Revisiting the financial volatility – derivatives products relationship on Euronext.liffe, using a frequency domain analysis

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- preliminary version -

Abstract

The present paper analyse the relationship between the volume of transactions with futures equity index products and the return volatility of their underlying assets. The study addresses the case of five stock markets, members of the Euronext.liffe: London, Paris, Amsterdam, Brussels and Lisbon. We employ a frequency domain analysis, using monthly data for the period 2001.09 – 2010.06, which allows us to identify the direction of the causality between the derivatives volume and the index return volatility. In addition, we test the relationship between the volume of futures contracts and both negative and positive shocks in terms of historical volatility of index return. Our results prove the frequency-causality only in case of Brussels financial market. For Lisbon the relationship exists, but it is not validated by the confidence level tests, while for London, Paris and Amsterdam, no causality can be observed. In case of Brussels, there is bidirectional causality at short and long run frequencies. The futures equity index volume Granger-cause the positive shocks in term of volatility at long run and the negative shocks at short run.

Keywords: Financial volatility, futures index products, frequency domain analysis, Granger causality Euronext.liffe.

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1. Introduction

The impact of financial derivatives (in particular of futures products) on the volatility of their underlying assets was extensively studied. These products were considered responsible for an

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increased volatility of the financial markets, beside other elements as the incertitude related to the financial flows and to the discount rate (BIS, 2006), the real economic activity volatility and financial liberalisation (Levine and Zervos, 1998; Miles, 2002) or the distribution of assets ownership and the costs of the transactions (Bekaert and Harvey, 2000).

However, little attention was paid to the implications of the financial market volatility on the derivatives volume. If a stronger volatility is anticipated, both risk managers and speculators decide to hedge or to strength their position by means of derivatives products. Therefore, a bidirectional relationship has to be analysed and several theoretical arguments support this demarche.

Studding the single influence of the index return volatility on the volume of transactions with derivative products suppose the existence of perfect markets with homogeneous information, being also required that the volume of transactions does not provide information to the operators in respect of the future volatility of the underlying assets. Nevertheless, some traders are better informed than others and lead the market. If these market-makers are not capable of anticipating with accuracy the underlying assets return volatility, the causality from financial volatility towards the volume of transactions with derivative products is no longer necessarily a unidirectional relation but a bidirectional one. Another argument is related to lower transaction costs with derivatives products and higher leverage effects of these instruments. If the traders who are better informed are susceptible of being more attracted by the derivatives, the volume of transactions with derivative products has to forego the price volatility of the underlying assets.

The literature almost lack in studies approaching the bidirectional relationship between the derivatives products and the volatility of their underlying assets. In a previous study of ours (Albulescu and Goyeau, 2011), we have investigated the bidirectional Granger causality between the equity index products (futures and options) and the index return volatility in countries which were members of the Euronext.liffe, except form Lisbon. The results obtained based on the respective time series analysis were mixed. The causality relationships which occurred were considerably different depending on the analysed products and countries.

The present research differs from the previous one in several ways. First, it is based on the short and long run Granger-causality using the frequency domain approach of Breitung and Candelon (2006). Second, in order to assess the financial derivatives volume we make appeal to the value of the volume and not to the number of contract as in the previous work (Albulescu and Goyeau, 2011)[1]. However, this choice reduces considerably our sample to the period 2001 – 2010, for which the value of the volume is available. Third, we focus our research on equity futures index products, leaving outside the options contract. This choice is motivated by the willingness of including in the analysis all the Euronext.liffe members[2]. Finally, beside the whole sample analysis, we assess the Granger causality in terms of positive and negative volatility shocks.

All in all, the contribution of the present paper to the literature is twofold. First, we conduct a causality analysis between derivatives volume and the volatility of their underlying asset in frequency domain. The key idea of this approach, which considers that a stationary process can be described as a weighted sum of sinusoidal components with a certain frequency, is related to the possibility of analysing separately the slowly fluctuating components and the quickly fluctuating components of our variables (see Croux and Reusens, 2013). Consequently, the Granger causality is calculated for each individual frequency component, and, to the best of our knowledge, the financial volatility – derivatives products relationship has not yet been explored in the frequency domain. This approach complements a conventional time domain framework (McCullough, 1995; Orlov, 2011).

Second, we want to see if an increasing volume of derivatives cause positive or negative shocks in terms of volatility[3]. If the derivatives volume Granger-cause positive volatility shocks, we associate this with a predominance of speculative operations on the market. Reversely, if the derivatives volume Granger-cause negative volatility shocks, the hedging operations prevail.

