Markets, 24 (11), 1005-1028.

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.

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.

Virdi, N. K. (2011). A Review of Backtesting Methods for Evaluating Value-at-Risk. International Review of Business Research Papers, 7(4), 14-24.