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REVISITING THE FINANCIAL VOLATILITY– DERIVATIVE PRODUCTS RELATIONSHIP ON EURONEXT.LIFFE USING A FREQUENCY DOMAIN ANALYSIS

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ABSTRACT:

The present paper analyses 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. We employ a frequency domain analysis to identify the direction of the causality. In addition, we test the relationship between the volume of futures contracts and both negative and positive shocks in terms of the historical volatility of index returns. Our results indicate the frequency causality only in the case of Brussels financial market. For Lisbon, the causality is present, but it is not validated by the confidence level tests, while for London, Paris and Amsterdam, no causality can be observed. In the case of Brussels, the causality is bidirectional, both in the short and long run frequencies. The futures equity index volume Granger-causes the positive shocks in terms of volatility in the long run and the negative shocks in the short run.

JEL CODES: C32, F37, G12, G15.

KEYWORDS: Volatility, futures index products, frequency domain Granger causality, Euronext.

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INTRODUCTION

The impact of derivative products on the volatility of their underlying assets was intensively assessed during last decades and it still stands for a subject of interest nowadays. However, only few studies approached the bidirectional relationship which may exist between the volume of derivatives and the financial volatility.

The theoretical literature on the topic developed in a single direction and its endeavour was to emphasize the impact of derivative products on the volatility of their underlying assets. Nevertheless, two antagonising 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. The second approach shows that the introduction of derivatives diminishes the price volatility of their underlying assets (Skinner, 1989). This situation can be explained by the conditions which must be accomplished by the underlying assets, in order to allow the derivatives transactions, conditions which ameliorate the confidence of investors 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 (Chan et al., 2002).

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 financial volatility before and after the introduction of derivative products and a large part of these studies discovered that the introduction of derivatives amplified 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 and has been intensively developed, reaching two different sets of results, depending on the theoretical background. A series of studies showed that the introduction of derivative products have led to an increased volatility on the spot markets, destabilising thus these markets (see e.g., Figlewski, 1981; Stein, 1987). Other studies sustained the opposite and demonstrated that the introduction of derivative products contributed to reducing the volatility (see e.g., Powers, 1970; Schwarz and Laatsch, 1991; Fedenia and Grammatikos, 1992). In the same line, more recently, Kasman and Kasman (2008) reached the conclusion that the futures introduction lowered the conditional volatility of the ISE 30 index. Nevertheless, a considerable number of papers either did not find a significant effect of derivatives on the market volatility (Edwards, 1988; Darrat and Rahman, 1995) or reported 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 considered assets, by the volatility calculation and by the employed empirical methodology.

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. If a stronger volatility

is anticipated, both risk managers and speculators decide to hedge or to strengthen their positions by means of derivative products. Therefore, a bidirectional relationship has to be analysed and several theoretical arguments support this demarche.

First, assuming a one-way causality between derivatives and financial volatility supposes 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 able to accurately anticipate the underlying assets return volatility, the causality between the volume of transactions with derivative products and the financial volatility is no longer necessarily a unidirectional relation, but a bidirectional one. Another argument supporting the bidirectional causality is related to lower costs associated with derivative products transactions and thus, higher leverage effects of these instruments. If the traders who are better informed are susceptible of being more attracted by derivatives, the volume of transactions with derivative products has to forego the price volatility of their underlying assets.

Kim et al. (2004) studied for the bidirectional causality and discovered a positive contemporaneous relationship between the stock market volatility and the derivatives volume, while Sarwar (2005) tested the double potential causality between the volume of transactions with options products and the volatility of the S&P 500 index. More recently Albulescu and Tiwari (2013) have analysed the double causality between derivative products and the price return of their underlying assets on Euronext.liffe, using the hidden cointegration technique.

All the above mentioned studies developed their researches in the time domain. The present paper differs from the previous ones 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). This methodology is theoretically appealing because the bidirectional causality can be observed for different frequencies (i.e., period of cycles). The traditional approach tacitly ignores the possibility that the strength and the direction of the Granger-causality can vary (Lemmens et al., 2008). Second, we identify positive and negative shocks in terms of volatility, employing the Hamilton's (2003) methodology. This way, we are able to see if the bidirectional causality manifests differently in the case of net increases or decreases of the volatility. Finally, we focus on the historical volatility and the value of the derivatives volume. The value of the volume is more appropriate than the number of contracts in order to estimate the amplitude of transactions involving derivatives. We also want to see if an increasing volume of derivatives causes positive or negative shocks in terms of volatility¹. If the derivatives volume Granger-causes positive volatility shocks, then, the speculative operations prevail on the market. Speculators induce a higher volatility on the stock markets through derivatives transaction, in order to benefit afterwards from this increased volatility. Reversely,

¹ Positive volatility shocks are associated with an increased volatility, above the average of the last observations, while negative shocks reveal a reduction of the volatility below the average (see Section 2 for a description of shocks computation).

if the derivatives volume Granger-causes negative volatility shocks, the hedging operations are predominant.