The reminder of the paper is structured as follows. Section 2 presents a short overview of the literature. Section 3 describes the data and the frequency domain methodology. Section 4 depicts the empirical results and Section 5 concludes.

[1] The number of contracts can be considered a proxy for derivatives volume as the futures contracts are standardised. However, there exist some differences regarding the prices of the contract from one period to another, which recommends the use of the volume value.

[2] For Lisbon stock exchange, data related to options contracts are not available.

[3] Positive volatility shocks are associated with an increased volatility, above the average, while negative shocks reveal a reduction of the volatility below the average (see Section 3 for a description of shocks computation).

2. Literature review

Antoniou and Holmes (1995) showed that the impact of futures contracts upon the spot markets was questioned since 1865, when we had the first transaction with futures on Chicago Board of Trade. Since that moment, the analyses have focused on the speculators' role in amplifying the undesirable volatility of the stock markets. The impact of derivative products on the volatility of their underlying assets was intensively assessedduring last decades and it still stands for a subject of interest nowadays. However, the public debate slows down after overlapping crisis episodes and regains its importance in times of crisis.

The theoretical literature analysing the topic was extended in a single direction and its endeavour was to emphasize the impact of derivative products on the volatility of their underlying assets. Nevertheless, two antagonizing approaches were developed. The first approach, which is the dominant one, supports the idea that the transactions with derivatives lead to an increase of the volatility on the spot markets, through the leverage effect. This effect is susceptible to attract an increasing number of investors on the derivatives markets, situation which may generate an augmentation of the volatility on the spot markets. Moreover, if important amounts are oriented towards the derivatives markets, the spot markets liquidity decreases and might amplify the index return volatility.

The second approach shows that the introduction of derivatives diminishes the price volatility of their underlying assets. Several arguments are advanced in the literature in order to sustain this theory. According to Skinner (1989), the derivatives determine the reduction of the spot market volatility. This situation can be explained by the conditions which must be accomplished by the underlying assets, in order to allow the derivatives transactions. The imposed conditions ameliorate the investors' confidence on the spot market, favouring thus a smaller volatility. Moreover, the additional information obtained on the derivatives markets acts as a break for the financial volatility. Indeed, given the complexity of the derivatives markets, the investors are in general better informed[4]. Consequently, the volatility of the stock market would decrease[5].

From the empirical point of view, the influence of derivative products on the volatility of the underlying assets was also analysed in two different ways. The first approach compares

[4] See Chan et al. (2002) for an ample discussion.

[5] About the informational content of option trading for future movements in underlying stock prices see Pan and Poteshman (2006).

financial volatility before and after the introduction of derivative products and a large part of these studies discovered that the introduction of derivatives amplifies the underlying assets volatility (Robinson, 1994; Antoniou and Holmes, 1995; Reyes, 1996; Antoniou et al., 1998). The second approach investigates the impact of derivatives on the behaviour of their underlying assets, including their volatility. This latter approach has been intensively developed and reaches two different sets of results, depending on the theoretical background (Bandivadekar and Ghosh, 2003). A series of studiesshow that the introduction of derivative products leads to an increased volatility on the spot markets, destabilising thus these markets (see e.g., Figlewski, 1981; Stein, 1987). Other studies sustain the opposite and demonstrate that the introduction of derivative products contributes to the volatility reducing (see e.g., Powers, 1970; Schwarz and Laatsch, 1991; Fedenia and Grammatikos, 1992). At the same line, more recently,Kasman and Kasman(2008) reach the conclusion that the futures introduction lowers the conditional volatility of the ISE 30 index.

Nevertheless, a considerable number of papers either do not find a significant effect of derivatives on the market volatility (Edwards, 1988; Darrat and Rahman, 1995) or highlight a reduced effect (Dennisa and Sim, 1999; Jeanneau and Micu, 2003). Consequently, the empirical literature provides mixed results (Charupat, 2006).

These contradictory results are influenced by the analysed market and retained periods, by the assets type, by the volatility calculation and by the employed empirical methodology. Considerable efforts were made in order to better assess the financial volatility, a key element of these researches. Thus, on the one hand, it is necessary to make a distinction between long run volatility (months, years) and the short run volatility (hours, days)[6]. On the other hand, we must distinguish between non-conditional volatility and conditional volatility (see Daly (2008) for an exhaustive presentation of the financial volatility calculation techniques)[7].

In respect to the methodology, the developments were not less important. While Koch (1993) showed the superiority of the simultaneous equations models for this type of analysis, Chan and Chug (1995) founded that theVAR models can better reveal the underlying process. More recently, the instrumental variables approach was advanced. At this line, Kim et al. (2004)

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[6]If the long term volatility is influenced in particular by the economic fundamentals and institutional changes, on short run, the volatility is generated by the pressure related to the transaction process and noises.

