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Are volatility indices in international stock markets forward looking?

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Abstract. We analyze the information content in volatility indices of international stock markets regarding current and future market conditions. We find strong negative relationships between changes in volatility indices and current market returns, as well as Granger causality running in both directions. Unfortunately, these correlations cannot be exploited, at least using linear models, to successfully forecast future realized volatility or future returns over long time horizons. Forecasts of future realized volatility obtained from volatility indices are as good as those obtained from historical volatility, but not good enough to be used for risk management. Volatility indices seem to reflect much better current market's sentiment than any sensible expectation about future market conditions.

Índices de volatilidad en mercados internacionales de renta variable: ¿anticipan información futura?

Resumen. Analizamos el contenido informativo de los índices de volatilidad de mercados internacionales de renta variable, en relación con las condiciones de mercado actuales y futuras. Encontramos fuertes relaciones negativas entre cambios en los índices de volatilidad y las rentabilidades actuales del mercado, así como causalidad de Granger en ambas direcciones. Lamentablemente, estas correlaciones no pueden utilizarse, al menos utilizando modelos lineales, para predecir con éxito la volatilidad realizada o las rentabilidades futuras, sobre horizontes temporales amplios. Las predicciones de volatilidad realizada futura que se obtienen a partir de los índices de volatilidad son tan buenas como las calculadas a partir de volatilidad histórica, pero no suficientemente buenas para ser utilizadas en gestión de riesgos. Los índices de volatilidad parecen reflejar mejor el sentimiento actual del mercado que expectativas razonables sobre las condiciones de mercado futuras.

1 Introduction

The financial disasters of the last decades, including the bankruptcy of large corporations, the failure of important funds and the debt default of some major countries, not to mention the current credit crisis, have shown the need to hedge against changes in the level of volatility in the financial markets. Simultaneously, frequent and sudden fluctuations in volatility have also created the opportunity for volatility trading (Carr and Madan [3, (1998)], Guo [8, (2000)], Poon and Pope [10, (2000)]).

The double motivation of hedging against volatility risk and profit trading in volatility has led to the success of the recently created markets for volatility derivatives, having a volatility index as underlying asset. But volatility indexes themselves have only recently been introduced and defined on the basis of

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the implied volatilities in specific classes of options, and a great deal of attention has been placed on their construction and properties. The first volatility index, introduced by the Chicago Board Option Exchange in 1993 remains the most popular among such indices. Afterwards, several volatility indices have been introduced in Europe, like the French VX1, the German VDAX or the Swiss VSMI, all constructed from options on their main stock exchange indices. A similar volatility index has not been produced yet for the Spanish market.

We start our analysis by filling that gap through the construction of the VIBEX volatility index following Deutsche Borse [4, (2005)] methodology, which does not rest on any option pricing model and uses a relatively wide range of the implied volatility smile. This methodology is very convenient for illiquid markets, like the Spanish option market on IBEX-35, versus the alternative of focusing on a narrow set of options, which may preclude calculation of the volatility index because of lack of trades. We consider in our analysis this VIBEX index, together with VIX, VDAX and VSMI. There are essentially two ways to interpret a volatility index: under one possible view, market participants are actively forecasting the future level of volatility, and their forecasts are reflected in a volatility index computed using option prices on the stock market index, with a given maturity. Alternatively, the volatility index can be though of as capturing the sentiment of market participants regarding the current level of risk.

There are different ways to test between these two alternative views of the volatility index. One has to do with the forecasting ability of the index regarding future realized volatility over the residual life to maturity of the options used to compute the volatility index. This should be relatively important under the first view, while being irrelevant under the alternative view. In fact, if the volatility index is shown not to have any ability to forecast future realized volatility, one would be forced under the first approach to believe that market participants have that same lack of forecasting ability, an undoubtedly strong statement. Under the alternative view, we would expect a relatively strong contemporaneous relationship between market return and the volatility index, with the level of the latter having essentially no role to predict future volatility. A second class of tests would be based on the relationship between the volatility index and the current market return.

Under the second interpretation, we would expect a negative relationship between current volatility and returns that does not need to arise under the first interpretation. Skiadopoulos [12, (2004)] for the Greek market, and Fleming et al. [5, (1995)] for the VIX and SP100, find a significant relationship between the volatility index and market returns. Skiadopoulos [12, (2004)] finds additional evidence of a relationship between current returns and future changes in volatility, opening the possibility of devising trading rules for volatility derivatives. Therefore, a volatility index obtained as a relatively complex average of implied volatilities seems to incorporate information beyond that contained in individual options.

