Towards new volatility measures for the EU stock market

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Abstract

This paper analyzes the role of the VSTOXX volatility index as a measure of risk for the EU stock market. Employing daily data from 2007 to 2017, we study and contrast the properties of the VSTOXX index in various market conditions. Moreover, to investigate the information content of each country-specific index for the VSTOXX, we exploit the Ordered Weighted Averaging (OWA) operator, which provides a flexible aggregation procedure ranging between the minimum and the maximum of the input values.

The VSTOXX index can correctly measure the volatility risk only for France and Germany, while the results depend on the period under investigation for the other countries. Moreover, VSTOXX acted more like an OR-like measure than an AND-like measure of volatility for the EU stock markets and represented an average for the EU volatility only during periods of extreme volatility.

Keywords

Volatility indices, EU markets, OWA aggregation, uncertainty

1. Introduction

This paper investigates the role of the VSTOXX volatility index as a measure of risk for the EU stock market. Despite many studies highlight the importance of using option-implied measures in asset pricing and portfolio management (see, e.g., [1]), and in measuring market-wide risk [2], such as consumption disasters [3], only a few countries (mainly from northern and central Europe, the most developed ones) adopt a volatility index traded in the internal stock market. Moreover, none of the EU financial markets is provided with a more advanced index to measure market risk.

Nowadays, the only option-implied index based on various EU markets is the VSTOXX index. The VSTOXX, officially Euro Stoxx 50 Volatility Index, is referred to as the "European VIX" since it represents the equivalent of the VIX index for the European markets [4], and it is the most widely used measure of expected volatility in Europe [5]. The VSTOXX is designed to reflect the investor sentiment and overall EU economic uncertainty by measuring the 30-day implied volatility of the EURO STOXX 50, using near-term Euro Stoxx 50 option prices. The EURO STOXX 50 Index is the most widely followed benchmark to track equity market performance and development in the Eurozone. The Dow Jones EURO STOXX 50 Index comprises fifty of the largest and most liquid stocks covering Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain [6].

Although the VSTOXX is generally accepted as the leading market indicator on risk sentiment in the Eurozone (see, e.g., [7]; [8]) and some studies provide empirical evidence supporting the importance of VSTOXX as a measure of risk for the EU stock market (see, e.g., [9]; [10]), it has received many criticisms in the literature. First, there is mixed evidence about its importance in stock pricing exercises in the EU market. Second, ref. [5] points out that EURO STOXX 50 companies account for less than 35% of the European stock market value. Third, important EU financial markets such as the UK and Switzerland are not considered in the EURO STOXX 50 index, even if many studies (see e.g., [11])

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find significant interactions between these markets, especially before the campaign for the EU referendum started in January 2016. Fourth, the VSTOXX is most often characterized by a non-quick response to shocks of non-equity market origin, and it is not an ideal hedge for specific sectors of the stock market [12]. Finally, ref. [13] provides evidence that VSTOXX reacts to the German unemployment rate and ESI (Economic sentiment indicator) release, but not the release of the corresponding economic indicators for the Eurozone, thus casting doubt on the VSTOXX ability to capture volatility risk in the whole EU market.

In addition, two countries if combined (France and Germany) make up more than 50% of the Eurostoxx 50 index in terms of capitalization during the 2007-2017 period. This observation could raise further doubts about the ability of the VSTOXX to reflect the investor sentiment and the overall EU economic uncertainty for all European markets, especially the peripheral ones. More specifically, the EU markets show heterogeneous behaviors during the last decade. For instance, the Italian stock market recorded many left-tail events during the 2008–2012 period due to the effects of both the subprime crisis and the European debt crisis, and was characterized by the highest level of volatility among major European market indices [14]. On the other hand, other European markets (e.g., Germany and France) have been characterized by a more resilient equity market and a rapid recovery after the crises. This heterogeneity could compromise the VSTOXX to act as a proper volatility measure for all European countries. Since there is a lack of studies investigating the behavior of the VSTOXX index as a measure of risk for all the EU markets, we aim to fill this void.