[7] Another concept of volatility is the implied volatility, calculated using the Black and Scholes model and which stands for a measure of volatility anticipated by the market (Kim and Kim, 2003 and Jeanneau and Micu, 2003 used the implied volatility in their analysis).

used a three-stage least squares method in order to assess the impact of derivatives trading on the underlying cash market volatility for the Korean stock exchange.

However, despite the well-defined theoretical framework and despite the empirical developments, the analysis of the bidirectional causality between the stock market volatility and derivatives is of recent interest in the literature. Kim et al. (2004) discovered a positive contemporaneous relationship between the stock market volatility and the derivatives volume and a negative relationship between the volatility and the open interest[8]. Other papers in this area are those of Sarwar (2005) and Buhr et al. (2010) which have tested the double potential causality between the volume of transactions with options products and the volatility of the S&P 500 index, respectively that of the ASX 200 index. More recently, Albulescu and Goyeau (2011) have analysed the double causality between derivatives products and the price return of their underlying assets on Eurnonext.liffe and discovered mixed evidences.

All the above mentioned studies developed their researches in time domain. However, the time series usually prove to be non-stationary and the obtained results can thus be biased. Moreover, the conventional Granger causality tests do not assess the statistical causality. In order to overcome these limitations, the present paper offers some insights regarding the financial volatility – derivatives products relationship on Euronext.liffe, using a frequency domain analysis, based on Breitung and Candelon (2006) approach (for a short description of this technique see Section 3.2.).

3. Data and methodology

3.1. Data

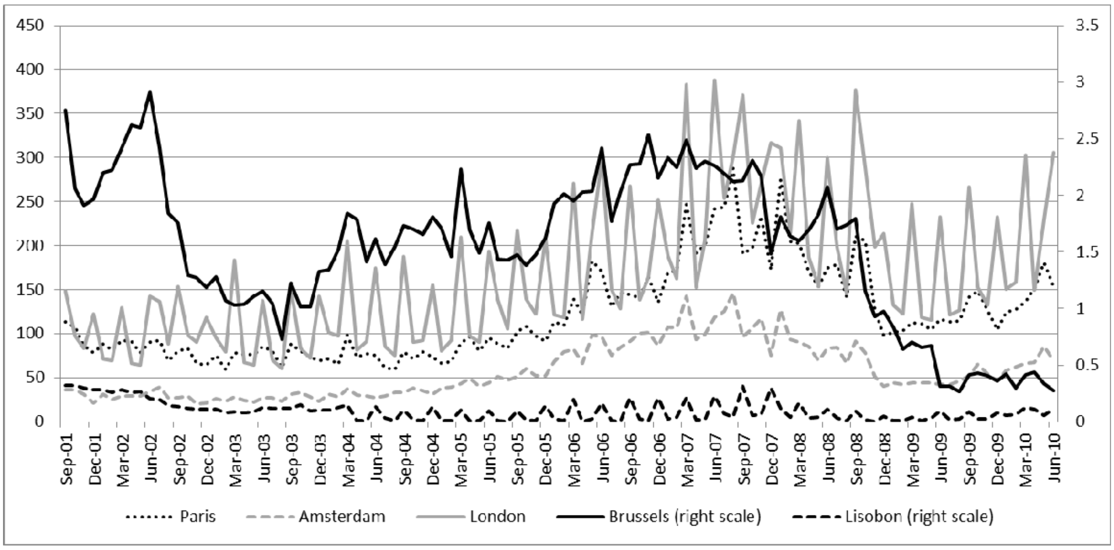
The derivatives data were extracted from Euronext.liffe database and covers the period 2001.09 – 2010.06 (monthly data). This timeframe is large enough to present significant evolutions of derivatives volume[9] and of index returns volatility, which proves high during crisis periods.

[8] Sarwar (2004) highlights the informational role of the option volume in predicting the future price volatility of the S&P 500 index.

[9] According to Jeanneau and Micu (2003), there are two main methods for assessing the derivative related activity. The first possibility considers their turnover (or volume), and it refers to the number of contracts traded in a specific period or to the value of this volume. The other approach is the open interest, which shows the total number of on-going contracts.

The volume of futures equity index products for each stock market is described in Figure 1.

