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Construction and properties of volatility indices for Austria, Finland and Spain

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Abstract

The volatility index of the Chicago Board Options Exchange (VIX) is the first to have been introduced and it has attracted international imitators world-wide since it is considered as a barometer of investor fear. The aim of the paper is threefold. First, by following the VIX methodology, we construct a volatility index for three European countries (Austria, Finland and Spain) that do not have yet that piece of market information for investors. Second, we investigate the properties of the new volatility indices. In particular, we test their ability to act as fear indicators and as predictors of future returns. Moreover, we shed light on the term structure of the proposed volatility indices, by computing spot and forward implied volatility indices for different time to maturities (30, 60 and 90 days). Our results indicate that volatility indices are useful not only for investors to improve their trading decisions, but also for policy makers to choose the appropriate economic measure to guarantee stability in the market.

Keywords: Volatility indices; Market risk; Model free, Implied Forward Volatility, Volatility Term Structure.

1 Introduction

Volatility indices play a key role for investor trading decisions since they contain relevant information on future stock market volatility and are deemed as indicators of market sentiment. The volatility index of the Chicago Board Options Exchange (VIX) is the first to have been introduced and it has attracted international imitators world-wide since it is considered as a barometer of investor fear (see Moran (2014) for a recent list of volatility indices).

The development of volatility indices in Europe has suffered a considerable delay compared to North America. The main cause is due to the underdevelopment of European financial markets with respect to the North American and Asian contexts. Today, eight are the European volatility indices listed on

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exchanges. The VSTOXX is the volatility index of the EUROSTOXX 50 that is an aggregate stock index of the Euro-zone. The other seven volatility indices are country based: the VDAX NEW for the German market, the VSMI for the Swiss market, the VCAC volatility index for the French market, the VAEX for the Dutch market, the VBEL for the Belgian market, the VFTSE for the British market and the FTSE MIB IVI for the Italian market.

The aim of the paper is to introduce a volatility index, based on the VIX formula, for three other European markets: Austria, Finland and Spain[1]. Nowadays, an official volatility index is not traded in these financial markets. In order to compute the indices we use the same methodology of the VIX index (adapted to European markets). In this way we provide directly comparable volatility indices that can be used to compare the performance of each market with respect to the others. Introducing a volatility index is of primary importance for investors and policy makers. Investors may benefit from a volatility index for portfolio allocation and hedging. Policy makers may use the volatility index as a barometer of market health in order to improve monetary policy. It is important to have a standard index in order to make comparisons for economic analysis purposes (see for example Connolly and Hartwell (2014), Dew-Becker *et al.* (2019), Berger *et al.* (2020)). As pointed out by Muzzioli (2013b), the possibility to trade volatility as a separate asset has several advantages. It helps to better hedge the portfolio with a pure position in volatility; second, investors have the possibility to hedge with more dramatic events thanks to the negative correlation of these indices with the market, furthermore it is possible to speculate on future volatility levels by exploiting the mean-reversion of volatility. Finally, there is a research area analysing the component volatility model that focuses on the characteristics of option-implied volatility term structure (see for example Guo *et al.* (2014)). According to this research field, volatility can be divided in several components (long-term, medium-term, short-term volatilities) each one affected by a particular factor. The long-term volatility is driven by macroeconomic financial variables, the medium-term by market default risk, and the short-term by financial market conditions. To this purpose, in order to consider a term structure of the volatility, we analyse the three indices to different time to maturities, in detail we consider time to maturities of 30, 60 and 90 days. As a further instrument to better understand the volatility term structure, we make use of forward implied volatility (see Egelkraut and Garcia (2006), Egelkraut *et al.* (2007), Della Corte *et al.* (2011)) as it represent the average volatility that market participant expect to prevail during non-overlapping time interval.

The contribution of the paper is threefold. First, we introduce three new volatility indices for three derivatives markets where similar indices are not present. Second, following Rubbaniy *et al.* (2014) and Elyasiani *et al.* (2018), we investigate their usefulness in prediction of market returns. Third, we study also the term structure of market volatility computing these indices for different time to maturities (30, 60, 90 days).

In our analysis we involve several regression specifications largely used in empirical finance literature. In detail, we consider the contributions of Rubbaniy *et al.* (2014) and Muzzioli (2013b) for the contemporaneous relation between returns and volatility. Moreover, empirical evidence shows an asymmetric relation

[1]Gonzalez-Perez and Novales (2011) proposed a model free version of the Spanish volatility index, the VIBEX-NEW. We improve their methodology by using an interpolation and extrapolation method to cope with truncation and discretization errors. Moreover, our dataset is the IvyDB Europe database.

between stock index returns and changes in the volatility, that is, negative returns have a greater impact on the volatility index than positive returns. In particular, there are two existing hypotheses that characterize this asymmetric relation: the leverage effect (Black (1976) and Christie (1982)) and feedback effect hypotheses (French *et al.* (1987), Campbell and Hentschel (1992), Bekaert and Wu (2000)). According to the leverage effect hypothesis, when returns are negative the leverage ratio of the firm increases, and the firm's debt gets higher than total equity. As the equity of a firm is more exposed to the firm's total risk, the volatility of the equity should increase as a result. On the other hand, the feedback hypothesis explains that the asymmetric relation is based on the change in conditional volatility, which implies a change in market stock price (for further details see Badshah (2013) and Bekiros *et al.* (2017)). To this purpose, we assess the asymmetric returns-volatility relation splitting both returns (Whaley (2000) and Whaley (2009)) and change in volatility (Giot (2005) and Muzzioli (2013b)) in positive and negative. Moreover, we test also the forecasting power of the volatility indices with the models of Rubbaniy *et al.* (2014) and Elyasiani *et al.* (2018). We attempt to extrapolate the best regression specification among the proposed ones making use of R^2 metric.

Our main results can be summarized as follow: first, we confirm the negative contemporaneous returns-volatility relationship for all the markets in our analysis. We do not find out a stronger evidence of negative asymmetric and size effects of returns on volatility. For ATX and IBEX all specifications show similar results and R^2, while for OMX the best model is presented by Specification 4. Concerning forecasting regressions, except for OMX case, all regressions highlight future positive co-movements between volatility and returns for all time to maturities while the opposite is true for OMX. When considering forward implied volatilities we observe a lagged effect of past volatilities. Moreover, in forecasting regressions (Specification 8) the ATX index shows the highest R^2 while, for the remaining stock indices, the evidence of forecasting power of volatilities is rather weak.