We contribute to the literature in many respects. First, we introduce model-free implied volatility indices for nine index options markets in the EU during the 2007-2017 period. The index options markets under investigation include AEX (The Netherlands), BEL (Belgium), CAC (France), DAX (Germany), FTSE (the United Kingdom), IBEX (Spain), MIB (Italy), OMX (Sweden), and SMI (Switzerland). The sample period is a suitable framework to investigate the behavior of implied volatility measures because it is characterized by the occurrence of both the subprime crisis (2008-2009) and the European debt crisis (2011-2012). Second, the occurrence of high-volatility periods in the sample allows us to investigate and contrast the properties of the VSTOXX index in various market conditions and economies under stress, such as EU peripheral countries. Third, we provide for the first time a deep analysis of the relationship between the VSTOXX and the country-specific volatility indices computed from major EU economies and their behavior over time. To investigate the information content of each country-specific index for the VSTOXX, we exploit the Ordered Weighted Averaging (OWA) operator, which provides a flexible aggregation procedure ranging between the minimum and the maximum of the input values. The results of the paper are interest both for investors and policymakers.

In particular, the VSTOXX index is found to be strongly related to the French and German volatility indices during the entire sample. On the other hand, the relationship between the VSTOXX and volatility measures in other countries highly depends on the specific period under investigation (especially for peripheral ones), thus casting doubt on the ability of the VSTOXX to measure risk for these countries correctly. Moreover, the results of the fitting exercise show that the VSTOXX index acts more like an OR-like measure than as an AND-like measure of volatility for the EU stock markets. More specifically, the VSTOXX resides in the upper part of the volatility indices distribution, acting more like an average only during periods of extreme volatility. The remainder of the paper is as follows: Section 2 introduces the dataset and the methodological approach adopted in our study. Section 3 investigates the properties of the VSTOXX and the volatility indices obtained for the nine countries, and exploit the OWA operator to assess the information content of the nine volatility indices compared to the VSTOXX. Finally, Section 4 concludes.

2. Data and Methodology

This section introduces our dataset and the methodology used to obtain the volatility indices for the nine EU countries. The data set consists of daily closing prices of index options in nine different countries, recorded from 2 January 2007 to 29 December 2017. The options data set, the dividend yield, and the risk-free rates are obtained from OptionMetrics (IvyDB Europe). The underlying assets, the time series of the underlying assets, and the daily closing values of the VSTOXX are obtained from

Bloomberg. As for the underlying asset, closing prices of the corresponding indices recorded in the same time-period, adjusted for dividends (see e.g. [15]), are used. The data on option prices has been filtered according to ref [16], in order to eliminate arbitrage opportunities and other irregularities in the prices.

The standard approach used to compute an option-implied volatility index is the one introduced by the Chicago Board Options Exchange (CBOE) for the VIX index, the measure of 30-day volatility of the S&P 500 index. Many market volatility indices have been quoted in European markets based on the same formula, such as the VSTOXX, VDAX, and the Italian volatility index (IVI MIB), among others. Given the market prices of at- and out-of-the-money options for a single option series, the volatility index can be computed as the square root of the model-free implied variance, which is estimated by using the following equation by ref. [17]:

$$E^{Q}\left[\int_{0}^{T}\left(\frac{dS_t}{S_t}\right)^2\right]=2\int_{0}^{\infty}\frac{C_0\left(T,Ke^{rT}\right)-\max\left(S_0-K,0\right)}{K^2}dK \tag{1}$$

where Q represents the expectation under the risk-neutral probability, S_t is the underlying asset price at time $t = 0, \ldots, T$ and $C_0\,(T, K)$ is a call option price at $t = 0$, with maturity T and strike price K; r is the risk-free rate.

