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Designing volatility indices for Austria, Finland and Spain

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Abstract The volatility index of the Chicago Board Options Exchange (VIX) was the first to be established and it has given rise to international imitations world-wide as it is considered to be a barometer of investor fear. Starting from this volatility index, the aim of this paper is threefold. By adopting the VIX methodology, we construct a volatility index for three European countries (Austria, Finland and Spain) which currently do not provide this kind of market information for investors. Second, we investigate the properties of various volatility indices. In particular, we test their ability to act as fear indicators and as predictors of future returns. Moreover, we seek to cast light on the term structure of the proposed volatility indices, by computing spot and forward implied volatility indices for different times to maturity (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 measures to promote stability in the market.

Keywords Volatility indices · Market risk · Model-free volatility · Implied Forward Volatility · Volatility Term Structure

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1 Introduction

Volatility indices play a key role in investor trading decisions since they contain relevant information on future stock market volatility and are recognized as indicators of market sentiment. The volatility index of the Chicago Board Options Exchange (VIX), the first to be established, has given rise to imitators world-wide since it is considered to be a barometer of investor fear (see Fassas and Siriopoulos (2020) for a list of volatility indices).

The development of volatility indices in Europe has lagged behind the US. Today, eight European volatility indices are provided by Stock Exchanges. The VSTOXX is the volatility index of the EUROSTOXX 50 that is an aggregate stock index of the Eurozone. 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[1], and the FTSE MIB IVI for the Italian market.

This paper aims to provide a volatility index, based on the VIX formula, for three other European markets: Austria, Finland and Spain[2]. At present, an official volatility index is not available for these financial markets. In order to compute the indices, we used the methodology of the VIX index (adapted to European markets). In this way we provide directly comparable volatility indices that can be used to assess the performance of each market with respect to the others.
The availability of a volatility index can be of fundamental importance for investors and policy-makers (see Alexander et al. (2015) for a survey). Investors can benefit in terms of portfolio allocation and hedging. Implied volatility indices can be used as underlying instruments for derivatives. Equity volatility indices can be used for indicative quotes on variance swap rates (since volatility is the square root of variance, replication of the variance swap rate is not

[1] Historical daily values for VBEL and VFTSE date back to January 2000. However, both indices have been discontinued, in particular in November 2010 and June 2019 respectively (see Fassas and Siriopoulos (2020)). The VFTSE was delisted in June 2019, and replaced by the IVUK30.

[2] Gonzalez-Perez and Novales (2011) proposed a model-free version of the Spanish volatility index, the VIBEX-NEW. We build on their methodology by using an interpolation and extrapolation method to cope with truncation and discretization errors.

perfect). Since these indices are highly negatively correlated with their underlying indices, they may offer benefits in terms of diversification for an equity investor, through over-the-counter trades on variance swaps. As pointed out by Muzzioli (2013b), the chance to trade volatility as a separate asset presents several advantages. In particular, it may serve to hedge the portfolio with a pure position in volatility, thanks to the negative correlation between volatility and market index returns. Moreover, it is possible to speculate on future volatility levels by exploiting the mean-reversion characteristic of volatility. Policy-makers can use the volatility index as a barometer of market health in order to shape monetary policy to stabilize the markets in case of turmoil. In addition, implied volatility indices across different asset classes make it possible to investigate their interaction.

In this regard, Daigler et al. (2014), among others, examine volatility spillover effects from equities to the foreign exchange market. The provision of a volatility index, based on a standardized formula, can also be important to make comparisons across countries for the purposes of economic analysis (see Connolly and Hartwell (2014), Dew-Becker et al. (2019), Berger et al. (2020)). The volatility indices provided in this paper, constructed by means of the CBOE VIX methodology, are comparable with other leading traded volatility indices, such as the VIX and the VSTOXX. We leave for future research the analysis of the relationship between volatility indices of different countries.
Finally, there is promising research focusing on implied volatility term structure (see for example Guo et al. (2014)). For this purpose, in order to analyze the term structure of volatility, we compute volatility indices for 30, 60 and 90-day maturities. As a further means 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 represents the average volatility that traders expect to prevail over non-overlapping time intervals.

In addition to serving as a barometer of market health, volatility indices have been used to predict stock market returns. The prediction of returns is of great importance in many fields of finance and has been widely analyzed by researchers for decades. Giot (2005) argues that high implied volatility levels indicate oversold markets and could be viewed as short- to medium-term buy signals. Zhu (2013) investigates the US stock and bond returns using a distribution-based framework and finds evidence that the VIX helps to forecast the US stock returns distribution. Lubnau and Todorova (2015) find that

periods of low volatility are followed by significant positive mean returns over 20, 40 and 60 trading days. Gonzalez-Perez (2015) provides a comprehensive literature review of forecasting volatility models.

We contribute to the existing literature in three main respects. First, we introduce new volatility indices based on the VIX formula for Austria, Finland and Spain, where volatility indices are not yet published. Second, we investigate the properties of the volatility indices in terms of market returns and their usefulness in predicting future market returns. To this end, we include in our analysis several regression specifications widely used in the empirical financial literature. Third, in order to ascertain the term structure of implied volatility, we examine the forecasting power of spot and forward volatility indices on future returns.

The main results are as follows. The proposed volatility indices act as fear indices, thus confirming their role in reporting periods of market turbulence. Negative returns are associated with changes in volatility for all three markets (leverage effect). Asymmetric effects are found in all the markets with positive changes in volatility associated with negative returns more often than negative changes in volatility are associated with positive returns (feedback effect).

The spot volatility indices are found to be effective in forecasting future returns at 30, 60 and 90 days.

Both spot volatilities and forward implied volatilities are useful in forecasting future returns over 30 and 60 days, 60 and 90 days and 30 and 90 days, in the Austrian and the Spanish markets. In the Finnish market the evidence is less clear-cut.

The paper proceeds as follows. Section 2 provides details of the construction of the volatility indices and the term structure of implied volatility. Section 3 presents the volatility indices for Austria, Finland and Spain. Section 4 analyzes the properties of the volatility indices and their forecasting power in predicting future returns. Section 5 concludes.

2 Construction of the volatility indices

The procedure used to construct the volatility indices for Austria, Finland and Spain relies on the CBOE VIX index methodology (CBOE (2009)). In particular, the CBOE VIX index is based on the concept of fair value of future variance (DDKZ variance, in short) introduced by Demeterfi et al. (1999)

while the notion of model-free implied volatility is based on Britten-Jones and Neuberger (2000). Both studies 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) finds that DDKZ variance is equivalent to model-free implied variance as outlined by Britten-Jones and Neuberger (2000). For this purpose, we compute model-free volatility indices as the square root of 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 under the risk-neutral measure, σ_R^2 is the realized variance, r is the risk-free 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 in Equation (1).

Given that in the financial markets only a limited and discrete number of strike prices are quoted, Equation (1) is subject to both truncation and discretisation errors[3] (see Jiang and Tian (2005), Carr and Wu (2009)). The domain of strike prices is extended by using a factor u such that $S/(1+u) \leq K \leq S(1+u)$, where S is the index value and K is the strike price; for the current implementation, u was determined to be equal to 0.5. In order to obtain discrete values for the integration domain, we computed strikes spaced by an interval $\triangle K = 10$.

The parameter u and $\triangle K$ adopted for the current implementation are likely to reduce both the truncation and the discrete value errors to a negligible value. For this reason we use an interpolation and extrapolation method to generate the missing strikes. In particular, this procedure consists of three steps. First, we obtain the implied volatilities by using the Black-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)). The use

[3] It is important to point out an additional significant type of error that may affect the results. In particular, Andersen et al. (2015) argue that by averaging an invariant portion of the stock index risk-neutral density, a further approximation error appears as a result of a lack of a coherent time-invariant criterion to select minimum and maximum strikes in the VIX formula. As we extend the domain of strike prices by using a factor u such that $S/(1+u) \leq K \leq S(1+u)$, where S is the index value and K is the strike price, we expect the error to be negligible for the current implementation.

of cubic splines enables 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. Finally, we use the Black-Scholes model to compute the call and put prices to be inserted into Equation (1). We carefully check the newly generated implied volatilities to determine the absence of arbitrage.
Due to the nonlinear relation between option prices and strike prices, we follow Shimko (1993) and Aït-Sahalia and Lo (1998) and perform a curve-fitting method to interpolate implied volatilities between strike prices, rather than option prices. We point out that, unlike existing works implementing a direct method to generate the missing strikes (e.g. Ting et al. (2007) and Siriopoulos and Fassas (2012)), following Shimko (1993) and Aït-Sahalia and Lo (1998) we choose to interpolate implied volatilities between strike prices, rather than option prices. Moreover, the direct method has been shown to give inferior results by, among others, Figlewski (2010). Although this procedure implies the use of the Black and Scholes (1973) formula, this formula is used only as a mirror to convert option prices into implied volatilities to be interpolated and then in turn to convert implied volatilities into option prices. Therefore the use of the Black and Scholes (1973) formula has no influence on the interpolation mechanism. Moreover, we rely on the work of Jiang and Tian (2007) building on the methodology of Jiang and Tian (2005). This ensures that the implied volatility function constructed is smooth everywhere and fits the known implied volatilities exactly. Interpolating among volatilities instead of prices has the advantage of being less prone to arbitrage violations. Moreover, Ulrich and Walther (2020) show that interpolating among volatilities is widely used and that spline interpolation is one of the best methods for the European market.

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

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

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^2_{near} and σ^2_{next} 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) and Egelkraut et al. (2007)). The implied forward volatility represents market expectations at time t of the average volatility between the future time interval $t+j$, $t+j+i$. It is given by the formula below:

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

where $\sigma^{IFV}_{t,t+j,t+j+i}$ 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 referring to the time intervals $t, t+j+i$ and $t, t+j$, $j = 30, 60$, $i = 30, 60$.
In order to construct the volatility indices, we use the IvyDB Europe database. The IvyDB Europe database covers 12 European countries and the decision to investigate Austria, Finland and Spain is motivated by the lack of volatility indices published for these countries. The underlying asset is adjusted for dividends[4] 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. The risk-free rate is proxied by BBA LIBOR rates with maturities of one week, and one, two and three months. Following Muzzioli (2013a) and Elyasiani et al. (2017) we apply several filters to our data set. First, we begin by eliminating options with a trading volume lower than a contract. Second, we eliminate options close to expiration that may suffer from pricing anomalies that might occur close to expiration. Third, following 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 $K/S < 1.03$). Finally, we eliminate option prices violating the standard no-arbitrage constraints and positive prices for butterfly spreads.

[4] The volatility indices for Austria and Finland are computed with options on stock indices while the volatility index for Spain is computed with options on IBEX-35 futures. In particular, for the volatility index for Spain we used the Black (1976) formula to compute implied volatilities and did not apply dividend correction.

3 Volatility indices for the Austrian, Finnish, and the Spanish markets

The volatility index for the Austrian market is based on the ATX index, that is provided by the Vienna Stock Exchange and includes the 20 most capitalized Austrian stocks. It was established for the first time on 2 January 1991 and reached its historical peak on 9 July 2008, before the Lehman Brothers collapse. In order to compute the volatility index, we use an average of 25 options per day.
The volatility index for the Austrian market, the ATXVX index, is computed for a time period from 2014 to 2017, based on option availability in the Ivy Database. During the sampling period, and for all the times to maturity considered, the ATXVX volatility index remains relatively stable. The period under investigation was not affected by particular events in the Austrian market. From Table (2) we see that the ATXVX for all maturities fluctuates between 15% and 36% and its historical peak was reached on March 2016. A close reading of Figure (1) casts light on some particular features of the ATXVX index. We note that, similarly to the OMXVX and IBEXVX indices, the ATXVX for 30-day time to maturity is the most volatile. The ATXVX index for 60-day maturity is on average the lowest.

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 consisting of the 25 most liquid Finnish stocks trading on the Helsinki Stock Exchange. The firms with the largest market capitalization include Nokia, Sampo e Fortum. For each day, we use an average of 22 options to compute the volatility index. Table (2) reports the descriptive statistics of the OMXVX volatility index for the entire time span. Figure (1), panel (b), shows the evolution of OMXVX for each time to maturity. It may be seen that the OMXVX reached its lowest levels (between 10% and 20%) in the $2004-2006$ and $2013-2015$ periods. It reached the highest levels in 2002 (41%) during the dot-com bubble, then during the $2008-2009$ crisis and the European sovereign debt crisis in $2010-2012$.