The paper proceeds as follows. Section 2 provides details on the construction of volatility indices and the term structure of implied volatility used in the empirical part. Section 3 presents the data set used for each country highlighting the different features of each market. In Section 4 we perform contemporaneous and forecasting regressions in order to analyze the contemporaneous relation between returns and volatility and the forecasting power of the new volatility indices in predicting future returns. Section 5 concludes our work.

2 Volatility indices and the term structure of volatility

The procedure used to construct the volatility indices for the three markets of Austria, Finland and Spain relies on the computational method of the CBOE VIX index (CBOE (2009)). In particular, the CBOE VIX index is based on the concept of fair value of future variance (the DDKZ variance, for short) introduced by Demeterfi *et al.* (1999) while the notion of model free implied volatility is based on the work of Britten-Jones and Neuberger (2000). Both authors show how to replicate the risk-neutral expectation of variance with a portfolio of options with strike price ranging from zero to infinity. Jiang and Tian (2007) find that the DDKZ variance is equivalent to the model free implied variance introduced by Britten-Jones and Neuberger (2000). To this purpose, we compute our model free volatility indices as the square root of the model free variance given by:

$$E_q\left[\sigma_R^2\right] = \frac{1}{T}E_q\left[\int_0^T \sigma^2(t,\dots)dt\right] = \frac{2\exp^{rT}}{T}\int_0^\infty \frac{M(K,T)}{K^2}dK \tag{1}$$

where E_q is the expectation of the risk neutral measure, σ_R^2 is the realized variance, r is the risk-free discount rate corresponding to maturity T, $M(K,T)$ is the minimum between a call or put option price, with strike price K and maturity T. Note that only at-the-money and out-of-the-money options are used.

Given that in the financial markets only a limited and discrete set of strike prices are quoted, Equation (1) is subject to both truncation and discretization errors (see Jiang and Tian (2005), Carr and Wu (2009)). To this end we use an interpolation and extrapolation method to generate the missing strikes. In detail, this procedure consists of three steps. First, we obtain the implied volatilities by using the Black and Scholes model. Second, we interpolate implied volatilities between strike prices by means of cubic splines (see Campa *et al.* (1998), Jiang and Tian (2005), Muzzioli (2013a)). Indeed, cubic splines allows us to obtain a smooth volatility function and an exact fit to the known implied volatilities (for details see Jackwerth (1999)). We then extrapolate volatilities outside the interval $[K_{min}, K_{max}]$ using a constant function equal to $\sigma(K_{min})$ ($\sigma(K_{max})$) for strikes below (above) K_{min} (K_{max}), where K_{min} (K_{max}) is the minimum (the maximum) strike price traded. Last, we use the B-S model to compute the call and put prices to be inserted in Equation (1).

In order to compute the volatility indices with a constant maturity of $30, 60, 90$ days, we use the same interpolation scheme adopted by the Chicago Board of Exchange, that is:

$$\sigma_{t,t+j} = \sqrt{\left[w\frac{T_{near}}{365}\sigma_{near}^2 + (1-w)\frac{T_{next}}{365}\sigma_{next}^2\right]\frac{365}{j}} \tag{2}$$

where $w = (T_{next} - (j))/(T_{next} - T_{near})$ with $j = 30, 60, 90$, T_{near} and T_{next} are the time to expiration and σ_{near}^2 and σ_{next}^2 are the model free variance measures which refer to the near and the next term options, i.e. the two option series with maturities closest to j.

In order to estimate the forecasting power of our volatility indices we compute implied forward volatility as in (see Egelkraut and Garcia (2006), Egelkraut *et al.* (2007)). The implied forward volatility that represents the market's expectation at time t of the average volatility between the future time interval $t+j$, $t+j+i$. It is given by the formula below:

$$\sigma_{t,t+j,t+j+i}^{IFV} = \sqrt{\frac{\sigma_{t,t+j+i}^2 - \sigma_{t,t+j}^2}{(t+j+i)-(t+j)}} \tag{3}$$

where $\sigma_{t,t+j,t+j+i}^{IFV}$ is the forward implied volatility between $t+j$ and $t+j+i$, $\sigma_{t,t+j+i}$ and $\sigma_{t,t+j}$, are the two spot volatilities that refer to the time intervals $t, t+j$ and $t, t+j+i$, $j = 30, 60$, $i = 30, 60$.

3 Volatility indices in Finland, Spain and Austria

In order to construct the volatility indices we use the IvyDB Europe database. The underlying asset is adjusted for dividends as follows:

$$\hat{S}_t = S_t e^{-\delta_t \Delta t} \tag{4}$$

where S_t is the 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 BBA LIBOR rates with maturities of one week, and one, two and three months. Following Muzzioli (2013a), Elyasiani *et al.* (2017) we apply several filters to our data set. First, options with trading volume lower than a contract are eliminated. Second, options near to expiry which may suffer from pricing anomalies that might occur close to expiration are eliminated. Third, as Aït-Sahalia and Lo (1998), we retain only at-the-money options and out-of-the-money options (call options with moneyness $K/S > 0.97$ and put options with moneyness $K/S < 1.03$). Last, option prices violating the standard no-arbitrage constraints and positive prices for butterfly spreads are eliminated. In the following we describe the properties of the volatility indices for each country.

The volatility index for the Austrian market is based on the ATX index. It is listed on the Vienna Stock Exchange and it includes the most 20 capitalized Austrian firms. It is listed for the first time on 2 January 1991 and reached its historical maximum on 9 July 2008, before the Lehman Brothers bankruptcy. Our IvyDB Europe database contains a time series of this index from 7 February 2007 to 31 December 2017. Each day, we use an average of 25 options to compute the volatility index. We have on average 22 maturities traded each day. 2016 is the year with the maximum number of available options, while 2014 we have the lower availability. For what it concerns the data availability of options and their underlying Austria collocates between Spain and Finland (Finland is the less complete in terms of data). The ATX index is always listed in the same market, the Eurex Stock Exchange, for all the time horizons analysed. The volatility index for the Austrian market, the ATXVX index, is calculated for a time period ranging from 2014 to 2017. For all time to maturities considered, the ATXVX volatility index remains relatively stable. The period considered for ATXVX do not have affected by particular events which have influenced the Austrian market. From Table (1) we see that the ATXVX fluctuates between 15% and 36% and its maximum value is reached in March 2016. An inspection of Figure (1) sheds light on some particular features of the ATXVX index. We can note that, similarly to the OMXVX and IBEXVX indices, for 30 days time to maturity the ATXVX reaches its highest and lowest values. The 60 days ATXVX level ranges between the ATXVX on 30 and 90 days.

