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Research article

The Information Content of Corridor Volatility Measures During Calm and Turmoil Periods

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Abstract: Measurement of volatility is of paramount importance in finance because of the effects on risk measurement and risk management. Corridor implied volatility measures allow us to disentangle the volatility of positive returns from that of negative returns, providing investors with additional information beyond standard market volatility. The aim of the paper is twofold. First, to propose different types of corridor implied volatility and some combinations of them as risk indicators, in order to provide useful information about investors' sentiment and future market returns. Second, to investigate their usefulness in prediction of market returns under different market conditions (with a particular focus on the subprime crisis and the European debt crisis). The data set consists of daily index options traded on the Italian market and covers the 2005–2014 period. We find that upside corridor implied volatility measure embeds the highest information content about contemporaneous market returns, claiming the superiority of call options in measuring current sentiment in the market. Moreover, both upside and downside volatilities can be considered as barometers of investors' fear. The volatility measures proposed have forecasting power on future returns only during high volatility periods and in particular during the European debt crisis. The explanatory power on future market returns improves when two of the proposed volatility measures are combined together in the same model.

Keywords: model-free implied volatility; corridor implied volatility; market turmoil; financial crises; return predictability

1. Introduction and Literature Review

The disentanglement of the volatility of positive and negative returns is of paramount importance in finance because of their potentially distinct effects on the level of overall risk, risk measurement and risk management. Corridor implied volatility, introduced by Carr and Madan (1998), is obtained from model-free implied volatility (Britten-Jones and Neuberger, 2000) by truncating the integration domain between two barriers. In particular, downside and upside corridor implied volatilities measure the volatility of the left (negative returns) and the right (positive returns) parts of the risk-neutral distribution. They are computed by setting the barriers to: (-∞, Forward price) for the downside corridor and (Forward price, +∞) for the upside corridor and therefore they use put and call option prices, respectively. As a consequence, upside and downside corridor implied volatility measures have the advantage, over the commonly used volatility, that they better capture and distinguish the pricing of downside and upside risk because they rely on a specific part of the distribution.

Andersen and Bondarenko (2007) are the first to employ corridor implied volatility measures to forecast future market volatility. They use different corridors that focus on the central part of the distribution, by cutting the tails with symmetric cuts. These authors find that narrow corridor measures perform better than broad corridor measures for forecasting future market volatility. Muzzioli (2013a) analyzes the high volatility period of June–November 2009. The author employs various corridor implied volatility measures based on different barrier levels to shed light on the information content of different parts of the risk-neutral distribution and to find an optimal cut for the purpose of forecasting future market volatility. The results suggest that, during this high volatile period, a symmetric cut in each tail of about 25% to 30% of the area under the risk-neutral distribution is optimal for this purpose. Moreover, the author investigates the forecasting power of implied volatility measures about realized volatility by splitting the total volatility into the volatility of the left and the volatility of the right part of the distribution. The results show that upside corridor implied volatility better forecasts future upside volatility, than downside corridor implied volatility does for future downside volatility. This result suggests that investors more heavily price downside risk, as they significantly overestimate the volatility of the left part of the distribution.

Muzzioli (2013b) and Muzzioli (2015) investigate the performance of different implied volatility measures in forecasting future volatility. In particular, Muzzioli (2013b) compares different option-based symmetric volatility measures and finds that corridor implied volatilities achieve a better forecasting performance in forecasting future realized volatility, compared to both Black-Sholes (1973) and model-free implied volatility measures. In particular, heavy cuts of the risk-neutral distribution are preferred during turmoil periods, while low cuts (5–10% in each tail) are preferred during calm periods. Muzzioli (2015) extends the above analysis by investigating also asymmetrical cuts of the risk-neutral distribution (corridor volatility measures which focus more on call or put option prices). The results show that corridor volatility measures obtained by using only put prices outperform those obtained by using only call prices in forecasting future realized volatility, both in low and high volatility periods. However, the superiority of downside corridor volatility is more pronounced in high volatility periods.

Few authors try to aggregate the information content in the left tail of the distribution with that from the right tail in order to combine them into a unique measure of risk. Among them, Liu and Faff (2017) provide an appealing insight into the possibility of computing a measure of asymmetry as the ratio between the volatility of the left and the right part of the risk-neutral distribution of the asset returns. However, this formula suffers from the following drawbacks. First, it is a model-based approach, since it relies on the Black-Scholes formula. As a result, it cannot be easily generalized to different asset price processes. The inconsistency of the assumption of a constant volatility, used in the Black-Scholes model, with the empirical evidence found in the financial markets is highlighted in many studies (e.g. Jackwerth and Rubinstein, 1996; Rubinstein, 1985; Rubinstein, 1994). Second, Liu and Faff (2017) consider only four around-the-money options in estimation of the implied volatility to plug in the Black-Scholes formula and discard all other options traded. This results in a considerable loss of information.

In order to overcome these limitations, we propose to compute in a model-free setting, the market symmetric index measure (SIX) proposed in Liu and Faff (2017), as the ratio between the volatility of the left part and the volatility of the right part of the distribution. In this way, we exploit more information available in the market (as we use both at-the-money and out-of-the-money option prices). Moreover, we aggregate the information of the left and the information of the right hand side of the distribution in a new volatility measure computed as the difference between the downside and the upside corridor implied volatility. We call this measure relative semi-volatility (RSV), following a suggestion in Feunou et al. (2016) who use the same definition to model realized semi-variance. Since investors like positive spikes in returns while they dislike negative ones (Feunou et al., 2017), we expect that the proposed measures of risk based on corridor implied volatilities, which treat the good and bad volatility differently, could provide further information content on future returns, beyond standard volatility measures.

The rationale under our research question is the following. Investors dislike bad uncertainty (i.e. the variability of returns during adverse market conditions) since it increases the probability of large losses. On the other hand, they dislike less, or like more, good uncertainty (i.e. the variability of returns during good market conditions) since it increases the probability of large gains. These two points are reflected in the concept of upside and downside corridor implied volatility. To elaborate, downside corridor implied volatility shows to what extent, or how much, investors are willing to pay to hedge against volatility in bad market conditions. Upside corridor implied volatility, in turn, shows, in volatility terms, how much investors are willing to pay to hedge against volatility in good market conditions. Since investors ask for a premium to bear unfavorable risks and are willing to pay to be exposed to favorable risks, the investors' preferences are reflected in higher or lower future returns. Therefore, upside and downside corridor implied volatilities may convey information about future returns.