The Spanish stock index is the IBEX35 listed on the Madrid Stock Exchange. It consists of the 35 most liquid and heavily traded equities on the Madrid Stock Exchange. The database covers the period from 7 May 2007 to 31 December 2017. For each day, we use an average of 22 options to compute the volatility index. The IBEXVX volatility index for 30-, 60- and 90- day maturities is shown in Figure (1) panel (c). Like the OMXVX, the IBEXVX reached

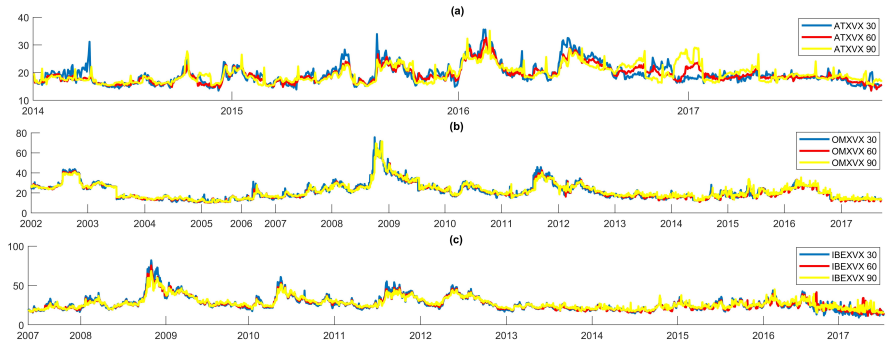


Figure 1 Volatility indices for different times to maturity.

Table 1 Comparison between VIBEX and IBEXVX

	VIBEX	**IBEXVX**
Horizon	30 calendar days	30,60,90 calendar days
Underlying	Futures on IBEX-35	Futures on IBEX-35
Option valuation model	model-based	model-free
Risk-free r	MIBOR 1 month	BBA LIBOR 1 week and 1,2,3 months.

its peak during the sub-prime crisis. In that period the IBEXVX attained levels between 40% and 81%. The Bolsas y Mercados Españoles (BME) provides a model-based volatility index called VIBEX that underlies the expected volatility for the Spanish stock index, IBEX-35. We computed the volatility index for Spain, in order to provide a model-free implied volatility index based on the Bakshi et al. (2003) formula and to compare it with the other volatility indices. In fact, the VIBEX index is not based on the model-free formula, since it is computed as an average of the implied volatilities of an at-the-money call and an at-the-money put. Given that the strike prices of the at-the-money call and put are above or below the future index value, the implied volatilities are adjusted for the skew (for more details see Bolsas y Mercados Españoles documentation or Gonzalez-Perez and Novales (2011)). For the sake of comparison, in Table (1) we report the main differences between the VIBEX and the IBEXVX.

The comparison between the three indices is possible only for a short time horizon ($2014 - 2017$) due to the limited time span of ATX options in the dataset. Figure (2) shows the evolution of OMXVX, IBEXVX and ATXVX for times to maturity of 30, 60 and 90 days respectively, while Table (3) reports their descriptive statistics. It is evident that, even though the three volatility

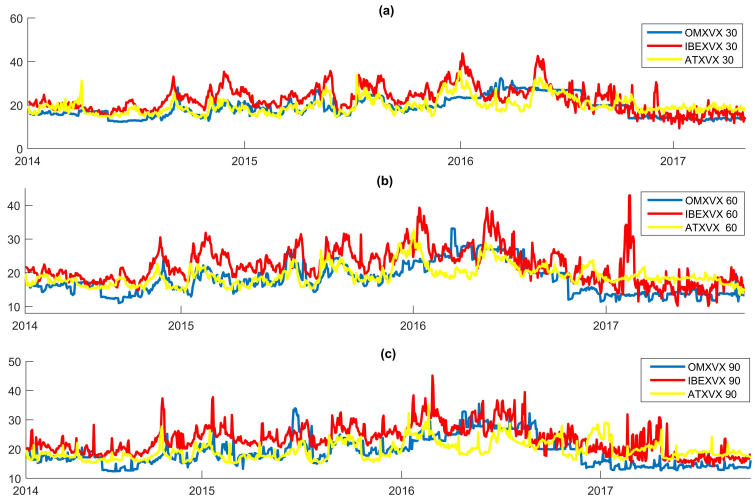


Figure 2 Comparing OMXVX, IBEXVX and ATXVX volatility indices on the same time-period 2014-2017.

Table 2 Descriptive statistics for the ATXVX, OMXVX and IBEXVX volatility indices

	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%

indices tend to move together most of the time, the IBEXVX index is highest and the most volatile. On the other hand, the OMXVX is the least volatile, particularly at the beginning and at the end of the time period in Figure (2). In general, all three volatility indices reach their maximum values for the 30-day time to maturity. The volatility term structure is u-shaped for all the volatility indices as 90-day volatility is slightly higher than 30-day volatility for the ATVX and the OMXVX indices, whereas the opposite is the case for the IBEXVX.

Table 3 Descriptive statistics for the ATXVX, OMXVX and IBEXVX volatility indices from 2014 to 2017

	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	12,19%	31,97%	18,42%	0,10%	3,22%
60 days	12,36%	33,09%	18,41%	0,07%	2,6%
90 days	12,38%	36,26%	18,51%	0,08%	2,88%
			IBEXVX		
30 days	7,92%	43,82%	22,15%	0,31%	5,55%
60 days	15,12%	41,92%	22,46%	0,22%	4,74%
90 days	16,27%	42,93%	24,00%	0,23%	4,76%

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

In this section we focus on two main goals. First, we examine the contemporaneous relationship between the new volatility indices and market returns. Second, we test the utility of the proposed volatility indices 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 because high values of the VIX are indicative of investor anxiety regarding a potential drop in the stock market (see Whaley (2009, 2000)). A volatility index is labelled as a fear index when it signals that returns react negatively to any increase. On the contrary, we refer to a volatility index as a measure of market greed if returns react positively to any increase (Elyasiani et al. (2016)). From asset pricing theory (Sharpe (1964)) it is well known that the expected return depends on the expected volatility. Moreover, in the implied volatility index literature, Whaley (2000), Giot (2005), Simon (2003) found a negative relationship between volatility and index returns. One possible reason is that if expected market volatility increases (decreases), investors demand higher (lower) rates of return on stocks, so stock prices fall (rise).
In line with previous studies (e.g. Giot (2005), Muzzioli (2013b)), we analyze the return-volatility relationship and examine whether the new volatility indices act as indices of fear or of greed in the market.

There are two main hypotheses that may explain the negative relation between stock index returns and changes in the volatility index: the leverage effect (Black (1976) and Christie (1982)) and the feedback effect (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 exceeds total equity. As the equity of a firm is more exposed to the firm's total risk, the volatility of the equity should increase in turn. On the other hand, the feedback hypothesis states that the asymmetric relation is based on the change in conditional volatility, which implies a change in the stock market price (for further details see Badshah (2013) and Bekiros et al. (2017)). However, both the leverage hypothesis and the volatility feedback theory have been questioned. Some empirical studies utilizing different metrics instead of conditional volatility measures, report weak evidence regarding the explanatory power of both classical theories (see Bekiros et al. (2017), Badshah (2013), Padungsaksawasdi and Daigler (2014)). Therefore, both the leverage effect hypothesis and the volatility feedback hypothesis may be inadequate to fully account for the negative and asymmetric relationship between returns and volatility. A different explanation is proposed by Hibbert et al. (2008) who put forward a behavioural justification for the negative asymmetric return–volatility relation. In particular, the authors attribute the asymmetric return-volatility feature to representativeness, affect and extrapolation bias. Representativeness is related to the concept of overconfidence on stereotypes and is the reason for the use of rules of thumb to make quick judgements. Affect and extrapolation bias reinforce representativeness by allowing quick judgements based on emotions.

We approach the study of the contemporaneous relationship between returns and volatility performing several regression models following the contributions of different authors. In order to account for the change in the relationship between variables in different parts of the distribution, we apply the Quantile Regression (QR) approach relying on Badshah et al. (2018), Bekiros et al. (2017), Badshah (2013). As stressed by Badshah et al. (2018) it is a methodology less sensitive to outliers, requiring weaker distributional assumption, and is thus well-suited to skewed and leptokurtic distributions such as implied volatility changes and returns. In particular, we selected eight different regression models employed by Rubbaniy et al. (2014), Muzzioli (2013b), Whaley (2009), Giot (2005), Whaley (2000), Fleming et al. (1995), Hibbert et al. (2008) (see Table (5)).

The choice of these models is motivated by the widely debated question among economists concerning a convincing explanation of the negative and asymmetric contemporaneous relationship between returns and volatility. In order to consider the three hypotheses, the leverage effect hypothesis, the feedback effect hypothesis and the behavioural explanation, we perform different regression models.
First, we investigate the contemporaneous relationship between returns and daily changes in the volatility index performing the regressions in Models 1 and 2. Second, we explore the possibility for the relationship to be asymmetric, i.e., with different signs if we investigate negative and positive stock index returns or negative and positive changes in the volatility index. In order to consider the three hypotheses, we test the presence of asymmetric effects taking positive and negative returns as regressors (leverage hypothesis) in Models 3 and 4 and changes in volatility as regressors (feedback hypothesis) in Models 5 and 6. Moreover, to test the behavioural hypothesis we take into account the Model of Hibbert et al. (2008) and Fleming et al. (1995) considering lagged returns and volatilities in Models 7 and 8 respectively. Finally, to provide a robustness analysis compared to our prior findings, we re-examine all the models using Quantile Regression.

Estimation results are shown in Tables (7), (8), (9) for the Austrian, Finnish and Spanish volatility indices respectively. In the following, $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^{-}_{t,t+1}$ ($R^{+}_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^{-}_{t,t+j}(\triangle\sigma^{+}_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the daily one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $|R_{t,t+1}|$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. All the regressions in Tables (7)-(9) were run using Ordinary Least Squares (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix. Tables (10)-(15) show the results of the Quantile Regressions at extreme quantiles ($\tau = 0.05$, $\tau = 0.95$).

On the basis of the results shown in Tables (7), (8), (9), in both models (models 1 and 2), all the β coefficients are negative and significantly different from zero at the 1% level. Consequently, 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, comparing the R^2s for various models shows that the IBEXVX has the best fit. From descriptive statistics of the three indices (see Table (3)) we note that the IBEXVX index attained the highest value and displayed the highest volatility for all the maturities under investigation. From this initial analysis we can conclude that an increase in the new volatility indices is perceived by investors as a negative development and associated with a decrease in the underlying index. This suggests that the proposed volatility indices can be used as indicators of market fear, i.e. when the volatility index increases, returns are negative.

For this purpose, we assess the asymmetric returns-volatility relation splitting both returns (Whaley (2000) and Whaley (2009)), and changes in volatility (Giot (2005) and Muzzioli (2013b)) in positive and negative.
From Tables (7), (8), (9) it may be seen that only Model 6 is able to capture negative asymmetric effects for all three markets. Both positive and negative changes in volatility (β_5 and β_6) are highly significant at the 1% level, for all the time horizons. Moreover, the slope coefficient of positive changes in the volatility index (β_5) is greater 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.
On the other hand, Model 5 only confirms the negative relationship between returns and volatility, since the slope coefficient β_5 of positive changes in volatility is not statistically significant for all the times to maturity in all three cases.
When assessing asymmetric effects taking returns as regressors (Models 3 and 4), we find evidence of asymmetric effects only in Model 4. In particular, ATX and IBEX indices exhibit negative and asymmetric effects, the slope coefficient of negative returns is statistically significant at the 1% level for all times to maturity (see Tables (7) and (9)).
Concerning the OMX index (see Table (8)), both positive and negative returns are statistically significant in explaining changes in volatility (negative returns are associated with an increase in volatility and positive returns with a decrease in volatility).
Finally, we rely on Models 7 and 8 to test the validity of the behavioural hypothesis with respect to the leverage and feedback hypotheses. In this respect, following Hibbert et al. (2008) we tested his first hypothesis: contemporaneous return is the most important factor that determines changes in

current implied volatility. As the author suggests, if this hypothesis is true, then the behavioural explanation of the return-volatility relation is superior to the leverage or volatility feedback hypothesis, since the latter explanations involve lagged relations. In all three markets, the results of Model 7 show that when lagged values of changes in volatility indices are included in the model then the lagged returns are all significant at the 1% level for all time horizons and are more important than past volatilities. Otherwise, the results of Model 8 show that when only returns (leads, lags, and contemporaneous) and absolute return (i.e. a measure of the magnitude and the size of market returns) are used to explain changes in the volatility indices we obtain mixed results. This corroborates the leverage hypothesis, since the behavioural hypothesis involves only contemporaneous relations.