The volatility index for the Finnish market is based on the OMX Helsinki 25 market index (OMX25 for short). OMX25 is a value weighted index composed by the 25 most liquid Finnish stocks trading in the Helsinki Stock Exchange. Among the firms with the largest market share we find Nokia, Sampo e Fortum. Daily data of index options traded in the Eurex Stock Exchange from 1 January 2002 to 20 December 2006 and in the Helsinki Stock Exchange from 21 December 2006 to 31 December 2017 are used[2]. Each day, we use an average of 22 options to compute the volatility index. We have on average of 19 maturities traded each day. We compute the OMXVX volatility index for the 30, 60 and 90 days

[2] The OMX25 was listed in the Eurex Stock Exchange up to 20 December 2006, subsequently it was listed in the Helsinki Stock Exchange.

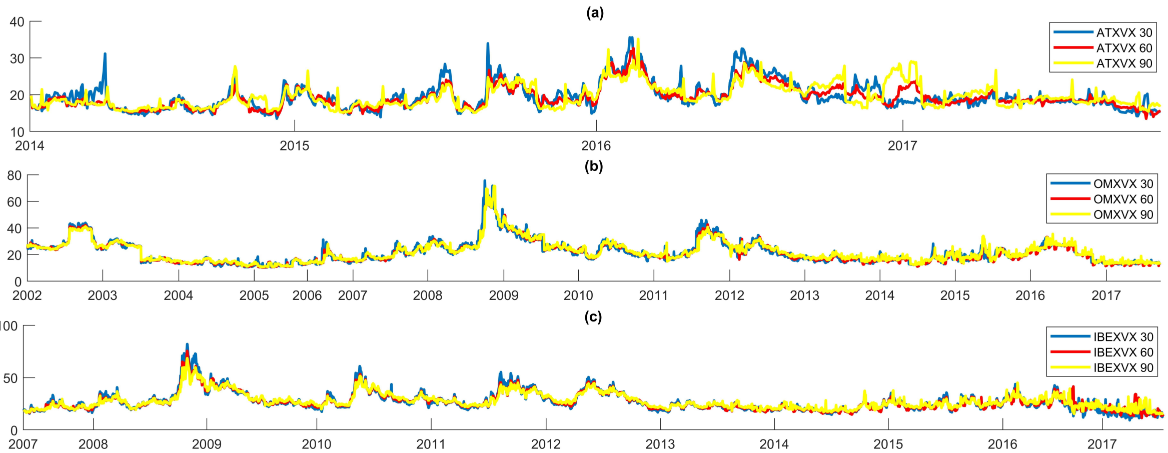

Figure 1: Volatility indices for different time to maturities.

time to maturity. Table (1) reports the descriptive statistics of the OMXVX volatility index. Figure (1), panel (b), shows the evolution of OMXVX for each time to maturity. We can see that OMXVX reaches its minimum values (between 10% and 20%) on the periods $2004-2006$ and $2013-2015$. Beyond the years 2008 and 2009, OMXVX reaches its maximum on 2002 (41%) with the diffusion of the dot-com bubble.

The Spanish stock index is the IBEX35 listed in the Madrid Stock Exchange. It is composed by the 35 most liquid and exchanged equities in the Madrid Stock Exchange. The database ranges from 7 May 2007 to 31 December 2017. Each day, we use an average of 22 options to compute the volatility index. We have on average of 10 maturities traded each day. Unlike the OMX, the IBEX35 has always been listed on the same stock market, the Meffmercado Espanol Financiero. We compute the IBEXVX volatility index for different tradig horizons for daily frequencies (i.e., 30, 60 and 90 days). Our results are displayed on Figure (1). Like the OMXVX, the IBEXVX also reached its maximum value during the sub-prime crisis. In that period the IBEXVX reaches levels between 40% and 81%. Similarly to the previous case, the level of 60 days IBEXVX ranges between that of IBEXVX on 30 and 90 days (see Fig. (1) panel (c)).

The comparison among the three indices is available only for a short time horizon $(2014-2017)$ due to the lack of data of ATX index in the dataset. Figure (2) shows the evolution of OMXVX, IBEXVX and ATXVX for time to maturities of 30, 60 and 90 days respectively. We can see that even though most of the time the three volatility indices tend to move together, the IBEXVX index seems to be more volatile. On the other hand, the OMXVX seems to be less volatile both at the beginning and at the end of the time series showed in Figure (2). In general, all three indices reach their maximum values for time to maturity at 30 days.