Since the formula in Eq. (1) requires as input a continuum of strike prices ranging from zero to infinity, and in the market only a discrete and limited number of strike prices is available, the CBOE computes the VIX index using a subset of quoted option prices (see, e.g., [15], for a detailed discussion). Consequently, truncation and discretization errors could occur due to a finite range of strike prices and a discrete summation instead of the integral in Eq. (1), and be very high for peripheral European markets, which are characterized by a limited number of strike prices traded [18].

To mitigate both truncation and discretization errors, we adopt an interpolation-extrapolation method based on an interpolation among implied volatilities of available option prices with cubic splines and an extrapolation procedure outside the domain of quoted option prices using a constant volatility function. For each country, the procedure takes the following steps. First, we create a table of available strike prices and implied volatilities, which serves as our initial input. Second, following [19], implied volatilities are interpolated between two adjacent knots using cubic splines to keep the function smooth in the knots and extrapolated outside the traded domain of strike prices. Volatility is assumed constant for strike prices higher (resp. lower) than the maximum (resp. minimum) strike price available. A fixed-value parameter u equal to 2 for all countries is used to extend the integration domain by computing a matrix of strike prices and implied volatility in the interval $S/(1+u) \le K \le S(1+u)$, where S is the underlying asset value. Finally, a country-specific space interval is adopted to ensure insignificant discretization errors and compute missing implied volatility and strike prices from the interpolated-extrapolated smile. The implied volatilities obtained are finally converted into option prices and used to compute model-free variance through the approximated variance formula:

$$2\int_{0}^{\infty}\frac{C_0\left(T,Ke^{rT}\right)-\max\left(S_0-K,0\right)}{K^2}dK \approx \sum_{i=1}^{m}\left[g\left(T,K_i\right)+g\left(T,K_{i-1}\right)\right]\Delta K \tag{2}$$

where $g\left(T,K_i\right)=\left[C_0\left(T,K_i\right)-\max\left(0,F_0-K_i\right)\right]/K_i^2$, $C_0\left(T,K_i\right)$ is the price of a call option with strike price K_i and time to maturity T, $\Delta K=\left(K_{max}-K_{min}\right)/m$, m is the number of abscissas; $K_i=K_{min}+i\Delta K$, $0<i<m$, K_{min} and $K_{\max}$ are the minimum and the maximum strike prices, respectively.

Moreover, to have constant 30-day measures of implied volatility that can be directly compared with the VSTOXX index, the daily estimate of volatility is computed by linear interpolation, using a formula consistent with the one adopted for the VIX index. In particular, two values of risk-neutral variance obtained from Eq. (2) with different time to maturity (i.e., one for each of the two-option series considered, given a first option series with a maturity of less than 30 days and a second one with time to maturity greater than 30 days) are used:

$$VIX=100\times\sqrt{\left[T_1\sigma_1^2\left(\frac{N_2-30}{N_2-N_1}\right)+T_2\sigma_2^2\left(\frac{30-N_1}{N_2-N_1}\right)\right]\times\left(\frac{365}{30}\right)} \tag{3}$$

where T_1 and T_2 are the time-to-maturity of the first and the second option series used, respectively, and σ_1^2 and σ_2^2 the estimated variances.

After the transformation in Eq. (3) is applied, claiming that a volatility index is equal to 10 means that there is about 68% chance (one standard deviation) that the absolute magnitude of the underlying market's return will be less than 2.89% over the next 30 days (one month). Consequently, the greater the volatility, the higher the uncertainty and, therefore, the volatility risk. The rationale is as follows: 2.89% is obtained as $10/\sqrt{12}$, where 10 is the index value and √12 is the factor that allows us to move from the annualized index (obtained using Eq. (3)) to that on a monthly basis (further details are available at: https://www.cboe.com/tradable_products/vix/faqs/).

3. Properties of the European volatility indices

This section presents the properties and the information content of the nine volatility indices obtained by applying to our dataset the methodology described in Section 2. As a result, we obtain 2869 daily closing values for each of the nine volatility indices, spanning from January 2, 2007, to December 28, 2017.