Tables (10)-(15) show the results for the eighth QR models at the extreme quantiles $\tau = 0.05$ and $\tau = 0.95$, for ATXVX, OMXVX and IBEXVX respectively. The results of Models 1 and 2 show that the negative relationship between stock market returns, and change in volatility is confirmed for extreme quantiles of the three volatility indices. In this regard, we found evidence of the superiority of the leverage effect in the return-volatility explanations, since it involves lagged relations.
The absolute value of market returns $|R_{t,t+1}|$ measures size effect of actual returns upon the change in actual market volatility. If we compare this coefficient estimate to the estimate derived by the OLS we find clear evidence that QR is able to capture the size effect for extreme quantiles. However, the sign of this coefficient is different in the lower and upper quantile.
This implies that the magnitude of market returns has a positive effect upon implied volatility in upward market conditions. However, the size effect shows a reverse negative impact on changes in expectations in downside markets, i.e. the magnitude of market returns has a negative effect on changes in volatility in bear markets.

Additionally, except for ATXVX and OMXVX at the lowest quantile, lagged returns are negative and significant for all indices with model 7 providing a better fit. Moreover, lagged returns are more important than lagged changes in volatilities. These results provide evidence against the behavioural hypothesis. In fact, if past returns are significant then the leverage effect explains the return-volatility relation more than the behavioural hypothesis does, in contrast with previous studies (see Badshah (2013); Badshah et al. (2018), Bekiros et al. (2017), Hibbert et al. (2008)).

It may be concluded that, overall, in the three markets, the volatility indices act as fear indices in the sense of Whaley (2000). Asymmetric effects are found in all the volatility indices when splitting positive and negative returns (Model 4) and positive and negative changes in the volatility index (Model 6). In addition, while the OLS results for absolute returns are insignificant, by means of Quantile Regression we obtain a range of results. We observe from our results that absolute returns are significant although the sign of this coefficient tends to diverge from the lower and upper quantile (Model 8). In particular, the magnitude of market returns has a positive effect on implied volatility in upward market conditions, while the size effect shows a reverse negative impact on changes in expectations in downside markets. Finally, we find evidence of the superiority of the leverage effect explanation in the return-volatility relation.

4.2 The forecasting performance of the proposed volatility indices

As regards the second aim of our investigation, we seek 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 result of high levels of implied volatility. Muzzioli (2013b) suggests a possible justification of this fact, arguing that if volatility is high, investors are over-reacting, selling stocks without a clear rationale and as a result stocks could be undervalued. Thus, high volatility can be viewed as a "buy" signal.

In order to examine the forecasting power of the volatility indices, we use OLS regressions shown in Table (6). Before proceeding with the analysis, we provide in Table (4) the correlations between $\sigma_{t,t+j}$ and $\sigma^{IFV}_{t,t+j,t+j+i}$ for the ATXVX, OMXVX and IBEXVX volatilities. As you can see in Table (4), for all times to maturity the variables $\sigma_{t,t+j}$ and $\sigma^{IFV}_{t,t+j,t+j+i}$, are moderately correlated. Moreover, in order to exclude the presence of multicollinearity we have computed the variance inflation factors[5] (VIF) for each regressor of model 10 and the regressors exhibit a VIF lower than 2 for all times to maturity and for each country.

[5] The variance inflation factor for regressor j is defined as $\frac{1}{1-R_j^2}$ where R_j^2 is the coefficient of multiple correlation between regressor j and the other regressor. As stated in the literature, a value greater than 10 indicates the presence of multicollinearity (see Neter et al. (1990), Cottrell and Lucchetti (2020)).

Table 4 Correlation between $\sigma_{t,t+j}$ and $\sigma^{IFV}_{t,t+j,t+j+i}$ for the ATXVX, OMXVX and IBEXVX volatilities for $30, 60, 90$ days times to maturity.

Pearson correlations	
ATXVX	
30 days	-0,5181
60 days	-0.1052
90 days	0,3300
OMXVX	
30 days	-0,2241
60 days	-0,1029
90 days	-0,0784
IBEXVX	
30 days	-0,5768
60 days	-0,3938
90 days	-0,2834

In the first model we follow Elyasiani et al. (2018) and Rubbaniy et al. (2014):

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

where $R_{t,t+j}$ is the daily return at time t that refers to a window of j days with $j = 30, 60, 90$, and $\sigma_{t,t+j}$ is the daily implied volatility index at time t with maturity $t + j$ with $j = 30, 60, 90$.

As shown in Table 16, for Model 9 all the coefficients are significant at the 1% level. For the Spanish and the Austrian markets an increase in the volatility index is associated with positive returns over the next 30, 60 and 90 days, while for the Finnish market the opposite is the case.

One interesting model we consider relies on the use of implied forward volatility (IFV) as defined in Section 2 (Egelkraut and Garcia (2006), Egelkraut et al. (2007)). In particular, implied forward volatility can be computed by applying Eq. (3). In our analysis we consider the implied forward volatility indices, ATXVX, OMXVX and IBEXVX, between 30 and 60 days, 60 and 90 days and between 30 and 90 days ($\sigma^{IFV}_{30,60}$, $\sigma^{IFV}_{60,90}$, $\sigma^{IFV}_{30,90}$) and the corresponding future returns of the stock indices, ATX, OMX, IBEX35. To capture this relationship, we regress the implied volatility on forward-looking returns using the regression equation shown in Table (16), Model 10. As in the previous analysis, all the regressions were run using the Ordinary Least Square (OLS), with the Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix.

In the estimation results in Table 16, Model 10, we focus on the effect of expected average volatility for non-overlapping time intervals on future market returns. In this way, we attempt to extrapolate investor expectations on future

market returns given an average level of volatility. Moreover, we 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 9 should be statistically insignificant while β_8 should be significant.
The analysis of future log-returns and implied volatility indices enables us to provide insights into the volatility term structure. This could be useful for forecasting future realized volatility (Luo and Zhang (2012), Feldman et al. (2018)).

For the Spanish market, the values of the coefficients in Table 16, Model 10 (β_7 and β_8), are both positive and statistically significant at the 1% level. As a result, it is clear that in order to predict returns between 30 and 60 days, 60 and 90 days, 30 and 90 days, we need to consider both the spot and the forward volatilities although they exhibit low R^2. The forward implied volatilities for all three time horizons do not subsume all the information in spot volatilities.

The Austrian case is similar to the Spanish one for time horizons between 30 and 60 and between 30 and 90 days. In particular, both coefficients, β_7 and β_8, are positive and statistically significant at the 1% level. Only returns between 60 and 90 days are negatively related to their forward implied volatilities, whereas spot volatility is not significant.

The Finnish market shows different results. Forward implied volatility is negative and statistically significant only in the case of forecast returns between 30 and 60 days, whereas in the remaining cases it is not significant.

Overall, from estimation results in Table (16) the following conclusion can be drawn. In order to forecast future returns, investors need to consider two volatility components: spot volatility $\sigma_{t,t+j}$, and forward implied volatility $\sigma^{IFV}_{t,t+j,t+j+i}$. Moreover, our results on volatility term structure are in line with the findings of Johnson (2017). In particular, the significance of spot volatilities 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 other components in the analysis of the term structure of the volatility indices, such as variance risk premia. Concerning the estimated coefficients of the Austrian and Spanish markets, in Model 10, the positive sign seems to confirm the mean-reverting property of volatility. As argued by Whaley (2009) and

Siriopoulos and Fassas (2012), volatility does not follow an identifiable trend: when implied volatility is high, it tends to revert back down to its long-run average value, and when implied volatility is too low, it tends to revert back up. This evidence is not observed for the OMXVX volatility index which exhibits negative coefficients. However, it is important to stress that the analysis was performed over a short time horizon ($2014-2017$) due to the limited time span of ATX options in the dataset. This is evident if we compare Table 2 and Table 3, and we note that the maximum value of both OMXVX and IBEXVX significantly decreases in the restricted time horizon considered, suggesting that important information has been lost.
Moreover, our results for the Spanish market are in line with those of Gonzalez-Perez and Novales (2011): we found that both coefficients β_7 and β_8 are positively related to the future level of IBEX-35 returns. It is worth noting that the R^2 values in our forecasting regressions are very low (except for Specification 9 of ATX) and that the proposed volatility measures can explain only a small proportion of the total variation in returns in the entire sample. However, as underlined by Fassas and Hourvouliades (2019), considering that we are evaluating future returns, these results are economically significant and potentially useful.

5 Conclusions

The main aim of this study was to outline new implied volatility indices for three financial markets, Austria, Finland and Spain, for which a volatility index is not yet available.

The proposed volatility indices act as fear indices in line with the findings for the US market (see Whaley (2009)), thus confirming their role in reporting turbulent market periods. Negative returns are associated with changes in volatility for all three markets (the leverage effect). Asymmetric effects are found in all the markets with positive changes in volatility associated with negative returns more often than negative changes in volatility being associated with positive returns (the feedback effect).

In order to account for the change in different parts of the distribution of the variables under investigation and to provide a more robust analysis in relation to our prior findings, we apply several quantile regressions on extremes quantiles of the distribution following Badshah et al. (2018), Bekiros et al. (2017), Badshah (2013).

In forecasting future returns at 30, 60 and 90 days, the corresponding volatility indices are effective with a positive sign for the Austrian and Spanish markets and with a negative sign for the Finnish market. Indeed, the Austrian and Spanish volatility indices seem to be characterized by a mean-reverting property. The results are not significant for the OMXVX volatility index. This index, however, exhibits an extremely low R-squared for all times to maturity considered suggesting that both implied and forward volatilities are insufficient to forecast future returns of the OMX25 index.

In forecasting future returns between 30 and 60 days, 60 and 90 days and 30 and 90 days, we find that it is useful to use both spot volatilities and forward implied volatilities in the Austrian and the Spanish market. In the Finnish market it is useful only for forecasting returns between 30 and 60 days.

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Conflict of interest

The authors declare that they have no conflict of interest.

Availability of data and materials

Data are obtained from the IvyDB Europe database, provided by the University of Modena and Reggio Emilia.

Code availability

The codes written by the authors are not published.

Table 5 Review of regressions analysis on the contemporaneous relationship between volatility indices and stock market returns

Author(s)	Regression equation
1)Rubbaniy et al. (2014)	$\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \epsilon_t$
2)Muzzioli (2013b)	$R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3)Whaley (2009)	$\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_2 R^-_{t,t+1} + \epsilon_t$
4)Giot (2005)	$\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+1} + \beta_3 R^+_{t,t+1} + \epsilon_t$
5)Whaley (2000)	$R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6)Muzzioli (2013b)	$R_{t,t+1} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$
7)Hibbert et al. (2008)	$\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{13} R_{t-3,t-2} + \beta_{15} \triangle\sigma_{t-1,t+j-1} + \beta_{16} \triangle\sigma_{t-2,t+j-2} + \beta_{17} \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8)Fleming et al. (1995)	$\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_9 R_{t+1,t+2} + \beta_{10} R_{t+2,t+3} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{14} \lvert R_{t,t+1} \rvert + \epsilon_t$

Note: $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $|R_{t,t+1}|$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$.

Table 6 Forecasting regressions

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

Note: $R_{t,t+j} = ln(index_{t+j}/index_t)$, is the daily return that refers to a window of j days, $\sigma_{t,t+j}$ is the daily implied volatility index at time t with maturity $t+j$ with $j = 30, 60, 90$, and $\sigma^{IFV}_{t,t+j,t+j+i}$ is the forward implied volatility between $t+j$ and $t+j+i$ with $j = 30, 60$, $i = 30, 60$.

