Corruption and Co-Movements in European Listed Sport Companies: Did Calciocaos really matter?

Joao Leitao and Manuel Rocha Armada and Joaaquim Ferreira

University of Beira Interior and CEG-IST, University of Minho, Núcleo de Investigação em Políticas Económicas, University of Minho

6 November 2012

Corruption and Co-Movements in European Listed Sport Companies:

Did Calciocaos really matter?

João Leitão[1]

University of Beira Interior, Technical University of Lisbon (CEG-IST) and Polytechnic Institute of Portalegre

Covilhã, Portugal

Manuel da Rocha Armada

University of Minho, School of Economics and Management

Braga, Portugal

Joaquim Ferreira

University of Minho, School of Economics and Management

Braga, Portugal

Abstract

This paper analyses whether the Calciocaos, which involved some Italian listed sport companies, impacted on the performance of the Dow Jones Stoxx Football index and if this was spread through shock propagation. The Calciocaos impact is assessed by using a cointegrated vector autoregression model. The results provide evidence of the occurrence of spreading mechanisms of the effects originated by the corruption episode. After this episode Juventus' stock and Sporting's stock have particular importance in determining the performance of the Dow Jones Stoxx Football index. The investors/supporters of la Vecchia Signora revealed sentimental behaviour, and did not sell their participations.

Keywords: Cointegration, Contagion, Corruption, Stocks performance.

[1] **Corresponding Author**: João Leitão, University of Beira Interior, Convento de Santo António, 6201-001, Covilhã Portugal. Phone: + 351275319000. E-mail: jleitao@ubi.pt.

1 Introduction

Until the beginning of the 1980s, financial crises were seen as events which happened in individual markets, without a systemic nature. For this reason, at that time the possibility of transmission of shocks between countries or international stock markets merited little attention in the literature on international finance.

During the 1990s there were changes, due to the occurrence of exogenous shocks, mainly originated by unpredictable terrorist attacks or corruption episodes. One of the most impressive characteristics of these crises was that related to the moment of their occurrence and their intensity, which did not seem to be related to stock performance. Furthermore, the negative effects associated with the instability caused by certain episodes were not limited to the stocks directly affected by exogenous shocks, being quickly transmitted through contagion over the most representative international stocks.

It is important to study shock transmission among international stocks for different reasons. For example, contagion may have deep implications for portfolio management, particularly in processes of international diversification of risk. Also, there is a tendency towards the integration of stock markets on a worldwide basis.

According to the literature on contagion, the limited focus of previous studies at the aggregate level which embrace the co-movements of international financial markets should be underlined, since they are strongly concentrated on analysing the behaviour of stock markets in emerging economies.

In the short term, daily data allows detection of contagion effects that could be not detected in analysis that uses less frequent data, and so we used daily data in this paper. This allowed us to present a different analysis in relation to the generality of contagion studies which used monthly or weekly data.

This paper is particularly related to study of the effects of a corruption episode named Calciocaos on the performance of the stocks of European listed sport companies, especially by analysing leading football clubs.

The paper’s contribution to the literature on contagion and performance of sport companies is three-fold. First, it is a pioneering attempt to measure the effects of a corruption episode on the performance of hitherto neglected stocks of European listed sport companies. Secondly, it is an attempt to explain the changes in the stock prices of some leading clubs which belong to the DJ STOXX Football Index, by making a comparative analysis between two sub-samples from different time periods: before and after Calciocaos. Thirdly, it shows that the impact of corruption episodes on listed football club performance, rather than resulting in a mechanism of shock propagation, can reveal complex and emotional behaviour[2], by investors who are simultaneously football supporters.

A cointegrated vector autoregression (CVAR) model is applied, in order to detect cointegrating vectors and forecast the performance of stocks under study. A dynamic analysis is also carried out, using block exogeneity tests to check for the existence of causality relationships, in a Grangerian sense. To forecast the degree of impact and correspondent signal of the causality relationship, coefficients of the Cholesky variance decomposition, and of the impulse response functions, are also computed.