The reminder of the paper is structured as follows. Section 1 presents the frequency domain methodology. Section 2 describes the data. Section 3 depicts the empirical results and the conclusion.

1. METHODOLOGY

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 the variables (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–derivative products relationship has not yet been explored in the frequency domain. This approach complements a conventional time domain framework (McCullough, 1995).

The causality between two variables x_t and y_t is usually analysed based on the Granger (1969) approach, which is meant to show how much of the current y_t can be explained by the 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 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 know 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) showed, the extent and the direction of the causality differ between frequency bands and the conventional Granger causality tests are unable to assess them. Yet, it was Granger (1969) itself who advanced the idea of further disentangling of the causality relationship between two time series and suggested that a spectral-density approach would give a better-off and more complete picture than an one-shot Granger causality measure².

To overcome this limitation, Breitung and Candelon (2006) proposed a new approach where the causal relationship between variables is decomposed by frequencies. However, the approach of Breitung and Candelon (2006) is based on the work of Granger (1969). This approach provides an elegant interpretation of the frequency domain Granger causality, as it decomposes the total spectral interdependence between the two series into a sum of “instantaneous”, “feed-forward” and “feed-back” causality terms (Tiwari, 2012). This new measure of the Granger causality can be applied across all frequencies and allows knowing exactly for which frequency one variable Granger-causes the other.

² 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).

Therefore, in the present study we employ the Breitung and Candelon (2006) approach to assess the Granger causality in the frequency domain³. 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; Assenmacher-Wesche and Gerlach, 2008b; Assenmacher-Wesche et al., 2008; Lemmens et al., 2008; Gronwald, 2009). The Breitung and Candelon (2006) approach can be described as follows:

Let z_t be observed at $t = 1, \dots, T$ and have a finite-order VAR representation of the form:

$$z_t = \Theta(L)z_t \quad (1)$$

where

$\Theta(L) = I - \Theta_1 L - \dots - \Theta_p L^p$ is a 2×2 lag polynomial with $L^k z_t = z_{t-k}$.

We assume that the error vector ε_t is a white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t') = \Sigma$, where Σ is positive. In order to simplify the description, any deterministic terms in (1) are 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:

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

$$= \psi(L)\eta_t = \begin{bmatrix} \psi_{11}(L) & \psi_{12}(L) \\ \psi_{21}(L) & \psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \quad (3)$$

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:

$$f_x(\omega) = \frac{1}{2\pi} \{ |\psi_{11}(e^{-i\omega})|^2 + |\psi_{12}(e^{-i\omega})|^2 \} \quad (4)$$

³ In statistics, frequency domain describes the domain for analysis of mathematical functions or signals with respect to frequency, rather than time.

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

$$M_{y \rightarrow x}(\omega) = \log \left[\frac{2\pi f_x(\omega)}{|\psi_{11}(e^{-i\omega})|^2} \right] \quad (5)$$

$$= \log \left| 1 + \frac{|\psi_{12}(e^{-i\omega})|}{|\psi_{11}(e^{-i\omega})|} \right| \quad (6)$$

If $|\psi_{12}(e^{-i\omega})|^2 = 0$, then the Geweke (1982)'s measure will be zero and the y will not Granger-cause the x at frequency ω .

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

$$\Delta z_t = \tilde{\Phi}(L)\varepsilon_t = \tilde{\psi}(L)\eta_t \quad (7)$$

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:

$$M_{y \rightarrow x}(\omega) = \log \left| 1 + \frac{|\tilde{\psi}_{12}(e^{-i\omega})|}{|\tilde{\psi}_{11}(e^{-i\omega})|} \right| \quad (8)$$

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

$$M_{y \rightarrow x}(\omega) = 0 \quad (9)$$

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

$$x_t = a_1x_{t-1} + \dots + a_px_{t-p} + \beta_1y_{t-1} + \dots + \beta_py_{t-p} + \varepsilon_{1t} \quad (10)$$

The null hypothesis tested by Geweke (1982), $M_{y \rightarrow x}(\omega) = 0$, corresponds to the null hypothesis of:

$$H_0 : R(\omega)\beta = 0 \quad (11)$$

where β is the vector of the coefficients of y and

$$R(\omega) = \begin{bmatrix} \cos(\omega) \cos(2\omega) \dots \cos(p\omega) \\ \sin(\omega) \sin(2\omega) \dots \sin(p\omega) \end{bmatrix} \quad (12)$$

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 cointegrating framework, Breitung and Candelon (2006) suggest to replace x_t in the regression (10) by Δx_t , while the right-hand side of the equation remains the same⁴. In cointegrated systems the definition of the causality at a frequency equal to zero is equivalent to the concept of “long run causality” and, in a stationary framework, there is no long run relationship between the time series. A series may nevertheless explain future low frequency variation of another time series. Hence, in a stationary system, the 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.