Table 7 ATX Contemporaneous relative changes in IV indices versus stock returns

	α	$\beta_1(R_{t,t+1})$	$\beta_2(R^-_{t,t+1})$	$\beta_3(R^+_{t,t+1})$	$\beta_4(\triangle\sigma_{t,t+j})$	$\beta_5(\triangle\sigma^+_{t,t+j})$	$\beta_6(\triangle\sigma^-_{t,t+j})$	$\beta_9(R_{t+1,t+2})$	$\beta_{10}(R_{t+2,t+3})$	$\beta_{11}(R_{t-1,t})$	$\beta_{12}(R_{t-2,t-1})$	$\beta_{13}(R_{t-3,t-2})$	$\beta_{14}(\lvert R_{t,t+1}\rvert)$	$\beta_{15}(\triangle\sigma_{t-1,t+j-1})$	$\beta_{16}(\triangle\sigma_{t-2,t+j-2})$	$\beta_{17}(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	0.0006	−2.5290***															0.2721
	(0.0002)	(0.1956)															
$\triangle\sigma_{t,t+60}$	0.0004	−1.6005***															0.2501
	(0.0011)	(0.1513)															
$\triangle\sigma_{t,t+90}$	0.0004	−1.3802***															0.1766
	(0.0012)	(0.1388)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0003				−0.1076***												0.2721
	(0.0003)				(0.0079)												
$R_{t,t+1}$	0.0003				−0.1562***												0.2500
	(0.0003)				(0.0134)												
$R_{t,t+1}$	0.0003				−0.1279***												0.1766
	(0.0004)				(0.0174)												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	0.0002	−2.4811***	−0.0882														0.2721
	(0.0027)	(0.314)	(0.5996)														
$\triangle\sigma_{t,t+60}$	−0.0003	−1.5473***	−0.0980														0.2501
	(0.0019)	(0.226)	(0.4665)														
$\triangle\sigma_{t,t+90}$	−0.0010	−1.2166***	−0.3011														0.1776
	(0.0019)	(0.236)	(0.4213)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	−0.0144***		−3.3774***	−0.0414													0.1990
	(0.0025)		(0.3876)	(0.2779)													
$\triangle\sigma_{t,t+60}$	−0.0087***		−2.1476***	−0.1172													0.1853
	(0.0017)		(0.3028)	(0.2131)													
$\triangle\sigma_{t,t+90}$	−0.0080***		−1.9135***	−0.0464													0.1393
	(0.0016)		(0.2519)	(0.2043)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	0.0006				−0.0977***	−0.0185											0.2731
	(0.0005)				(0.0143)	(0.0216)											
$R_{t,t+1}$	0.0006				−0.1420***	−0.0257											0.2509
	(0.0004)				(0.0230)	(0.0359)											
$R_{t,t+1}$	0.0008				−0.1063***	−0.0422											0.1795
	(0.0006)				(0.0228)	(0.0481)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0006					−0.1161***	−0.0977***										0.2731
	(0.0005)					(0.0123)	(0.0143)										
$R_{t,t+1}$	0.0006					−0.1677***	−0.1420***										0.2509
	(0.0004)					(0.0218)	(0.0230)										
$R_{t,t+1}$	0.0008					−0.1484***	−0.1063***										0.1795
	(0.0006)					(0.0354)	(0.0228)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	0.0009	−2.5130***								−0.5637***	−0.3394**	−0.0235		−0.1809***	−0.0551	−0.0685*	0.3025
	(0.0025)	(0.1937)								(0.2021)	(0.1662)	(0.1533)		(0.0445)	(0.0379)	(0.0371)	
$\triangle\sigma_{t,t+60}$	0.0006	−1.6040***								−0.4722***	−0.1745	0.0862		−0.1209***	0.0126	0.0044	0.2733
	(0.0011)	(0.1480)								(0.1606)	(0.1169)	(0.1006)		(0.0430)	(0.0402)	(0.0338)	
$\triangle\sigma_{t,t+90}$	0.0006	−1.3847***								−0.3363***	−0.1209	0.0586		−0.0714**	0.0121	0.0202	0.1884
	(0.0012)	(0.1357)								(0.1602)	(0.1227)	(0.1007)		(0.0358)	(0.0408)	(0.0299)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	0.0009	−2.5365***						0.0599	0.0884	−0.1137	−0.1698		−0.0236				0.2759
	(0.0027)	(0.1880)						(0.1673)	(0.1531)	(0.1710)	(0.1390)		(0.2922)				
$\triangle\sigma_{t,t+60}$	0.0011	−1.5964***						−0.1228	0.0082	−0.2858**	−0.1695*		−0.05614				0.2628
	(0.0019)	(0.1420)						(0.1177)	(0.1067)	(0.1349)	(0.0971)		(0.2304)				
$\triangle\sigma_{t,t+90}$	0.0001	−1.3642***						−0.2062	0.0608	−0.2278	−0.1279		0.0548				0.1881
	(0.0018)	(0.1355)						(0.1080)	(0.1131)	(0.1406)	(0.1019)		(0.2061)				

Note: The table reports the estimated output of the regressions:
1. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_2 R^-_{t,t+1} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+1} + \beta_3 R^+_{t,t+1} + \epsilon_t$
5. $R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+1} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{13} R_{t-3,t-2} + \beta_{15} \triangle\sigma_{t-1,t+j-1} + \beta_{16} \triangle\sigma_{t-2,t+j-2} + \beta_{17} \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_9 R_{t+1,t+2} + \beta_{10} R_{t+2,t+3} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{14} \lvert R_{t,t+1}\rvert + \epsilon_t$

for the ATX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $\lvert R_{t,t+1}\rvert$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 8 OMX Contemporaneous relative changes in IV indices versus stock returns

	α	$\beta_1(R_{t,t+1})$	$\beta_2(R^-_{t,t+1})$	$\beta_3(R^+_{t,t+1})$	$\beta_4(\triangle\sigma_{t,t+j})$	$\beta_5(\triangle\sigma^+_{t,t+j})$	$\beta_6(\triangle\sigma^-_{t,t+j})$	$\beta_9(R_{t+1,t+2})$	$\beta_{10}(R_{t+2,t+3})$	$\beta_{11}(R_{t-1,t})$	$\beta_{12}(R_{t-2,t-1})$	$\beta_{13}(R_{t-3,t-2})$	$\beta_{14}(\lvert R_{t,t+1}\rvert)$	$\beta_{15}(\triangle\sigma_{t-1,t+j-1})$	$\beta_{16}(\triangle\sigma_{t-2,t+j-2})$	$\beta_{17}(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	0.0001	−1.2846***															0.1176
	0.0008	0.0883															
$\triangle\sigma_{t,t+60}$	0.0002	−0.8160***															0.0760
	0.0007	0.0750															
$\triangle\sigma_{t,t+90}$	−0.0002	−0.6705***															0.0427
	0.0007	0.0791															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0002				−0.0915***												0.1176
	0.0002				0.0081												
$R_{t,t+1}$	0.0002				−0.0932***												0.0760
	(0.0002)				(0.0117)												
$R_{t,t+1}$	0.0002				−0.0637***												0.0427
	(0.0002)				0.0094												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	0.0003	−1.3059***	0.0415														0.1176
	(0.0013)	(0.1387)	(0.2657)														
$\triangle\sigma_{t,t+60}$	0.0001	−0.8274***	0.0221														0.0760
	(0.0011)	(0.1266)	(0.2293)														
$\triangle\sigma_{t,t+90}$	−0.0007	−0.5990***	−0.1389														0.0429
	(0.0012)	(0.1382)	(0.2398)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	0.0003		−1.2644***	−1.3059***													0.1176
	(0.0013)		(0.1768)	(0.1387)													
$\triangle\sigma_{t,t+60}$	0.0001		−0.8052***	−0.8274***													0.0760
	(0.0011)		(0.1460)	(0.1266)													
$\triangle\sigma_{t,t+90}$	−0.0007		−0.7380***	−0.5990***													0.0429
	(0.0012)		(0.1484)	(0.1382)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	0.0005				−0.0827***	−0.0178											0.1184
	(0.0003)				(0.0124)	(0.0203)											
$R_{t,t+1}$	0.0003				−0.0899***	−0.0067											0.0761
	(0.0003)				(0.0179)	(0.0279)											
$R_{t,t+1}$	0.0003				−0.0584***	−0.0108											0.0430
	(0.0003)				(0.0003)	(0.0216)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0005					−0.1005***	−0.0827***										0.1184
	(0.0003)					(0.0136)	(0.0124)										
$R_{t,t+1}$	0.0003					−0.0966***	−0.0899***										0.0761
	(0.0003)					(0.0185)	(0.0179)										
$R_{t,t+1}$	0.0003					−0.0692***	−0.0584***										0.0430
	(0.0003)					(0.0151)	(0.0136)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	0.0002	−1.2852***								−0.2803***	−0.1535**	−0.1432*		−0.1572**	−0.0889***	−0.0524	0.1442
	(0.0008)	(0.0869)								(0.0871)	(0.0711)	(0.0788)		(0.0351)	(0.0300)	(0.0409)	
$\triangle\sigma_{t,t+60}$	0.0006	−0.8220***								−0.2551***	−0.1762***	0.1086		−0.1724***	−0.0399*	−0.0397	0.1077
	(0.0007)	(0.0733)								(0.0757)	(0.0535)	(0.0723)		(0.0429)	(0.0218)	(0.0318)	
$\triangle\sigma_{t,t+90}$	0.0007	−0.6686***								−0.2709***	−0.2047***	−0.1381*		−0.1780**	−0.0426	−0.0231	0.0777
	(0.0007)	(0.0774)								(0.0934)	(0.0610)	(0.0766)		(0.0484)	(0.0313)	(0.0322)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	0.0005	−1.2840***						−0.0468	0.0518	−0.0774	−0.0293		−0.0357				0.1185
	(0.0014)	(0.0869)						(0.0698)	(0.0612)	(0.0811)	(0.0571)		(0.1359)				
$\triangle\sigma_{t,t+60}$	0.0005	−0.8166***						−0.0409	0.0873	−0.1153*	−0.1254***		−0.0426				0.0807
	(0.0012)	(0.0739)						(0.0584)	(0.0590)	(0.0684)	(0.0484)		(0.1153)				
$\triangle\sigma_{t,t+90}$	−0.0003	−0.6702***						0.0123	0.0679	−0.1484*	−0.1458***		0.0323				0.0478
	(0.0012)	(0.0779)						(0.0579)	(0.0687)	(0.0799)	(0.0515)		(0.1196)				

Note: The table reports the estimated output of the regressions:
1. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_2 R^-_{t,t+1} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+1} + \beta_3 R^+_{t,t+1} + \epsilon_t$
5. $R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+1} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{13} R_{t-3,t-2} + \beta_{15} \triangle\sigma_{t-1,t+j-1} + \beta_{16} \triangle\sigma_{t-2,t+j-2} + \beta_{17} \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_9 R_{t+1,t+2} + \beta_{10} R_{t+2,t+3} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{14} \lvert R_{t,t+1}\rvert + \epsilon_t$

for the OMX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $\lvert R_{t,t+1}\rvert$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 9 IBEX Contemporaneous relative changes in IV indices versus stock returns