Before Calciocaos, the results reveal the importance of two stocks of leading European football clubs in explaining the performance of other stocks that integrate the above-mentioned benchmark. After Calciocaos, the stock prices of Juventus lost explanatory power, whereas other previously less influential stocks, such as Sporting and Porto, played an important role in explaining the performance of European listed sport companies, in a cointegrated approach.

The structure of the paper is as follows. First, it reviews the literature on episodes of financial crisis and contagion, to reveal the missing link between corruption and contagion. Subsequently, it presents the research methodology, data and descriptive statistics, and econometric method. Then, it presents the empirical findings and discusses the contrasting results obtained for the two sub-samples used in the econometric approach. Lastly, it concludes and provides implications and guidelines for future research.

---

[2] In the present paper, we consider that investors who have an emotional behaviour take decisions that with discipline they would not take. This type of investor behaviour may have unexpected effects on the performance of stocks, in the long term.

2 Literature review

2.1 Corruption and contagion: Is there a missing link?

Corruption is abuse of organizational responsibility or a position of authority for personal or organizational gains, in violation of rules or norms. The phenomenon of contagion corresponds to propagation of international economic shock waves, leading for example to risk aversion by investors due to the fall of stock prices, increased interest rates and a drop in demand for products of affected countries. In the literature up to now, the connection between these two phenomena has not been explored, despite the importance of analysing if cases of corruption adhere to the logic of shock transmission analogical to that portrayed in the literature of reference on contagion between international stock markets.

Treisman (2000) asks why corruption is linked to countries where investment, growth and development are less, but in spite of empirical studies carried out so far there has been no determination of the collective, individual and emotional motivations that make corruption greater in some countries than others.

Corruption is an obstacle to a country's economic and social development (Ciocchini *et al.*, 2003), and can be understood as excessive use of public functions for private ends (Vinod, 2003). It can also correspond to wrong use of organizational responsibility or any position of authority for personal gain or that of a given organization (Zyglidopoulos *et al.*, 2008).

According to Ahlin & Pang (2008), high economic-financial development in a country contributes to lower levels of corruption. On the contrary, low economic-financial development encourages an increase of corrupt practices, increasing in this way the gains associated with illegal individual acts, rather than greater collective development.

In a context of interdependence of financial and international markets, the expected effects of contagion can contribute to increased corruption between bribe-takers and bribe-givers, when these agents become more daring in guaranteeing other forms of revenue, for example, carrying out corrupt actions from observation of others who are involved in similar deeds (Goel & Nelson, 2007).

For Corsetti *et al.* (2000), in a scenario of international crisis, volatility of stock prices in a given market leads to changes in the prices of financial stocks quoted in other interdependent markets.

In the view of Dornbusch *et al.* (2000), contagion corresponds to a significant increase in cross-market connections after a shock in a country (or in several countries), that increase being observed through the joint movements (or co-movements) of stock prices and financial fluxes.

Forbes & Rigobon (2001) designate as shift-contagion an increase in cross-market connections after the occurrence of a shock in one economy or in a group of economies.

Contagion can originate in financial connections between economies, especially for those highly dependent on direct foreign investment (Jokipii & Lucey, 2007).

Interdependence is a phenomenon of divergence, although stability persists and there is no recorded structural change in relationships between markets. Therefore, although contagion is a phenomenon where cross-market connections are different after the occurence of a shock, for Jokipii & Lucey (2007), interdependence does not necessarily imply any change in the links or relationships between markets.

The interdependence of links between international financial markets can be assessed through the correlation coefficients of cross-market connections. Therefore, a high correlation corresponds to a situation of interdependence, while a low correlation suggests a scenario of contagion (Fazio 2007).

Propagation of contagion occurs through transmission channels. These can be commercial financial channels of competitive devaluation (Dornbusch *et al.*, 2000; Haile & Pozo, 2007; Didier *et al.*, 2007) or fundamentally macroeconomic (Fazio, 2007; Haile & Pozo, 2007). This situation is due to the fact that contagion is intrinsically related to commercial links, common external shocks and investors' tendency to face risk (Kumar & Persaud, 2002). However, noisy contagion can also be spread through financial intermediaries, namely banks (Schoenmaker, 1996).