Regarding the volatility forecasting issue, the relevant one under the first interpretation we suggested for a volatility index, there is a huge and ever increasing literature exploring the forecasting ability that historical volatility and implied volatility measures have for each other. This is of utmost interest for risk management, which explains the extensive attention that analyzing the forecasting ability in a volatility index has received in the empirical finance literature. We focus on exploring the information provided by implied volatilities, through a volatility index, on future realized volatility. Unfortunately, results come out as a rather disparate evidence. Bluhm and Yu [2, (2001)] find that VDAX ranks first among a set of volatility predictors when the forecasting interval is of 45 calendar days. Blair et al. [1, (2001)] use R^2 statistics and some regression-based parametric tests to show the preference of the daily VIX index over an ARCH measure as a predictor of future volatility in the S&P100 index over 1- to 20-day forecasting horizons. Blair et al. [1, (2001)] do not provide information on the forecasting error made by the VIX index as predictor of volatility, which precludes us from comparing its forecasting performance with that obtained for the VDAX index in Bluhm and Yu [2, (2001)]. Finally, Fleming et al. [5, (1995)] find that it is necessary to introduce a regression-based correction on VIX so that it may be an acceptable predictor for S&P100 volatility. They identify the constant in the regression as the historical bias in VIX, and use that fact to produce a bias-corrected VIX index. The problem is that the constant used to correct the index each period is obtained by relating historical volatility measures, which do not need to be stable over time. In fact, the correction constant needs to be changed over time, so the correction procedure is not very robust and it remains a function of some subjective estimation. We will conduct again this forecasting exercise for this sample, enlarged over time and across markets, including now a Spanish index, paying attention to possible bias corrections, and checking for robustness of results across countries.

A nontrivial decision has to do with the sample period to be used. Tempting as it is to analyze the evolution of markets through the current crisis, it is hard to believe that the structure of the processes and the return-volatility relationships would have been unaltered through the turbulences, relative to the pre-crisis period. We need to explore the two samples separately, to test for what seems an unlikely structural homogeneity hypothesis. Focusing on a time span that ends in March 2008, this paper should be seen as the first step in that direction.

The paper is organized as follows. We describe in Section 2 the data and methodology used in estimating volatility indices, paying special attention to the construction of the Spanish volatility index (VIBEX). The relationship between volatility and market returns is explored in Section 3, while Section 4 is devoted to analyzing the forecasting ability of the volatility indices on future returns and future realized volatility. The paper closes with conclusions and suggestions for future research.

2 Estimating volatility indexes

Daily data on volatility indices for options traded on the SP500, SMI, and DAX indexes are readily available from their respective markets. That is not the case for IBEX, for which an official volatility index does not exist yet. We compute that volatility index using the methodology described in Deutsche Borse [4, (2005)], which is the same one used to construct the other volatility indices. We use a horizon of 22 trading days, as it is the case with the VXO and VIX volatility indexes in the US or the Swiss VSMI index. Details can be consulted in González and Novales [7, (2007)]. Each day we consider two maturities, one shorter and the other longer than the 22 trading days horizon. In both cases we calculate the so-called ATM strike price, those for which call and put premia are more similar. To estimate the volatility index we use put options with strike below the ATM strike price, and call options with strike above the ATM strike price. A formula that takes into account differences in strike prices in the chosen set of options as well as their premia, together with a discount factor, is used to compute a measure of variance for each of the two maturities. These two variances are finally aggregated, weighting them by relative time to maturity. The methodology does not require an option valuation model, which could be a source of errors is the embedded assumptions fail to hold. Secondly, time to maturity is measured in minutes, which eliminates some anomalous intraday behavior in implicit volatility which was observed under the old methodology.[1] Third, the methodology uses a significantly larger part of the volatility smile to compute the volatility index, rather than focusing on just ATM options, allowing for higher estimation efficiency and an ease of calculation in option markets with low liquidity. These features facilitate the interpretation of the index as well as valuation of options that could be issued with the volatility index as underlying asset.

3 Volatility indices as indicators of current risk

3.1 Volatility indices and market returns

Financial volatility is usually associated with the arrival of news to the market and the implied increase in both, volume and number of orders crossed. The same intuition suggests that the arrival of *bad news* may give raise to a larger volatility increase than the arrival of *good news* of the same relevance. Since it is hard to obtain a numerical measure of the relevance of the new information, it is customary to focus on the change in price, i.e., the return on a given asset, and expect a larger increase in volatility associated to a given negative return, than to a positive return of the same size.

[1] In fact, this does not play any role in our estimation because we implement it at market closing, when time to maturity is common to all options considered.

