9th Annual Conference of the

EuroMed Academy of Business

Innovation, Entrepreneurship and Digital Ecosystems

Edited by: Demetris Vrontis,
Yaakov Weber,
Evangelos Tsoukatos

Published by: EuroMed Press

PERFORMANCE OF VIX INDEX AS A TOOL FOR VOLATILITY FORECASTING IN BULL AND BEAR MARKETS

Bongiovanni, Alessio; De Vincentiis, Paola; Isaia, Eleonora

Department of Management, University of Turin, Unito, Turin, Italy

ABSTRACT

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.

Furthermore, we carry out a specific analysis of the determinants of forecasting 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).

The results of the analysis are not clear-cut. The VIX index shows strong information content, but is an upward biased forecast of realized volatility. When comparing VIX to Garch and historical volatility, the former is dominant, but only when the outlier period of the sub-prime crisis is excluded from the sample. The information content of VIX seems unaffected by the event of becoming the underlying of option contracts. The errors made by VIX are more pronounced in market phases characterized by high volatility and decreasing prices, highlighting a dependence of its forecast ability on market dynamics.

Keywords: *VIX, historical volatility, Garch models, forecast ability, information content*

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).

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 analysed 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. Martens and Zein (2004) confirm the superiority of implied volatility, compared to time-series models, while showing that long memory models based on high-frequency data are able to equal and, in some cases, beat IV forecasting performance. 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.

 ISBN: 978-9963-711-43-7

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 Prabhala (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, the authors 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 of 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. 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. 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.

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

- 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;
- similarly to Shu and Zhang (2003), we use four different methods to compute the ex-post realized volatility, characterized by increasing levels of complexity;
- 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 forecasting 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).

METHODOLOGY AND SAMPLE

As briefly synthesized before, our paper aims 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 and Garch-based volatility measurements.

In the analyses, we use the daily closing prices directly calculated by the CBOE, which represent the implied volatilities of S&P500 over the next 30-day period (22 trading days). The time horizon of our analysis 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 and the others methodologies based on historical data as independent variable. For brevity, this kind of analysis is not reported, but its results are essentially in line with those obtained in the successive analysis and with the dominant part of previous studies.

Afterwards, 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:

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

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

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

Where:

 ISBN: 978-9963-711-43-7

VIX = Volatility index computed by CBOE; SMA = simple moving average, computed on 22 most recent daily returns of S&P500 Index; EMWA = exponential moving average computed on 22 most recent daily returns using as decay factor calibrated on the historical return on the three previous years; GARCH: volatility computed with a Garch (1;1) model with parameters calibrated on 5 years of historical returns for the model applied in the entire period and calibrated on 3 years for the ones used in the two sub-periods.

Now two problems need to be overcome: overlapping data (Canina and Figlesky 1993, 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 regression analysis for each of the different measurements of realized volatility, considered in turn as dependent variable.

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 (VIF). In fact, a potential imperfect collinearity between these two variables cannot be ruled out *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, 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, we analyse the determinants of the forecasting errors made by VIX defined as follows:

$$ER_t = \sigma_t - VIX_{t-1} \qquad (8)$$

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 values 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.

Volatility estimators for the period 01/1995-12/2014						
	Mean	Median	Minimum	Maximum	Standard deviation	Root mean square error
VIX	20,54%	19,61%	10,05%	80,06%	8,41%	7,363%
GARCH	16,24%	14,08%	7,72%	58,65%	7,68%	7,124%
SMA	16,56%	14,48%	5,39%	80,76%	9,74%	7,172%
EWMA	16,67%	14,52%	6,09%	74,43%	9,46%	6,878%
Volatility estimators for the period 01/1995-02/2006						
	Mean	Median	Minimum	Maximum	Standard deviation	Root mean square error
VIX	20,29%	20,18%	10,77%	37,52%	6,31%	6,598%
GARCH	11,66%	10,95%	8,59%	21,75%	2,78%	7,458%
SMA	15,94%	14,64%	5,84%	44,92%	7,35%	6,368%
EWMA	16,16%	15,02%	6,14%	40,27%	7,17%	6,171%
Volatility estimators for the period 03/2006-12/2014						
	Mean	Median	Minimum	Maximum	Standard deviation	Root mean square error
VIX	20,76%	17,66%	10,05%	80,06%	10,51%	8,328%
GARCH	16,51%	13,50%	8,26%	61,28%	9,54%	7,771%
SMA	17,33%	14,24%	5,39%	80,76%	12,06%	8,355%
EWMA	17,30%	14,27%	6,40%	74,64%	11,67%	7,769%

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.*

RESULTS

In order to present our findings in a clear way, this section is organized in three steps. We initially run a bivariate regression in order to compare the information content of both VIX and the historical methods by entering them as independent variables in the same regression. This part of the analysis is quite standard in the specific literature. The following two steps provide some innovations to the previous

 ISBN: 978-9963-711-43-7

studies dealing with collinearity problems and deepening the analysis of the factors bearing on the forecasting errors made of the VIX.

1. *Comparison between the predictive power of the various estimation methods*

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

Tables 2 and 3 present the results of this analysis. In particular, they only report the results obtained using EWMA, but an unreported robustness check made by substituting EWMA with SMA confirms the evidence. 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 confirmed in all regression, regardless of the method adopted to measure realised volatility.