However, we should not neglect the importance of herding behaviour by investors, together with risk aversion and information asymmetry. Indeed, in a climate of crisis, the investor can choose to reform his portfolio, so as be less exposed to risky stocks. In addition, information asymmetry can generate an information cascade inasmuch as investors act in their own interests, without informing the issuer of shares and other investors (Haile & Pozo, 2007).

For Guégan (2008) contagion refers to the propagation of shock waves in financial markets more than the propagation of crises between national economies. Those shocks affect a country's wealth and aggregate demand, since the liquidity of financial markets is less and therefore affect stock prices and investment.

Contagion is a wide concept of systemic crises which can result from an episode of propagation or a common shock affecting simultaneously financial and banking institutions (Gropp *et al.*, 2009).

In the literature, the relationships between corruption and economic-financial development are minimally explored, from both the theoretical and empirical point of view. However, a missing link is detected concerning study of the relationship between episodes of corruption and the volatility they create, with expected effects on the performance of stocks quoted in international stock markets.

2.2 Crises and contagion

The issue of contagion is very topical, and has been approached from different angles directed towards better understanding of the mechanisms and effects of transmission of crisis episodes. In this context, the studies by Schoenmaker (1996) and Forbes & Rigobon (2000) deserve special attention. The former carried out a pioneering measurement of contagion in the US banking system, revealing the need to identify the banks that can set off the so-called domino effect. In the latter, the correlation coefficients of the different markets in Latin America were analysed according to two sub-samples referring to the pre-shock and post-shock periods, suggesting an increase in cross-market connections after occurrence of the shock.

In the analysis of crisis episodes motivated by investors' panic behaviour, Baig & Goldfajn (2000) conclude on the occurence of shock transmission mechanisms, in the period between the Russian crisis (August 1998) and the Brazilian crisis (January 1999). In this way, when the Russian crisis erupted, it provoked a speculative attack on the local currency by investors resident in Brazil. The role of foreign banks should also be highlighted, as they were one of the channels through which the Russian crisis was propagated in Brazil.

Chakravorti & Lall (2004) developed a model of investment strategies whose main contribution was to demonstrate that contagion is transmitted through the institutional structures of international markets. In that same line of investigation, Corsetti *et al.* (2005), Chiang *et al.* (2007), Haile & Pozo (2007) and Lee *et al.* (2007) obtained empirical evidence of contagion between the stock markets of emerging economies and developed economies.

Different episodes of an anomalous nature and their impact on connections between international financial markets have been studied, as for example: (i) the crash of 19 October 1987 (Yang & Bessler, 2008); (ii) deconstructing the NASDAQ bubble (Hon *et al.*, 2007); (iii) September 11 (Leitão & Cristóvão, 2007); and (iv) the South-East Asian Tsunami in December 2004 (Lee *et al.*, 2007). All episodes supply evidence of different intensities of contagion among economies or international market stocks.

Although the literature detects growing concern with assessment of the impact of anomalous and exogeneous factors on the relationships formed among international financial markets, there is still a lack of knowledge of the mechanisms of propagating effects associated with anomalous episodes of corruption on the combined functioning of transmission channels and the intensity of shock transmission among international financial markets.

2.3 Structural changes and financial crises in European football

In December 1995, European football was subject to great structural changes following application of the Bosman Ruling, in which various restrictions in the European labour market were lifted. In addition, a tendency was observed for clubs to give up training players, which led to the search for players in the European Union. However, this tendency has gradually been reversed through concentration on development of academies and schools for training new assets, i.e footballers.

Hann *et al.* (2002) studied the effects of those changes in the national and international competitions in seven European countries with data starting in the 1945/1946 season, concluding on the strengthened competitive capacity of clubs from the richest championships, compared to clubs competing in less competitive championships.

To evaluate the effects of changes in contract regulations and television rights on sporting performance, Barajas *et al.* (2005) analysed 34 Spanish football teams in the first and second divisions in the period 1998-2002. The authors conclude that the relationship between clubs' sporting performance and their income, both from competition and television, is statistically significant. Nevertheless, the authors find evidence of poor explanatory power of economic results related to clubs' sporting performance.