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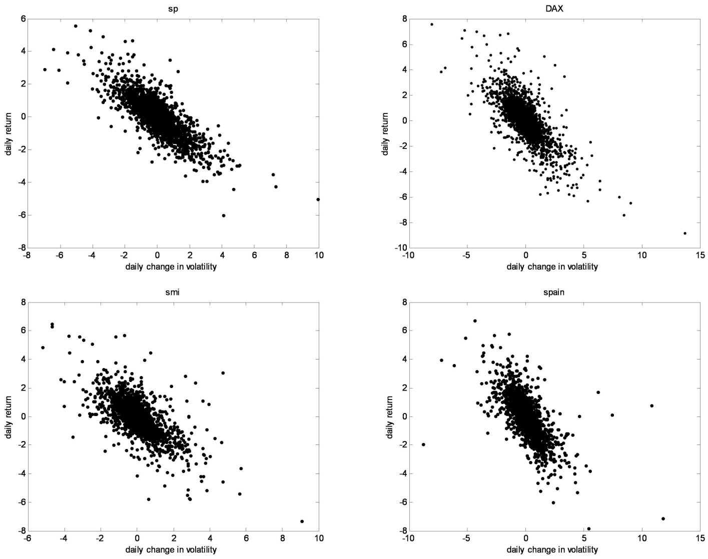

Figure 1. Market returns vs. volatility indices.

A similar, negative relationship should be expected for the market's perception of risk. For implied volatility measures like the ones we use, obtained from option prices, the argument is usually made that a rise in the perception of risk leads to a sudden increase in the purchase of put options, thereby increasing their price and hence, implied volatility. An increase in uncertainty, because of the publication of some economic data, some policy intervention or even some political announcement that increases the general perception of risk, may raise the level of volatility in the financial markets at the same time that induces selling decisions that lead to negative returns. Indeed, a negative relationship between market return and a volatility index has been found (Whaley [13, (2000)], Giot [6, (2005)], Simon [11, (2003)]) for daily changes in the VIX index and S&P100 returns, as well as with daily changes in the VXN index and NASDAQ100 returns.

Scatter diagrams of daily market returns against changes in the logarithm of the volatility index in Figure 1 suggest such a clear negative relationship. In this section we try to model the contemporaneous relationship between daily changes in stock prices (through the market index) and volatility (through the volatility index) for the four international markets considered. In particular, we will examine whether there is some evidence of asymmetry in this relationship. After that, we will pay attention to possible dynamic relationships between changes in prices and volatility and beyond that, we will search for possible evidence in favor of the use of the volatility index to forecast future returns.

The relationship between changes in a volatility index and in the associated stock market index has been studied by Whaley [13, (2000)], Giot [6, (2005)], Simon [11, (2003)], Skiadopoulos [12, (2004)], who have found not only a strong connection between these two variables but also, evidence of asymmetry in the relationship. We explore this relationship in our sample for the four markets by estimating:

$$\nabla \ln \mathrm{IBEX35}_t = \alpha_0 + \alpha_0^+ D_t^+ + \alpha_1 \nabla Z_t + \alpha_1^+ (D_t^+ . \nabla Z_t) + u_t$$

where the dummy variable D_t^+ characterizes days when the level of volatility increased ($D_t^+ = 1$ if $\nabla \ln Z_t > 0$, $D_t^+ = 0$ otherwise). We would expect an increase in volatility to come together with a fall in the index, while a reduced volatility will generally arise in days when the index raises. The volatility index, with a percentage interpretation, is used without logs, so that its coefficient can be interpreted as a semielasticity.

Table 1 displays estimates for the symmetric model. Below the coefficient estimates for each model, we present average estimated returns associated to volatility increases and volatility decreases. It is a nice regularity that slope estimates are consistently around -0.80 for the four markets, but they are not easy to interpret, since we already have percent volatility changes as the explanatory variable. In this symmetric model, the only difference between effects of increases or decreases in volatility comes form the estimated constant. Since it happens to be everywhere small, the implication is that, as shown in the table, a one-percent change in volatility up or down would come associated with a 0.80 negative or positive return. The last rows display the number of observations, the adjusted R^2 and the Residual Sum of Squares (RSSQ).

	Index			
	SP500	DAX	SMI	IBEX
C	$0.0097\,(0.0140)$	$0.0070\,(0.0215)$	$0.0047\,(0.0181)$	$0.0198\,(0.0202)$
∇Z_t	$-0.7047\,(0.0109)$	$-0.8278\,(0.0154)$	$-0.7938\,(0.0179)$	$-0.7885\,(0.0177)$
	Average returns			
Volatility increases	-0.695	-0.821	-0.789	-0.769
Volatility reductions	0.714	0.835	0.799	0.808
N	2320	2345	2321	2291
Adjusted R^2	0.644	0.553	0.460	0.463
RSSQ	1055.7	2529.6	1769.5	2147.8

Table 1. Estimates of the parameters for the single regime model, with the estimated standard deviations in parenthesis and average estimated returns associated to volatility increases and volatility decreases. The dependent variable is the daily returns.