3.1. Correlation analysis

While it is well-known (see, e.g. [20]) that correlations between the EU volatility indices have been very high in the last decades, we are interested in providing further insight by investigating the relationship between the volatility indices in different market volatility phases. To investigate the relationship between the VSTOXX and the EU volatility indices, we represent it in Figure 1, by disentangling the scatterplots depending on the level of volatility measured by the VSTOXX. The dashed grey line represents the case of a volatility index perfectly correlated with the VSTOXX in terms of daily levels: the more the observations deviate from the grey line, the less the volatility index under investigation is correlated with the VSTOXX.

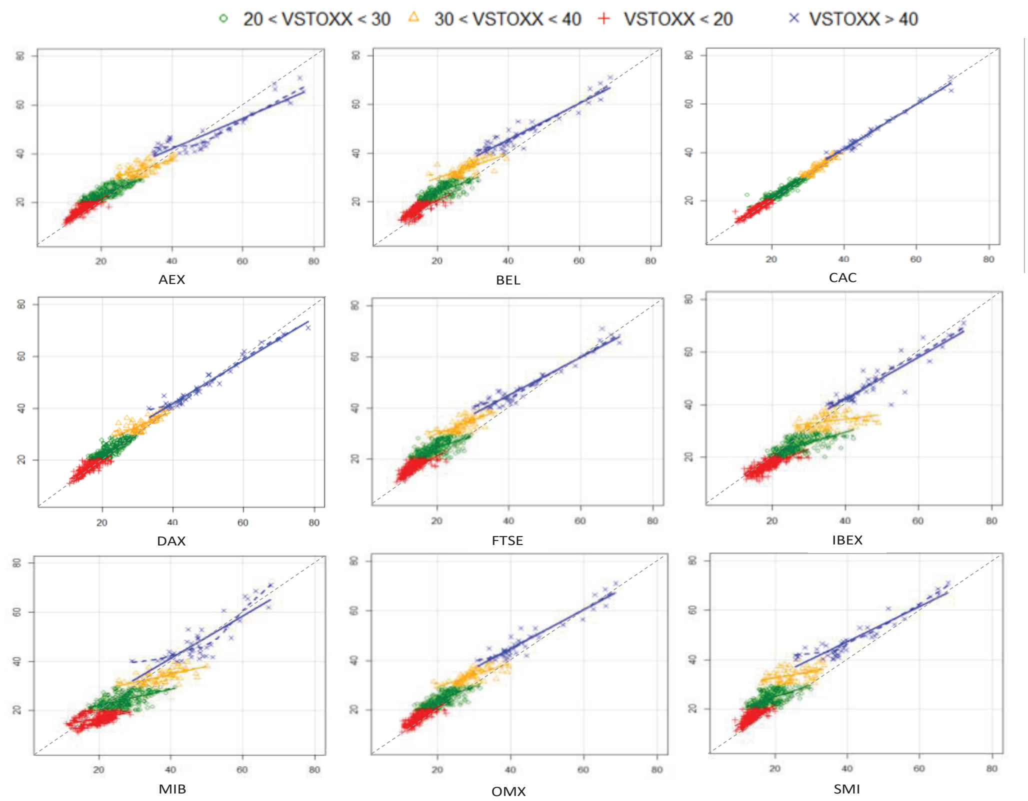

Figure 1: Relation between VSTOXX and EU volatility indices for different volatility levels

We can observe that the relation between the VSTOXX and the other volatility indices is strong during very low or very high volatility periods (depicted in blue) and in all the subperiods with the volatility indices of France (CAC) and Germany (DAX). On the other hand, the relationship tends to weaken when the volatility ranges between 20 and 40, especially for peripheral EU countries in our dataset (Italy and Spain), for which the relationship (depicted in yellow) flattens. This period mainly corresponds to the 2010-2012 European debt crisis. A similar, even if weaker, pattern could also be detected for BEL, FTSE, and SMI. Therefore, the VSTOXX well represented volatility condition for France and Germany during all the periods, while it has not fully captured the different levels of risks, especially for the peripheral EU countries, during the 2010-2012 period. This result is explained by the fact that, while the VSTOXX was experiencing intermediate levels of volatility, consistent with the market conditions of Germany and France, some other countries experienced very high levels of volatility and stressful market conditions.