The effects of financial crises on the sporting results obtained in different competitions organized in Europe has been the subject of special attention in studies applied to different national championships, namely the Italian (Baroncelli & Lago, 2006), German (Frick & Prinz, 2006), English (Buraimo *et al.*, 2006), Scottish (Morrow, 2006), Spanish (Ascari & Gagnepain, 2006) and Portuguese (Barros, 2006).

The same studies converge on the need to have a pro-efficiency orientation, i.e. for clubs to have a balanced financial situation in the short and medium-term, club administration should: (i) cut salaries; (ii) sell new assets – footballers; (iii) loan players; and (iv) transfer property to third parties.

The success of football clubs was also studied by Berument *et al.* (2006), analysing the most representative Turkish football clubs quoted on the stock market: Galatasaray, Fenerbahce and Besiktas. The authors concluded that victories by Besiktas led to increased price of their shares on the stock market, contrary to what happened with the other two clubs, although this increase was greater when Besiktas won away than when they won at home.

Through analysis of the impact of a football club's victory, defeat or draw on the same club's quotation, Batyrbekov (2007) concluded that share quotations have a substantial reaction immediately after the game, accounting for an increase on return of 1.1% in the case of a win, and a reduction of 0.6% in the case of a defeat.

Boido & Fasano (2006) analysed the influence caused by the mood or "emotional effect" of investors on the stock performance of three Italian clubs: Lazio, Roma and Juventus. The authors concluded that investor behaviour is influenced positively by a win in an important competition. However, they found that the ratio average between price and return following a win is above the average ratio between price and return following a defeat. They also concluded that investors do not like games to end in a draw.

More recently, Leitão (2008) analysed the effect of implementation of the regulation arising from the Taylor Report[3] on the performance of the Manchester United brand. The results suggested a positive effect on the sporting performance of the most internationally well-known English clubs.

[3] The 'Taylor Report', led by Lord Justice Taylor aimed to determine the causes of the disaster which occurred on 15th of April 1989 at Hillsborough (Sheffield), when 95 Liverpool supporters were crushed to death at a game between Liverpool and Nottingham Forest, in the semi-finals of the English FA Challenge Cup. From this report, it was ruled that steel barriers should be removed from stadia and stadia should provide all seated accommodation.

3 Research methodology

3.1 Data set and methodological procedures

The situation of European listed sport companies, especially large football clubs, is particularly interesting to test the influence of cases of corruption on their stock market performance, for three reasons: (1) the economic power and international recognition of clubs at the top of European football; (2) episodes arising from corruption (not always proven and legally punished) with forecast impact on the economic and sporting performance of those same clubs; and (3) investor behaviour of supporters of major European football clubs.

The previous literature review allowed us to identify a matter of investigation which is unexplored until now, i.e. what is the importance assumed by exogenous shocks related to cases of corruption, not only in terms of mechanisms for propagating crisis but also as a function of investor behaviour by investors and supporters. To answer this question, with this approach we aim to analyse whether the Calciocaos corruption case caused the occurrence of mechanisms of crisis propagation between the Dow Jones Stoxx Football (DJSF) Index and stocks of European listed football clubs integrating the benchmark referred to.

With this purpose, secondary data[4] was collected, considering the following selection criteria of stocks: (i) the relative importance of the stock in composition of the index (see table 1); (ii) the availability and consistency of daily data to make up time series; and (iii) non-observance of situations of suspension of quotation, for several consecutive days, motivated by anomalous situations, increases in capital or dividend distribution.

Table 1 European listed football clubs and percentage weight in composition of the Dow Jones Stoxx Football Index

European Football Clubs	***Country***	***Percentage***
Borussia Dortmund	Germany	8.5477
Juventus	Italy	6.9554
Tottenham Hotspur	England	4.9256
AS Roma	Italy	4.0237
Celtic	Scotland	2.7594
AFC Ajax	The Netherlands	2.3141
Birmingham City	England	1.1942
Sheffield United	England	1.0406
Sporting Clube de Portugal	Portugal	0.8078
Futebol Clube do Porto	Portugal	0.4220

Source: http://www.stoxx.com/

According to the selection criteria, 10 stocks were considered when forming the database: Juventus (JUVE); Borussia Dortmund (BVB); Tottenham (TOT); Ajax (AJAX); Celtic (CELT); AS Roma (ROM); Sheffield United (SHEF); Birmingham (BMC); F.C. Porto (FCP); and Sporting C.P. (SCP)[5].