Table 2 presents estimates from the return-volatility relationship, allowing for asymmetries. Only the constant dummy turns out to be significant, but it is not large enough to produce a noticeable asymmetry. The models provide a reasonable fit. The correlation between returns and fitted values from these regressions is 0.780 for SP500, 0.743 and 0.744 for SDAX, 0.664 for SMI and 0.670 for IBEX. The structure of these estimates, with (i) a positive α_0 and a negative α_0^+ with $\left|\hat{\alpha}_0^+\right| > \hat{\alpha}_0$, together with (ii) a negative slope α_1, and a non significant α_1^+ implies that the expected return is positive when volatility decreases, and negative when volatility increases. This relationship exhibits some discontinuity at a zero volatility change.[2] As the table shows, estimated returns associated to a one-point change in volatility are again around 0.80, positive or negative, with a sign opposite to that of the volatility change.

The last row shows the Residual sum of squares that is obtained from estimating the model without the use of the dummy variable. A standard comparison between the two rows next to the last one could be used as a global test for asymmetry in the return-volatility relationship, using a standard likelihood ratio test argument. The point is that a mechanical application of such inferential approach would lead to rejecting the null hypothesis of a symmetric relationship at 5% significance for the four markets, and 1% significance for Spain and Germany, even though the evidence of a symmetric elasticity is clear. As a further check on this issue, a regression that omits the two terms with the dummy variable produces almost the same fit. In fact, the correlation coefficient between the residuals from both models is above 0.997 for all markets, as shown in the last row.

There is therefore clear evidence on a simultaneous inverse relationship between returns and changes in the volatility index, for the four markets considered. There is however, no evidence of asymmetry, with negative returns (i.e., bad news) possibly having a stronger relationship with volatility changes than positive returns (i.e., good news).

[2] For small reductions in volatility, estimated return would be of α_0, while the return associated to small volatility increases would be of $\alpha_0 + \alpha_0^+$.

	Index			
	SP500	DAX	SMI	IBEX
C	$0.0482\,(0.0140)$	$0.1125\,(0.0426)$	$0.0853\,(0.0352)$	$0.2444\,(0.0359)$
D_t^+	$-0.0952\,(0.0392)$	$-0.1621\,(0.0596)$	$-0.1732\,(0.0496)$	$-.5002\,(0.0523)$
∇Z_t	$-0.6864\,(0.0221)$	$-0.7553\,(0.0332)$	$-.7376\,(0.0381)$	$-.6545\,(0.0347)$
$D_t^+.\nabla Z_t$	$0.0141\,(0.0305)$	$-0.0582\,(0.0432)$	$0.0031\,(0.0495)$	$0.0136\,(0.0461)$
	Average returns			
Volatility increases	-0.719	-0.863	-0.823	-0.897
Volatility reductions	0.734	0.868	0.823	0.899
N	2320	2345	2321	2291
Adjusted R^2	0.645	0.554	0.463	0.484
RSSQ	1052.9	2520.4	1760.2	2064.9
Restricted rssq	1055.7	2529.6	1769.5	2147.8
Res. correlation	0.999	0.998	0.997	0.978

Table 2. Estimates of the parameters for the asymmetric model, with the estimated standard deviations in parenthesis and average estimated returns associated to volatility increases and volatility decreases. The dependent variable is the daily returns.

3.2 Volatility regimes

A possibly even more interesting asymmetry has to do with whether the return-volatility relationship may depend on the level of volatility. That would be the case if a given increase in volatility was associated to a larger or smaller negative return depending on the level of volatility on which the increase takes place. Figure 2 displays the evolution of the Residual sum of squares for the symmetric return-volatility relationship, as a function of the volatility threshold we establish to split the sample between low and high volatility regimes. The range of Residual Sum of Squares is not terribly large, of about 4% for all markets except the US, for which is of only 2%. This is preliminary evidence regarding the possible convenience of a volatility regime model.