Figure 1. Value of the futures equity index products traded on Euronext.liffe (bill. EUR)

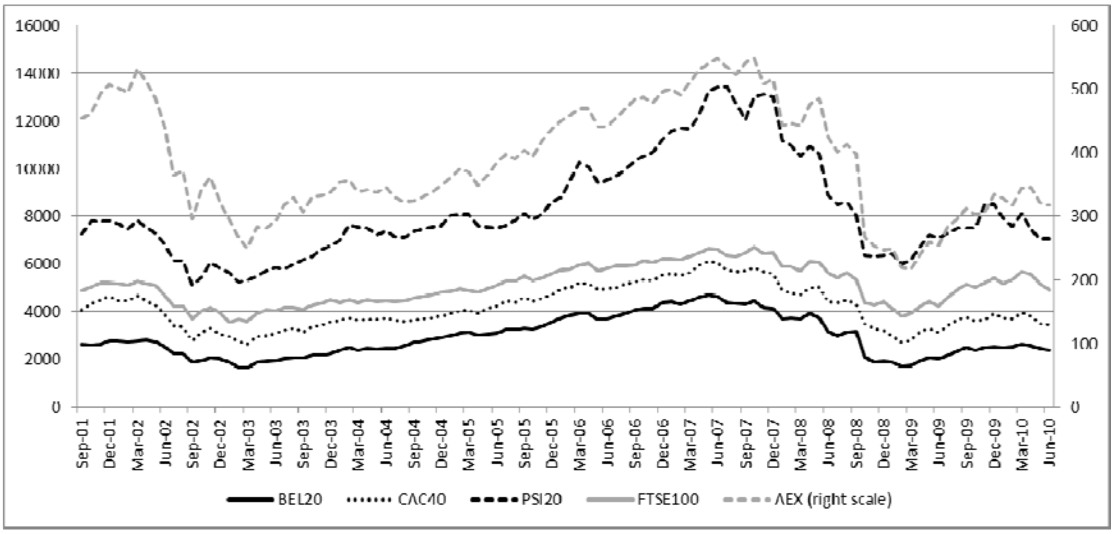


Source: Euronext.liffe

We can observe that in the analysed period, London, Paris and Amsterdam represents the main stock markets for transactions with futures equity index products while Brussels and Lisbon lag far behind. We can also see that the derivatives volume is higher around the 2007 – 2008 financial markets turbulences and descries latter.

In Figure 2 we can observe the trend of the stock indexes which are representatives for the Euronext.liffe stock markets (Yahoo.finance monthly data). We observe their correlation and also an increased volatility after the crisis burst-out.

Figure 2. Stock indexes (close values)



Source: Yahoo.finance

In order to proceed to data analysis and to ensure the stationarity of the series, a number of data transformations were necessary. First, we have detrended both the derivatives volume and stock indexes series, using X-12-ARIMA methodology for monthly data (3x5 filters)[10]. Second, we have computed the natural logarithm of both series. Third, we have calculated the first difference for both the derivatives volume and the stock indexes[11]. Finally, we have assessed the financial volatility based on the standard deviation of the obtained index return, using a 12 month rolling window (t-12:t).

Based on this volatility assessment, we have computed the positive and negatives shocks in terms of volatility, employing the Hamilton' methodology (developed in order to identify the shocks in the spot oil prices). Hamilton (1996, 2003) proposes a methodology in order to identify positive shocks, based on the difference between the log oil price in month *t* and its maximum value over the previous *n* months. Cong et al. (2008) developed this seminal work and proposed a new methodology for identifying also negative shocks. Adopting the same approach, we transform each volatility series into two different series characterising the positive and negative shocks, respectively. If the volatility in month *t* is higher that its level over the past 6 months, then a positive shock occurs. It is equal to the difference between the level of the volatility in *t* and its maximum values in the previous 6 months. Contrary to this, an absence of the shock is recorded. The same reasoning is applied for the negative shocks, according to the following two formulae:

$$vol^{+} = IF(vol_t > MAX(vol_{t-1} : vol_{t-6}), vol_t - MAX(vol_{t-1} : vol_{t-6}), 0) \quad (1)$$

$$vol^{-} = IF(vol_t < MIN(vol_{t-1} : vol_{t-6}), vol_t - MIN(vol_{t-1} : vol_{t-6}), 0) \quad (2)$$

where "vol+" and "vol-" represent positive and negative volatility shocks

3.2. Methodology

The causality between two variable x_t and y_t is usually analysed based on Granger (1969) approach, which is meant to show how much of the current y_t can be explained by past values of y_t, and then to see whether adding lagged values of x_t can improve the explanation regarding the present values of y_t. Consequently, y_t is said to Granger-cause x_t if, x_t helps

[10]Kim et al. (2004) proceeded in a similar way in their research, using an ARIMA (10, 0, 10) model.

[11] The first difference of the natural log of the stock index is associated in this case with the index return.

in the prediction of y_t, or if the coefficients of the lagged x_t are statistically significant (and vice-versa).