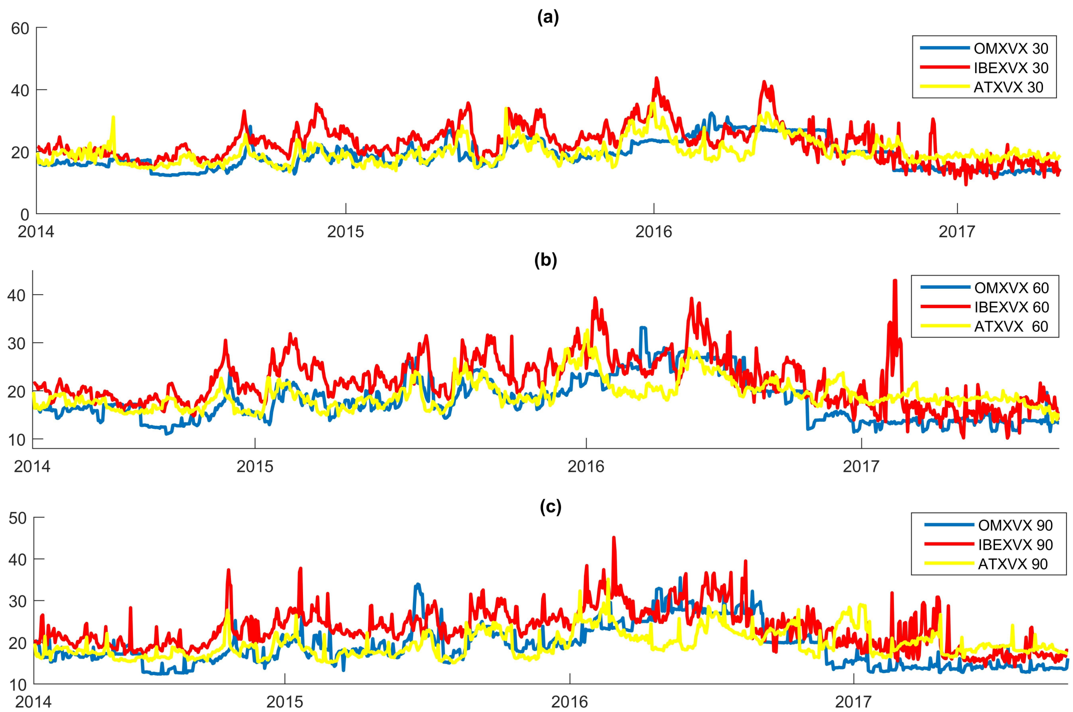

Figure 2: Comparing OMXVX, IBEXVX and ATXVX volatility indices for all time to maturities.

Table 1: Descriptive statistics for the ATXVX, OMXVX and IBEXVX volatility indicies

	Minimum value	Maximum value	Mean value	Variance	Standard deviation
			ATXVX		
30 days	13,51%	35,57%	19,49%	0,14%	3,70%
60 days	13,48%	32,63%	19,19%	0,09%	3,02%
90 days	15,11%	35,13%	19,50%	0,1%	3,16%
			OMXVX		
30 days	10,29%	75,56%	21,77%	0,76%	8,69%
60 days	10,26%	71,47%	21,62%	0,69%	8,32%
90 days	10,58%	71,50%	22,03%	0,66%	8,12%
			IBEXVX		
30 days	9,36%	81,96%	27,19%	0,85%	9,23%
60 days	10,19%	75,48%	26,5%	0,68%	8,23%
90 days	13,77%	68,48%	26,98%	0,58%	7,65%

4 The performance of volatility indices as contemporaneous and future sentiment indicators

In this section we focus on two main goals. First we try to understand the relationship between the new volatility indices and market returns. Second, we test the usefulness of the proposed measures in forecasting future market returns.

4.1 Contemporaneous relationship between stock market returns and implied volatility indices

One of the most important and analyzed volatility indices, the CBOE volatility index (VIX), has been interpreted as a benchmark of "investor fear gauge" because high values of the VIX indicate investor anxiety regarding a potential drop in the stock market (see Whaley (2009, 2000)). A volatility index is labelled as fear index when it signals that returns react negatively to its increase. On the contrary, we refer to a volatility index as a measure of market greed if returns react positively to its increase (Elyasiani *et al.* (2016)). From asset pricing theory (Sharpe (1964)) it is well known that expected return depends on the expected volatility. Moreover, within the implied volatility index literature, Whaley (2000), Giot (2005), Simon (2003) found a negative relationship between returns and VXO/VXN. One possible reason of this is that if expected market volatility increases (decreases), investors demand higher (lower) rates of return on stocks, so stock prices fall (rise). To test this proposition. the contemporaneous relationship between our volatility indices and their stock indices returns are analyzed deeply in this section, where we analyze not only the sign, but also the symmetry in the relationship between ATXVX, IBEXVX and OMXVX and their respectively stock indices returns. In line with previous studies (e.g. Giot (2005), Muzzioli (2013b)), we analyze the return-volatility relationship and we establish if our new volatility indices act as fear or greed ones.

We approach the study of the contemporaneous relationship between returns and volatility performing several regression models following the contributions of different authors. In detail, we have chosen seven different regression models employed in the works of Rubbaniy *et al.* (2014), Muzzioli (2013b), Whaley (2009), Giot (2005), Whaley (2000) respectively (see Table 2).

We first investigate the contemporaneous relation between daily changes in the volatility index and in returns performing the regressions in models 1 and 2. Second, in describing the aforementioned relationship, we explore the possibility that this relationship might be asymmetric, i.e., the contemporaneous relationship could be different for negative and positive stock index returns or negative and positive changes in volatility index. To this purpose we use models 3, 4, 5, 6.

Estimation results are reported in Tables (4), (5), (6). In the following, $R_{t,t+j}$ is the market aggregate log-returns of the corresponding index computed between day t and day $t+j$, that is $R_{t,t+j} = \ln(index_{t+j}/index_t)$, where $index_{t+j}$ and $index_t$ are the values of the index at time $t+j$ and t with $j = 30, 60, 90$ representing the time horizon in calendar days. $\triangle\sigma_{t,t+j}$ is the relative change in the volatility index of the corresponding market computed with respect a time horizon of $j = 30, 60, 90$. stock returns and volatility. $R^-_{t,t+j}$ ($R^+_{t,t+j}$) is the rate of change of the returns conditional on the mar-

Table 2: Review of regressions analysis on the contemporaneous relationship between volatility indices and stock market returns

Author(s)	Regression equation
1)Rubbaniy *et al.* (2014)	$\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \epsilon_t$
2)Muzzioli (2013b)	$R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3)Whaley (2009)	$\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \beta_2 R^-_{t,t+j} + \epsilon_t$
4)Giot (2005)	$\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+j} + \beta_3 R^+_{t,t+j} + \epsilon_t$
5)Whaley (2000)	$R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6)Muzzioli (2013b)	$R_{t,t+j} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$

ket going down (up), and zero otherwise. $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), otherwise $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = 0$ indicates the negative (positive) changes in volatility. All the regressions have been run by using the Ordinary Least Square (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix.