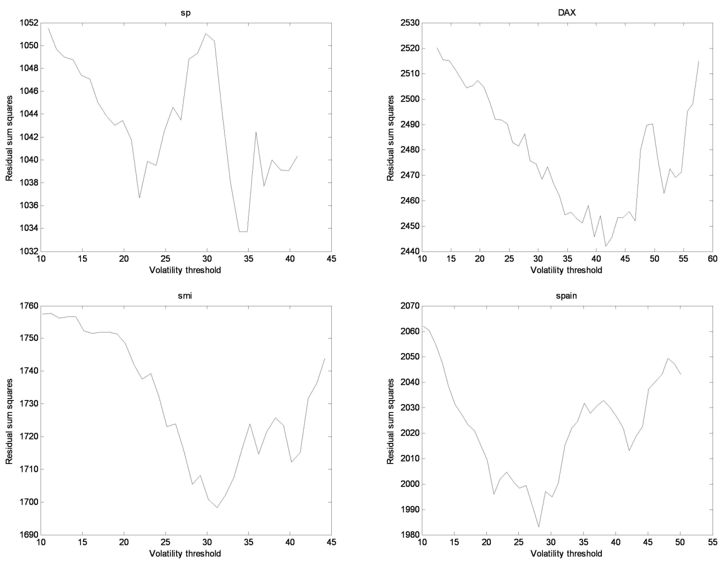

Figure 2. Residual sum of squares as a function of the volatility threshold.

Table 3 shows the estimates for the two regimes, the number of points included in each regime, the estimated volatility threshold, and the Residual sum of squares obtained under that threshold. The Residual sum of squares should be compared to the one obtained for the single regime in the first table in the paper, for the single regime regression model. The current table also summarizes the estimates by presenting the average return associated with a one-point increase or decrease in the volatility index. Analogue estimates for the single regime are shown first, for the sake of a comparison.

	Average return			
	SP500	DAX	SMI	IBEX
Single regime model				
Volatility increases	-0.719	-0.863	-0.823	-0.897
Volatility reductions	0.734	0.868	0.823	0.899
N	2320	2345	2351	2291
Threshold	33.9	41.6	31.2	28.1
Low volatility regime				
Volatility increases	-0.709	-0.800	-0.784	-0.923
Volatility reductions	0.738	0.844	0.734	0.903
N	2243	2139	2096	2069
Average return				
Volatility increases	-1.216	-1.665	-1.341	-1.372
Volatility reductions	0.213	1.152	0.932	1.234
N	77	206	255	222
Restricted rssq (one-regime)	1052.9	2520.4	1760.2	2064.9
rssq (two-regime model)	1037.0	2459.8	1704.6	1973.3

Table 3. Estimates for the two regimes.

According to these estimates, the return-volatility relationship is noticeably stronger in the high- than in the low-volatility regime. Market falls associated a one-point increase in volatility are almost twice as large in the high- than in the low-volatility regime. The positive return that is associated to a one-point reduction in volatility is also larger in the high-volatility regime, but the difference between regimes is now smaller. The estimate for the SP500 index for this case should be taken as an anomaly. The high volatility regime contains a small number of days in all countries, and coefficient estimates in this regime are not very precise. In fact, we already pointed out that for the variation in Residual Sum of Squares was smaller for US market, suggesting weaker evidence in favor of the two-regime model. It might be the case that estimates for this market might be spurious. Leaving aside this case, these estimates suggest that not only bad news, but also good news have more impact when they arise in the high-volatility regime. They are also consistent with the high volatility regime being persistent: being in that state, a change in volatility induces a relatively large return which, in turn, contributes to higher volatility, and so on. The comparison between Residual Sum of Squares (RSSQ) for both models clearly suggests the preference of the two-volatility regime model in the return-volatility relationship.

4 The volatility index as a predictor of future market conditions

4.1 Volatility indices as predictors of future returns

Scatter diagrams for daily returns and changes in the level of volatility for the four stock indices in the previous section display a clear negative correlation, with correlation coefficients being similar across international stock markets. That correlation had a clear reflection in the models estimated in the previous paragraph. Simple regressions estimated to explain returns by the change in the level of volatility led to very similar slopes, estimated around -0.80. It would be interesting to know whether this close relationship extends through time, so that it could allow a portfolio manager to improve return or volatility forecasts. As shown in this section, there are statistically significant relationships displaying bidirectional causality in the four markets considered, but estimated relationships cannot be directly used to improve forecasts for either variable.

This view is based on the results shown in Table 4. The left panel shows F-statistics and p-values, in brackets, to test for Granger causality in each direction, using the whole sample, and estimating VAR(12) models. Coefficients on lagged returns appear as jointly significant in the equation for volatility, while the evidence for a dynamic effect of volatility on returns is much weaker.

Index	Volatility $\rightarrow$ Return	Return $\rightarrow$ Volatility
SP500	18.5 (0.102)	24.4 (0.018)
DAX	17.2 (0.143)	27.1 (0.007)
SMI	15.0 (0.242)	30.4 (0.002)
IBEX	23.9 (0.021)	24.6 (0.017)

Table 4. Granger causality.

In spite of this result, VAR residuals for daily returns do not seem too different from the ones obtained from a univariate autoregressive model of the same length. Consequently, it is not surprising that forecasts from both models are essentially the same, suggesting that the causality relationships cannot be exploited for risk management, at least through simple linear representations for return and volatility.