3.2. EU volatility indices ranking

In the previous section, we have investigated the correlations between volatility indices, which provides us with a useful indication about the degree of association between the VSTOXX on the one hand and core and peripheral EU markets on the other. However, the analysis of volatility indices in terms of levels and their evolution over time can provide further insights into the EU markets' uncertainty. To investigate the EU volatility indices ranking and its evolution during the sample period (2007-2017), each day, we rank the nine volatility indices plus the VSTOXX from the highest (1) to the lowest (10). Since the raking evolution over time is highly volatile, we compute for each volatility index its 5-day moving average to enhance the readability of the plots, and we display the results in Figure 2. Several observations are in order.

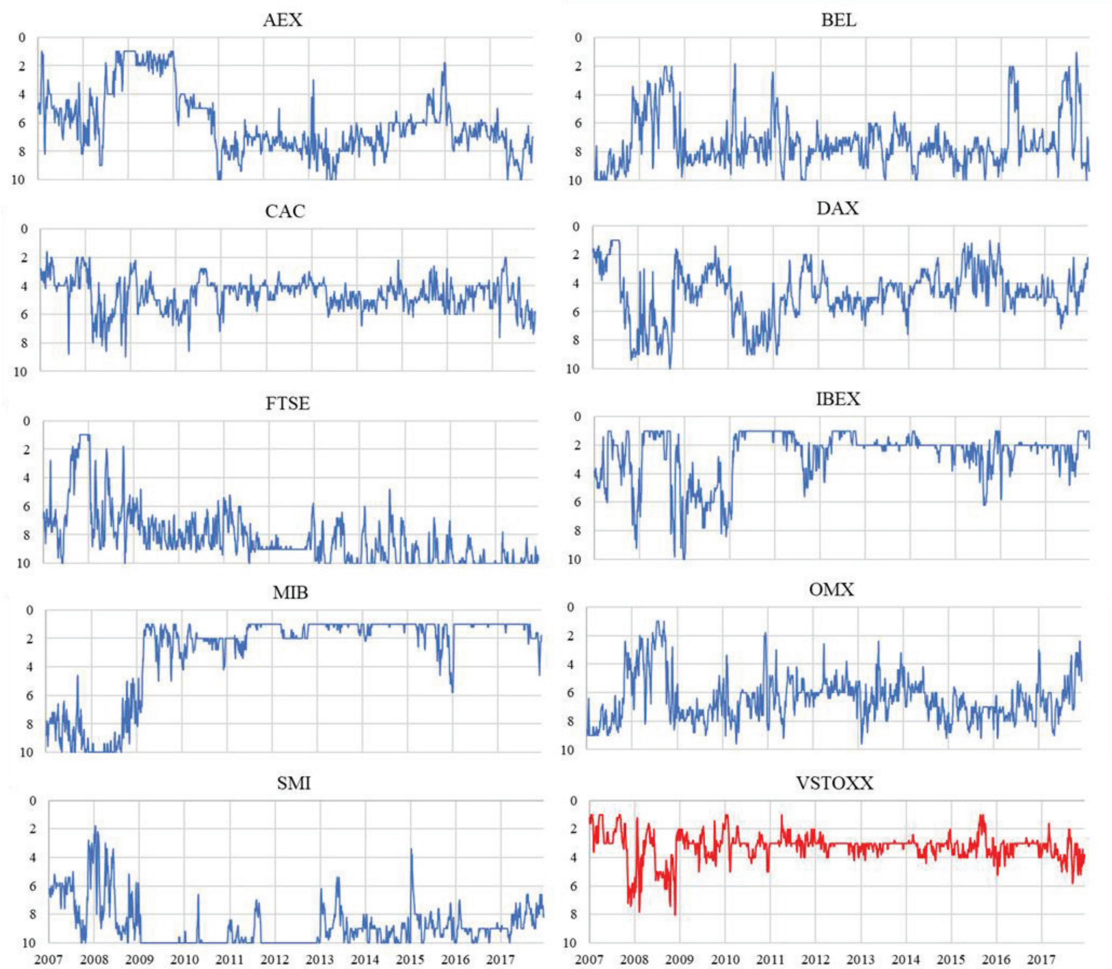

Figure 2: Volatility indices ranking over the sample period (2007-2017).