According to the results reported in Tables (4), (5), (6), in both models (models 1 and 2), all the β coefficients are negative and significantly different from zero at the 1% level. Therefore, it seems from our results, that the negative relationship between stock market returns and changes in volatility is confirmed in line with the findings for the US market (Whaley (2009)), the Italian market (Elyasiani *et al.* (2018)) and the European market (Rouetbi and Chaabani (2017), Badshah (2013)). In particular, the IBEX case shows the highest R^2 while the OMX the smallest. From descriptive statistics of the three indices (see Table 1) we recall that the IBEXVX index attained the highest value and displayed the highest volatility for all the maturities under investigation. From this first analysis we can conclude that all the new volatility indices are perceived by investors as bad news and associated with a contemporaneous decrease in stock prices. This suggests that the proposed volatility indices can be used as indicators of market fear, i.e. when the volatility index increases, returns are negatives.

As discussed in the Introduction, there are two main hypotheses that justify the asymmetric relation between stock index returns and changes in the volatility: the leverage effect and feedback effect hypotheses. In order to consider both assumptions we test the presence of asymmetric effects considering, first, changes in volatility as regressors (feedback hypothesis) and then taking positive and negative returns as regressors (leverage hypothesis). From Tables (4), (5), (6) we note that only Model 6 is able to capture negative asymmetric effects for all three markets. Indeed both positive and negative changes in

Table 3: Forecasting regressions

Author(s)	Regression equation
7) Elyasiani *et al.* (2018) and Rubbaniy *et al.* (2014)	$R_{t,t+j} = \alpha + \beta_7 \sigma_{t,t+j} + \epsilon_t$
8) Implied Forward volatility with controls	$R_{t,t+j} = \alpha + \beta_7 \sigma_{t,t+j} + \beta_8 \sigma^{IFV}_{t,t+j,t+j+i} + \epsilon_t$

volatility (β_5 and β_6) are highly significant at the 1% level, for all time horizons. Moreover, the slope coefficient of positive changes in the volatility index (β_5) is bigger than the slope coefficient of negative changes (β_6): a rise in the volatility index affects the returns more than a decrease in the volatility index. In particular, positive changes in the volatility index are associated with negative changes in the returns for the stock index than are negative volatility changes.
Differently, Model 5 only confirms the negative relationship between returns and volatility, in fact the β_5 coefficient is statistically not significant for all time to maturities in all three cases.

Finally, we assess asymmetric effects taking returns as regressors (Models 3 and 4). In all cases, we find evidence of asymmetric effects only in the Model 4. In detail, ATX and IBEX indices exhibit negative and asymmetric effects, indeed their β_2 coefficient (which measures the effect of the rate of change of the stock index conditional on the market going down) is negative and statistically significant at the 1% level for all time to maturities (see Tables (4) and (6)). In particular, negative returns for these two stock indices are associated with changes in their implied volatility indices than are positive returns.
Concerning the OMX index (see Table (5)), we observe slightly different results. Looking at the Model 4 we realize that coefficient β_3 is higher in absolute value than β_2 for time horizons 30 and 60, while for 90 days time to maturity we have a contrary relationship. These results highlights two different scenarios. First, OMX exhibits a weak positive asymmetric effect for 30 and 60 time to maturities that is, positive returns of the stock indices are associated with changes in their implied volatility indices than are negative returns. On the contrary, for medium horizon returns display a negative asymmetric effect.

Overall, in all the three markets the volatility indices act as fear indices in the sense of Whaley (2000), while when we study the asymmetric effects, we find that Models 4 (when we split returns in negatives and positives) and 6 (when we split changes in the volatility in positives and negatives) are the only ones to give us such evidence. Moreover, for ATX and IBEX Models $1, 2, 3, 5, 6$ exhibit the highest R^2 while in the OMX case Models 5 and 6 perform better than others.

4.2 The forecasting performance of the proposed volatility indices

As for the second goal of our investigation, we aim to assess whether the volatility indices can be considered as indicators of future market returns. Skiadopoulos (2004) found that investors can use past market returns in order to forecast future changes in implied volatility. Giot (2005) has argued that positive returns are to be expected as a consequence of high level of implied volatility. Muzzioli (2013b) gives a possible justification of this fact, the author asserts that if volatility is high, investors are over-reacting, selling stocks without a clear rationale and as a consequence stocks could be undervalued. Therefore high volatility can be viewed as a ”buy” signal.

In order to examine the forecasting power of our model-free volatility indices we use the OLS regression model. In the first model we follow Elyasiani *et al.* (2018) and Rubbaniy *et al.* (2014) resulting in the equation below:

$$R_{t,t+j} = \alpha + \beta_7 \sigma_{t,t+j} + \epsilon_t \tag{5}$$

where $R_{t,t+j}$ is the market aggregate log-returns of the index computed between day t and day $t+j$, that is $R_{t,t+j} = \ln(index_{t+j}/index_t)$, where $index_{t+j}$ and $index_t$ are the values of the index at time $t+j$ and $j = 30, 60, 90$ representing the time horizon in calendar days. $\sigma_{t,t+j}$ is the implied volatility index of the specific market considered between day t and day $t+j$ with $j = 30, 60, 90$,

As we can see in Table 7, for Model 7 all the coefficients are significant at the 1% level. For the IBEX and the ATX indices the sign of the coefficients is positive denoting a co-movement on the same direction between returns and volatility, while for the OMX index the sign is negative and the returns-volatility pattern exhibits an inverse relation. However, the R^2 is low for all three markets denoting a limited explanation power of the results.

An interesting model we consider in this work relies on the use of forward implied volatility (IFV) as defined in 2. In detail implied forward volatility can be computed applying Eq. (3) or simply as the difference between two implied volatilities from options maturing in t and $t + j$. In our analysis we consider the level of implied volatility indices, ATXVX, OMXVX and IBEXVX, between day t and day $t+j$ ($\sigma^{IFV}_{30,60}$, $\sigma^{IFV}_{60,90}$, $\sigma^{IFV}_{30,90}$) and the forward-looking 30−, 60−, 90-days relative changes in the underlying stock indices, ATX, OMX, IBEX35. To capture this relationship, we regress the implied volatility on forward looking returns using the regression equation reported in Table 7, Model 8. As in the previous analysis, all the regressions have been run by using the Ordinary Least Square (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix.