	α	$\beta_1(R_{t,t+1})$	$\beta_2(R^-_{t,t+1})$	$\beta_3(R^+_{t,t+1})$	$\beta_4(\triangle\sigma_{t,t+j})$	$\beta_5(\triangle\sigma^+_{t,t+j})$	$\beta_6(\triangle\sigma^-_{t,t+j})$	$\beta_9(R_{t+1,t+2})$	$\beta_{10}(R_{t+2,t+3})$	$\beta_{11}(R_{t-1,t})$	$\beta_{12}(R_{t-2,t-1})$	$\beta_{13}(R_{t-3,t-2})$	$\beta_{14}(\lvert R_{t,t+1}\rvert)$	$\beta_{15}(\triangle\sigma_{t-1,t+j-1})$	$\beta_{16}(\triangle\sigma_{t-2,t+j-2})$	$\beta_{17}(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	−0.0004	−2.3562***															0.3638
	(0.0009)	(0.0920)															
$\triangle\sigma_{t,t+60}$	−0.0003	−1.9480***															0.4929
	(0.0006)	(0.0612)															
$\triangle\sigma_{t,t+90}$	−0.0002	−1.7156***															0.3426
	(0.0008)	(0.0626)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	−0.0002				−0.1544***												0.3639
	(0.0003)				(0.0106)												
$R_{t,t+1}$	−0.0002				−0.2530***												0.4930
	(0.0002)				(0.0090)												
$R_{t,t+1}$	−0.0001				−0.1997***												0.3426
	(0.0003)				(0.0201)												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	−0.0032*	−2.0974***	−0.4872*														0.3657
	(0.0018)	(0.1441)	(0.2921)														
$\triangle\sigma_{t,t+60}$	−0.0023**	−1.7675***	−0.3399*														0.4947
	(0.0011)	(0.1049)	(0.1836)														
$\triangle\sigma_{t,t+90}$	−0.0023*	−1.5300***	−0.3483*														0.3443
	(0.0013)	(0.1244)	(0.1941)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	−0.0189***		−3.2408***	−0.0364													0.2785
	(0.0016)		0.203	(0.0964)													
$\triangle\sigma_{t,t+60}$	−0.0153***		−2.6611***	−0.0666													0.3720
	(0.0010)		(0.124)	(0.0711)													
$\triangle\sigma_{t,t+90}$	−0.0139***		−2.3629***	−0.0673													0.2630
	(0.0873)		(0.0012)	(0.1127)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	0.0008				−0.1826***	−0.0419											0.3673
	(0.0007)				(0.0229)	(0.0342)											
$R_{t,t+1}$	0.0004				−0.2347***	−0.0338											0.4940
	(0.0004)				(0.0183)	(0.0287)											
$R_{t,t+1}$	0.0003				−0.1844***	−0.0288											0.3436
	(0.0010)				(0.0364)	(0.0657)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0008					−0.1745***	−0.1326***										0.3673
	(0.0007)					(0.0164)	(0.0229)										
$R_{t,t+1}$	0.0004					−0.2685***	−0.2347***										0.4940
	(0.0004)					(0.0154)	(0.0183)										
$R_{t,t+1}$	0.0003					−0.2133***	−0.1844***										0.3436
	(0.0010)					(0.0403)	(0.0364)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	−0.0008	−2.3073***								−0.8589***	−0.1459*	−0.0038		−0.2353***	−0.0490**	0.0018	0.4153
	(0.0009)	(0.0891)								(0.1213)	(0.0831)	(0.0866)		(0.0390)	(0.0244)	(0.0248)	
$\triangle\sigma_{t,t+60}$	−0.0003	−1.9143***								−0.5686***	−0.0742	0.0135		−0.1618***	−0.0170	0.0123	0.5308
	(0.0006)	(0.0595)								(0.0838)	(0.0607)	(0.0669)		(0.0314)	(0.0231)	(0.0244)	
$\triangle\sigma_{t,t+90}$	−0.0003	−1.6914***								−0.6722***	−0.1728**	−0.0683		−0.2483***	−0.0660*	−0.0260	0.3878
	(0.0008)	(0.0618)								(0.1492)	(0.0824)	(0.0663)		(0.0798)	(0.0350)	(0.0246)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	−0.0034*	−2.3346***						0.1699**	−0.0185	−0.2929***	0.0686		0.2359				0.3869
	(0.0019)	(0.0864)						(0.0741)	(0.0699)	(0.0693)	(0.0569)		(0.1444)				
$\triangle\sigma_{t,t+60}$	−0.0021*	−1.9251***						0.1171**	−0.0290	−0.2438***	−0.1684		0.1546*				0.5220
	(0.0011)	(0.0577)						(0.0478)	(0.0490)	(0.0470)	(0.0411)		(0.0907)				
$\triangle\sigma_{t,t+90}$	−0.0019	−1.7038***						0.0721	−0.0208	−0.2405***	0.0123		0.1398				0.3518
	(0.0013)	(0.0631)						(0.0453)	(0.0471)	(0.0488)	(0.0485)		(0.0983)				

Note: The table reports the estimated output of the regressions:
1. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_2 R^-_{t,t+1} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha + \beta_2 R^-_{t,t+1} + \beta_3 R^+_{t,t+1} + \epsilon_t$
5. $R_{t,t+1} = \alpha + \beta_6 \triangle\sigma_{t,t+j} + \beta_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+1} = \alpha + \beta_7 \triangle\sigma^+_{t,t+j} + \beta_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{13} R_{t-3,t-2} + \beta_{15} \triangle\sigma_{t-1,t+j-1} + \beta_{16} \triangle\sigma_{t-2,t+j-2} + \beta_{17} \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha + \beta_1 R_{t,t+1} + \beta_9 R_{t+1,t+2} + \beta_{10} R_{t+2,t+3} + \beta_{11} R_{t-1,t} + \beta_{12} R_{t-2,t-1} + \beta_{14} |R_{t,t+1}| + \epsilon_t$

for the IBEX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $|R_{t,t+1}|$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 10 ATX Contemporaneous relative changes in IV indices versus stock returns

	α^q	$\beta^q_1(R_{t,t+1})$	$\beta^q_2(R^-_{t,t+1})$	$\beta^q_3(R^+_{t,t+1})$	$\beta^q_4(\Delta\sigma_{t,t+j})$	$\beta^q_5(\Delta\sigma^+_{t,t+j})$	$\beta^q_6(\Delta\sigma^-_{t,t+j})$	$\beta^q_9(R_{t+1,t+2})$	$\beta^q_{10}(R_{t+2,t+3})$	$\beta^q_{11}(R_{t-1,t})$	$\beta^q_{12}(R_{t-2,t-1})$	$\beta^q_{13}(R_{t-3,t-2})$	$\beta^q_{14}(\lvert R_{t,t+1}\rvert)$	$\beta^q_{15}(\Delta\sigma_{t-1,t+j-1})$	$\beta^q_{16}(\Delta\sigma_{t-2,t+j-2})$	$\beta^q_{17}(\Delta\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\Delta\sigma_{t,t+30}$	−0.0727***	−2.0402***															0.3184
	(0.0065)	(0.5227)															
$\Delta\sigma_{t,t+60}$	−0.0505***	−1.4867***															0.2866
	(0.0044)	(0.3622)															
$\Delta\sigma_{t,t+90}$	−0.0512***	−1.3845***															0.1669
	(0.0041)	(0.3466)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	−0.0167***				−0.0922***												0.2639
	(0.0012)				(0.0170)												
$R_{t,t+1}$	−0.0164***				−0.1244***												0.2726
	(0.0013)				(0.0273)												
$R_{t,t+1}$	−0.0179***				−0.1062***												0.1562
	(0.0011)				(0.0282)												
Model 3: Whaley (2009)																	
$\Delta\sigma_{t,t+30}$	−0.0551***	−4.5599***	3.2515*														0.3415
	(0.0077)	(1.0860)	(1.9459)														
$\Delta\sigma_{t,t+60}$	−0.0368***	−2.9159***	3.1688***														0.2407
	(0.0049)	(0.4279)	(0.8684)														
$\Delta\sigma_{t,t+90}$	−0.0392***	−2.3448***	2.7038***														0.1298
	(0.0051)	(0.3214)	(0.9735)														
Model 4: Giot (2005)																	
$\Delta\sigma_{t,t+30}$	−0.0925***		−2.3178*	−0.1856													0.1576
	(0.0092)		(1.3113)	(1.1624)													
$\Delta\sigma_{t,t+60}$	−0.0605***		−0.5423	−0.7023													0.0092
	(0.0056)		(0.5423)	(0.7912)													
$\Delta\sigma_{t,t+90}$	−0.0585***		−1.4644*	−1.0101													0.0235
	(0.0055)		(0.8301)	(0.8325)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	−0.0130***				−0.0415	−0.1565*											0.2819
	(0.0014)				(0.0403)	(0.0816)											
$R_{t,t+1}$	−0.0091***				0.1158*	−0.5692***											0.1468
	(0.0010)				(0.0615)	(0.1192)											
$R_{t,t+1}$	−0.0102***				0.1130	−0.5967***											0.0281
	(0.0011)				(0.0799)	(0.1280)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	−0.0130***					−0.1980***	−0.0977										0.2819
	(0.0014)					(0.0593)	(0.0403)										
$R_{t,t+1}$	−0.0091***					−0.4535***	0.1158*										0.1468
	(0.0010)					(0.0842)	(0.0614)										
$R_{t,t+1}$	−0.0102***					−0.4836***	0.1130										0.0281
	(0.0011)					(0.0795)	(0.0799)										
Model 7: Hibbert et al. (2008)																	
$\Delta\sigma_{t,t+30}$	−0.0759***	−2.0704***								−0.3996	−0.9919**	−0.2945		−0.2457***	−0.2225***	−0.2084**	0.2732
	(0.0049)	(0.3674)								(0.3516)	(0.3996)	(0.3997)		(0.0352)	(0.0842)	(0.0864)	
$\Delta\sigma_{t,t+60}$	−0.0539***	−1.2670***								−0.6202**	−0.4439	0.2113		−0.1495*	−0.0544	−0.1189	0.2129
	(0.0044)	(0.2528)								(0.2474)	(0.2761)	(0.2050)		(0.0777)	(0.0675)	(0.0817)	
$\Delta\sigma_{t,t+90}$	−0.0530***	−1.4106***								−0.2643	−0.0861	0.3080		−0.0474	−0.0327	0.0138	0.1290
	(0.0043)	(0.3171)								(0.3330)	(0.3325)	(0.3421)		(0.1017)	(0.0837)	(0.1049)	
Model 8: Fleming et al. (1995)																	
$\Delta\sigma_{t,t+30}$	−0.0591***	−3.3685***						−0.0910	0.1131	0.3539	0.2814		−1.7777*				0.2622
	(0.0084)	(0.7148)						(0.4663)	(0.4112)	(0.4183)	(0.4637)		(1.030)				
$\Delta\sigma_{t,t+60}$	−0.0336***	−1.1534***						−0.4880**	−0.3647**	−0.2552	−0.2744		−2.0129***				0.1979
	(0.0035)	(0.1587)						(0.2062)	(0.1414)	(0.1586)	(0.1744)		(0.3415)				
$\Delta\sigma_{t,t+90}$	−0.0378***	−0.9704**						−0.8238***	0.3505	−0.0.15	0.0017		−1.5593***				0.1003
	(0.0051)	(0.3909)						(0.1084)	(0.1938)	(0.2545)	(0.2481)		(0.5321)				

Note: The table reports the estimated output of the quantile regressions at the lowest quantile ($q = 0.05$):

1. $\Delta\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha^q + \beta^q_6 \Delta\sigma_{t,t+j} + \epsilon_t$
3. $\Delta\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \beta^q_2 R^-_{t,t+1} + \epsilon_t$
4. $\Delta\sigma_{t,t+j} = \alpha^q + \beta^q_2 R^-_{t,t+1} + \beta^q_3 R^+_{t,t+1} + \epsilon_t$
5. $R_{t,t+1} = \alpha^q + \beta^q_6 \Delta\sigma_{t,t+j} + \beta^q_7 \Delta\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+1} = \alpha^q + \beta^q_7 \Delta\sigma^+_{t,t+j} + \beta^q_8 \Delta\sigma^-_{t,t+j} + \epsilon_t$
7. $\Delta\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \beta^q_1 R_{t-1,t} + \beta^q_{12} R_{t-2,t-1} + \beta^q_{13} R_{t-3,t-2} + \beta^q_{15} \Delta\sigma_{t-1,t+j-1} + \beta^q_{16} \Delta\sigma_{t-2,t+j-2} + \beta^q_{17} \Delta\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\Delta\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \beta^q_9 R_{t+1,t+2} + \beta^q_{10} R_{t+2,t+3} + \beta^q_{11} R_{t-1,t} + \beta^q_{12} R_{t-2,t-1} + \beta^q_{14} |R_{t,t+1}| + \epsilon_t$

for the ATX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\Delta\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\Delta\sigma^-_{t,t+j}(\Delta\sigma^+_{t,t+j}) = \Delta\sigma_{t,t+j}$ if $\Delta\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $|R_{t,t+1}|$ is the absolute value of the contemporaneous return. $\Delta\sigma_{t-1,t+j-1}$, $\Delta\sigma_{t-2,t+j-2}$, $\Delta\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 11 ATX Contemporaneous relative changes in IV indices versus stock returns