Period	VAR		Univariate	
	RMSE	MAE	RMSE	MAE
1999–2000	1.217	0.910	1.124	0.821
2000–2001	0.687	0.498	0.677	0.987
2001–2002	0.672	0.522	0.642	0.505
2002–2003	0.683	0.535	0.676	0.526
2003–2004	0.910	0.723	0.856	0.677
2004–2005	1.752	1.375	1.755	1.386
2005–2006	1.232	0.944	1.200	0.906
2006–2007	1.504	1.144	1.451	1.102
2007–2008	1.704	1.368	1.399	1.087

Table 5. US market, RMSE / MAE return forecast errors: SP500 .

Table 5 shows Root Mean Square Errors (RMSE) and Mean Absolute Errors (MAE) from a bivariate VAR as well as from a univariate autoregression model, both of order 12, are shown in the table for each year in the sample (from March to March) for the US market. Forecast errors are even generally higher in the model that includes lags from both variables to explain returns, possibly due to the loss of precision of estimating an overparameterized model. Results for the other markets are similar, and are not shown here for the sake of simplicity. The main conclusion is that volatility indices do not contain information that may improve upon forecasts of future realized volatility obtained from historical volatility. That essentially amounts to saying that implied volatilities do not contain information that is not already in historical volatility, relative to predicting future realized volatility.[3]

[3]Incidentally, we found a similarly negative outcome when trying to use the past of the volatility index to forecast future returns. There does not seem to be any evidence in the volatility index regarding future market prices which is not already incorporated in past prices.

4.2 Volatility indices as predictors of future realized volatility

The second interpretation of volatility indices we advanced in the Introduction rests on the fact that they are constructed from implicit volatility estimates in a given set of options. This suggests that, as it is supposedly also the case with implicit volatilities themselves, a volatility index should have a reasonable forecasting ability on future realized volatility. In fact, some articles conclude that a volatility index performs well as a predictor of future realized volatility: Fleming et al. [5, (1995)] and Blair et al. [1, (2001)] find forecasting ability in VIX, Bluhm and Yu [2, (2001)] obtain a similar result for VDAX, while Moraux et al. [9, (1999)] obtain forecasting ability for future volatility in VX1. We contribute to the literature in this section by analyzing the forecasting ability of volatility indices on future realized volatility, on the horizon of 22 trading days, in the four stock markets we consider.

We use as an approximate measure of realized volatility the standard deviation of daily[4] returns $\{r_t\}_{t=1}^{N}$: $\mathrm{DT22}_t = \sqrt{250\frac{\sum_{j=1}^{22}(r_{t+j}-\bar{r})^2}{21}}$. We first ask whether the volatility index, by itself, is a good predictor of future realized volatility. If the volatility index, used by itself, happens to be the best possible linear predictor, we would say that the volatility index is an *unbiased predictor* of future market volatility. If that was not the case, we could use an alternative linear predictor by means of a regression of the type:

$$\mathrm{DT22}_t = \beta_0 + \beta_1 \cdot \mathrm{VIBEX}_t + \varepsilon_t$$

The problem here is that using the whole sample to estimate such a regression only tells us how closely together the two volatility indicators move over time, but it does not say much about the forecasting ability of one on the other. We actually need to do some real forecasting exercise using only the information available at the time the forecast is made.

In order to accommodate that issue, and to also take into account possible changes over time in the relationship between the volatility index and future realized volatility by estimating the linear projection above, using a 1-year moving window (250 market days). This gives us a sequence of estimated parameters over time. Notice that, in spite of the time indices in the previous equation, we are explaining at each point in time realized volatility over the next 22 market days (between $t+1$ and $t+22$) by using only the level of the volatility index observed at time t and the coefficients estimated with a sample window $(t-250, t)$, which can be seen in Figure 3 to display wide oscillations, but always remaining below 1.0, except for the US index. This is because the sample average for realized volatility, DT22, and the volatility indices are not similar. They are 19.46 and 24.86 for DAX, 22.34 and 20.29 for SMI, and 17.05 and 22.05 for IBEX. They are closer to each other for the SP500, being of 17.68 and 19.47, respectively, which may explain the different behavior of the recursive slope estimate. Clearly, testing for the null hypothesis $H_0 : \beta_0 = 0$, $\beta_1 = 1$ as it is usually done in the literature on unbiased predictors does not make much sense in this context.[5]

Root Men Squared Error (RMSE) and Mean Absolute Error (MAE) measures are always very similar to each other, in all markets and time periods, so we only present MAE values in Tables 6–9. They therefore provide a similar picture:

- predictions of future realized volatility obtained from the volatility index can compare with those obtained from past observed volatility in most years. However, with the exception of the US market, there are periods when the volatility index does very badly as a predictor of volatility,
- predictions from the rolling window linear projections clearly beat the use of both, the volatility index and observed market volatility, by themselves, as predictors of future realized volatility. Therefore, these are far from being unbiased predictors,

[4]A volatility proxy constructed with intra-day data might be preferable, but we lack that kind of data over part of the sample. Nevertheless, we could check that the forecasting ability of VIBEX-NEW over the 2001-2003 period is similar when we consider realized volatility measures for IBEX35 calculated using either daily or intraday returns.