When we split the sample using March 2006 as divide, the evidence is strongly confirmed in the first sub-period 01/1995-02/2006 where the higher forecasting ability of VIX surfaces once again. In particular, this sub-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 which even subsumes the information of EWMA and Garch-based volatility.

The analysis of the second sub-period, instead, provides evidence of a weak forecasting performance for the VIX index, especially when compared to the EWMA. Surprisingly the coefficients of EMWA are higher in all the measurement methods considered and VIX coefficients are not significantly different from zero. Thus, basically, the information content of IV is subsumed by the historical volatility. The Garch estimates too, in this specific sub-period, retrieve predictive power, although the clear superiority of one estimation method over the other cannot be observed. Order relations are variable and depend on the measuring techniques analysed; moreover, the differences between coefficients is not large enough to argue which presents the better performance.

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**

 ISBN: 978-9963-711-43-7

	(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 2. *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)*

Hence, the results obtained for the second sub-period seem to contradict the evidence that characterizes the entire 20-year period and the first sub-period. During the years 2006-2014, 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. The evidence is even more surprising when we consider that the trading of option contracts on VIX should have increased – not reduced – its information content and forecasting power.

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**

 ISBN: 978-9963-711-43-7

	(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

Table 3. *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*

2. *Analysis of collinearity problems and identification of outliers*

In order to deepen the understanding of the contrasting results obtained for the first and the second sub-periods, we deemed it necessary to analyse a potential problem of multi-collinearity that could affect the coefficients' estimates when two volatility measures are jointly used as independent variables in the same regression. To this end, we computed the Variance Inflation Factors (VIF) for the three different volatility forecasting methods during the analysed periods.

First of all, it is important to underscore the fact that all VIFs are lower than the critical value usually accepted, which is ten. However the sub-period 03/2006-12/2014 is characterised by VIFs very close to their critical value and this raises the doubt of a potential misinterpretation in evaluating the relative forecasting ability of different methods based on the above regressions. The significant gap between the VIFs computed in the first and second sub-period could be potentially related to the existence of some

 ISBN: 978-9963-711-43-7

extreme observations that characterize the period 2006-2014 and that might have a significant influence on the tested relations between the different estimation methods.

In order to reduce the collinearity problem, we re-ran all regressions using a different sub-sample that excludes the outliers identified using the leverage influence measure and the Cook's distance applied to the original regressions. In particular, these analysis led to the identification of 7 outliers, all located in the period September 2008 – April 2009. Indeed, for all the variables studied, the new "polished" sub-samples present considerable reductions in the VIF that halve their values. The reduction in VIFs, excluding the volatility peak reached during the years 2008-09, confirms the initial hypothesis that these observations have a significant impact on the relations examined.

Table 4 refers only to second sub-period (2006-2014), showing the results of the regressions based on the revised sub-sample. Excluding the outliers from the data, the implied volatility dominates both Garch and EWMA volatilities in terms of predictive power, and their contribution becomes statistically non-significant.

These results, which are more consistent with previous literature on the topic, confirm that the volatility implied in the option prices, which directly reflects market expectations, better approximate actual market movements. However, our empirical evidence highlights as well an inability of VIX to capture correctly extreme market movements as already surfaced, at a descriptive level, when observing the values of RMSE in Table 1.

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				

 ISBN: 978-9963-711-43-7

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

Table 4. *Regression models for the different measurements of realized volatility for the subperiod 03/2006-12/2014, excluding the outlier*

3. *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. This evidence prompted as us to try and analyse more in depth the determinants of VIX forecasting errors. In particular, we used as independent variables the levels of realised volatility and the market return, both at time t and t-1. The first two columns of the table show the regressions in which the realized volatility is used as sole 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 specification (2) 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. This evidence indicates that VIX is unable to capture sudden surges in market volatility, notwithstanding its forward-looking nature.

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
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

Table 5. *Regression model for the forecast errors made by the VIX, assuming as independent variables the standard deviation and the return of S&P500*

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 market return, suggesting that in bear phases, such as the years 2008-09, the loss in the predictive power of VIX is more sizeable, thus explaining the divergence of empirical results that characterizes the sub-period 03/2006-12/2014 whether the heart of the post-Lehman crisis is included or not.

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 interaction term and the forecast error. The error made by VIX tend to be more pronounced in market phases characterized by high volatility accompanied by market downturns, highlighting a difference

 ISBN: 978-9963-711-43-7

in its forecasting 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.

CONCLUSIONS

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. Despite the possibility of taking a direct stand in terms of expected volatility by introducing options contracts written on VIX, the information content of this index has not changed significantly. By directly analysing the predictive power of VIX against other 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 clear cut. 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 2006-2014, 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 empirical evidence is consistent with the previous studies, confirming the better predictive power of VIX.

Furthermore, 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 affected by biased reactions to market shocks.

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.

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.

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.
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.
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 (1991), "Estimating variance from high, low and closing price", *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.
Yang D., Zhang Q. *(2000)*, "Drift-Independent volatility estimation based on high, low, open and close prices", *The Journal of Business Vol. 3 n.73*, 477-492.

 ISBN: 978-9963-711-43-7