However, it is important to known that the conventional Granger causality tests measure precedence and information content, but do not indicate the causality in its conventional sense. As Granger and Lin (1995) shows, the extent and the direction of causality differ between frequency bands and the conventional Granger causality tests are unable to assess it. Yet, it was Granger (1969) itself who advanced the idea of further disentangling of thecausality relationship between two time series and suggested that a spectral-density approach would give a better-off and more complete picture than a one shot Granger causality measure[12].

To overcome this limitation, Breitung and Candelon (2006) propose a new approach where the causal relationship between variables is decomposed by frequencies[13]. However, the approach of Breitung and Candelon (2006) is based on the work of Granger (1969). This approach provides an elegant interpretation of frequency domain Granger causality as it decomposes the total spectral interdependence between the two series (based on the bivariate spectral density matrix, and directly related to the coherence), into a sum of "instantaneous", "feed-forward" and "feed-back" causality terms (see Tiwari, 2012). This new measure of Granger causality can be applied across all periodicities and allows us to know exactly for which periodicity one variable Granger-cause the other.

Therefore, in the present study we employ the Breitung and Candelon (2006) approach to assess the Granger causality in the frequency domain[14]. This approach has been used in quite a few studies limited to the monetary policy and stock markets analyses (Assenmacher-Wesche and Gerlach, 2007; Assenmacher-Wesche and Gerlach, 2008a,2008b; Assenmacher-Wesche et al., 2008; Lemmens et al.; 2008; Gronwald, 2009)[15]. The Breitung and Candelon (2006) approach can be described as follows:

Let z_t be observed at $t = 1,...,T$ and it has a finite-order VAR representation of the form:

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[12] The causality is supposed to apply across all periodicities (e.g., in the short run, over the business-cycle frequencies, and in the long run).

[13] The traditional Granger causality approach ignores the possibility that the strength and/or the direction of the causality, (if any), can vary over different frequencies (Lemmens et al., 2008).

[14]In statistics, frequency domain describes the domain for analysis of mathematical functions or signals with respect to frequency, rather than time.

[15] One exception is represented by the work of Tiwari (2012), in the area of public finance.

$$z_t = \Theta(L) z_t \tag{3}$$

where $\Theta(L) = I - \Theta_1 L - ... - \Theta_p L^p$ is a 2×2 lag polynomial with $L^k z_t = z_{t-k}$. We assume that the error vector ε_t is white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t^{'}) = \Sigma,$; where Σ is positive definite. In order to simplify the description, any deterministic terms in (3) is neglected.

Let G be the lower triangular matrix of the Cholesky decomposition $G'G = \Sigma^{-1}$, such that $E(\eta_t \eta_t^{'}) = I$ and $\eta_t = G\varepsilon_t$. If the system is assumed to be stationary, the Moving Average (MA) representation of the system is:

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{4}$$

$$= \psi(L)\eta_t = \begin{bmatrix} \psi_{11}(L) & \psi_{12}(L) \\ \psi_{21}(L) & \psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \tag{5}$$

where $\Phi(L) = \Theta(L)^{-1}$ and $\psi(L) = \Phi(L)G^{-1}$. Using this representation, the spectral density of x_t can be expressed as:

$$f_x(\omega) = \frac{1}{2\pi}\{|\psi_{11}(e^{-i\omega})|^2 + |\psi_{12}(e^{-i\omega})|^2\} \tag{6}$$

The measure of causality suggested by Geweke (1982) and Hosoya (1991) is defined as:

$$M_{y \to x}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{\left|\psi_{11}(e^{-i\omega})\right|^2}\right] \tag{7}$$

$$= \log\left|1 + \frac{\left|\psi_{12}(e^{-i\omega})\right|}{\left|\psi_{11}(e^{-i\omega})\right|}\right| \tag{8}$$

If $\left|\psi_{12}(e^{-i\omega})\right|^2 = 0,$ then the Geweke's measure will be zero, then the *y* will not Granger-cause the *x* at frequency ω.