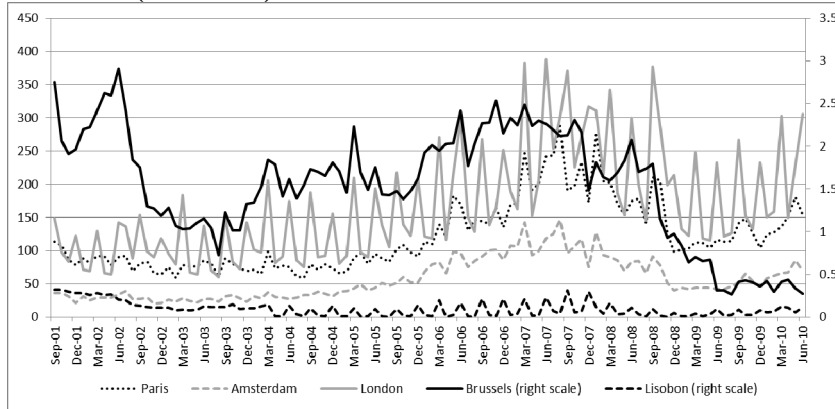
2. DATA

The derivatives data were extracted from Euronext.liffe database and cover the period 2001:09–2010:06 (monthly data). This timeframe is large enough to present significant evolutions of the derivatives volume and of the index returns volatility, which proves to be high during crisis periods.

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

⁴ See Breitung and Candelon (2006) for a detailed discussion in the case when one variable is $I(1)$ and other is $I(0)$.

**FIGURE 1. FUTURES EQUITY INDEX PRODUCTS TRADED ON EURONEXT.LIFFE
(BILL. EUR)**

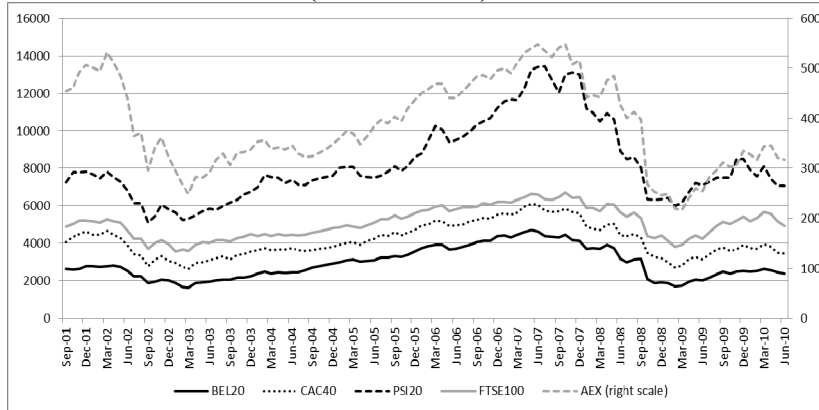


Source: Euronext.liffe.

We can observe that in the analysed period, London, Paris and Amsterdam represent 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 decreases latter.

Fig. 2 illustrates the trend of the stock indexes which are representative for the Euronext.liffe stock markets. We observe their correlation and also an increased volatility after the crisis outburst.

FIGURE 2. STOCK INDEXES (CLOSE VALUES)



Source: Yahoo.finance.

In order to proceed with the data analysis and to ensure the stationarity of the series, a number of transformations were necessary. First, we have detrended both the derivatives volume and the stock indexes series, using X-12-ARIMA methodology for monthly data (3x5 filters)⁵. Second, we have computed the natural logarithm of

⁵ Kim et al. (2004) proceeded in a similar way in their research, using an ARIMA (10, 0, 10) model.

both series. Third, we have calculated the first difference for both the derivatives volume and the stock indexes⁶. Finally, we have assessed the financial volatility based on the standard deviation of the obtained index returns, using a 12 months rolling window ($t-12:t$).