The objective of this study is twofold. First, to investigate the properties of the proposed volatility measures (SIX and RSV) and their relation with model-free implied volatility and with contemporaneous market returns. This will help us to assess whether these volatility measures can be used as an indicator of current investors' fear or greed in the market (see e.g. Giot, 2005; Whaley, 2000). Second, to assess whether these volatility measures can be used to forecast future aggregate market returns, both during calm and turmoil market periods.

The paper proceeds as follows. First, we introduce the upside and downside corridor implied volatility measures and their combination into two new measures of risk: the market symmetric index (SIX), and the relative semi-volatility index (RSV), which are obtained as model-free versions of the indices proposed by Liu and Faff (2017), and Feunou et al. (2016), respectively.

Second, we investigate the relationship between the relative semi-volatility (RSV), the market symmetric index (SIX) and the two corridor volatility measures (CIV_{DW}, CIV_{UP}) on the one hand and the volatility of the entire distribution and the contemporaneous market returns on the other. This allows us to assess whether the proposed measures can capture the investors' fear, or contrariwise, the investors' greed.

Third, following Rubbaniy et al. (2014), we analyze the information content of our proposed volatility measures about future market returns, during both calm and turmoil market periods, in order to assess whether these measures can be used to improve trading strategies or as an early warning indicator about future market realizations. In particular, we disaggregate the results for the subprime crisis (2007–2009) and the European debt crisis (2011–2012), in order to assess in which of these market declines the proposed volatility measures could have been useful in forecasting the aggregate market drawdowns. The data set consists of daily option prices listed on the Italian stock market index FTSE MIB[1] and covers the 2005–2014 period.

We obtain several findings. First, the downside corridor volatility measure (bad volatility) is significantly higher in value than the upside one (good volatility) and displays a wider range of fluctuation. This suggests that investors are more concerned about negative realizations of FTSE MIB returns than they are attracted by positive returns. Moreover, downside corridor volatility measure displays the highest association with model-free implied volatility. The fact that the downside corridor volatility measure is computed using put option prices, suggests that put options play a prevailing role in determining the volatility of the entire distribution.

Second, the upside corridor volatility measure embeds the highest information content about contemporaneous market return, claiming the superiority of call options in measuring current fear in the market. Third, both upside and downside volatilities can be considered as barometers of investors' fear. This means that even good volatility (the volatility associated to an increase in the returns) is perceived by investors as an increase in uncertainty and it is, therefore, associated with a decrease in stock prices.

Fourth, when we investigate the relation between the volatility measures and future aggregate market returns over the next 30 days in order to assess whether option implied measures have a predictive power on future market returns (see e.g. Cremers and Weinbaum, 2010; Lin and Lu, 2015), we find poor results, in line with previous finding in Rubbaniy et al. (2014) for the DAX and the US stock markets. When we split the sample into high and low volatility periods, we find that model-free implied volatility and corridor volatility measures are useful in forecasting future market returns only during high volatility periods. More specifically, all the volatility measures embed a significant explanatory power on future aggregate market returns during the European debt crisis and not during the subprime crisis. This result may be explained by the fact that, while the 2008 crisis affected the Italian market from abroad, the European debt crisis was triggered within the Eurozone peripheral countries including Italy and, therefore, investors had anticipated the future drawdowns in option prices.

Last, during the European debt crisis, we find that the explanatory power of volatility measures on future market returns improves when two of the proposed volatility measures are combined together in the same model. In particular, the best forecasting performance is provided by combining one volatility measure (model-free implied volatility, upside corridor volatility, downside corridor volatility) and the relative semi-volatility index.

[1] The **FTSE MIB** (Milano Italia Borsa) is the benchmark stock market index for the Borsa Italiana, the Italian national stock exchange. The index consists of the 40 most-traded stock classes on the exchange. The index was administered by Standard & Poor's from its inception until June 2009, when this responsibility was passed to FTSE Group, which is 100% owned by the Borsa Italiana's parent company London Stock Exchange Group.

Our results are important for both investors and regulators. Investors could benefit from the proposed volatility measures to improve their trading strategies by using the volatility measures introduced here to predict future market returns. Regulators might benefit from our measures by disentangling the positive volatility (good news) and the negative volatility (bad news) to achieve more detailed information about investors' expectation and the level of fear prevailing in the market.

The plan of the paper is as follows: in Section 2 we present the corridor implied volatility measures and their computational methodology. In Section 3 we analyze the properties of the proposed volatility measures and in Section 4 we investigate their relation with future market returns. In Section 5 we investigate the forecasting power of combinations of the proposed corridor volatility measures during the European debt crisis. The last section concludes.

2. Data and Methodology

In order to have a model-free measure of the upside and downside volatility, we exploit the concept of corridor implied volatility (CIV), introduced by Carr and Madan (1998) and Andersen and Bondarenko (2007). Corridor implied volatility can be obtained from model-free implied volatility (Britten-Jones and Neuberger, 2000) by truncating the integration domain between two barriers. The authors show that it is possible to compute the expected value of corridor variance (and consequently the CIV measure as its square root) under the risk-neutral probability measure, by using a portfolio of options with strikes ranging from B_1 to B_2, as follows:

$$\hat{E}\left[CIV(0,T)\right]=\hat{E}\left[\frac{1}{T}\int_0^T\sigma^2(t,\ldots)I_t(B_1B_2)dt\right]=\frac{2e^{rT}}{T}\int_{B_1}^{B_2}\frac{M(K,T)}{K^2}dK \tag{1}$$

where $M(K,T)$ is the minimum between a call or put option price, with strike price K and maturity T, r is the risk-free rate and B_1 and B_2 are the barrier levels within which the variance is accumulated. In particular if B_1 and B_2 are set equal to 0 and ∞, respectively, the corridor variance will coincide with model-free variance.

In order to compute the downside (upside) corridor variance we set B_1 equal to 0 (F_t) and B_2 equal to F_t (∞); we obtain:

$$\sigma^2_{DW}(0,T)=\frac{2e^{rT}}{T}\int_0^{F_t}\frac{M(K,T)}{K^2}dK \tag{2}$$

$$\sigma^2_{UP}(0,T)=\frac{2e^{rT}}{T}\int_{F_t}^{\infty}\frac{M(K,T)}{K^2}dK \tag{3}$$

with $F_t = K^* e^{rT} * difference$, where K^* is the reference strike price (i.e. the strike at which the $difference$ in absolute value between the at-the-money call and put prices is the smallest). We recall that the sum of upside and downside variance is equal to total variance of the distribution. This is not true if we work with volatility instead of variance. However, given the higher interpretability and the wider use of volatility, compared to variance (e.g. because volatility indices are widely traded on various stock exchanges), we prefer to compute the measures in terms of volatility, rather than variance.