Following the assumptions used in the studies by Eun & Shim (1989), Koch & Koch (1991), and Yang & Bessler (2008), the analysis was made based on the daily closing quotations of each stock and the index, in the period from 20 September 2002 to 7 May 2008, making a total sample of 1430 daily observations. Following the methodology of Khalid & Kawai (2003) and Miralles & Miralles (2003), the data are expressed in the local currency, and subject to logarithmic transformation so as to align the series and give a greater subsequent convergence of the coefficients obtained through forecasting techniques.

[4] Data source: http://investing.businessweek.com.
[5] To designate the different stocks, we use the abbreviations of the original notation appearing in the data source.

As in the procedure adopted in the study by Yang & Bessler (2008), the sample was divided in two sub-samples[6]. The first sub-sample covers the pre-Calciocaos period (i.e. before the initial announcement of corruption in Italian football) and forms a total of 919 daily observations. The second sub-sample concerns the post-Calciocaos period and is made up of 511 daily observations[7].

3.2 Econometric method

3.2.1 The cointegrated VAR model

The CVAR model employed in the present paper provides the possibility of identifying long-term economic relationships and carrying out dynamic analyses (Juselius, 2007). The econometric methodology follows an outline of four procedures: (1) selection of an initial model specification; (2) study of the integration order of the variables; (3) estimation process of the CVAR model; and (4) dynamic analysis.

According to Sims (1980), the VAR model allows determination of the inter-relationships between a set of endogenous variables considered in a system. The advantage of using the VAR model is based on the capacity to analyze the dynamic response of endogenous variables, related to exogenous shocks, through two forecasting techniques: (i) decomposition of the variance of the prediction error; and (ii) impulse-response functions.

The VAR model, by not making a distinction between endogenous and exogenous variables, makes the exlusion restrictions used to identify the traditional models of simultaneous equations cease to make sense. As an alternative, Watson (1994) used sets of restrictions which normally involve the error co-variance matrix. A VAR model of the p order can be expressed as follows:

$$X_t = m + A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_p X_{t-p} + \varepsilon_t \qquad (1);$$

where: m is a vector of independent terms; A_i is a coefficient matrix of the kxk type; and ε_t is an error correction vector of the kx1 type, satisfying that: (i) $E(\varepsilon_t) = 0$, then each error term is 0; (ii) $E(\varepsilon_t, \varepsilon_t) = \Omega$, assuming that the co-variance matrix Ω as defined is positive; and (iii) $E(\varepsilon_t, \varepsilon_{t-k}) = 0$, not being correlated in series.

The VAR(p) process with k variables can be represented as follows:

$$X_t = \begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} m_1 \\ m_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} X_{1,t-1} \\ X_{2,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = m + AX_{t-1} + \varepsilon_t \qquad (2)$$

To make a re-parameterization of the VAR(p) model, we consider a model with an error correction mechanism, which is expressed as follows:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma \Delta X_{t-i} + \Pi X_{t-1} + \mu + \varepsilon_t \qquad (3);$$

where: Γ is the matrix of short-term relationships, Π is the matrix representing long-term relationships (its rank r indicates the number of cointegrating vectors); Δ is the differentiation operator; and μ is constant.