After the identification of the historical volatility, we have computed the positive and negatives shocks, employing the Hamilton's (2003) methodology, relative to net increases and decreases in the oil price. 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 than 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 the month t and its maximum values over the previous 6 months. If the volatility in month t is lower than its level over the past 6 months, the absence of the shock is recorded. The same reasoning applies for the negative shocks, according to the following two formulae:

$$vol^+ = IF(vol_t > MAX(vol_{t-1} : vol_{t-6}), vol_t - MAX(vol_{t-1} : vol_{t-6}), 0) \quad (13)$$

$$vol^- = IF(vol_t < MIN(vol_{t-1} : vol_{t-6}), vol_t - MIN(vol_{t-1} : vol_{t-6}), 0) \quad (14)$$

where “ vol^+ ” and “ vol^- ” represent positive and negative volatility shocks

3. RESULTS

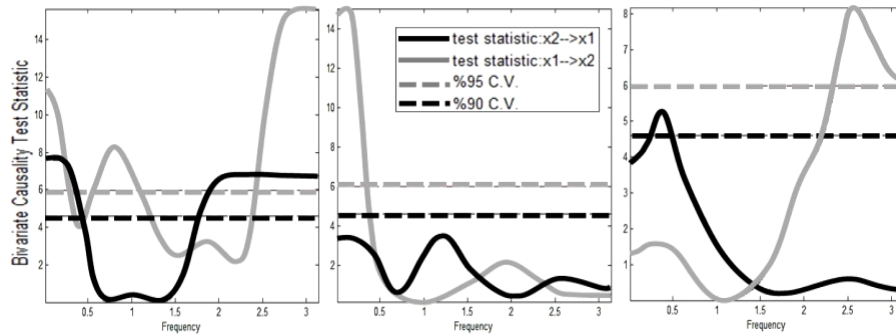
The transformation of data described in the previous section allows to obtain stationary series. For each stock market we first compute a VAR and we retain the Schwarz information criterion for the lag length selection.

In what follows, we present the Granger causality results in frequency domain, for the Brussels stock exchange (Fig. 3), for the Lisbon stock exchange (Fig. 4) and for those of London, Paris and Amsterdam (Fig. 5). These figures report the test statistics, along with their critical values (5% – grey 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 by the number of observations, and π takes its usual value. Consequently, a frequency of $\pi/4$ corresponds to a period of 8 observations (months)⁷. The variable $x1$ represents the derivatives volume while $x2$ stands for the underlying asset volatility/shocks in terms of volatility.

⁶ The first difference of the natural log of the stock index is associated in this case with the index return.

⁷ Note that, since high frequencies are having short periods and vice versa, the figures of the Granger causality in the frequency domain stand reversed, with short term fluctuations/cycles at the right end and long term movements/cycles at the left side.

FIGURE 3. GRANGER BIDIRECTIONAL CAUSALITY IN THE FREQUENCY DOMAIN FOR BRUSSELS



Note: The first chart from Figure 3 analyses the bidirectional causality in terms of general volatility, while the second and the third chart analyse the bidirectional causality in terms of positive and negative volatility shocks respectively.

Based on Fig. 3, we can first analyse if the futures contracts volume Granger-causes the index return volatility (the grey continuous line)⁸. It is obvious that, at 95% confidence level, the derivatives volume is able to predict the volatility of their underlying assets, both at low frequencies, in the range $\omega \in (0,1)$, and high frequencies, with $\omega \in (2.5,3.2)$. Furthermore, if we look to the positive shocks in terms of volatility (Figure 3b), we can see that in the long term (low frequencies), they are predicted by the derivatives volume. At the same time, in the short run (high frequencies), the volume of derivatives Granger-causes the negatives shocks in terms of volatility, in the range $\omega \in (2.2,3.2)$ – Fig. 3c. These findings show that, in the short run, the hedging operations prevail, while in the long run, the speculative operations are dominant, as the derivatives cause an extreme volatility. These outcomes highlight the strategy behind the decisions made by speculators with the purpose of taking advantage of the increased volatility induced on the market.

The second step is to see if the index returns volatility Granger-causes the futures contracts volume on the Brussels stock exchange, analysing thus the black continuous line. Figure 3a shows that both in the short and long runs the null hypothesis of no causality is rejected at 5% level of significance. Consequently, the past values of the index returns volatility predict the derivatives volume⁹. No causality can be observed in the case of positive shocks (Figure 3a). Nevertheless, in the case of negative shocks at 90% confidence level, it seems that, in the short run, the volatility Granger-causes the derivatives volume in the range $\omega \in (0.3,0.6)$.

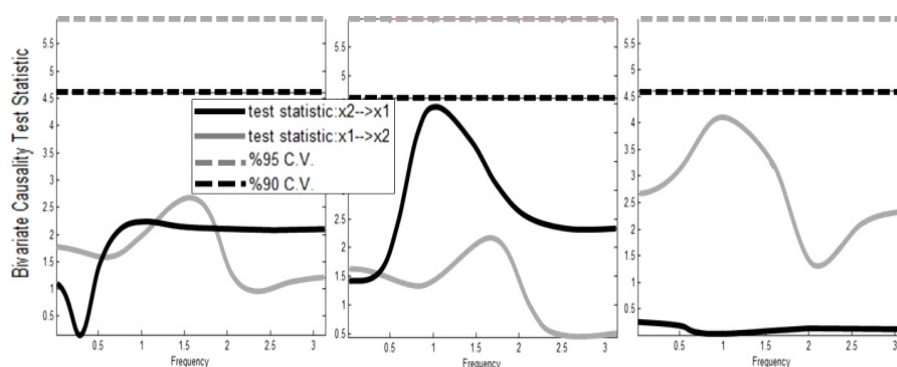
⁸ We associate this causality with speculative activities (see the Section 1).