In order to have a constant 30-days measure for model-free implied volatility and CIV measures, we adopt a linear interpolation with the same formula, which is used for the computation of the Chicago Board Option Exchange Volatility Index ($CBOE\ VIX$) index:

$$\sigma_{30}=\sqrt{\left[w\frac{T_{near}}{365}\sigma^2_{near}+(1-w)\frac{T_{next}}{365}\sigma^2_{next}\right]\frac{365}{30}} \tag{4}$$

With $W = (T_{next} - 30)/(T_{next} - T_{near})$, and T_{near} (T_{next}) is the time to expiration of the near (next) term options, σ^2_{near} (σ^2_{next}) is the variance measure which refers to the near (next) term options, respectively.

The volatility of the left tail of the distribution (downside corridor implied volatility, CIV_{DW}) and the volatility of the right tail of the distribution (upside corridor implied volatility, CIV_{UP}) are aggregated in order to compute the relative semi-volatility (RSV) as the simple difference between the volatility of the left and the volatility of the right part of the distribution:

$$RSV = CIV_{DW} - CIV_{UP} \tag{5}$$

The RSV measure assumes a value of zero when the volatility measured in the left part of the distribution is equal to the volatility measured in the right part of the distribution and it increases (decreases) in value when the volatility of the left tail increases (decreases) relative to the volatility of the right tail.

Moreover, we follow the intuition in Liu and Faff (2017) to compute the market symmetric index (SIX) measure in a model-free setting as the ratio between the volatility of the left part and the volatility of the right part of the distribution:

$$SIX = \frac{CIV_{DW}}{CIV_{UP}} \tag{6}$$

Differently from the RSV, the SIX measure attains a value of 1 when volatility of the left hand side equals the volatility of the right hand side and it increases (decreases) in value when bad volatility increases (decreases) or when good volatility decreases (increases).

Our data set consists of daily closing prices on FTSE MIB index options data (MIBO)[2] and covers the 2005-2014 period. The FTSE MIB index, the underlying asset, is adjusted for dividends as follows (see e.g. Muzzioli, 2013a):

$$\hat{S}_t = S_t e^{-\delta_t \Delta t} \tag{7}$$

where S_t is the FTSE MIB index value at time t, δ_t is the dividend yield at time t and Δt is the time to maturity of the option. Risk-free rate is proxied by Euribor rates with maturities of one week, and one, two and three months. The appropriate yield to maturity is computed by linear interpolation. The option dataset is kindly provided by Borsa Italiana S.p.A. The time series of the FTSE MIB index, the dividend yield and the Euribor rates are obtained from Datastream. The choice of the Italian market is motivated by two main reasons. First the Italian derivatives market is one of the major derivatives market in Europe (Muzzioli, 2013b). Second, the FTSE MIB index suffered from a sharp decline during the 2008–2012 period due to the effect of both the subprime and the European debt crisis. Specifically, the Italian market played a crucial role in the European debt crisis, due to the high exposure of the Italian financial system to the spread dynamics between the Italian and the German government debt. Therefore, the Italian market framework can be taken as a representative example of a European country that contributed to the crisis, representing an ideal candidate for investigating the behavior of implied volatility measures during market turmoil. Moreover, given that the Italian market suffered from two different types of crises: one external to the country, which is the subprime crisis, and one internal crisis, which is the European sovereign debt crisis, it is a good example for investigating the predictability of returns during internal or external caused turmoils.

[2] MIBO are European options on the FTSE MIB, which is a capital weighted index composed of 40 major stocks quoted on the Italian market.

In line with Muzzioli (2013b), we apply several filters to the option data set in order to eliminate arbitrage opportunities and other irregularities in the prices. Specifically, we eliminate options near to expiry which may suffer from pricing anomalies that might occur close to expiration (options with time to maturity of less than eight days). Moreover, in line with Ait-Sahalia and Lo (1998), we retain only at-the-money options and out-of-the-money options (put options with moneyness lower than 1.03 and call options with moneyness higher than 0.97). Last, option prices violating the standard no-arbitrage constraints and positive prices for butterfly spreads (Carr and Madan, 2005) are eliminated.

3. Properties of Proposed Volatility Measures

Table 1 provides the descriptive statistics of the FTSE-MIB index returns (R) and the levels and first differences of model-free implied volatility (VOL), upside and downside corridor implied volatilities (CIV_{UP}, CIV_{DW}), and the two measures of volatility proposed here, computed as the difference (RSV) and as the ratio (SIX) of corridor downside implied volatility and corridor upside implied volatility. Several observations are noteworthy. First, physical returns of the FTSE-MIB are far from following a normal distribution and they display a slightly negative skewness and a pronounced excess kurtosis. The hypothesis of a normal distribution is strongly rejected for the volatility measures discussed above, indicating the presence of extreme movements, i.e. fat tails, in these measures. Second, when we split the model-free implied volatility distribution into its upside and downside components, we can see that each of the two components is still far from following the normal distribution, with downside corridor implied volatility being slightly more positively skewed and fat tailed than the upside volatility. This indicates that extreme movements are more heavily present in the left part (downside) of the risk neutral distribution.

Third, the proposed aggregate volatility measures (RSV and SIX) are both on average higher than their corresponding threshold level of 0 and 1. This indicates that the volatility of the left part of the distribution (CIV_{DW}) is significantly greater than the volatility of the right part of the distribution (CIV_{UP}). This finding points to a highly negatively skewed risk-neutral distribution. In other words, this indicates that investors are more concerned about negative realizations of FTSE MIB returns than they are attracted by positive ones, and they attribute more (risk-neutral) probability to events in the left tail of the distribution (see e.g. Foresi and Wu, 2005; Kozhan et al., 2013). More specifically, the average estimate of downside corridor implied volatility stands at 0.19, whereas the average estimate of upside corridor volatility is 0.15 (average daily differences between downside and upside corridor implied volatility are statistically significant based on the Newey-West adjusted errors (t-stat = 29.48 p-value = 0.00)). These results are in line with previous evidence in Muzzioli (2015) on the data set 2005-2010. The latter study found the average estimate for upside corridor implied volatility to be equal to 0.16 and the average estimate for downside implied volatility to be equal to 0.19.