First, the volatility indices ranking is highly volatile and changed significantly during the sample period. Changes in the ranking are observed, particularly in crisis and market turbulence, such as the 2008 financial crises and the European debt crisis in 2011-2012. Second, both Switzerland and the UK, which show high ranks during the financial crises (probably attributable to the central role of these financial markets in the transmission of the financial crisis and to large banking groups listed on the Zurich and London stock exchanges), show low average ranks in the last part of the dataset. This result is probably motivated by the non-belonging of these two countries to the Euro area, thus allowing them to act as a safe haven for investors during the European debt crisis. A rare exception is the peak at the beginning of 2015 for the Swiss market due to the unexpected end of peg between the Swiss francs and the Euro. Third, the Spanish and the Italian volatility indices, characterized by low ranks at the beginning of the sample period, change significantly after the global financial crisis and during EU sovereign debt crisis, remaining among the highest until the end of the sample period. Fourth, the remaining indices are characterized by a fairly volatile ranking, with AEX and BEL showing a slightly lower ranking than CAC and DAX. Last, the VSTOXX index has maintained one of the top ranks (around the third position) for most of the sample, being in many occurrences higher than both the CAC and the DAX volatility. The plot suggests that the average VSTOXX value is above the mean of the nine volatility indices for almost the entire sample, suggesting the VSTOXX acted more like an OR-like measure than an AND-like measure of volatility for the EU stock markets. The behavior of the VSTOXX like an OR-like measure will be better investigated in the next section.

3.3. Fitting exercise

The results obtained in Section 3.2 reveal that the VSTOXX is in general higher than the average volatility of the nine EU markets in our dataset. In this section, we propose a different strategy to investigate the OR-like properties of the VSTOXX index for the volatility of the European market. Investigating the behavior of the VSTOXX is important for investors who monitor this index as a measure of volatility for all European markets. Moreover, we aim at understanding whether its behavior has been fairly homogeneous over time, or whether on the contrary, it has been determined by the market phase. As far we know, there are currently no studies in the literature evaluating the effectiveness of the VSTOXX volatility index for representing risk and uncertainty in different EU markets. To fill this gap, we propose an approach based on the Ordered Weighted Averaging aggregation operator (hereafter, OWA operator), introduced in [21], and successfully adopted in many fields (see e.g., [22] for a literature review). The OWA provides flexible aggregation operation ranging between the minimum and the maximum and effectively dealing with quantitative and qualitative information.

Given w, a weighting vector of dimension N, refs. [21] and [23] define a mapping OWA_w: $\mathbb{R}^N \rightarrow \mathbb{R}$ as an Ordered Weighting Averaging (OWA) operator of dimension N if:

$$OWA_w(a_1,...,a_N) = \sum\nolimits_{i=1}^{N} w_i a_{\sigma(i),} \tag{4}$$

where $(\sigma(1),...,\sigma(N))$ is a permutation of $(1,...,N)$ such that $a_{\sigma(i-1)} \geq a_{\sigma(i)}$ for all $i = \{2,...,N\}$, i.e. $a_{\sigma(i)}$ is the ith largest element in the input vector a, and the weights w respect the properties $w_i \in [0,1]$ and $\sum_i w_i = 1$.