⁹ We associate this with hedging activities (a higher volatility implies an increase of derivatives contracts). However, it is not very clear if these new contracts are designated to cover risks on the spot market or to speculate an increased volatility. If we make a comparison with the Granger causality, going 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.

All in all, in the case of the Brussels stock exchange we observe a bivariate causality between the derivatives volume and the volatility of their underlying assets, both in the short and long runs¹⁰. The futures equity index volume predicts positive shocks in terms of volatility in the long run and negative shocks in the short run.

For the Lisbon stock exchange, the null hypothesis on no causality is not rejected at 5% level of significance for all frequencies (Fig. 4). This implies that the derivatives volume does not Granger-cause the index return volatility (the gray line – Fig. 4a). At the same time, the volatility does not Granger-cause the derivatives volume (the black continuous line). Regarding the shocks in terms of volatility (Figs. 4b and 4c), the situation looks similar. To conclude, we observe a bidirectional Granger causality relationship which is not however validated by the confidence level tests. Similar results were reported by Albulescu and Tiwari (2013) in a hidden cointegration framework.

FIGURE4. GRANGER BIDIRECTIONAL CAUSALITY IN THE FREQUENCY DOMAIN FOR LISBON



Note: The first chart from Figure 4 analyses the bidirectional causality in terms of general volatility, while the second and the third chart analyse the bidirectional causality in terms of positive and negative volatility chocks respectively.

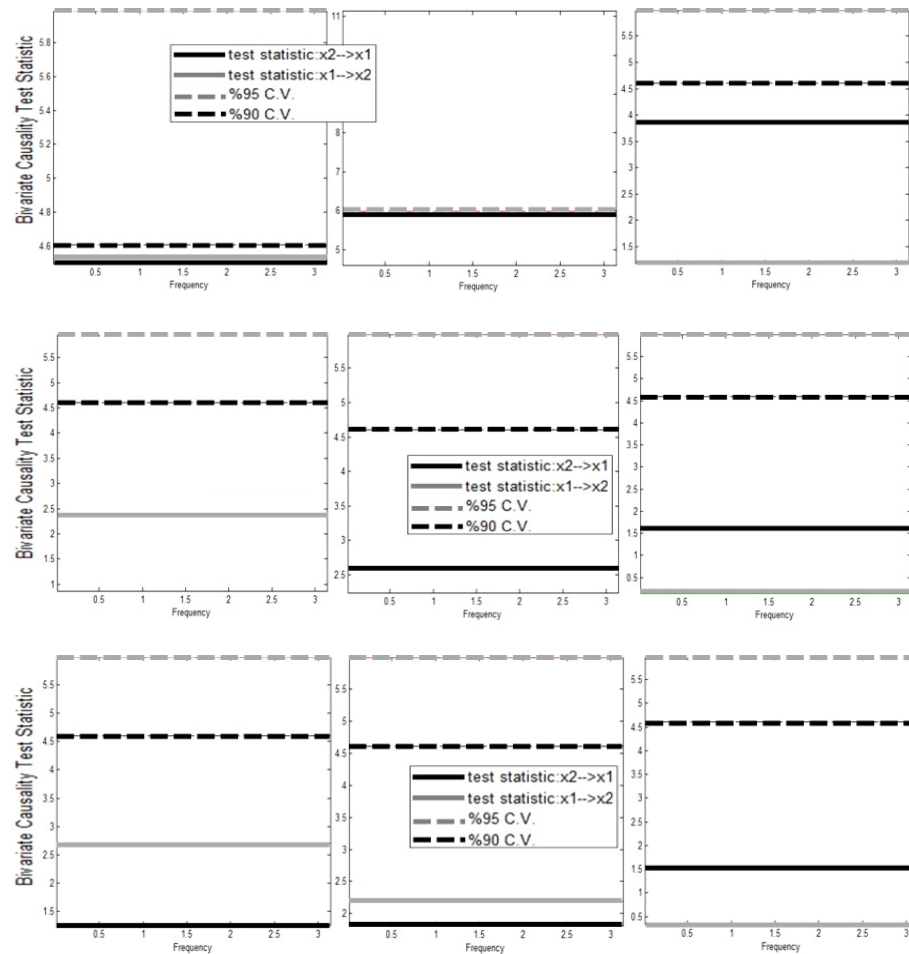
In the Fig. 5 we have grouped the results of the causality analysis for the Amsterdam, London and Paris stock exchanges, as the situation is similar for these markets. The findings show that the derivatives volume does not Granger-cause the volatility of the underlying assets, as the null hypothesis of no predictability is not rejected at 5% level of significance for all frequencies in the interval $(0, \pi)$ ¹¹. This implies that the futures products volume is unable to forecast the low and high frequency components of the volatility (or of the positive and negative shocks in terms of volatility), one period ahead. The findings prove that in the large stock exchange markets the predominance of speculative or hedging operations cannot be