In order to assess whether the series under investigation are adversely affected by non-stationarity, we perform the Augmented Dickey Fuller unit root test on both levels and first differences of our data (R, VOL, CIV_{DW}, CIV_{UP}, RSV and SIX). The results, not reported to save space, but available upon request, show that the null hypothesis of a unit root process (non-stationarity) is strongly rejected for all the series under investigation, both in terms of levels and first differences.

Table 1. Descriptive statistics.

	VOL	CIV_{DW}	CIV_{UP}	RSV	SIX	R	ΔVOL	ΔCIV_{DW}	ΔCIV_{UP}	ΔRSV	ΔSIX
Mean	0.25	0.19	0.15	0.04	1.29	-0.00	0.00	0.00	0.00	0.00	0.00
Median	0.23	0.18	0.14	0.03	1.27	0.00	-0.00	-0.00	-0.00	-0.00	0.00
Maximum	0.80	0.61	0.50	0.24	2.82	0.11	0.28	0.21	0.17	0.75	1.43
Minimum	0.09	0.07	0.05	-0.00	0.96	-0.09	-0.15	-0.11	-0.09	-0.67	-1.18
Std. Dev.	0.11	0.08	0.06	0.03	0.13	0.02	0.02	0.01	0.01	0.08	0.08
Skewness	1.23	1.31	1.06	2.29	3.31	-0.05	1.72	1.69	1.31	0.00	1.22
Kurtosis	5.08	5.38	4.50	10.96	24.31	7.72	34.39	31.26	30.82	19.56	85.89
Jarque-Bera	1070	1284	693	8824	52133	2291	102487	83278	80307	28199	720031
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: The table reports the descriptive statistics of implied volatility measures, FTSE MIB returns and daily changes in volatility measures. VOL is the annualized model-free implied volatility, CIV_{UP} and CIV_{DW} are the volatility of the right and the left part of the distribution, respectively, RSV and SIX are the difference and the ratio between downside and upside corridor implied volatility, respectively ($RSV = (CIV_{DW} - CIV_{UP})$, $SIX = (CIV_{DW}/CIV_{UP})$), R is the FTSE MIB daily return (continuously compounded). ΔVOL, ΔCIV_{DW}, ΔCIV_{UP}, ΔRSV and ΔSIX are the daily changes in volatility measures computed using first differences. The p-value refers to the Jarque-Bera test, the null hypothesis is that both skewness and kurtosis are zero.

In Table 2 we report the correlation coefficients between the returns and the levels and the first differences of the measures of volatility presented in Table 1. We observe that while the index SIX is almost uncorrelated with model-free implied volatility (Rho = 0.024), RSV displays a high and significant correlation (Rho = 0.806) with the latter, suggesting a strong a positive association between the two measures. The correlation coefficients between model-free implied volatility and upside and downside corridor implied volatilities are close to 1, showing a higher degree of association between the two and between each of them and the model-free implied volatility. Interestingly, while the model-free implied volatility and the two (downside and upside) corridor volatility measures are negatively correlated with market returns, the SIX index displays a positive relation.

By looking at daily changes in the aggregate measures RSV and SIX, we observe that while the changes in the RSV index are positively associated with changes in model-free implied volatility, changes in the SIX are unrelated to volatility changes, suggesting that the standardization by the upside corridor implied volatility has the effect of isolating the SIX measure from volatility changes. In line with previous findings in the Italian (e.g. Muzzioli, 2013b) and in the US stock markets (e.g. Giot, 2005; Whaley, 2000), the correlation between market returns and daily changes in model-free implied volatility measures (model-free implied volatility, upside and downside corridor implied volatility) is strongly negative. This means that an increase in any of the volatility measures is associated with a decrease in returns. In particular, the (negative) correlation is the highest in absolute terms between returns and upside corridor implied volatility (the volatility of the right tail) pointing to a higher sensitivity of returns to increases in the volatility of the right part of the distribution.

Table 2. Correlations.

	VOL	CIV_{DW}	CIV_{UP}	RSV	SIX	R	ΔVOL	ΔCIV_{DW}	ΔCIV_{UP}	ΔRSV	ΔSIX
VOL	1.000										
CIV_{DW}	0.997*** (0.000)	1.000									
CIV_{UP}	0.990*** (0.000)	0.976*** (0.000)	1.000								
RSV	0.806*** (0.000)	0.849*** (0.000)	0.715*** (0.000)	1.000							
SIX	0.024 (0.238)	0.089*** (0.000)	-0.097*** (0.000)	0.523*** (0.000)	1.000						
R	-0.074*** (0.000)	-0.0706*** (0.000)	-0.078*** (0.000)	-0.039* (0.052)	0.027 (0.178)	1.000					
ΔVOL	0.076*** (0.000)	0.076*** (0.000)	0.075*** (0.000)	0.062*** (0.002)	-0.007 (0.735)	-0.574*** (0.000)	1.000				
ΔCIV_{DW}	0.075*** (0.000)	0.079*** (0.000)	0.066*** (0.000)	0.093*** (0.000)	0.042** (0.035)	-0.502*** (0.000)	0.973*** (0.000)	1.000			
ΔCIV_{UP}	0.069*** (0.000)	0.062*** (0.002)	0.082*** (0.000)	-0.001 (0.955)	-0.097*** (0.000)	-0.620*** (0.000)	0.915*** (0.000)	0.798*** (0.000)	1.000		
ΔRSV	0.033 (0.100)	0.049** (0.013)	0.002 (0.920)	0.151*** (0.000)	0.196*** (0.000)	-0.021 (0.298)	0.415*** (0.000)	0.615*** (0.000)	0.015 (0.468)	1.000	
ΔSIX	-0.003 (0.878)	0.010 (0.607)	-0.029 (0.150)	0.103*** (0.000)	0.291*** (0.000)	0.129*** (0.000)	-0.001 (0.953)	0.168*** (0.000)	-0.310*** (0.000)	0.685*** (0.000)	1.000

Note: The table reports the correlation coefficients between the measures used in the study; p-values in parentheses. For the definition of the measures see Table 1. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

The relation between changes in the proposed volatility measures on the one hand and changes in the volatility of the entire distribution and the contemporaneous market return on the other is of interest both for investors and regulators, and will be further investigated below using linear regression models. Specifically, investigating the degree of association between our volatility measures and the volatility of the entire distribution allows us to assess whether the proposed volatility measures embed the same information content as the total volatility, or, on the contrary, they convey different indications. Moreover, we will be able to detect which specific part of the distribution (left or right tail) is more important in determining the volatility of the entire distribution.