If the elements of z_t are $I(1)$ and cointegrated, in that case, in the frequency domain, the measure of causality can be defined by using the orthogonalized MA representation

$$\Delta z_t = \tilde{\Phi}(L)\varepsilon_t = \tilde{\psi}(L)\eta_t \tag{9}$$

where $\tilde{\psi}(L) = \tilde{\Phi}(L)G^{-1}, \eta_t = G\varepsilon_t,$ and G is a lower triangular matrix, such that $E(\eta_t \eta_t^{'}) = I$. Note that in a bivariate cointegrated system $\beta'\tilde{\psi}(1) = 0,$ where β is a cointegration vector, such that $\beta' z_t$ is stationary (Engle and Granger, 1987). As in the stationary case, the resulting causality measure is

$$M_{y \to x}(\omega) = \log \left| 1 + \frac{\left| \tilde{\psi}_{12}(e^{-i\omega}) \right|}{\left| \tilde{\psi}_{11}(e^{-i\omega}) \right|} \right| \tag{10}$$

To test the hypothesis that the y does not cause the x at frequency ω, we consider the null hypothesis:

$$M_{y \to x}(\omega) = 0 \tag{11}$$

within a bivariate framework. Following Breitung and Candelon (2006), we can present this test by reformulating the relationship between x and y in VAR (p) equation:

$$x_t = a_1 x_{t-1} + ... + a_p x_{t-p} + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} + \varepsilon_{1t} \tag{12}$$

The null hypothesis tested by Geweke, $M_{y \to x}(\omega) = 0$, corresponds to the null hypothesis of:

$$H_0 : R(\omega)\beta = 0 \tag{13}$$

where β is the vector of the coefficients of y and

$$R(\omega) = \begin{bmatrix} \cos(\omega)\cos(2\omega).....\cos(p\omega) \\ \sin(\omega)\sin(2\omega).......\sin(p\omega) \end{bmatrix} \tag{14}$$

The ordinary F statistic for (13) is approximately distributed as $F(2, T-2p)$ for $\omega \in (0, \pi)$. In order to perform the frequency domain Granger causality tests within a co-integrating framework, Breitung and Candelon (2006) suggest to replace x_t in regression (12) by Δx_t, while the right-hand side of the equation remains the same[16]. In co-integrated systems the definition of causality at frequency equal to zero is equivalent to the concept of "longrun causality" and in stationary framework, there exists no longrun relationship between the time series. A series may nevertheless explain future low frequency variation of another time series. Hence, in a stationary system, causality at low frequencies implies that the additional variable is able to forecast the low frequency component of the variable of interest, one period ahead.

[16]See Breitung and Candelon (2006) for a detailed discussion in the case when one variable is I(1) and other is I(0).

4. Results

The transformation of data described in the previous section allows us to obtain stationary series. First, we have computed a VAR and we have retained the Schwarz information criterion for the lag length selection (see Table 1)

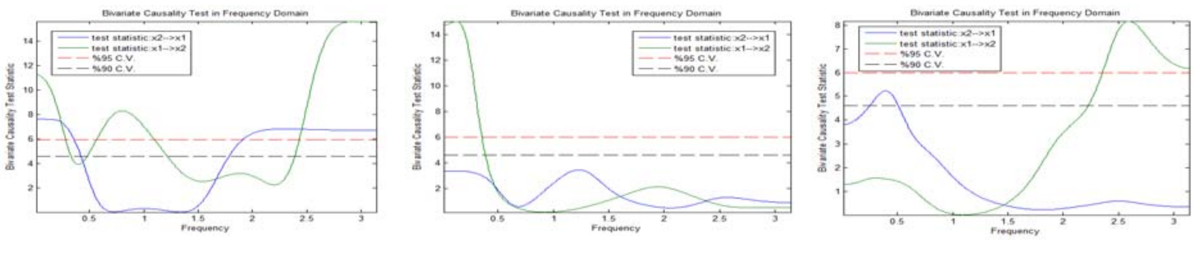
Table 1. VAR lag length selection

	Amsterdam	*Brussels*	*Lisbon*	*London*	*Paris*
Schwarz information criterion	2	1	3	1	2

Second, we present the results for Brussels stock exchange (Figure 3), for Lisbon stock exchange (Figure 4) and for London, Paris and Amsterdam (Figure 5) – Granger causality in frequency domain.These figures report the test statistics, along with their critical values (5% – red broken lines; 10% – black broken lines) for all frequencies ω (which are expressed as fraction of π) in the interval $(0,\pi)$. On the horizontal axis, the frequency ω is translated into a cycle or periodicity of T months by $T = 2\pi/\omega$, where T is the period. Thus, the frequency ω of a cycle is related to its period T, assessed in number of observations, and π takes its usual value. Consequently, a frequency of $\pi/4$ correspond to a period of 8 observations (months)[17].The variable $x1$ represents the derivatives volume while $x2$ stand for the underlying asset volatility/shocks in terms of volatility.

Figure 3. Granger bidirectional causality in frequency domain – Brussels

volatility (a) ***vol⁺ (b)*** ***vol⁻ (c)***



[17] Note that since high frequencies are having short periods and vice versa, figures of Granger causality at frequency domain stand reversed, with short term fluctuations/cycles at the right end and long term movements/cycles at the left.