¹⁰ A bidirectional causality between the derivatives volume and the index return volatility was reported in the time domain by Sarwar (2005).

¹¹ Darrat and Rahman (1995) showed in their turn the absence of the relationship between the derivatives and financial volatility in a time domain analysis.

observed. Furthermore, on these stock markets, investors are either specialised on derivatives or spot markets transactions and do not interfere on the two markets in the same time. This is also due to the difficulty to influence individually a large market in comparison to a small one.

FIGURE 5. GRANGER BIDIRECTIONAL CAUSALITY IN THE FREQUENCY DOMAIN FOR AMSTERDAM, LONDON AND PARIS



Note: The rows of charts represent the Amsterdam, London and Paris stock exchange. The first chart from each row analyses the bidirectional causality in terms of general volatility, while the second and the third chart analyse the bidirectional causality in terms of positive and negative volatility checks respectively.

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

These mixed results determine us to check for the robustness of our findings. Consequently, we perform a resampling of the initial data-series, and we test for the presence of the same characteristics in data, after 2003, in order to avoid the influence of the stock market crash from 2000 to 2002. The results are similar, except for the London stock exchange, where a bidirectional but non-significant causality appears (Appendix A). However, altogether our results are robust and are similar to those obtained using time domain approaches for a similar period. Albulescu and Tiwari (2013) showed in their turn that Brussels and Lisbon stock exchanges present a higher number of hidden cointegration situations, as compared to more developed markets. All in all, our findings shows that on the small market, the bivariate relationship between derivatives and financial volatility is more intense, as the financial shocks are much more easily perceived by the market players.

CONCLUSION

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 the Schwarz criterion. Second, we have computed the bivariate causality for each financial market.

Our results can be summarized as follows. In the case of the Brussels stock exchange, we found bidirectional causality between derivatives and the volatility of their underlying assets, both in the short and long runs. After computing the positive and negative shocks in terms of volatility, we also have discovered that the derivatives volume predicts positive shocks in terms of volatility in the long run and predicts negative shocks in the short run. In the case of the 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 exist 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. The results are robust when using the resampling approach.

Due to the fact that small markets as Brussels or Lisbon can be influenced by individual players, being thus more vulnerable, our results are not surprising. It is easy to observe on these markets the predominance of the speculative or of the hedging operations. However, for Amsterdam, Paris and London, the bidirectional relationship is absent because individual investors can hardly influence by themselves a large market. Moreover, on large markets, investors are either specialized on futures or spot markets transactions and are rarely involved in both markets in the same time, in order to take advantage from volatility increases