On the other hand, by investigating the relation between volatility measures and contemporaneous market returns, we are able to evaluate whether the proposed measures capture the investors' fear, or contrariwise, the investors' greed[3]. A correct measurement of the level of current fear or greed in the market is important for regulators, who can promptly ease the market in case of a strong deterioration of the investors' sentiment about the quality of the investment opportunity set.

Table 3. Regression output for the model describing the relationship between changes in model-free implied volatility and changes in others volatility measures (equation (8)).

	α	β	Adj R^2(%)
ΔCIV_{DW}	-0.000 (-0.61)	1.179^{***} (63.38)	94.61
ΔCIV_{UP}	0.000 (0.52)	1.406^{***} (43.92)	83.78
ΔRSV	-0.000 (-0.05)	0.834^{***} (8.93)	17.22
ΔSIX	0.000 (0.17)	-0.000 (-0.05)	0.00

Note: The table presents the estimated output of the regression: $\Delta VOL_t = \alpha + \beta\Delta x_t + \varepsilon_t$, where for Δx_t we use daily changes in CIV_{DW}, CIV_{UP}, RSV and SIX; t-stats in parentheses. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *. The number of observations is 2513.

In order to better investigate the relation between changes in the proposed volatility measures (ΔCIV_{DW}, ΔCIV_{UP}, ΔRSV and ΔSIX) and changes in model-free implied volatility (ΔVOL), we estimate the following regression:

$$\Delta VOL_t = \alpha + \beta \Delta x_t + \varepsilon_t \tag{8}$$

In this specification, ΔVOL_t is the daily change in model-free implied volatility computed using first differences and Δx_t is proxied by daily changes in downside corridor volatility (CIV_{DW}), upside corridor volatility (CIV_{UP}), relative semi-volatility (RSV) and market symmetric index (SIX). All the regressions have been run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix. The results, presented in Table 3, point to a positive and strong relation between changes in corridor upside volatility measures on one side, and model-free implied volatility on the other. Moreover, changes in downside corridor implied volatility (i.e. the volatility of the left part of the distribution) display the highest explanatory power for changes in model-free implied volatility, suggesting that most of the variation in the total volatility measure is addressed by the variation in the left tail of the distribution. Being that the volatility in the left part of the distribution is computed using put options, this result indicates that put prices play a crucial role in determining the volatility of the entire distribution.

Between the two aggregate measures of volatility (RSV and SIX), we observe that changes in the RSV index are positively and significantly related to changes in model-free implied volatility.

[3] Whaley (2000) defines the VIX index as the investors' fear barometer due to its strong negative relationship with contemporaneous market returns; the opposite, i.e. investors' greed, is defined as the investors' excitement in a market rally.

This confirms the previous results based on the correlation coefficients between volatility measures: if market volatility increases, the volatility of the left tail tends to increase more than the volatility of the right and, as a consequence, the difference between the two corridor volatility measures (i.e. the RSV measure) widens. On the other hand, the SIX measure, being computed as the downside corridor volatility measure standardized by the upside corridor volatility measure, is totally uncorrelated with changes in volatility. Therefore, it could provide additional information content beyond standard volatility measures.

In order to investigate whether the volatility measures can be considered as an indicator of market stress (fear) or market greed, we look at the relation between changes in the volatility measures and the daily log-returns of the FTSE-MIB index, we estimate the following regression:

$$R_t = \alpha + \beta \Delta x_t + \varepsilon_t \tag{9}$$

where R_t are the daily FTSE MIB log-returns and changes in the volatility measures (Δx_t) are proxied by ΔCIV_{DWt}, ΔCIV_{UPt}, ΔRSV_t, ΔSIX_t. All the regressions have been run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix. Results are presented in Table 4.

Table 4. Regression output for the model describing the relationship between market aggregate returns and daily changes in the volatility measures (equation (9)).

	α	β	Adj R^2(%)
ΔCIV_{DW}	-0.000	-0.569***	25.13
	(-0.49)	(-14.24)	
ΔCIV_{UP}	-0.000	-0.891***	38.41
	(-0.76)	(-15.30)	
ΔRSV	-0.000	-0.039	0.11
	(-0.53)	(-0.55)	
ΔSIX	-0.000	0.026***	1.61
	(-0.59)	(3.16)	

Note: The table presents the estimated output of the regression: $R_t = \alpha + \beta\Delta x_t + \varepsilon_t$, where for Δx_t we use daily changes in CIV_{DW}, CIV_{UP}, RSV and SIX; t-stats in parentheses. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *. The number of observations is 2513.

According to the figures reported in Table 4, the slope coefficients of changes in both left and right hand side corridor implied volatility measures are negative and highly significant, suggesting that the corridor volatility measures can be used as an indicator of market fear for the Italian stock market (see e.g. Giot, 2005; Whaley, 2000). More specifically, the volatility of the right part of the distribution displays a higher association with market returns than the volatility of the left part (the Adjusted R-squared are equal to 38.41% and 25.13%, respectively). A possible explanation for the inferior performance of the downside corridor volatility measure is that investors heavily price downside risk, in line with Muzzioli (2013b), and the hedging pressure exercised on put options reduces its information content. The surprising result is that an increase in good volatility has the effect of reducing the contemporaneous return, at the same manner as an increase in bad volatility. Therefore, it seems from our results, that volatility, even in the case of an increase in returns, is perceived by investors as bad news and associated with a contemporaneous decrease in stock prices.

On the other hand, the RSV index is not useful in capturing current fear or greed in the market, since its changes are unrelated with contemporaneous market returns. Interestingly, changes in the SIX index display a positive and significant association with market returns. However, the relation is weak (Adjusted R-squared is equal to 1.61%).

4. Can the Proposed Volatility Measures be Used as Indicators of Future Stock Returns?

As a second goal of our study, we want to assess whether the proposed volatility measures can be used to forecast future market returns. To examine the forecasting power of implied volatility indices on future stock returns, Rubbaniy et al. (2014) test the relationship between implied volatility levels and the 1-, 5-, 20- and 60-day forward looking returns of different markets and portfolios. They find mixed results. Specifically, while implied volatility indices can predict forward looking 20- and 60-day returns, the results for shorter term returns (1- and 5-day returns) are insignificant.