	α^q	$\beta_1^q(R_{t,t+1})$	$\beta_2^q(R^-_{t,t+1})$	$\beta_3^q(R^+_{t,t+1})$	$\beta_4^q(\triangle\sigma_{t,t+j})$	$\beta_5^q(\triangle\sigma^+_{t,t+j})$	$\beta_6^q(\triangle\sigma^-_{t,t+j})$	$\beta_9^q(R_{t+1,t+2})$	$\beta_{10}^q(R_{t+2,t+3})$	$\beta_{11}^q(R_{t-1,t})$	$\beta_{12}^q(R_{t-2,t-1})$	$\beta_{13}^q(R_{t-3,t-2})$	$\beta_{14}^q(\lvert R_{t,t+1}\rvert)$	$\beta_{15}^q(\triangle\sigma_{t-1,t+j-1})$	$\beta_{16}^q(\triangle\sigma_{t-2,t+j-2})$	$\beta_{17}^q(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	0.0857***	−3.2838***															0.2532
	(0.0047)	(0.3133)															
$\triangle\sigma_{t,t+60}$	0.0515***	−2.0626***															0.3420
	(0.0040)	(0.2942)															
$\triangle\sigma_{t,t+90}$	0.0528***	−1.4311***															0.2350
	(0.0043)	(0.3607)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0162***				−0.0924***												0.2235
	(0.0010)				(0.0165)												
$R_{t,t+1}$	0.0160***				−0.1260***												0.2333
	(0.0010)				(0.0254)												
$R_{t,t+1}$	0.0167***				−0.1017***												0.1608
	(0.0009)				(0.0207)												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	0.0725***	−1.6855***	−3.2112*														0.2250
	(0.0077)	(0.4596)	(1.8231)														
$\triangle\sigma_{t,t+60}$	0.0368***	−0.1353	−3.2557*														0.3201
	(0.0065)	(0.9349)	(1.8224)														
$\triangle\sigma_{t,t+90}$	0.0363***	0.4234	−3.6381***														0.2070
	(0.0065)	(0.9307)	(1.7656)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	0.0574***		−6.1588***	−0.0895													0.2228
	(0.0072)		(1.2625)	(1.4320)													
$\triangle\sigma_{t,t+60}$	0.0356***		−3.4213***	0.4274													0.2881
	(0.0057)		(1.1376)	(0.6275)													
$\triangle\sigma_{t,t+90}$	0.0366***		−3.1889***	0.0172													0.2462
	(0.0060)		(1.1729)	(0.7324)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	0.0131***				−0.1656***	0.1131**											0.2613
	(0.0012)				(0.0396)	(0.0490)											
$R_{t,t+1}$	0.0117***				−0.3426***	0.3424***											0.1617
	(0.0009)				(0.0744)	(0.1051)											
$R_{t,t+1}$	0.0127***				−0.2746***	0.2648**											0.1601
	(0.0011)				(0.0822)	(0.1055)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0131***					−0.0524***	−0.1656***										0.2613
	(0.0012)					(0.0189)	(0.0396)										
$R_{t,t+1}$	0.01167***					−0.0002	−0.3426***										0.1617
	(0.0009)					(−0.0546)	(0.0744)										
$R_{t,t+1}$	0.0127***					−0.0097	−0.2746***										0.1601
	(0.0011)					(0.0460)	(0.0822)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	0.0808***	−3.2643***								−0.9898***	−0.6346***	0.1702		−0.2366***	−0.1070	−0.0557*	0.3253
	(0.0054)	(0.3044)								(0.3107)	(0.2058)	(0.3905)		(0.0752)	(0.0726)	(0.0831)	
$\triangle\sigma_{t,t+60}$	0.0512***	−2.0540***								−0.6723***	−0.2743	0.4658***		−0.1694**	0.0559	0.1199*	0.3511
	(0.0031)	(0.2075)								(0.2175)	(0.2357)	(0.1435)		(0.0758)	(0.0671)	(0.0678)	
$\triangle\sigma_{t,t+90}$	0.0506***	−1.4345***								−0.6205**	−0.2301	0.4401		−0.0711	0.0767	0.0942	0.2787
	(0.0044)	(0.3104)								(0.3092)	(0.2504)	(0.2687)		(0.0929)	(0.1011)	(0.0844)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	0.0722***	−3.3127***						0.5592	0.1552	−0.2932	−0.2473		1.1191				0.2878
	(0.0072)	(0.7040)						(0.4179)	(0.4264)	(0.3736)	(0.3676)		(0.9541)				
$\triangle\sigma_{t,t+60}$	0.0388***	−1.6702***						0.1024	−0.1181	−0.5154**	−0.5387*		1.3915**				0.3274
	(0.0056)	(0.4781)						(0.3192)	(0.2349)	(0.3327)	(0.3046)		(0.7053)				
$\triangle\sigma_{t,t+90}$	0.0402***	−1.3775**						−0.0308	0.2206	−0.5843*	−0.4299*		1.1238				0.2686
	(0.0053)	(0.6202)						(0.3172)	(0.3176)	(0.3144)	(0.2418)		(0.8813)				

Note: The table reports the estimated output of the quantile regressions at the upper-most quantile ($q = 0.95$):

1. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_2^q R^-_{t,t+1} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_2^q R^-_{t,t+1} + \beta_3^q R^+_{t,t+1} + \epsilon_t$
5. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \beta_7^q \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+1} = \alpha^q + \beta_7^q \triangle\sigma^+_{t,t+j} + \beta_8^q \triangle\sigma^-_{t,t+j} + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{13}^q R_{t-3,t-2} + \beta_{15}^q \triangle\sigma_{t-1,t+j-1} + \beta_{16}^q \triangle\sigma_{t-2,t+j-2} + \beta_{17}^q \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_9^q R_{t+1,t+2} + \beta_{10}^q R_{t+2,t+3} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{14}^q \lvert R_{t,t+1}\rvert + \epsilon_t$

for the ATX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $\lvert R_{t,t+1}\rvert$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 12 OMX Contemporaneous relative changes in IV indices versus stock returns

	α^q	$\beta_1^q(R_{t,t+1})$	$\beta_2^q(R^-_{t,t+1})$	$\beta_3^q(R^+_{t,t+1})$	$\beta_4^q(\triangle\sigma_{t,t+j})$	$\beta_5^q(\triangle\sigma^+_{t,t+j})$	$\beta_6^q(\triangle\sigma^-_{t,t+j})$	$\beta_9^q(R_{t+1,t+2})$	$\beta_{10}^q(R_{t+2,t+3})$	$\beta_{11}^q(R_{t-1,t})$	$\beta_{12}^q(R_{t-2,t-1})$	$\beta_{13}^q(R_{t-3,t-2})$	$\beta_{14}^q(\lvert R_{t,t+1}\rvert)$	$\beta_{15}^q(\triangle\sigma_{t-1,t+j-1})$	$\beta_{16}^q(\triangle\sigma_{t-2,t+j-2})$	$\beta_{17}^q(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	−0.0575***	−1.2718***															0.1842
	(0.0030)	(0.2090)															
$\triangle\sigma_{t,t+60}$	−0.0398***	−0.8736***															0.1556
	(0.0026)	(0.1507)															
$\triangle\sigma_{t,t+90}$	−0.0453***	−0.8128***															0.1205
	(0.0033)	(0.2265)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	−0.0216***				−0.0885***												0.1318
	(0.0008)				(0.0129)												
$R_{t,t+1}$	−0.0217***				−0.0923***												0.1127
	(0.0008)				(0.0097)												
$R_{t,t+1}$	−0.0227***				−0.0534***												0.0470
	(0.0008)				(0.0078)												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	−0.0407***	−3.5293***	3.4655***														0.1172
	(0.0041)	(0.5131)	(0.7135)														
$\triangle\sigma_{t,t+60}$	−0.0287***	−2.4793***	2.5448***														0.0625
	(0.0030)	(0.3816)	(0.5868)														
$\triangle\sigma_{t,t+90}$	−0.0325***	−2.2830***	2.2958***														0.0975
	(0.0047)	(0.5893)	(0.7705)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	−0.0407***		−0.0638	−3.5293***													0.1172
	(0.0041)		(0.3444)	(0.5131)													
$\triangle\sigma_{t,t+60}$	−0.0287***		0.0655	−2.4793***													0.0625
	(0.0030)		(0.3306)	(0.3816)													
$\triangle\sigma_{t,t+90}$	−0.0325***		0.0128	−2.2830***													0.0975
	(0.0047)		(0.3269)	(0.5893)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	−0.0137***				0.0045	−0.3738***											0.1463
	(0.0006)				(0.0074)	(0.0157)											
$R_{t,t+1}$	−0.0141***				0.0344	−0.5805***											0.1160
	(0.0008)				(0.0504)	(0.0713)											
$R_{t,t+1}$	−0.0168***				0.0289**	−0.4736***											0.0798
	(0.0007)				(0.0120)	(0.0696)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	−0.0137***					−0.3693***	0.045										0.1463
	(0.0006)					(0.0128)	(0.0074)										
$R_{t,t+1}$	−0.0141***					−0.5461***	0.0344										0.0116
	(0.0008)					(0.0412)	(0.0504)										
$R_{t,t+1}$	−0.0168***					−0.4447***	0.0289**										0.0798
	(0.0007)					(0.0662)	(0.0110)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	−0.060***	−1.1574***								−0.4701*	−0.0905	−0.2009		−0.1978***	−0.0851***	−0.1008***	0.1516
	(0.0033)	(0.1810)								(0.1993)	(0.1724)	(0.1758)		(0.0576)	(0.0307)	(0.0470)	
$\triangle\sigma_{t,t+60}$	−0.0408***	−0.7739***								−0.2508	−0.1831	−0.1989		−0.1334**	−0.0542	−0.0949	0.1507
	(0.0029)	(0.1512)								(0.1686)	(0.1555)	(0.11538)		(0.0555)	(0.0570)	(0.0413)	
$\triangle\sigma_{t,t+90}$	−0.0463***	−0.6537***								−0.1618	−0.2381	0.3399		−0.1341***	−0.0472	0.1075	0.0618
	(0.0041)	(0.2103)								(0.2081)	(0.1993)	(0.2262)		(0.0174)	(0.0588)	(0.0691)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	−0.0403***	−1.8390***						−0.2240	−0.1657	−0.1393	0.0258		−1.6556***				0.1363
	(0.0041)	(0.2679)						(0.1943)	(0.1953)	(0.1944)	(0.2007)		(0.3898)				
$\triangle\sigma_{t,t+60}$	−0.0284***	−1.1841***						−0.0696	0.1117	−0.1612	−0.0995		−1.2482***				0.0839
	(0.0032)	(0.2026)						(0.1416)	(0.1391)	(0.1115)	(0.1479)		(0.2944)				
$\triangle\sigma_{t,t+90}$	−0.0333***	−1.1517***						−0.0288	0.0357	0.0302	−0.1917		−1.1525***				0.0301
	(0.0048)	(0.2481)						(0.1674)	(0.2205)	(0.1779)	(0.1843)		(0.3699)				

Note: The table reports the estimated output of the quantile regressions at the lowest quantile ($q = 0.05$):

1. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_2^q R^-_{t,t+1} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_2^q R^-_{t,t+1} + \beta_3^q R^+_{t,t+1} + \epsilon_t$
5. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \beta_7^q \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+1} = \alpha^q + \beta_7^q \triangle\sigma^+_{t,t+j} + \beta_8^q \triangle\sigma^-_{t,t+j} + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{13}^q R_{t-3,t-2} + \beta_{15}^q \triangle\sigma_{t-1,t+j-1} + \beta_{16}^q \triangle\sigma_{t-2,t+j-2} + \beta_{17}^q \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_9^q R_{t+1,t+2} + \beta_{10}^q R_{t+2,t+3} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{14}^q \lvert R_{t,t+1}\rvert + \epsilon_t$

for the OMX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0\ (> 0)$, zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $\lvert R_{t,t+1}\rvert$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 13 OMX Contemporaneous relative changes in IV indices versus stock returns