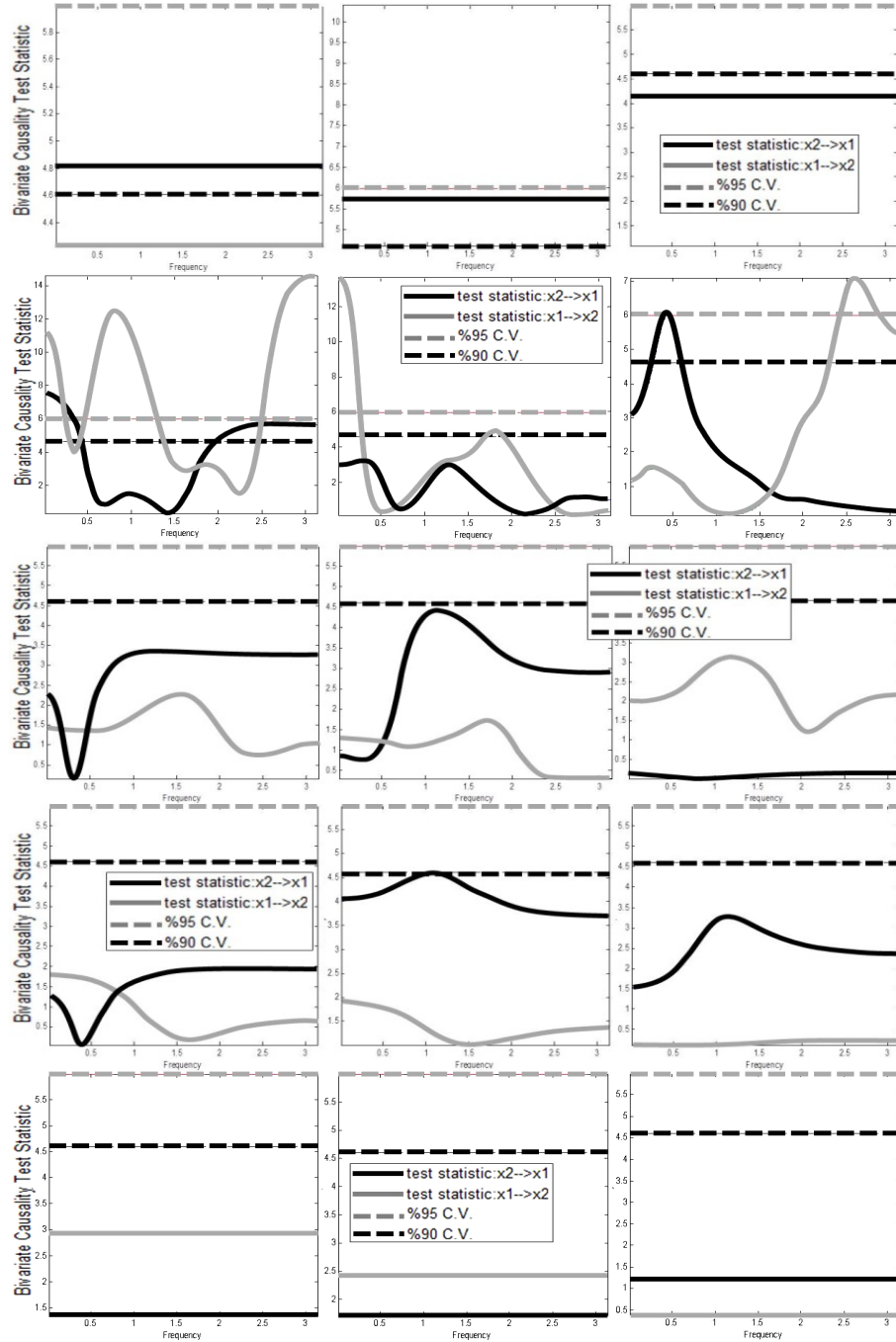
REFERENCES

- Albulescu, C.T. and K.A.,** Tiwari, 2013. "Asymmetric causality between futures contracts and the return volatility of their underlying assets on Euronext.liffe", *Journal of Economic and Financial Modelling*, 1, pp. 14-26.
- Antoniou, A. and P., Holmes,** 1995. "Futures Trading, Information and Spot Price Volatility: Evidence for the FTSE-100 Stock Index Futures Contract Using GARCH", *Journal of Banking & Finance*, 19, 117-129.
- Antoniou, A., O. Holmes and R. Priestley,** 1998. "The effects of stock index futures on stock volatility: An analysis of the asymmetric response of volatility to news", *Journal of Futures Markets*, 18, pp. 151-166.
- Assenmacher-Wesche, K. and S. Gerlach,** 2007. "Money at Low Frequencies", *Journal of the European Economic Association*, 5, pp. 534-542.
- Assenmacher-Wesche, K. and S. Gerlach,** 2008a. "Interpreting Euro Area Inflation at High and Low Frequencies", *European Economic Review*, 52, pp. 964-986.
- Assenmacher-Wesche, K. and S. Gerlach,** 2008b. "Money Growth, Output Gaps and Inflation at Low and High Frequency: Spectral Estimates for Switzerland", *Journal of Economic Dynamics and Control*, 32, pp. 411-435.
- Assenmacher-Wesche, K., S. Gerlach and T. Sekine,** 2008. "Monetary Factors and Inflation in Japan", *Journal of the Japanese and International Economies*, 22, pp. 343-363.
- Breitung, J. and B. Candelon,** 2006. "Testing for Short and Long-Run Causality: A Frequency Domain Approach", *Journal of Econometrics*, 132, pp. 363-378.
- Charupat, N.,** 2006. "The effect of derivative trading on the underlying markets: Evidence from Canadian instalment receipts trading", *International Review of Economics and Finance*, 15, pp. 276-293.
- Chan, K., Y.P. Chug and W-M. Fong,** 2002. "The Informational Role of Stock and Option Volume", *The Review of Financial Studies*, 15, pp. 1049-1075.
- Croux, C. and P. Reusens,** 2013. "Do stock prices contain predictive power for the future economic activity? A Granger causality analysis in the frequency domain", *Journal of Macroeconomics*, 35, pp. 93-103.
- Darrat, A.F. and S. Rahman,** 1995. "Has futures trading activity causes stock price volatility?", *Journal of Futures Markets*, 15, pp. 537-557.
- Dennisa, S.A. and A.B. Sim,** 1999. "Share price volatility with the introduction of individual share futures on the Sydney Futures Exchange", *International Review of Financial Analysis*, 8, pp. 153-163.
- Edwards, F.R.,** 1988. "Futures trading and cash market volatility: Stock index and interest rate futures", *Journal of Futures Markets*, 8, pp. 421-439.
- Engle, R.F. and C.W.J. Granger,** 1987. "Co-Integration and Error Correction: Representation, Estimation, and Testing", *Econometrica*, 55, pp. 251-276.
- Fedenia, M. and T. Grammatikos,** 1992. "Options Trading and the Bid-Ask Spread of the Underlying Stocks", *Journal of Business*, 65, pp. 335-351.
- Figlewski, S.,** 1981. "Futures Trading and Volatility in the GNMA Market", *Journal of Finance*, 36, pp. 445-484.
- Geweke, J.,** 1982. "Measurement of linear dependence and feedback between multiple time series", *Journal of American Statistical Association*, 77, pp. 304-324.
- Granger, C.W.J.,** 1969. "Investigation causal relations by econometric models and cross-spectral methods", *Econometrica*, 37, pp. 424-438.