In line with Rubbaniy et al. (2014), we examine the forecasting power of model-free volatility index (VOL), corridor upside and downside volatility (CIV_{UP} and CIV_{DW}) and the two proposed volatility measures (RSV and SIX), by estimating the following regression model:

$$R_{t,t+30} = \alpha + \beta x_t + \varepsilon_t \tag{10}$$

where $R_{t,t+30}$ is the market aggregate log-return computed between day t and day $t+30$ and x_t is proxied by the daily levels of VOL, CIV_{DW}, CIV_{UP}, RSV and SIX. All the regressions have been run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix.

Since the proposed volatility measures refer to a 30-day forecast horizon, we evaluate the information content of the volatility level at day t on the aggregate market return over the next 30 calendar days. The intuition behind equation (10) is that high volatility levels can be considered as indicators of a favorable or an unfavorable investment opportunity set, thereby highlighting the possibility of positive or negative returns in the market on a 30-days forecast horizon.

The results of the model are reported in Table 5, Panel A. We find that only the two measures obtained aggregating downside and upside corridor implied volatility (RSV, SIX) embed useful information about future market realizations. In particular, the RSV index displays a negative and marginally significant relation with future aggregate market returns. The negative relation suggests that high values of the RSV index are associated with negative future returns and vice versa. Given that the RSV index is computed as the difference between downside and upside corridor implied volatility, it attains higher values when the volatility of the left side of the distribution increases relative to the volatility of the right side. This result indicates that an increase in the volatility of the left part of the distribution (bad volatility) can be interpreted as a deterioration of the investment opportunity set.

A similar result is found for the SIX index (Table 5, Panel A, last row), which displays a negative relation with future market return significant at the 1% level. This suggests that high (low) values of the SIX index are associated with negative (positive) future market returns over the next 30 days. Given that the SIX index measure is computed as the ratio between the volatility of the left and the volatility of the right hand side of the distribution, it attains high values when the former increase as a percentage of the latter. To elaborate, an increase in downside corridor volatility (CIV_{DW})

relative to upside corridor volatility (CIV_{UP}), both in absolute and in percentage term, could be viewed as an early warning about future market returns. This can be of value to investors as well firm managers and regulators.

Table 5. Regression output for the model describing the relation between future aggregate market returns and volatility measures in terms of levels (equation (10)).

	α	β	Adj R^2(%)
Panel A: Entire sample			
VOL	-0.005 (-0.56)	0.007 (0.16)	0.00
CIV_{DW}	-0.002 (-0.28)	-0.005 (-0.11)	0.00
CIV_{UP}	-0.010 (-1.01)	0.042 (0.57)	0.11
RSV	0.010* (1.73)	-0.308** (-2.50)	1.30
SIX	0.105*** (3.82)	-0.083*** (-4.17)	2.47
Panel B: Low volatility (2005-2007 & 2013-2014)			
VOL	-0.000 (-0.03)	0.026 (0.43)	0.02
CIV_{DW}	0.002 (0.18)	0.018 (0.24)	0.00
CIV_{UP}	-0.003 (-0.36)	0.072 (0.75)	0.23
RSV	0.015** (2.27)	-0.354 (-1.55)	0.87
SIX	0.067*** (3.73)	-0.049*** (-3.71)	2.19
Panel C: High volatility (2008-2012)			
VOL	-0.045** (-2.42)	0.108* (1.72)	1.51
CIV_{DW}	-0.037** (-2.14)	0.105 (1.43)	0.91
CIV_{UP}	-0.058*** (-2.88)	0.247** (2.16)	2.82
RSV	-0.000 (-0.03)	-0.192 (-1.20)	0.37
SIX	0.151*** (2.90)	-0.125*** (-3.27)	3.26

Note: The table presents the estimated output of the regression: $R_t = \alpha + \beta x_t + \varepsilon_t$, where for x_t we use daily levels in CIV_{DW}, CIV_{UP}, RSV and SIX; t-stats in parentheses. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *. The number of observations in Panel A is 2513; in Panel B it is 1241 and in Panel C it is 1272.

The predictability of the proposed measures of volatility on future returns could be attributed to the "informed investors" theory, proposed by Cremers and Weinbaum (2010). These authors claim that options have a predictive power on future market returns, since informed investors trade first in the option market and it is only subsequently that the relevant information is reflected in the stock prices. Arguments supporting the theory are provided also in Lin and Lu (2015), who suggest that analysts inform options traders about their upcoming recommendation change, earnings forecast revision, or initiation coverage. As a consequence, expected positive news is reflected in higher call prices due to the informed investors trading activity. Higher call prices are associated with an increase in the volatility of the right hand side of the distribution relative to the left hand side, and in a lower value for the volatility measure (SIX). When some positive information is embedded in the underlying market, the stock price increases, resulting in a negative association between the SIX volatility measure and future market returns. On the other hand, expected bad news are reflected in higher put prices and in an increase of the downside volatility measure relative to the upside one. Once the information become public, the SIX measure increases while the stock price declines, engendering a negative relation between the SIX measure and future market returns. Therefore, as a practical hint for investors, we can say that, in particular during high volatility periods, when upside corridor implied volatility (CIV_{UP}) is high both in absolute terms and in relation to downside corridor implied volatility, we can expect future positive returns.

However, it is worth noting that the adjusted R-squared in our model are very low. This is in line with the analysis proposed in Rubbaniy et al. (2014), suggesting that the proposed measures of volatility (RSV, SIX) can explain only a low portion of the total variation in return, in the whole sample. Moreover, model-free implied volatility and the two corridors implied volatility measures do not provide any useful information about future market returns. This highlights the need of investigating the relation between volatility levels and future market returns in different market conditions.

4.1. Sub-period analysis

Two main volatility regimes can be distinguished during the sample period (2005–2014); one characterized by low volatility and positive market returns (2005–2007 and 2013–2014) and the other characterized by high volatility and a decline of about 70% in the stock market (2008–2012). To contrast the predictive power of volatility measures under calm and intense market volatility conditions, we estimate the models described by regressions (10) in both sub-periods. All the regressions have been run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix. The results for the calm period, reported in Table 5, Panel B, confirm the power of the SIX index in predicting the future FTSE MIB returns while the other volatility measures do not have any forecasting power. In terms of direction, the relation between levels of the SIX measure and future market returns is negative, as in Table 5, Panel A and it is significant at the 1% level. The model-free implied volatility, the two corridor volatility measures, and the RSV do not exhibit any significant relationship with future market returns.