From Figure 3 we can first analyse if the futures contracts volume Granger-cause the index return volatility (green line)[18]. It is evident that, at 95% confidence level, the derivatives volume is able to predict the volatility of their underlying assets, both at low frequency, in the range $\omega \in (0,1)$, and high frequency – $\omega \in (2.5,3.2)$. Furthermore, if we look to the positive shocks in term of volatility (Figure 3b), we can see that at long term (low frequencies), there are predicted by the derivatives volume. At the same time, at short run (high frequencies), the derivatives volume Granger-cause negatives shocks in terms of volatility, in the range $\omega \in (2.2,3.2)$ – Figure 3c. These findings show that on short run, the hedging operations prevail, while on long run, the speculative operations are dominant, as the derivatives cause an extreme volatility.

The second step is to see if the index returnvolatility Granger-cause the futures contracts volume on Brussels stock exchange, analysing thus the blue line. Figure 3a shows that both at short run and long run the null hypothesis of no causality is rejected at 5% level of significance. Consequently the index return volatility past values predict the derivatives volume[19]. No causality can be observed in case of positive shocks (Figure 3a). Nevertheless, in case of negative shocks, at 90% confidence level, it seems that at short run, in the range $\omega \in (0.3,0.6)$, the volatility Granger-cause the derivatives volume.

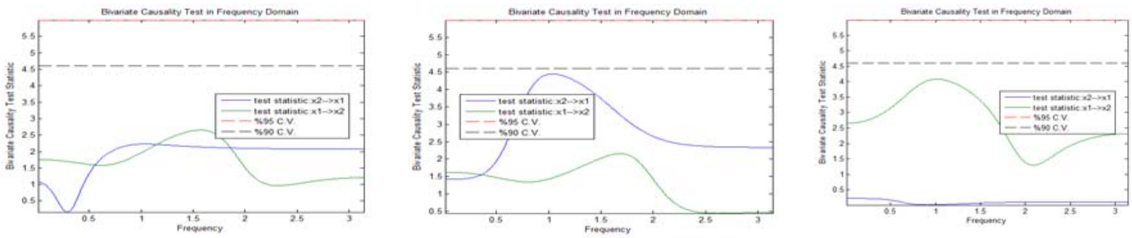
All in all, in case of Brussels stock exchange we observe a bivariate causality between the derivatives volume and the volatility of their underlying assets, both on short and long run. The futures equity index volume predicts positive shocks in term of volatility at long run and negative shocks at short run.

In case of Lisbon stock exchange (Figure 4), the null hypothesis on no causality is not rejected at 5% level of significance for all frequencies. This implies that the derivatives volume does not Granger-cause the index return volatility (green line – Figure 4a). At the same time, the volatility does not Granger-cause the derivatives volume (blue line). Regarding the shocks in terms of volatility (Figure 4b and Figure 4c), the situation is similar. To conclude, we observe a bidirectional Granger causality relationship but it is not validated by the confidence level tests.

[18] We associate this causality with speculative activities (see the Section 1).
[19] We associate this with hedging activities (a higher volatility implies an increase of the derivatives contracts). However, it is not very clear if these new contract are designated to cover risks on the spot market or to speculate an increased volatility. If we make a comparison with the Granger causality from derivatives to volatility, we observe that the last one is stronger. In this case, we can assert a dominance of the speculative activities with derivatives, on the Brussels stock exchange.

Figure 4. Granger bidirectional causality in frequency domain – Lisbon

volatility (a) *vol$^+$ (b)* *vol$^-$ (c)*



In the Figure 5 we have grouped the results of the causality analysis for Amsterdam, London and Paris stock exchange, as the situation is similar for these stock exchange markets.

Figure 5. Granger bidirectional causality in frequency domain – Amsterdam, London and Paris