[5]The test usually considers the joint hypothesis $H_0 : \beta_0 = 0, \beta_1 = 1$. In our case the sample mean of BT22 is 15.377, while that of VIBEX is 15.659, very similar, so that testing for $H_0 : \beta_1 = 1$ should be enough, if we were interesting in such a test.

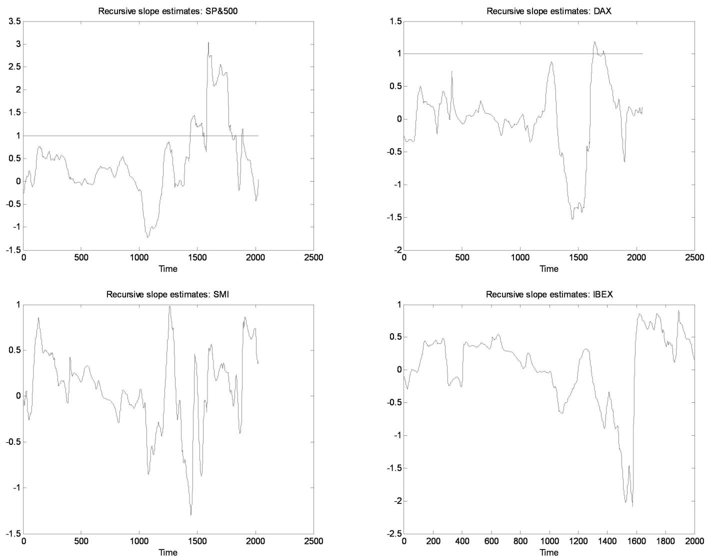

Figure 3. Recursive slope estimate in forecast regressions.

Period			Regression forecasts	
	BMK22	Volatility	BMK22	Volatility
2000–2001	6.42	5.55	5.73	**5.52**
2001–2002	5.54	6.54	3.89	**3.81**
2002–2003	4.47	7.80	**3.82**	3.85
2003–2004	3.90	5.46	3.65	**3.51**
2004–2005	4.95	4.79	3.78	**3.71**
2005–2006	6.89	8.56	4.40	**4.38**
2006–2007	10.65	13.10	9.67	**9.52**
2007–2008	10.31	11.54	8.52	**7.71**

Table 6. MAE Forecast error: SP500 (Bold figures indicate the lowest MAE for each year).

- once we apply the regression correction, volatility indices predict future realized volatility at least as well as past volatility. This is an striking result, since we are using in this case information only from implied volatilities to predict future realized volatility, without using its past values. It suggests that implied volatilities act as *sufficient statistics* for past historical volatility.

The gain from using a linear projection to construct forecasts is sometimes very large, reducing MAE sometimes by even more than 50%, as it is the case for some of the first years in the sample in the four markets considered. Since volatility was much higher during the last years in our sample, it is not surprising that forecast errors were also higher. however, percent error measures are comparable throughout the sample. In any event, percent forecast errors are generally around 20%, which seems like too large a level of forecast error in volatility for risk management purposes.

Summarizing, even though volatility index improve upon forecasts of future realized volatility obtained from past market volatility, their forecasting ability should be seriously questioned because of the high magnitudes of percent forecast errors. This negative result is consistently obtained for the four stock markets considered. However, the existence of a relationship between daily market returns and log changes

Period			Regression forecasts	
	BMK22	Volatility	BMK22	Volatility
2000–2001	**4.91**	7.71	5.05	6.63
2001–2002	8.18	11.77	6.37	**6.33**
2002–2003	4.31	23.77	**3.43**	3.45
2003–2004	5.47	10.84	4.41	**4.08**
2004–2005	4.07	4.11	3.82	**3.76**
2005–2006	5.91	**4.14**	4.21	4.22
2006–2007	5.32	5.85	**4.74**	4.97
2007–2008	6.37	4.96	4.57	**4.50**

Table 7. MAE Forecast error: DAX (Bold figures indicate the lowest MAE for each year).