The possible range of the OWA outcome varies from the minimum to the maximum value. Therefore, the OWA operator is similar to the weighted mean while departing from the latter in the ordering step, thus producing a different interpretation. While in the weighted mean, the weights are attached to the information sources, in the OWA operator, the weights are attached to the data regarding their relative position. In this way, a system can give more importance to a subset of the input values than to another subset, i.e., weights allow us to attribute more importance to, e.g., low values, central values, or high values, allowing for a degree of compensation. The degree of compensation in the OWA operator is measured with the *orness* degree. *Orness* indicates the position of the OWA operator on a continuum between the AND (i.e. min) and OR (i.e. max) operations. The larger the outcome, the larger the *orness* and the larger the compensation, i.e., the *orness* measures to what extent the outcome of an operator tends to be similar to the OR. The *orness* measure for the OWA operator is defined as [21]:

$$\text{orness}(W) = \frac{1}{n-1}\sum_{i=1}^{N}\left[(n-i) \times w_i\right] \tag{5}$$

Therefore, the OWA operators allow us to model any desired degree of *orness* between 0 (corresponding to a pure AND) and 1 (corresponding to a pure OR), by means of an appropriate selection of parameters, the so-called OWA weights.

To better understand the properties of the VSTOXX index and evaluate its OR-like behavior over the sample period we take the following steps. First, we collect the daily values of volatility indices and the VSTOXX over different pre-specified time horizons (one-, three-, and six-month). Second, for each time window, the series of daily values of the nine country-specific indices (sorted in descending order) are used as input for the OWA operator. Third, for each time horizon, we compute the weights for the OWA operator by solving the following optimization problem:

$$\min\ D_{OWA} = \sum\nolimits_{i=1}^{M} \mathrm{OWA}_{\mathrm{w}}(a_1^i,...,a_N^i) - b^i)^2$$

$$\text{Subject to: } \sum_{i=1}^{N} w_i = 1, \qquad 0 \le w_i \le 1, \qquad i = 1,2,...,N \tag{6}$$

where $\left(a_1^i,...,a_N^i\right)$ is the vector of volatility indices at day t, and b^i is the target of the optimization problem, which here is the value of the VSTOXX index at the same date. In this way, we obtain $\mathrm{w} = (w_1,...,w_N)$ as the vector of weights that minimizes the distance (D_{OWA}) between the aggregate index and the corresponding observations obtained from the VSTOXX for the different time windows. Our estimation windows include 21, 63, and 121 trading days as a proxy for 1-month, 3-month, and 6-month time horizons. As the last step, we move the window one week forward. The results for the fitting exercise are reported in Table 1, where we display for each estimation window the average values of weights, root mean square error (RMSE), and *orness*.

Several observations can be made. First, the choice of the estimation window has a limited influence on the weight associated with the input vectors. More specifically, weights are focused mainly on the third (around 30%), the second and the fourth inputs (both around 20%), followed by the first one (usually between 10% and 20%). Therefore, the VSTOXX index acts more like an OR-like measure than as an AND measure of volatility for the EU stock markets during the 2007-2017 period. This result is also confirmed by the average *orness*, which is slightly higher than 0.7; we recall that the *orness* measure is equal to 0 (resp. 1) if the aggregation result is equal to the minimum (maximum). Second, the sum of the weights associated with the indices ranging from the fifth to the ninth position is always lower than 20% and their relative weight tends to decrease as the time window considered increases.

Third, the RMSE increases with the increasing time window, suggesting that optimal weights frequently vary over time. Also, the estimated weights are highly time-varying, but the changes occurred mainly among the first five indices, confirming that VSTOXX acted more like a maximum than as a minimum. In particular, the index has always been above the 0.5 threshold except for one or two peaks (depending on the estimation window used) during the 2008-2009 financial crisis. This means that often the VSTOXX resides in the upper part of the volatility indices, acting more like an average during periods of extreme volatility. This result casts doubt on the ability of the VSTOXX to be a measure of market volatility for all the EU countries.