In the estimation results in Table 3, Model 8, we are focusing on the effect of expected average volatility for non-overlapping time intervals on future market returns. In this way, we attempt to extrapolate the investor's expectations on future market returns given an average level of volatility. Moreover, we have included in the regression equations the spot volatility $\sigma_{t,t+j}$ in order to control for lagged effects. In detail, we should expect that if the term structure of the forward implied volatility reflects the term structure of stock returns, then the coefficients β_7 of Model 7 should be statistically insignificant while β_8 should be significant.
Thanks to the involvement of future log-returns and implied volatility indices we are able to give some consideration on the volatility term structure, i.e. the curve connecting prices of volatility index to maturities across time. This analysis give an important information to traders because volatility term structure contains insight into the market's expectation of future realized volatility across different maturities (Luo and Zhang (2012), Feldman *et al.* (2018)).

For what it concerns the IBEX index, the values of the coefficients in Table 7, Model 8 (β_7 and β_8), are both positives and statistically significant at the 1% level. As a consequence, it is clear that in order to predict the returns between 30 and 60 days, 60 and 90 days, 30 and 90 time horizons, in the case of IBEX index, we need to consider both the spot and the forward volatilities although they exhibit low

R^2. To this regard, the forward implied volatilities alone, considered in all the three time horizons, do not subsume all the relevant information.

The ATX index behaves like the IBEX index for time horizons between 30 and 60 and between 30 and 90. In particular, both coefficients, β_7 and β_8, are positives and statistically significant at the 1% level. The returns between 60 and 90 are negatively related to their forward implied volatilities, indeed in the ATX case the coefficient β_8 of Model 7 is negative and statistically different from 0 while β_7 results to be statistically insignificant.

Unlikely, the OMX index, lead to divergent results with respect to the IBEX and the ATX indices. From the estimations of Table 7 we realize that the forward implied volatility is negative and statistically significant between 30 and 60 days while in the remaining cases it results statistically not significant.

Overall, from estimations results of Table 7 we come to the following conclusion. When investors use the proposed volatility indices for forecasting purposes they need to consider two volatility components: the spot volatility $\sigma_{t,t+j}$, and the forward implied volatility $\sigma^{IFV}_{t,t+j,t+j+i}$. This is because it emerges a lagged effect, that is the option prices of any particular horizon do not contain information only up to their maturity. Moreover, our results on volatility term structure are in line with the findings of Johnson (2017). In detail, the significance of volatility spot in our empirical results suggests the rejection of the expectations hypothesis (according to which time variations in the shape of the VIX term structure reflect changes in the expected path of future VIX) and the need to consider others components in the analysis of the term structure of the volatility indices, such as the variance risk premia.

It is worth to note that the R^2 in our forecasting regressions are very low (except for Specification 7 of ATX) then the proposed volatility measures can explain only a low portion of the total variation in returns, in the whole sample. However, as stressed by Fassas and Hourvouliades (2019), considering that we are evaluating future returns these results are economically significant and potentially useful.

5 Conclusions

The article has the main goal to introduce new implied volatility indices for three financial markets, Austria, Finnish and Spain. There is still no volatility index in these markets and given its importance documented by empirical literature (Whaley (2000), Giot (2005),Muzzioli (2013b), etc.) we believe that our paper can be useful for both investors and policy-makers.

After introducing the new indices we have tested their role in the respective markets by implementing several OLS regressions. In particular, we were able to conclude that the proposed volatility indices act as fear indices in line with the results of the empirical literature, thus confirming their role in reporting turbulent market periods.

The power of the aforementioned indices in forecasting future market returns has been tested via OLS forecasting regressions. The results show that all the indices are statistically and economically significant at the 1% level and they are useful to explain to an extent the future directions of the underlying stock price under investigation. However, we have stressed that the R^2 of all regression, except Model 8 of the

Table 4: ATX Contemporaneous relative changes in IV indices versus stock returns

	α	$\beta_1(R_{t,t+j})$	$\beta_2(R^-_{t,t+j})$	$\beta_3(R^+_{t,t+j})$	$\beta_4(\triangle\sigma_{t,t+j})$	$\beta_5(\triangle\sigma^+_{t,t+j})$	$\beta_6(\triangle\sigma^-_{t,t+j})$	R^2
Model 1: Rubbaniy *et al.* (2014)								
$\triangle\sigma_{30}$	0.0006	-2.5290^{***}						0.2721
	(0.0002)	(0.1956)						
$\triangle\sigma_{60}$	0.0004	-1.6005^{***}						0.2501
	(0.0011)	(0.1513)						
$\triangle\sigma_{90}$	0.0004	-1.3802^{***}						0.1766
	(0.0012)	(0.1388)						
Model 2: Muzzioli (2013b)								
R_{30}	0.0003				-0.1076^{***}			0.2721
	(0.0003)				(0.0079)			
R_{60}	0.0003				-0.1562^{***}			0.2500
	(0.0003)				(0.0134)			
R_{90}	0.0003				-0.1279^{***}			0.1766
	(0.0004)				(0.0174)			
Model 3: Whaley (2009)								
$\triangle\sigma_{30}$	0.0002	-2.4811^{***}	-0.0882					0.2721
	(0.0027)	(0.314)	(0.5996)					
$\triangle\sigma_{60}$	-0.0003	-1.5473^{***}	-0.0980					0.2501
	(0.0019)	(0.226)	(0.4665)					
$\triangle\sigma_{90}$	-0.0010	-1.2166^{***}	-0.3011					0.1776
	(0.0019)	(0.236)	(0.4213)					
Model 4: Giot (2005)								
$\triangle\sigma_{30}$	-0.0144^{***}		-3.3774^{***}	-0.0414				0.1990
	(0.0025)		(0.3876)	(0.2779)				
$\triangle\sigma_{60}$	-0.0087^{***}		-2.1476^{***}	-0.1172				0.1853
	(0.0017)		(0.3028)	(0.2131)				
$\triangle\sigma_{90}$	-0.0080^{***}		-1.9135^{***}	-0.0464				0.1393
	(0.0016)		(0.2519)	(0.2043)				
Model 5: Whaley (2000)								
R_{30}	0.0006				-0.0977^{***}	-0.0185		0.2731
	(0.0005)				(0.0143)	(0.0216)		
R_{60}	0.0006				-0.1420^{***}	-0.0257		0.2509
	(0.0004)				(0.0230)	(0.0359)		
R_{90}	0.0008				-0.1063^{***}	-0.0422		0.1795
	(0.0006)				(0.0228)	(0.0481)		
Model 6: Muzzioli (2013b)								
R_{30}	0.0006					-0.1161^{***}	-0.0977^{***}	0.2731
	(0.0005)					(0.0123)	(0.0143)	
R_{60}	0.0006					-0.1677^{***}	-0.1420^{***}	0.2509
	(0.0004)					(0.0218)	(0.0230)	
R_{90}	0.0008					-0.1484^{***}	-0.1063^{***}	0.1795
	(0.0006)					(0.0354)	(0.0228)	