Period			Regression forecasts	
	BMK22	Volatility	BMK22	Volatility
2000–2001	5.25	4.73	**4.54**	4.64
2001–2002	6.67	6.19	4.61	**4.33**
2002–2003	3.97	15.52	**3.26**	3.45
2003–2004	5.25	6.72	4.33	**3.99**
2004–2005	6.64	**4.57**	5.59	5.07
2005–2006	7.74	6.19	**4.98**	5.45
2006–2007	5.41	**4.47**	4.60	4.68
2007–2008	5.37	4.38	4.39	**3.87**

Table 8. MAE Forecast error: SMI (Bold figures indicate the lowest MAE for each year).

in volatility indices leaves open the possibility of finding a way to exploit that relationship for volatility forecasting purposes, our results suggest that such a forecasting mechanism should be significantly more sophisticated than the one used in this section.

5 Conclusions

We have estimated a daily volatility index for the Spanish market, using the methodology used by Eurex, the derivative exchange, to estimate the German (VDAX-NEW) and Swiss (VSMI) volatility indices. The simplicity of this methodology makes it specially suitable to estimate a volatility index in less than perfectly liquid markets, as it is the case of the options market on the IBEX35 index. The information requirements are weaker than for a previous methodology used to estimate volatility indices in international markets, and that enables us to compute the volatility index for a significantly higher percentage of market days than under the old methodology.

There are essentially two ways to interpret a volatility index: on the one hand, market participants are actively forecasting the future level of volatility, and their forecasts are reflected in a volatility index computed from option prices on a stock market index. Alternatively, the volatility index can be though of as capturing the sentiment of market participants regarding the current level of risk, but without incorporating any views about the future.

There are different ways to test between these two alternative views of the volatility index. One has to do with the forecasting ability of the volatility index regarding future realized volatility over the residual life to maturity of the options that were used to compute it. This should be relatively important under the first view, while being irrelevant under the alternative view. In fact, if the volatility index is shown not to have any ability to forecast future realized volatility, one would be forced under the first approach to believe that

Period			Regression forecasts	
	BMK22	Volatility	BMK22	Volatility
2000–2001	5.03	12.63	3.38	**3.33**
2001–2002	6.01	17.06	**4.56**	5.37
2002–2003	3.41	9.23	**2.53**	2.72
2003–2004	5.39	**4.24**	4.67	4.30
2004–2005	5.60	5.91	3.71	**3.53**
2005–2006	5.87	5.35	**4.92**	4.93
2006–2007	8.01	7.63	5.92	**5.56**

Table 9. MAE Forecast error: IBEX (Bold figures indicate the lowest MAE for each year).

market participants have that same lack of forecasting ability, an undoubtedly strong statement. Under the alternative view, we would expect a relatively strong contemporaneous relationship between market return and the volatility index, with the level of the latter having essentially no role to predict future volatility.

Working with daily market closing data from January 1st, 1999 to March 30, 2008, for market indices: S&P500, DAX, the Swiss SMI, and IBEX35, and their associated volatility indices, we have shown four main empirical results:

- there exists a negative and strong contemporaneous relationship between changes in the volatility index and market returns. A similar relationship is known not to arise for alternative implicit or conditional volatility indicators, which shows the better behavior of volatility indices to capture market's risk sentiment. That, in turn, suggests the appropriateness of issuing derivatives with a volatility index as underlying asset, in order to improve risk management. This is particularly encouraging for the Spanish market, clearly pointing out to the convenience of producing an official volatility index like the one we have used in this paper,

- the relationship between market returns and changes in the volatility index is essentially contemporaneous. It is also symmetric for increases and decreases in volatility, as opposed to results in some previous research. The relationship depends on the level of volatility, being quantitatively stronger for higher levels of volatility,

- even though some Granger causality can be found between these two variables through standard econometric techniques, this information content is inconsequential, and there does not seem to be a real chance of using either variable to predict the other,

- volatility indices are biased estimators of future realized volatility. A regression-corrected predictor improves significantly over the use of the volatility index by itself, and it shows a forecasting performance similar to using past market volatility. It suggests that implied volatilities act as sufficient statistics for past historical volatility. Unfortunately, in spite of the forecasting improvement, percent forecast errors still fall in the neighborhood of 20%, hard to accept for risk management purposes.

These results support the alternative interpretation we advanced above: the volatility index plays a good role in capturing the current perception of risk, while not being very useful to advance the future behavior of volatility, at least over long periods of time. According to this view, stock market participants seem to pay more attention to current conditions than to anticipating future fluctuations when trading options. This leads to implied volatilities which are more closely related to current and past than to future market conditions. Whether forecasting results are more encouraging when either we focus on short time horizons or use nonlinear methods, remains open as a question for future research.

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