If $\Pi = 0$, then there are no stationary linear combinations, so the X_t variable is not co-integrated. If the rank (r) of Π is above 0, then there will be r possibilities of stationary linear combinations and Π can therefore be decomposed in two matrixes α and β (each of the m×r type), and so $\Pi = \alpha\beta'$ and the error correction mechanism is expressed as follows:

[6] The first sub-sample includes quotations of stocks in the period 20 September 2002 to 2 May 2006. The second concerns the period 3 May 2006 to 7 May 2008.
[7] For information about selected descriptive statistics and correlation coefficients of the variables, see Table A of Appendix 1 (for the pre-*Calciocaos* period) and Table B of Appendix 2 (for the post-*Calciocaos* period).

$$\Delta X_t = \mu - \alpha Z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-1} + e_t \qquad (4)$$

According to the previously stated decision rule and supported by the principle of maximum likelihood, we carry out two contrasts by calculating two statistics: (i) trace (λ_{Trace}); and (ii) maximum auto-value (λ_{Max}).

The first statistic tests the null hypothesis of the number of co-integration vectors being equal to r, against the alternative hypothesis of the number of co-integration vectors being r+1, according to the following process:

$$\lambda_{Trace} = -T \log \sum_{i=r+1}^{k} \log(1-\lambda_i) \qquad (5);$$

whereas the second statistic tests the null hypothesis of the number of vectors being greater than r, against the alternative hypothesis of being r+1, being expressed as follows:

$$\lambda_{Max} = -T \log(1-\lambda_i) \qquad (6);$$

in which: T is the number of observations; and λ_i are estimated own values (i.e. the Eigenvalues), being arranged in decreasing order.

If divergence is found in the results obtained through calculation of the two previous statistics, Johansen (1991) and Kasa (1992) suggest taking, above all, the trace statistic (λ_{Trace}), in the decision not to reject, or to reject, the null hypothesis.

3.2.2 The initial model specification

Model specification is represented by a system of twelve equations, considering all the variables as endogenous, and is represented as follows:

$$\begin{bmatrix} DJSF_t \\ JUVE_t \\ BVB_t \\ TOT_t \\ AJAX_t \\ CELT_t \\ ROM_t \\ SHEF_t \\ BMC_t \\ FCP_t \\ SCP_t \\ DUMMY_t \end{bmatrix} = \begin{bmatrix} \theta_{1t} \\ \theta_{2t} \\ \theta_{3t} \\ \theta_{4t} \\ \theta_{5t} \\ \theta_{6t} \\ \theta_{7t} \\ \theta_{8t} \\ \theta_{9t} \\ \theta_{10t} \\ \theta_{11t} \\ \theta_{12t} \end{bmatrix} = \begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} & \cdots & \alpha_{1,12} \\ \alpha_{2,1} & \alpha_{2,2} & \cdots & \alpha_{2,12} \\ \vdots & \vdots & \cdots & \vdots \\ \alpha_{12,1} & \alpha_{12,2} & \cdots & \alpha_{12,12} \end{bmatrix} \begin{bmatrix} DJSF_{t-p} \\ JUVE_{t-p} \\ BVB_{t-p} \\ TOT_{t-p} \\ AJAX_{t-p} \\ CELT_{t-p} \\ ROM_{t-p} \\ SHEF_{t-p} \\ BMC_{t-p} \\ FCP_{t-p} \\ SCP_{t-p} \\ DUMMY_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \\ \varepsilon_{9t} \\ \varepsilon_{10t} \\ \varepsilon_{11t} \\ \varepsilon_{12t} \end{bmatrix} \qquad (7);$$

in which: $JUVE_t$; BVB_t; TOT_t; $AJAX_t$; $CELT_t$,; ROM_t; $SHEF_t$; BMC_t; FCP_t; and SCP_t; designate the variables referring to the performance of the stocks of European listed football clubs: and the $DJSF_t$ serves to note the Dow Jones Stoxx Football index.

The dummy variable noted by $DUMMY_t$, takes a value of *1*, when there is greater volatility of the stocks of Italian clubs, namely JUVE and ROM, having a value of *0*, in the other periods[8].

3.2.3 The integration order of the variables

The first step in determining the type of relationship between the variables under analysis is to carry out a test of unit roots, with the aim of determining the integration order of the time series. To check the existence, or non-existence, of unit roots, we use the three following test procedures: (i) the Augmented Dickey-Fuller (ADF) test; (ii) the Philips-Perron (PP) test; and (iii) the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test[9].