Note: The table reports the estimated output of the regressions:

1. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \epsilon_t$
2. $R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \beta_2 R^-_{t,t+j} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+j} + \beta_3 R^+_{t,t+j} + \epsilon_t$
5. $R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+j} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$

for the ATX stock returns and volatility. $R^-_{t,t+j}$ ($R^+_{t,t+j}$) is the rate of change of the returns conditional on the market going down (up), and zero otherwise. $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), otherwise $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = 0$. Significance at the 1% level is denoted by $***$, at the 5% level by $**$, and at the 10% level by $*$. Standard errors are shown in parentheses.

Table 5: OMX Contemporaneous relative changes in IV indices versus stock returns

	α	$\beta_1(R_{t,t+j})$	$\beta_2(R^-_{t,t+j})$	$\beta_3(R^+_{t,t+j})$	$\beta_4(\triangle\sigma_{t,t+j})$	$\beta_5(\triangle\sigma^+_{t,t+j})$	$\beta_6(\triangle\sigma^-_{t,t+j})$	R^2
Model 1: Rubbaniy *et al.* (2014)								
$\triangle\sigma_{30}$	0.0001	-1.2846^{***}						0.1176
	0.0008	0.0883						
$\triangle\sigma_{60}$	0.0002	-0.8160^{***}						0.0760
	0.0007	0.0750						
$\triangle\sigma_{90}$	-0.0002	-0.6705^{***}						0.0427
	0.0007	0.0791						
Model 2: Muzzioli (2013b)								
R_{30}	0.0002				-0.0915^{***}			0.1176
	0.0002				0.0081			
R_{60}	0.0002				-0.0932^{***}			0.0760
	(0.0002)				(0.0117)			
R_{90}	0.0002				-0.0637^{***}			0.0427
	(0.0002)				0.0094			
Model 3: Whaley (2009)								
$\triangle\sigma_{30}$	0.0003	-1.3059^{***}	0.0415					0.1176
	(0.0013)	(0.1387)	(0.2657)					
$\triangle\sigma_{60}$	0.0001	-0.8274^{***}	0.0221					0.0760
	(0.0011)	(0.1266)	(0.2293)					
$\triangle\sigma_{90}$	-0.0007	-0.5990^{***}	-0.1389					0.0429
	(0.0012)	(0.1382)	(0.2398)					
Model 4: Giot (2005)								
$\triangle\sigma_{30}$	0.0003		-1.2644^{***}	-1.3059^{***}				0.1176
	(0.0013)		(0.1768)	(0.1387)				
$\triangle\sigma_{60}$	0.0001		-0.8052^{***}	-0.8274^{***}				0.0760
	(0.0011)		(0.1460)	(0.1266)				
$\triangle\sigma_{90}$	-0.0007		-0.7380^{***}	-0.5990^{***}				0.0429
	(0.0012)		(0.1484)	(0.1382)				
Model 5: Whaley (2000)								
R_{30}	0.0005				-0.0827^{***}	-0.0178		0.1184
	(0.0003)				(0.0124)	(0.0203)		
R_{60}	0.0003				-0.0899^{***}	-0.0067		0.0761
	(0.0003)				(0.0179)	(0.0279)		
R_{90}	0.0003				-0.0584^{***}	-0.0108		0.0430
	(0.0003)				(0.0003)	(0.0216)		
Model 6: Muzzioli (2013b)								
R_{30}	0.0005					-0.1005^{***}	-0.0827^{***}	0.1184
	(0.0003)					(0.0136)	(0.0124)	
R_{60}	0.0003					-0.0966^{***}	-0.0899^{***}	0.0761
	(0.0003)					(0.0185)	(0.0179)	
R_{90}	0.0003					-0.0692^{***}	-0.0584^{***}	0.0430
	(0.0003)					(0.0151)	(0.0136)	

Note: The table reports the estimated output of the regressions:

1. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \epsilon_t$
2. $R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \beta_2 R^-_{t,t+j} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+j} + \beta_3 R^+_{t,t+j} + \epsilon_t$
5. $R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+j} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$

for the OMX stock returns and volatility. $R^-_{t,t+j}$ ($R^+_{t,t+j}$) is the rate of change of the returns conditional on the market going down (up), and zero otherwise. $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), otherwise $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = 0$. Significance at the 1% level is denoted by $***$, at the 5% level by $**$, and at the 10% level by $*$. Standard errors are shown in parentheses. for the OMX stock returns and volatility. Significance at the 1% level is denoted by $***$, a the 5% level by $**$, and at the 10% level by $*$. Standard errors are shown in parentheses.

Table 6: IBEX Contemporaneous relative changes in IV indices versus stock returns