The results for the high volatility period, reported in Table 5, Panel C show that both the model-free implied volatility (VOL), the upside corridor volatility (CIV_{UP}) and the SIX measure all embed useful information for predicting future market returns in the next 30 days. In particular, the SIX measure confirms the negative significant relation with future aggregate market returns as found earlier (Section 4). In other words, high levels of the SIX measure are associated with negative future returns, and vice versa. Contrary to this, the model-free implied volatility (VOL), and the volatility of the right side of the distribution (CIV_{UP}) display a positive and marginally significant relation with future market returns.

In brief, during market turmoil periods, high (low) levels of the volatility indices are associated to high (low) future market returns. This evidence is consistent with Rubbaniy et al. (2014) who find a significant positive relation between volatility indices and future stock returns in both the German and the US market. Moreover, this result is consistent with the prediction of the Capital Asset Pricing Model (CAPM): investors perceive an increase in market implied volatility as a negative shock for the investment opportunity set and, as a consequence, they expect higher returns in order to be compensated for the higher risk (higher uncertainty in the market). Moreover, as suggested in Giot (2005), high or very high implied volatility levels could indicate an oversold market. As a consequence, a strategy that sets a long position in the underlying asset when market volatility is high, should earn attractive returns.

Among the volatility indices, the corridor upside volatility index (CIV_{UP}) attains the better forecasting performance compared to the other volatility measures. Specifically, the adjusted R-squared value for CIV_{UP} is almost double the R-squared for the model-free implied volatility measure. However, the SIX index, that embeds the information content of both downside and upside corridor implied volatility, attains the highest explanatory power (adjusted R-squared equal to 3.26%). This result could be of interest for investors and traders since they can exploit the information contained in this measure to set profitable trades, or to promptly hedge portfolios, if the volatility of the left side of the distribution increases as a percentage of the volatility of the right hand side.

4.2. The forecasting power of volatility measures during crises

A very interesting issue is whether the information embedded in the considered volatility measures could have improved portfolio selection and trading strategies during the 2007–2009 subprime crises and the recent European debt crisis (2011–2012). To this end, we can further investigate the behavior of the volatility measures considered in the high volatility period, by splitting the sample period into the two major declines of the FTSE MIB index. The first one, due to the subprime crisis, started in the second half of 2007 and persisted until the first quarter of 2009. During this sub-period, the FTSE MIB index reached its top closing value of 44021.51 on May 15, 2007; then it suffered a continuing decline, worsened during 2008, going down to 12620.57 index points (-71.33%) on March 9, 2009. The second crisis period is associated with the European sovereign debt crisis and affected the Italian market from the early 2011 to July 2012. During this period, the FTSE MIB index declined from a closing value of 23178.38, reached on February 17, 2011, to a value of 12362.51 (-46.66%) index points, recorded on July 24, 2012.

In order to assess whether the proposed volatility measures embed useful information about future returns during the two market downturns, namely the subprime crisis and the European debt crisis, we estimate the model described by regressions (10) for these two sub-periods. All the regressions have been run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix. The results for the subprime crisis are reported in Table 6, Panel A. According to the figures in this table, during the 2007–2008 market declines none of the measures under investigation is useful for forecasting future market returns. The results for the European debt crisis are reported in Table 6, Panel B. From figures in this panel, we can see that all the volatility measures considered provide useful information about future market returns with the exception of the RSV. This suggests that the information content of the Italian option market was significantly higher during the European debt crisis, than during the subprime crisis. A possible explanation is that, while the 2008 crisis affected the Italian market from abroad, the European debt crisis was triggered in the Eurozone peripheral countries including Italy. For the same reasoning, if the implied volatility is useless for forecasting future market returns during the subprime crisis, it embeds important information during the European debt crisis. This result reinforces the argument for the "informed investors" theory proposed in Cremers and Weinbaum (2010). Specifically, informed traders in the Italian stock market were extremely worried about the spread dynamics between the Italian and the German government debt returns and they conveyed this information in option prices. On the other hand, useful information about the 2008 crisis, which affected the Italian market from abroad, was not embedded in option prices in the Italian market and it should be sought in the US market.

Among the volatility measures considered, the upside corridor implied volatility (CIV_{UP}) displays the highest explanatory power in predicting future market returns (adjusted R-squared is equal to 9.18%). On the other hand, the RSV index shows the worst forecasting performance.

Table 6. Regression output for the model describing the relation between future aggregate market returns and volatility measures in term of levels (equation (10)) during crises.

	α	β	Adj R^2(%)
Panel A: subprime crisis			
VOL	-0.035*** (-2.71)	-0.031 (-0.56)	0.06
CIV_{DW}	-0.034*** (-2.77)	-0.045 (-0.69)	0.15
CIV_{UP}	-0.038*** (-2.64)	-0.038 (-0.37)	0.00
RSV	-0.032*** (-2.89)	-0.243 (-1.56)	0.87
SIX	-0.006 (-0.14)	-0.029 (-0.96)	0.12
Panel B: European debt crisis			
VOL	-0.105*** (-3.56)	0.246*** (2.76)	7.85
CIV_{DW}	-0.099*** (-3.34)	0.288** (2.57)	6.93
CIV_{UP}	-0.112*** (-3.94)	0.437*** (3.05)	9.18
RSV	-0.045* (-1.81)	0.371 (1.02)	0.97
SIX	0.145 (0.17)	-0.129* (-1.66)	1.89

Note: The table presents the estimated output of the regression: $R_t = \alpha + \beta x_t + \varepsilon_t$, where for x_t we use daily levels in CIV_{DW}, CIV_{UP}, RSV and SIX; t-stats in parentheses. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *. The number of observations used in Panel A and Panel B is equal to 459 and 366, respectively.

5. Combined Forecasts During the European Debt Crisis

During the European debt crisis, we would like to assess whether the explanatory power of the model in predicting future returns increases if two measures of volatility are combined together. Therefore, we choose as regressors two variables, in such a way that the multicollinearity level remains low. The models estimated are as follows:

$$R_{t,t+30} = \alpha + \beta_1 VOL_t + \beta_2 RSV_t + \varepsilon_t \tag{11}$$

$$R_{t,t+30} = \alpha + \beta_1 VOL_t + \beta_2 SIX_t + \varepsilon_t \tag{12}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{DWt} + \beta_2 RSV_t + \varepsilon_t \tag{13}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{DWt} + \beta_2 SIX_t + \varepsilon_t \tag{14}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{UPt} + \beta_2 RSV_t + \varepsilon_t \tag{15}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{UPt} + \beta_2 SIX_t + \varepsilon_t \tag{16}$$

$$R_{t,t+30} = \alpha + \beta_1 RSV_t + \beta_2 SIX_t + \varepsilon_t \tag{17}$$

All the regressions have been run by using the Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix.