	α^q	$\beta_1^q(R_{t,t+1})$	$\beta_2^q(R_{t,t+1}^-)$	$\beta_3^q(R_{t,t+1}^+)$	$\beta_4^q(\triangle\sigma_{t,t+j})$	$\beta_5^q(\triangle\sigma_{t,t+j}^+)$	$\beta_6^q(\triangle\sigma_{t,t+j}^-)$	$\beta_9^q(R_{t+1,t+2})$	$\beta_{10}^q(R_{t+2,t+3})$	$\beta_{11}^q(R_{t-1,t})$	$\beta_{12}^q(R_{t-2,t-1})$	$\beta_{13}^q(R_{t-3,t-2})$	$\beta_{14}^q(\lvert R_{t,t+1}\rvert)$	$\beta_{15}^q(\triangle\sigma_{t-1,t+j-1})$	$\beta_{16}^q(\triangle\sigma_{t-2,t+j-2})$	$\beta_{17}^q(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	0.0611***	−1.4144***															0.1350
	(0.0035)	(0.1855)															
$\triangle\sigma_{t,t+60}$	0.0445***	−0.8964***															0.0983
	(0.0026)	(0.1786)															
$\triangle\sigma_{t,t+90}$	0.0461***	−0.8423***															0.0738
	(0.0025)	(0.1709)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0203***				−0.0776***												0.1059
	(0.0006)				(0.0113)												
$R_{t,t+1}$	0.0208***				−0.0554***												0.0630
	(0.0007)				(0.0155)												
$R_{t,t+1}$	0.0211***				−0.0480***												0.0362
	(0.0006)				(0.0108)												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	0.0449***	−0.4671	−2.7859***														0.1290
	(0.0043)	(0.3815)	(0.7224)														
$\triangle\sigma_{t,t+60}$	0.0321***	0.0427	−2.2691***														0.0773
	(0.0035)	(0.2839)	(0.6910)														
$\triangle\sigma_{t,t+90}$	0.0352***	0.1173	−2.3323**														0.0180
	(0.0038)	(0.5471)	(0.9746)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	0.0449***		−3.2530***	−0.4671													0.1290
	(0.0043)		(0.4948)	(0.3815)													
$\triangle\sigma_{t,t+60}$	0.0321***		−2.2264***	0.0427													0.0773
	(0.0035)		(0.5380)	(0.2839)													
$\triangle\sigma_{t,t+90}$	0.0352***		−2.2150***	0.1173													0.0180
	(0.0038)		(0.6410)	(0.5471)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	0.0140***				−0.3721***	0.3671***											0.0080
	(0.0007)				(0.0273)	(0.0342)											
$R_{t,t+1}$	0.0139***				−0.5190***	0.5276***											0.0785
	(0.0007)				(0.0457)	(0.0529)											
$R_{t,t+1}$	0.0167***				−0.3697***	0.3850***											0.0945
	(0.0007)				(0.0571)	(0.0611)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0140***					−0.0050	−0.3721***										0.0080
	(0.0007)					(0.0156)	(0.0273)										
$R_{t,t+1}$	0.0139***					0.0086	−0.5190***										0.0785
	(0.0007)					(0.0193)	(0.0457)										
$R_{t,t+1}$	0.0167***					0.0153	−0.3697***										0.0945
	(0.0007)					(0.0139)	(0.0571)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	0.0629***	−1.47660***								−0.6235***	−0.2536	−0.2586		−0.1139**	−0.1173**	−0.0642	0.1146
	(0.0036)	(0.1921)								(0.1751)	(0.2032)	(0.2065)		(0.0392)	(0.0574)	(0.0479)	
$\triangle\sigma_{t,t+60}$	0.0447***	−0.9651***								−0.4611***	−0.1791	−0.0907		−0.1898***	−0.0152	−0.0417	0.1141
	(0.0026)	(0.1516)								(0.1499)	(0.1515)	(0.1587)		(0.0566)	(0.0506)	(0.0430)	
$\triangle\sigma_{t,t+90}$	0.0477***	−0.8865***								−0.4384***	−0.2649***	−0.0515		−0.1869**	0.0352	0.0365	0.0624
	(0.0029)	(0.0996)								(0.1036)	(0.0758)	(0.1467)		(0.0527)	(0.0302)	(0.0404)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	0.0476***	−1.8078***						0.2506	0.2419	−0.5280***	0.1172		1.2001***				0.1146
	(0.0038)	(0.1784)						(0.1819)	(0.1870)	(0.1870)	(0.1686)		(0.2395)				
$\triangle\sigma_{t,t+60}$	0.0343***	−1.0931***						0.0154	0.2522**	−0.3995**	−0.2431**		1.1236***				0.0292
	(0.0035)	(0.1979)						(0.1223)	(0.1158)	(0.1615)	(0.1058)		(0.2697)				
$\triangle\sigma_{t,t+90}$	0.0372***	−0.9839***						0.1095	0.2437	−0.3744***	−0.2188		1.0993***				0.0030
	(0.0039)	(0.2627)						(0.1510)	(0.1806)	(0.1119)	(0.1754)		(0.3783)				

Note: The table reports the estimated output of the quantile regressions at the upper-most quantile ($q = 0.95$):
1. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_2^q R_{t,t+1}^- + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_2^q R_{t,t+1}^- + \beta_3^q R_{t,t+1}^+ + \epsilon_t$
5. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \beta_7^q \triangle\sigma_{t,t+j}^+ + \epsilon_t$
6. $R_{t,t+1} = \alpha^q + \beta_7^q \triangle\sigma_{t,t+j}^+ + \beta_8^q \triangle\sigma_{t,t+j}^- + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{13}^q R_{t-3,t-2} + \beta_{15}^q \triangle\sigma_{t-1,t+j-1} + \beta_{16}^q \triangle\sigma_{t-2,t+j-2} + \beta_{17}^q \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_9^q R_{t+1,t+2} + \beta_{10}^q R_{t+2,t+3} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{14}^q \lvert R_{t,t+1}\rvert + \epsilon_t$

for the OMX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R_{t,t+1}^-$ ($R_{t,t+1}^+$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma_{t,t+j}^-(\triangle\sigma_{t,t+j}^+) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $\lvert R_{t,t+1}\rvert$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 14 IBEX Contemporaneous relative changes in IV indices versus stock returns

	α^q	$\beta^q_1(R_{t,t+1})$	$\beta^q_2(R^-_{t,t+1})$	$\beta^q_3(R^+_{t,t+1})$	$\beta^q_4(\triangle\sigma_{t,t+j})$	$\beta^q_5(\triangle\sigma^+_{t,t+j})$	$\beta^q_6(\triangle\sigma^-_{t,t+j})$	$\beta^q_9(R_{t+1,t+2})$	$\beta^q_{10}(R_{t+2,t+3})$	$\beta^q_{11}(R_{t-1,t})$	$\beta^q_{12}(R_{t-2,t-1})$	$\beta^q_{13}(R_{t-3,t-2})$	$\beta^q_{14}(\lvert R_{t,t+1}\rvert)$	$\beta^q_{15}(\triangle\sigma_{t-1,t+j-1})$	$\beta^q_{16}(\triangle\sigma_{t-2,t+j-2})$	$\beta^q_{17}(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	-0.0722^{***}	-2.3516^{***}															0.4044
	(0.0029)	(0.1772)															
$\triangle\sigma_{t,t+60}$	-0.0484^{***}	-1.8516^{***}															0.5104
	(0.0018)	(0.1034)															
$\triangle\sigma_{t,t+90}$	-0.0508^{***}	-1.6423^{***}															0.4136
	(0.0021)	(0.1245)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	-0.0193^{***}				-0.1656^{***}												0.4177
	(0.0008)				(0.0121)												
$R_{t,t+1}$	-0.0177^{***}				-0.2705^{***}												0.5185
	(0.0006)				(0.0134)												
$R_{t,t+1}$	-0.0208^{***}				-0.2201^{***}												0.3838
	(0.0009)				(0.0161)												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	-0.0604^{***}	-3.3615^{***}	1.8576^{***}														0.4017
	(0.0045)	(0.4039)	(0.6807)														
$\triangle\sigma_{t,t+60}$	-0.0399^{***}	-2.7408^{***}	1.3137^{***}														0.5107
	(0.0019)	(0.0788)	(0.2262)														
$\triangle\sigma_{t,t+90}$	-0.0414^{***}	-2.5185^{***}	1.2750^{***}														0.4266
	(0.0029)	(0.1760)	(0.3257)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	-0.0979^{***}		-2.9774^{***}	-0.0601													0.2721
	(0.0043)		(0.4228)	(0.2740)													
$\triangle\sigma_{t,t+60}$	-0.0698^{***}		-2.3174^{***}	-0.3168													0.3162
	(0.0027)		(0.1573)	(0.2010)													
$\triangle\sigma_{t,t+90}$	-0.0704^{***}		-2.0499^{***}	-0.3222													0.2400
	(0.0035)		(0.1656)	(0.4682)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	-0.0126^{***}				-0.0196	-0.2831^{***}											0.3994
	(0.0008)				(0.0209)	(0.0375)											
$R_{t,t+1}$	-0.0114^{***}				-0.1116^{***}	-0.3277^{***}											0.5273
	(0.0008)				(0.0354)	(0.0692)											
$R_{t,t+1}$	-0.0119^{***}				-0.0283	-0.4583^{***}											0.3636
	(0.0008)				(0.0236)	(0.0390)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	-0.0126^{***}					-0.3027^{***}	-0.0196										0.3994
	(0.0008)					(0.0243)	(0.0209)										
$R_{t,t+1}$	-0.0114^{***}					-0.4393^{***}	-0.1116^{***}										0.5273
	(0.0008)					(0.0481)	(0.0354)										
$R_{t,t+1}$	-0.0119^{***}					-0.4866^{***}	0.0283										0.3636
	(0.0008)					(0.0240)	(0.0236)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	-0.0728^{***}	-2.3181^{***}								-0.6929^{***}	-0.0333	-0.0111		-0.1517^{***}	-0.0107	0.0291	0.4391
	(0.0030)	(0.1358)								(0.1806)	(0.1826)	(0.1999)		(0.0502)	(0.0553)	(0.0494)	
$\triangle\sigma_{t,t+60}$	-0.0477^{***}	-1.7883^{***}								-0.4037^{***}	-0143	-0.0068		-0.1518^{***}	-0.0217	0.0164	0.5341
	(0.0018)	(0.1003)								(0.1372)	(0.1181)	(0.0955)		(0.0485)	(0.0503)	(0.0293)	
$\triangle\sigma_{t,t+90}$	-0.0511^{***}	-1.6787^{***}								-0.5346^{***}	-0.2593	-0.0342		-0.1757^{***}	-0.0937^{*}	-0.0603	0.4275
	(0.0022)	(0.0967)								(0.1548)	(0.1590)	(0.1730)		(0.0561)	(0.0529)	(0.0638)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	-0.0647^{***}	-2.4420^{***}						0.2666*	-0.2158	-0.3412^{***}	0.0012		-0.5216^{**}				0.4438
	(0.0044)	(0.1875)						(0.1441)	(0.1325)	(0.1090)	(0.1460)		(0.2536)				
$\triangle\sigma_{t,t+60}$	-0.0394^{***}	-1.9894^{***}						0.1673**	0.07572	-0.1850^{***}	0.0394		-0.5926^{***}				0.5365
	(0.0023)	(0.0775)						(0.0756)	(0.0758)	(0.0704)	(0.0795)		(0.1260)				
$\triangle\sigma_{t,t+90}$	-0.0415^{***}	-1.8262^{***}						-0.0600	-0.0474	-0.1866^{*}	0.0381		-0.6271^{***}				0.4326
	(0.0026)	(0.0998)						(0.0817)	(0.0900)	(0.0956)	(0.0998)		(0.1466)				

Note: The table reports the estimated output of the quantile regressions at the lowest quantile ($q = 0.05$):