- Granger, C.W.J. and J-L. Lin**, 1995. "Causality in the long run", *Econometric Theory*, 11, pp. 530-536.
- Gronwald, M.**, 2009. "Reconsidering the macroeconomics of the oil price in Germany: Testing for causality in the frequency domain", *Empirical Economics*, 36, 441-453.
- Hamilton, J.D.**, 2003. "What is an oil shock?", *Journal of Econometrics*, 113, pp. 363-398.
- Hosoya, Y.**, 1991. "The decomposition and measurement of the interdependence between second-order stationary process", *Probability Theory and Related Fields*, 88, pp. 429-444.
- Jeanneau, S. and M. Micu**, 2003. "Volatility and derivatives turnover: a tenuous relationship", *BIS Quarterly Review*, March, pp. 57-66.
- Kasman, A. and S. Kasman**, 2008. "The impact of futures trading on volatility of the underlying asset in the Turkish stock market", *Physica A*, 387, pp. 2837-2845.
- Kim, M., G.R. Kim and M. Kim**, 2004. "Stock market volatility and trading activities in the KOSPI 200 derivatives markets", *Applied Economics Letters*, 11, pp. 49-53.
- Lemmens, A., C. Croux and M.G. Dekimpe**, 2008. "Measuring and Testing Granger Causality Over the Spectrum: An Application to European Production Expectation Surveys", *International Journal of Forecasting*, 24, pp. 414-431.
- McCullough, B.D.**, 1995. "A spectral Analysis of Transactions Stock Market Data", *The Financial Review*, 30, pp. 823-842.
- Powers, M.J.**, 1970. "Does Futures Trading Reduce Price Fluctuations in the Cash Markets?", *American Economic Review*, 60, pp. 460-464.
- Reyes, M.G.**, 1996. "Index futures trading and stock price volatility: Evidence from Denmark and France", *Journal of Economics and Finance*, 20, pp. 81-88.
- Robinson, G.**, 1994. "The effect of futures trading on cash market volatility: Evidence from the London stock exchange", *Review of Futures Markets*, 14, pp. 429-459.
- Sarwar, G.**, 2005. "The Informational Role of Option Trading Volume in Equity Index Options Markets", *Review of Quantitative Finance and Accounting*, 24, pp. 159-176.
- Schwarz, T.V. and F. Laatsch**, 1991. "Dynamic Efficiency and Price Leadership in Stock Index Cash and Futures Markets", *Journal of Futures Markets*, 11, pp. 669-683.
- Skinner, D.**, 1989. "Options markets and stock return volatility", *Journal of Financial Economics*, 23, pp. 61-78.
- Stein, J.C.**, 1987. "Information Externalities and Welfare Reducing Speculation", *Journal of Political Economy*, 95, pp. 1123-1145.
- Tiwari, A.K.**, 2012. "Tax burden and GDP: Evidence from Frequency Domain Approach for the USA", *Economics Bulletin*, 32, pp. 147-159.

REVISITING THE FINANCIAL VOLATILITY-DERIVATIVE PRODUCTS RELATIONSHIP ON
EURONEXT.LIFFE USING A FREQUENCY DOMAIN ANALYSIS

APPENDIX A. ROBUSTNESS CHECK FOR THE SUB-PERIOD 2003:01–2010:06



Note: The rows of charts represent the Amsterdam, Brussels, Lisbon, London and Paris stock exchange. The first chart from each row analyses the bidirectional causality in terms of general volatility, while the second and the third chart analyse the bidirectional causality in terms of positive and negative volatility chocks respectively.