volatility (a) *vol$^+$ (b)* *vol$^-$ (c)*

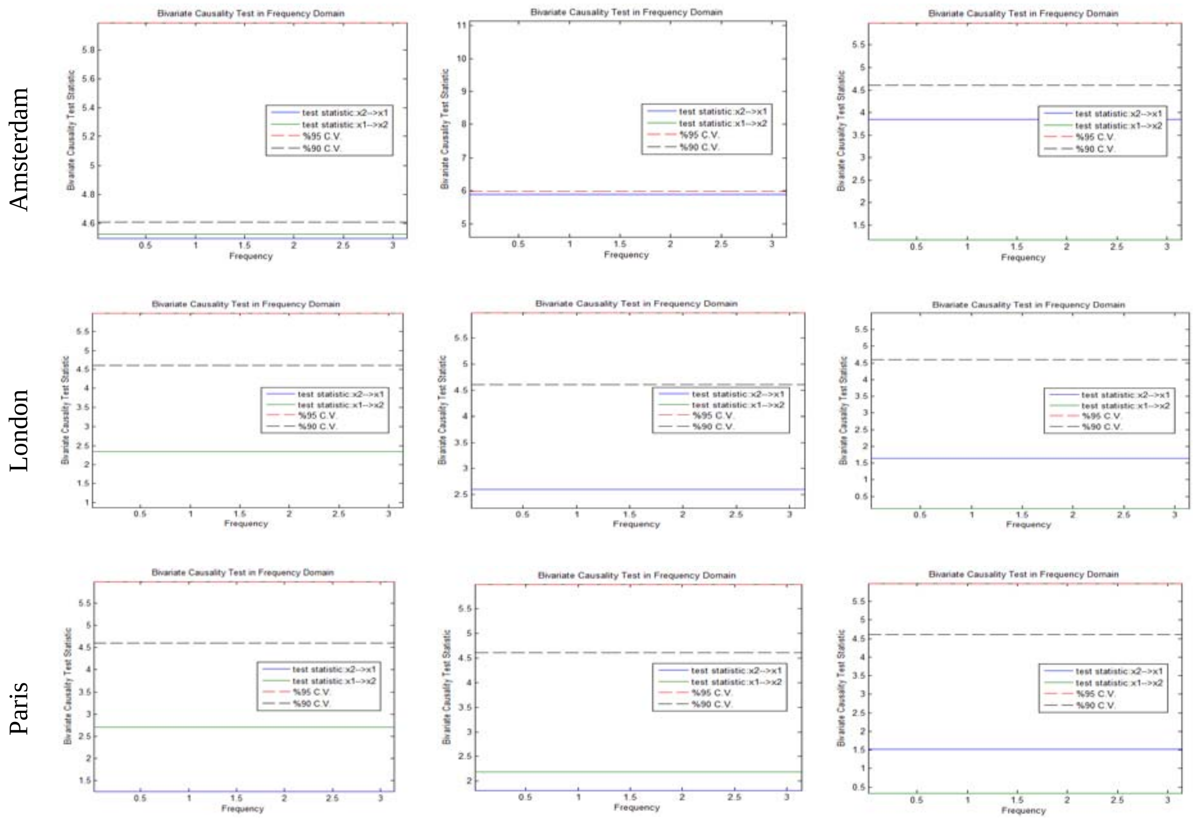


Figure 5 shows that the derivatives volume does not Granger-cause the underlying assets volatility, as the null hypothesis of no predictability is not rejected at 5% level of significance for all frequencies in the interval $(0, \pi)$. This implies that the futures products volume is unable to forecasts the low and high frequency component of the volatility (or of the positive and negative shocks in terms of volatility), one period ahead.

Subsequently, we also analyse the short and long run Granger causality from the financial volatility to derivatives volume and discover the same situation as previous in case of Amsterdam, London and Paris stock exchange. We conclude that there is no evidence of bidirectional causality between the financial volatility and the derivatives products on these markets.

5. Conclusions

In this paper, we used the frequency domain approach of Breitung and Candelon (2006) to investigate the short and long run bidirectional Granger causality between the volume of the futures equity index products and the volatility of their underlying assets. We analysed the case of five stock exchange markets, members of the Euronext.liffe, for the period 2001.09 – 2010.06.

First, we have transformed the data in order to obtain their stationarity and we have chosen the VAR lag length based on Schwarz criterion. Second, we have computed the bivariate causality for each financial market. Our results can be summarised as follows. In case of Brussels stock exchange, we found bidirectional causality between derivatives and the volatility of their underlying assets, both at short and long run. After computing the positive and negative shocks in terms of volatility, we also have discovered that the derivatives volume predicts positive shocks in term of volatility at long run and predicts negative shocks at short run. In case of Lisbon stock exchange the bidirectional causality is not validated by the significance or by the confidence level, while for Amsterdam, London and Paris, this relationship does not exists in a frequency domain analysis. Consequently, the causality can be observed for the small stock exchange markets members of Euronext.liffe, while for the large markets, it is absent.

Our results for Brussels are in line with several researches performed in time domain for other stock exchange markets and which reported bidirectional causality between the derivatives volume and the index return volatility (e.g. Sarwar, 2005). In case of large stock exchange markets, no relationship between the derivatives and the financial volatility can be observed, as in case of Darrat and Rahman (1995). To resume our findings, we state that exists small evidences regarding the financial volatility – derivatives products relationship on Euronext.liffe.

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