Table 7. Regression output for the multivariate model proposed in equations (11)–(17).

Eq.	α	VOL	CIV_{DW}	CIV_{UP}	RSV	SIX	Adj R^2(%)
(11)	-0.111***	0.424***			-0.889*		10.50
	(-3.81)	(3.66)			(-1.83)		
(12)	0.059	0.245***				-0.126*	9.66
	(0.524)	(2.72)				(-1.69)	
(13)	-0.111***		0.594***		-1.145**		10.47
	(-3.81)		(3.66)		(-2.14)		
(14)	0.088		0.301***			-0.146**	9.47
	(0.82)		(2.69)			(-2.01)	
(15)	-0.111***			0.594***	-0.551		10.47
	(-3.81)			(3.65)	(-1.28)		
(16)	0.007			0.415***		-0.088	9.91
	(0.95)			(2.75)		(-1.12)	
(17)	0.293***				1.029**	-0.290***	7.81
	(2.85)				(2.49)	(-3.50)	

Note: the table present the estimation output of the following multivariate models:

$$R_{t,t+30} = \alpha + \beta_1 VOL_t + \beta_2 RSV_t + \varepsilon_t \tag{11}$$

$$R_{t,t+30} = \alpha + \beta_1 VOL_t + \beta_2 SIX_t + \varepsilon_t \tag{12}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{DWt} + \beta_2 RSV_t + \varepsilon_t \tag{13}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{DWt} + \beta_2 SIX_t + \varepsilon_t \tag{14}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{UPt} + \beta_2 RSV_t + \varepsilon_t \tag{15}$$

$$R_{t,t+30} = \alpha + \beta_1 CIV_{UPt} + \beta_2 SIX_t + \varepsilon_t \tag{16}$$

$$R_{t,t+30} = \alpha + \beta_1 RSV_t + \beta_2 SIX_t + \varepsilon_t \tag{17}$$

Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *, t-stats are reported in parenthesis. The number of observations is 366.

The results are reported in Table 7. Several considerations are noteworthy. First, combining the information of two different measures of volatilities, strengthens the explanatory power of the model. Second, the slope coefficients of both model-free implied volatility and the two corridors implied volatility measures are still positive and statistically significant at the 1% level for all the proposed models. This suggests that future market returns are positively associated with the volatility levels, in line with the prediction of the Capital Asset Pricing Model and the results in Rubbaniy et al. (2014) for the US stock market. On the other hand, RSV and SIX display a negative sign for the slope coefficient in all the models, with the only exception being the RSV measure when combined with the SIX (equation 17). This suggests that high values in RSV and SIX are associated to negative future market returns, and vice versa.

Third, the model that provides the best forecast of future realized aggregate market return is the one that combines one of the volatility measures (model-free implied volatility, downside corridor implied volatility or upside corridor implied volatility) with the RSV measure (equations 11, 13 and 15). The Adjusted R-squared of the models is close to 10.50%, suggesting that the two volatility measures, if combined, can explain a significant portion of the market return over the next 30-days. This result calls upon new measures of risk that are able to combine the information content of different parts of the risk-neutral distribution in a proper manner.

6. Conclusion

Given the importance of disentangling positive and negative shocks to volatility, which are seen from investors as good and bad news, respectively, we use different volatility measures to investigate the information content embedded in different portions of the risk-neutral distribution. In particular, upside and downside corridor implied volatilities have been aggregated into two different measures: RSV, which is meant to capture the difference between upside and downside corridor implied volatilities, and SIX, which is computed as the ratio between the downside and the upside corridor volatility measures. We have investigated the information content of the obtained measures with respect to contemporaneous and future market returns in the Italian stock market during the 2005–2014 period. Our dataset allows us to assess the behavior of volatility measures in both calm and volatile market periods, and to disentangle the results for different types of crises (subprime crisis and European debt crisis). We would like to stress that we choose the Italian market as an ideal setting in order to test the forecasting ability of corridor implied volatility measures and our proposed combinations (the relative-semi volatility, RSV and the symmetric index SIX) on future returns. The Italian market suffered from two major declines during the sample period, the US subprime crisis (external) and the European sovereign debt crisis (internal). This allows us to disentangle the high and low volatility periods and the two crises of dissimilar characters. Therefore, the results obtained on the Italian market can be taken as an example of the results one would have obtained if a market with similar characteristics were investigated. We acknowledge that these results may not entirely generalize to all markets.

We obtain several findings. First, the volatility of the left part of the distribution (CIV_{DW}) is significantly higher than the volatility of the right part (CIV_{UP}), suggesting that the risk-neutral distribution of FTSE MIB stock returns is on average skewed to the left and the investors' expectations about future returns attributes more risk-neutral probability to negative outcomes (bad volatility). Second, upside corridor volatility measure embeds the highest information content about contemporaneous market return, claiming the superiority of call options in measuring current fear in the market. Third, both upside and downside volatilities can be considered as barometers of investors' fear. This result means that even good volatility (the volatility associated to an increase in the returns) is perceived by investors as an increase in uncertainty and therefore it is associated to a decrease in stock prices.

Fourth, in line with previous finding in Rubbaniy et al. (2014), volatility measures display a poor forecasting performance on future market returns during low volatility period. On the other hand, all the volatility measures considered (with the only exception of the RSV index) provide useful information about future returns during highly volatile market conditions. Fifth, while the option implied measures do not show any forecasting power on future returns during the subprime crisis, they are able to explain a significant portion of future aggregate market returns during the European debt crisis. This result is addressed by the fact that, while the 2008 crisis has affected the Italian market from abroad, the European debt crisis was triggered in the Eurozone peripheral countries including Italy and therefore investors have anticipated in option prices the future drawdowns. Last, during the European debt crisis, combining the information content of one of the two corridors implied volatility measures with the RSV further improves the explanatory power on future market returns. This result highlights the need of investigating measures of risk that are able to aggregate the information coming from different parts of the risk-neutral distribution. Moreover, future research may address the same questions for other European and non-European markets (such as the US). We expect the results to be similar in the European context, as far as the difference between the European sovereign debt crisis and the subprime crisis is concerned. On the other hand, we expect the information content of the implied volatility measures on future returns in the US to be higher during the subprime crisis (internal crisis) than during the European sovereign debt crisis (external crisis).

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Conflict of Interest

All authors declare no conflicts of interest in this paper.

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