1. $\triangle\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha^q + \beta^q_6 \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \beta^q_2 R^-_{t,t+1} + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha^q + \beta^q_2 R^-_{t,t+1} + \beta^q_3 R^+_{t,t+1} + \epsilon_t$
5. $R_{t,t+1} = \alpha^q + \beta^q_6 \triangle\sigma_{t,t+j} + \beta^q_7 \triangle\sigma^+_{t,t+j} + \epsilon_t$
6. $R_{t,t+1} = \alpha^q + \beta^q_7 \triangle\sigma^+_{t,t+j} + \beta^q_8 \triangle\sigma^-_{t,t+j} + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \beta^q_{11} R_{t-1,t} + \beta^q_{12} R_{t-2,t-1} + \beta^q_{13} R_{t-3,t-2} + \beta^q_{15} \triangle\sigma_{t-1,t+j-1} + \beta^q_{16} \triangle\sigma_{t-2,t+j-2} + \beta^q_{17} \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha^q + \beta^q_1 R_{t,t+1} + \beta^q_9 R_{t+1,t+2} + \beta^q_{10} R_{t+2,t+3} + \beta^q_{11} R_{t-1,t} + \beta^q_{12} R_{t-2,t-1} + \beta^q_{14} \lvert R_{t,t+1}\rvert + \epsilon_t$

for the IBEX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R^-_{t,t+1}$ ($R^+_{t,t+1}$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma^-_{t,t+j}(\triangle\sigma^+_{t,t+j}) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $\lvert R_{t,t+1}\rvert$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 15 IBEX Contemporaneous relative changes in IV indices versus stock returns

	α^q	$\beta_1^q(R_{t,t+1})$	$\beta_2^q(R_{t,t+1}^-)$	$\beta_3^q(R_{t,t+1}^+)$	$\beta_4^q(\triangle\sigma_{t,t+j})$	$\beta_5^q(\triangle\sigma_{t+j,t+j}^+)$	$\beta_6^q(\triangle\sigma_{t+j,t+j}^-)$	$\beta_9^q(R_{t+1,t+2})$	$\beta_{10}^q(R_{t+2,t+3})$	$\beta_{11}^q(R_{t-1,t})$	$\beta_{12}^q(R_{t-2,t-1})$	$\beta_{13}^q(R_{t-3,t-2})$	$\beta_{14}^q(\lvert R_{t,t+1}\rvert)$	$\beta_{15}^q(\triangle\sigma_{t-1,t+j-1})$	$\beta_{16}^q(\triangle\sigma_{t-2,t+j-2})$	$\beta_{17}^q(\triangle\sigma_{t-3,t+j-3})$	R^2
Model 1: Rubbaniy et al. (2014)																	
$\triangle\sigma_{t,t+30}$	0.0741***	−2.5597***															0.4143
	(0.0035)	(0.2090)															
$\triangle\sigma_{t,t+60}$	0.0528***	−2.1028***															0.4718
	(0.0022)	(0.1335)															
$\triangle\sigma_{t,t+90}$	0.0550***	−1.7888***															0.4193
	(0.0029)	(0.1727)															
Model 2: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0187***				−0.1488***												0.4173
	(0.0008)				(0.0090)												
$R_{t,t+1}$	0.0175***				−0.2451***												0.5051
	(0.0006)				(0.0103)												
$R_{t,t+1}$	0.0199***				−0.1682***												0.3960
	(0.0008)				(0.0029)												
Model 3: Whaley (2009)																	
$\triangle\sigma_{t,t+30}$	0.0604***	−1.7480***	−2.0698***														0.4229
	(0.0033)	(0.2731)	(0.3536)														
$\triangle\sigma_{t,t+60}$	0.0389***	−1.2761***	−1.9132***														0.4965
	(0.0025)	(0.2308)	(0.2468)														
$\triangle\sigma_{t,t+90}$	0.0432***	−1.0743**	−1.7819**														0.4213
	(0.0035)	(0.4455)	(0.7029)														
Model 4: Giot (2005)																	
$\triangle\sigma_{t,t+30}$	0.0523***		−4.0844***	−0.1004													0.3711
	(0.0035)		(0.3082)	(0.2714)													
$\triangle\sigma_{t,t+60}$	0.0332***		−3.4983***	−0.0337													0.4210
	(0.0024)		(0.1943)	(0.2480)													
$\triangle\sigma_{t,t+90}$	0.0343***		−3.2355***	0.3266													0.3725
	(0.0026)		(0.3833)	(0.2551)													
Model 5: Whaley (2000)																	
$R_{t,t+1}$	0.0121***				−0.3560***	0.3265***											0.3082
	(0.0008)				(0.0369)	(0.0487)											
$R_{t,t+1}$	0.0123***				−0.4472***	0.3217***											0.4689
	(0.0007)				(0.0365)	(0.0486)											
$R_{t,t+1}$	0.0125***				−0.4684***	0.4547***											0.3141
	(0.0009)				(0.0419)	(0.0564)											
Model 6: Muzzioli (2013b)																	
$R_{t,t+1}$	0.0121***					−0.0294	−0.3560***										0.3082
	(0.0008)					(0.0208)	(0.0369)										
$R_{t,t+1}$	0.01230***					−0.1256***	0.4472***										0.4689
	(0.0007)					(0.0215)	(0.0365)										
$R_{t,t+1}$	0.0125***					−0.0137	−0.4684										0.3141
	(0.0009)					(0.0255)	(0.0419)										
Model 7: Hibbert et al. (2008)																	
$\triangle\sigma_{t,t+30}$	0.0739***	−2.4707***								−1.1642***	−0.5511***	−0.1210		−0.3152***	−0.1288***	−0.0022	0.4377
	(0.0027)	(0.1549)								(0.1582)	(0.1848)	(0.1525)		(0.0375)	(0.0495)	(0.0474)	
$\triangle\sigma_{t,t+60}$	0.0516***	−1.9980***								−0.8234***	−0.2681*	−0.0206		−0.1996***	0.0048	0.0874	0.4978
	(0.0019)	(0.0947)								(0.1176)	(0.1391)	(0.1459)		(0.0514)	(0.0538)	(0.0538)	
$\triangle\sigma_{t,t+90}$	0.0542***	−1.8507***								−0.7802***	−0.3353**	−0.0753		−0.2240***	−0.1027	0.0539	0.4401
	(0.0026)	(0.0903)								(0.1535)	(0.1482)	(0.1177)		(0.0599)	(0.0524)	(0.0520)	
Model 8: Fleming et al. (1995)																	
$\triangle\sigma_{t,t+30}$	0.0601***	−2.7621***						0.0133	−0.1201	−0.5445***	0.1025		0.9345***				0.4508
	(0.0032)	(0.1413)						(0.1310)	(0.1331)	(0.1172)	(0.1398)		(0.1927)				
$\triangle\sigma_{t,t+60}$	0.0391***	−2.1808***						0.1042	−0.2619**	−0.4385***	−0.0745		0.8845***				0.5088
	(0.0025)	(0.1087)						(0.1056)	(0.1066)	(0.1002)	(0.1017)		(0.1581)				
$\triangle\sigma_{t,t+90}$	0.0423***	−1.9329***						0.1684	−0.1600	−0.3440***	0.1228		0.8825***				0.4383
	(0.0031)	(0.1771)						(0.1201)	(0.1287)	(0.1269)	(0.1299)		(0.2639)				

Note: The table reports the estimated output of the quantile regressions at the upper-most quantile ($q = 0.95$):
1. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \epsilon_t$
2. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \epsilon_t$
3. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_2^q R_{t,t+1}^- + \epsilon_t$
4. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_2^q R_{t,t+1}^- + \beta_3^q R_{t,t+1}^+ + \epsilon_t$
5. $R_{t,t+1} = \alpha^q + \beta_6^q \triangle\sigma_{t,t+j} + \beta_7^q \triangle\sigma_{t,t+j}^+ + \epsilon_t$
6. $R_{t,t+1} = \alpha^q + \beta_7^q \triangle\sigma_{t,t+j}^+ + \beta_8^q \triangle\sigma_{t,t+j}^- + \epsilon_t$
7. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{13}^q R_{t-3,t-2} + \beta_{15}^q \triangle\sigma_{t-1,t+j-1} + \beta_{16}^q \triangle\sigma_{t-2,t+j-2} + \beta_{17}^q \triangle\sigma_{t-3,t+j-3} + \epsilon_t$
8. $\triangle\sigma_{t,t+j} = \alpha^q + \beta_1^q R_{t,t+1} + \beta_9^q R_{t+1,t+2} + \beta_{10}^q R_{t+2,t+3} + \beta_{11}^q R_{t-1,t} + \beta_{12}^q R_{t-2,t-1} + \beta_{14}^q \lvert R_{t,t+1}\rvert + \epsilon_t$

for the IBEX stock returns and volatility. $R_{t,t+1}$ is the daily return. $\triangle\sigma_{t,t+j}$ is the daily change in the volatility index with time to maturity $j = 30, 60, 90$. $R_{t,t+1}^-$ ($R_{t,t+1}^+$) is equal to the return if the return is negative (positive), zero otherwise. Similarly, $\triangle\sigma_{t,t+j}^-(\triangle\sigma_{t,t+j}^+) = \triangle\sigma_{t,t+j}$ if $\triangle\sigma_{t,t+j} < 0$ (> 0), zero otherwise, indicates the negative (positive) changes in volatility. $R_{t+1,t+2}$ and $R_{t+2,t+3}$ are the one-, two-day lead return. $R_{t-1,t}$, $R_{t-2,t-1}$ and $R_{t-3,t-2}$ are the one-, two- and three-day lagged returns in the index. $\lvert R_{t,t+1}\rvert$ is the absolute value of the contemporaneous return. $\triangle\sigma_{t-1,t+j-1}$, $\triangle\sigma_{t-2,t+j-2}$, $\triangle\sigma_{t-3,t+j-3}$ are the one-, two- and three-day lag changes in the volatility index with time to maturity $j = 30, 60, 90$. 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 16 Models 9 and 10 : 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 9				
$R_{0,30}$	-0.1151^{***}	0.6239^{***}		0.1777
	(0.0080)	(0.0400)		
$R_{0,60}$	-0.2034^{***}	1.1137^{***}		0.2248
	(0.0109)	(0.0530)		
$R_{0,90}$	-0.1712^{***}	0.9728^{***}		0.1503
	(0.0147)	(0.0707)		
Model 10				
$R_{0,30}$	-0.0602^{***}	0.3469^{***}	0.6141^{***}	0.0440
	(0.0099)	(0.0484)	(0.1061)	
$R_{0,60}$	0.0167	-0.0412	-0.2840^{***}	0.0084
	(0.0109)	(0.0513)	(0.0705)	
$R_{0,90}$	-0.0518^{***}	0.3416^{***}	0.2314^{***}	0.0228
	(0.0149)	(0.0722)	(0.0705)	
Panel II: OMX				
Model 9				
$R_{0,30}$	0.01799^{***}	-0.0586^{***}		0.0066
	(0.0029)	(0.0145)		
$R_{0,60}$	0.0315^{***}	-0.0981^{***}		0.0081
	(0.0040)	(0.0202)		
$R_{0,90}$	0.0476^{***}	-0.1473^{***}		0.0116
	(0.0050)	(0.0246)		
Model 10				
$R_{0,30}$	0.0152^{***}	-0.0455^{***}	-0.1947^{***}	0.0046
	(0.0028)	(0.0135)	(0.0662)	
$R_{0,60}$	0.0163^{***}	-0.0501^{***}	-0.1106	0.0045
	(0.0033)	(0.0159)	(0.1204)	
$R_{0,90}$	0.0298^{***}	-0.0893^{***}	0.0262	0.0074
	(0.0044)	(0.0214)	(0.0860)	
Panel III: IBEX				
Model 9				
$R_{0,30}$	-0.0299^{***}	0.0987^{***}		0.0186
	(0.0042)	(0.0164)		
$R_{0,60}$	-0.0652^{***}	0.2174^{***}		0.0345
	(0.0062)	(0.0234)		
$R_{0,90}$	-0.0771^{***}	0.2477^{***}		0.0267
	(0.0096)	(0.0352)		
Model 10				
$R_{0,30}$	-0.0353^{**}	0.1192^{***}	0.1747^{**}	0.0193
	(0.0048)	(0.0179)	(0.0803)	
$R_{0,60}$	-0.0157^{***}	0.0471^{**}	0.6781^{***}	0.0184
	(0.0057)	(0.0206)	(0.1010)	
$R_{0,90}$	-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. Where $R_{t,t+j} = ln(index_{t+j}/index_t)$, is the daily return that refers to a window of j days, and $\sigma_{t,t+j}$ is the daily implied volatility index at time t with maturity $t+j$ with $j = 30, 60, 90$. 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.

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