	α	$\beta_1(R_{t,t+j})$	$\beta_2(R^-_{t,t+j})$	$\beta_3(R^+_{t,t+j})$	$\beta_4(\triangle\sigma_{t,t+j})$	$\beta_5(\triangle\sigma^+_{t,t+j})$	$\beta_6(\triangle\sigma^-_{t,t+j})$	R^2
Model 1: Rubbaniy *et al.* (2014)								
$\triangle\sigma_{30}$	-0.0004	-2.3562^{***}						0.3638
	(0.0009)	(0.0920)						
$\triangle\sigma_{60}$	-0.0003	-1.9480^{***}						0.4929
	(0.0006)	(0.0612)						
$\triangle\sigma_{90}$	-0.0002	-1.7156^{***}						0.3426
	(0.0008)	(0.0626)						
Model 2: Muzzioli (2013b)								
R_{30}	-0.0002				-0.1544^{***}			0.3639
	(0.0003)				(0.0106)			
R_{60}	-0.0002				-0.2530^{***}			0.4930
	(0.0002)				(0.0090)			
R_{90}	-0.0001				-0.1997^{***}			0.3426
	(0.0003)				(0.0201)			
Model 3: Whaley (2009)								
$\triangle\sigma_{30}$	-0.0032^{*}	-2.0974^{***}	-0.4872^{*}					0.3657
	(0.0018)	(0.1441)	(0.2921)					
$\triangle\sigma_{60}$	-0.0023^{**}	-1.7675^{***}	-0.3399^{*}					0.4947
	(0.0011)	(0.1049)	(0.1836)					
$\triangle\sigma_{90}$	-0.0023^{*}	-1.5300^{***}	-0.3483^{*}					0.3443
	(0.0013)	(0.1244)	(0.1941)					
Model 4: Giot (2005)								
$\triangle\sigma_{30}$	-0.0189^{***}		-3.2408^{***}	-0.0364				0.2785
	(0.0016)		0.203	(0.0964)				
$\triangle\sigma_{60}$	-0.0153^{***}		-2.6611^{***}	-0.0666				0.3720
	(0.0010)		(0.124)	(0.0711)				
$\triangle\sigma_{90}$	-0.0139^{***}		-2.3629^{***}	-0.0673				0.2630
	(0.0873)		(0.0012)	(0.1127)				
Model 5: Whaley (2000)								
R_{30}	0.0008				-0.1826^{***}	-0.0419		0.3673
	(0.0007)				(0.0229)	(0.0342)		
R_{60}	0.0004				-0.2347^{***}	-0.0338		0.4940
	(0.0004)				(0.0183)	(0.0287)		
R_{90}	0.0003				-0.1844^{***}	-0.0288		0.3436
	(0.0010)				(0.0364)	(0.0657)		
Model 6: Muzzioli (2013b)								
R_{30}	0.0008					-0.1745^{***}	-0.1326^{***}	0.3673
	(0.0007)					(0.0164)	(0.0229)	
R_{60}	0.0004					-0.2685^{***}	-0.2347^{***}	0.4940
	(0.0004)					(0.0154)	(0.0183)	
R_{90}	0.0003					-0.2133^{***}	-0.1844^{***}	0.3436
	(0.0010)					(0.0403)	(0.0364)	

Note: The table reports the estimated output of the regressions:

1. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \epsilon_t$
2. $R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+j} + \beta_2 R^-_{t,t+j} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+j} + \beta_3 R^+_{t,t+j} + \epsilon_t$
5. $R_{t,t+j} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+j} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$

for the IBEX stock returns and volatility. $R^-_{t,t+j}$ ($R^+_{t,t+j}$) is the rate of change of the returns conditional on the market going down (up), and zero otherwise. $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), otherwise $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = 0$. Significance at the 1% level is denoted by $***$, at the 5% level by $**$, and at the 10% level by $*$. Standard errors are shown in parentheses.

Table 7: Models 7 and 8 : Forecasting regressions

	α	$\beta_7(\sigma_{t,t+j})$	$\beta_8(\sigma^{IFV}_{t,t+j,t+j+i})$	R^2
Panel I: ATX				
Model 7				
R_{30}	-0.1151^{***}	0.6239^{***}		0.1777
	(0.0080)	(0.0400)		
R_{60}	-0.2034^{***}	1.1137^{***}		0.2248
	(0.0109)	(0.0530)		
R_{90}	-0.1712^{***}	0.9728^{***}		0.1503
	(0.0147)	(0.0707)		
Model 8				
$R_{30,60}$	-0.0602^{***}	0.3469^{***}	0.6141^{***}	0.0440
	(0.0099)	(0.0484)	(0.1061)	
$R_{60,90}$	0.0167	-0.0412	-0.2840^{***}	0.0084
	(0.0109)	(0.0513)	(0.0705)	
$R_{30,90}$	-0.0518^{***}	0.3416^{***}	0.2314^{***}	0.0228
	(0.0149)	(0.0722)	(0.0705)	
Panel II: OMX				
Model 7				
R_{30}	0.01799^{***}	-0.0586^{***}		0.0066
	(0.0029)	(0.0145)		
R_{60}	0.0315^{***}	-0.0981^{***}		0.0081
	(0.0040)	(0.0202)		
R_{90}	0.0476^{***}	-0.1473^{***}		0.0116
	(0.0050)	(0.0246)		
Model 8				
$R_{30,60}$	0.0152^{***}	-0.0455^{***}	-0.1947^{***}	0.0046
	(0.0028)	(0.0135)	(0.0662)	
$R_{60,90}$	0.0163^{***}	-0.0501^{***}	-0.1106	0.0045
	(0.0033)	(0.0159)	(0.1204)	
$R_{30,90}$	0.0298^{***}	-0.0893^{***}	0.0262	0.0074
	(0.0044)	(0.0214)	(0.0860)	
Panel III: IBEX				
Model 7				
R_{30}	-0.0299^{***}	0.0987^{***}		0.0186
	(0.0042)	(0.0164)		
R_{60}	-0.0652^{***}	0.2174^{***}		0.0345
	(0.0062)	(0.0234)		
R_{90}	-0.0771^{***}	0.2477^{***}		0.0267
	(0.0096)	(0.0352)		
Model 8				
$R_{30,60}$	-0.0353^{**}	0.1192^{***}	0.1747^{**}	0.0193
	(0.0048)	(0.0179)	(0.0803)	
$R_{60,90}$	-0.0157^{***}	0.0471^{**}	0.6781^{***}	0.0184
	(0.0057)	(0.0206)	(0.1010)	
$R_{30,90}$	-0.0468^{***}	0.1509^{***}	0.3570^{***}	0.0140
	(0.0078)	(0.0282)	(0.0716)	

Note: The table reports the estimated output of the following forecasting regressions:

1. $R_{t,t+j} = \alpha + \beta_7 \sigma_{t,t+j} + \epsilon_t$
2. $R_{t,t+j} = \alpha + \beta_7 \sigma_{t,t+j} + \beta_8 \sigma^{IFV}_{t,t+j,t+j+i} + \epsilon_t$

for the stock returns and volatility. Significance at the 1% level is denoted by $***$, a the 5% level by $**$, and at the 10% level by $*$. Standard errors are shown in parentheses.

ATX index, are not very high suggesting the need of a further analysis to better understand stock price dynamics.

Finally, we have made use of implied forward volatility in order to shed some light to the volatility term structure. In particular, for all the three markets, in the medium term horizon, all the volatility indices are affected to a lagged mechanism. This open the analysis for further investigation.

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