Table 1

Fitting exercise: OWA weight results and statistics

Window length:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**RMSE**	***orness***
1-month	16.65%	18.90%	30.42%	17.25%	7.50%	2.66%	3.01%	1.93%	1.68%	0.481	0.725
3-month	12.36%	20.41%	30.93%	21.96%	6.82%	1.92%	2.50%	1.16%	1.94%	0.649	0.720
6-month	10.54%	22.84%	29.82%	23.59%	5.87%	1.83%	2.44%	1.56%	1.52%	0.739	0.721

On the other hand, the VSTOXX can be obtained as the maximum three times during our sample period. However, this pattern occurs during periods of low (in the first part of 2007), medium (January 2010), and high volatility (autumn 2015), thus suggesting the absence of a clear relationship between the VSTOXX behavior and volatility levels. We empirically checked this hypothesis by computing the correlation coefficients between the VSTOXX level and the *orness* estimates, which turned out to be very close to zero. Therefore, the VSTOXX changed its behavior during the sample period, and the changes were not motivated by an increased or decreased volatility risk.

4. Conclusions

In the EU markets, there is a lack of instruments to measure the risk of each financial market and the risk of the EU financial market as a whole. Only a few countries (mainly from northern and central Europe, the most developed ones) adopt a volatility index traded in the internal stock market. The VSTOXX is the only option-implied index based on various EU markets, and it is commonly referred to as the "European VIX" since it represents the equivalent of the VIX index for the European markets [4]. However, the VSTOXX index has not gained the same outstanding reputation as the VIX, and has received some criticism in the literature (see, e.g., [5]; [13]). Despite the crucial role of the VSTOXX as a measure of risk for the EU stock market, there are still no studies investigating its behavior and the relationships between the VSTOXX and the country-specific volatility indices in the EU.

To fill this gap, we compute model-free implied volatility indices for nine index options markets in the EU during the 2007-2017 period. The index options markets in our sample include AEX (The Netherlands), BEL (Belgium), CAC (France), DAX (Germany), FTSE (the United Kingdom), IBEX (Spain), MIB (Italy), OMX (Sweden), and SMI (Switzerland). The introduction of these indices allows us to investigate the behavior of the VSTOXX in a period characterized by the occurrence of both the subprime crisis (2008-2009) and the European debt crisis (2011-2012) and contrast the properties of the indices under different market conditions and economies under stress. Moreover, to investigate the information content of each country-specific index for the VSTOXX, we exploit the Ordered Weighted Averaging (OWA) operator, which provides a flexible aggregation procedure ranging between the minimum and the maximum of the input values.

We find several results. First, the VSTOXX is strongly related to the French and German volatility indices, given the high weight of these countries in the Eurostoxx 50 index computation. On the other hand, the relationship between the VSTOXX and volatility measures in other countries depends on the specific period under investigation. Moreover, peripheral country volatility indices in our dataset (Italy, Spain) are less correlated with the VSTOXX index, especially for medium level of volatility recorded during the 2010-2012 period, thus casting doubt on the ability of the VSTOXX to measure risk for these countries correctly. Second, the results of the fitting exercise show that the VSTOXX index acted more like an OR-like measure than an AND-like measure of volatility for the EU stock markets during the 2007-2017 period. This result is also confirmed by the average *orness*, which is slightly higher than 0.7. In particular, the index has always been above the 0.5 threshold except for one or two peaks (depending on the estimation window used) during the 2008-2009 financial crisis. This means that often the VSTOXX resides in the upper part of the volatility indices, acting more like an average during periods of extreme volatility. Third, an *orness* value of about 0.7 indicates that the VSTOXX signals high risk when 4 out of the 9 EU volatility indices are high. Therefore, the VSTOXX can detect a risky situation when a group of countries experiences a high level of volatility. On the other hand, the VSTOXX fails to capture risky situations related to a single or a small group of countries such as peripheral ones. This result calls for new measures of risk that can complement the information provided by the VSTOXX and capture the complexity and heterogeneity of the EU markets. Future research should investigate several non-weighted, weighted, and fuzzy measures aggregation functions by including all the available information from the different EU countries to obtain a more informative volatility index and provide investors with an additional source of information.

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