The ADF test corresponds to a parametric correction consisting of adding the lagged terms of the ΔX_t variable, aiming to correct the higher order correlation, and is expressed as follows:

$$\Delta X_t = \alpha + \gamma t + \lambda X_{t-1} + \delta_1 \Delta X_{t-1} + \delta_2 \Delta X_{t-2} + \ldots + \delta_{p-1} \Delta X_{t-p+1} + \mu_t \qquad (8)$$

Application of the ADF (γ) test aims to test the null hypothesis H_0: $\gamma = 0$; against the alternative hypothesis H_1: $\gamma < 0$. If γ is not significant, then we cannot reject the null hypothesis. Therefore, we conclude that the variable is not stationary (i.e. integrated in p order) or that it presents a unit root (Dickey & Fuller 1979).

The non-parametric approach originally proposed by Phillips & Perron (1988) can also be used to deal with the problem of autocorrelation in μ_t. For this purpose, the following auto-regressive process should be followed:

$$\Delta X_t = \alpha + \gamma t + \lambda X_{t-1} + \mu_t \qquad (9)$$

Asymptotic distribution of the estimated regression coefficients, as well as their t-ratio depends on the parameters σ^2 and σ_u^2. In practice σ^2 and σ_u^2 are not known, and for this reason we continue with their consistent estimation (see table 2).

Unlike the previously presented tests, the KPSS test considers the null hypothesis of stationary series, against the alternative hypothesis of non-stationary series (Kwiatkowski *et al.*, 1992).

Table 2 Tests of Unit Roots, with constant and tendency

	First differences					
Stocks	*pre-Calciocaos*			*post-Calciocaos*		
	ADF	PP	KPSS	ADF	PP	KPSS
DJSF	-14.16*	-23.47*	0.03*	-20.59*	-20.85*	0.10*
JUVE	-27.58*	-27.68*	0.09*	-15.36*	-20.14*	0.07*
BVB	-33.99*	-34.50*	0.03*	-24.84*	-25.03*	0.04*
TOT	-24.99*	-34.50*	0.05*	-15.76*	-15.76*	0.10*
AJAX	-19.51*	-39.20*	0.14*	-17.35*	-44.96*	0.05*
CELT	-25.58*	-26.35*	0.10*	-17.40*	-15.94*	0.20
ROM	-29.63*	-29.64*	0.07*	-22.50*	-22.65*	0.06*
SHEF	-25.51*	-25.16*	0.10*	-20.93*	-20.93*	0.05*
BMC	-25.68*	-25.68*	0.14*	-21.79*	-21.91*	0.05*
FCP	-23.51*	-30.06*	0.07*	-18.04*	-38.28*	0.04*
SCP	-35.16*	-35.80*	0.03*	-17.53*	-52.32*	0.07*

Legend: * Indicates rejection of the null hypothesis of containing a unit root.

[8] Specification of the model used to analyze the performance of stocks in the pre-*Calciocaos* period does not include the dummy variable, as there is no need to make a correction of volatility.

[9] According to the results from application of the ADF test, PP test and KPSS test, all the variables present statistical significance in the pre-*Calciocaos* period, except the *AJAX* stock which only shows statistical significance when considering 5 lags). In the post-*Calciocao*s period, we find that all variables present statistical significance, except the *CELT* stock.

First, we study integration of the time series. From this, some series are transformed by differentiation to estimate the models only with variables *I(1)*. After this differentiation, the null hypothesis is rejected, i.e. the stationarity of the series is confirmed, and they are integrated in order 1 (or *I(1)*).

3.2.4 The estimation process of the CVAR model

In the estimation process, first we select the optimal number of lags (p_{max}), from five criteria of information. After confirmation of non-existence of error autocorrelation through carrying out the LM (Lagrange Multiplier) test, and considering the results of the Akaike information criterion (AIC), we find that the CVAR model should be estimated with two lags for both periods (see table 3).

Table 3 Selection of the Optimal Number of Lags

Lags	*LR*	*FPE*	*AIC*	*SBC*	*HQ*
			pre-Calciocaos		
0	-	7.53e-21	-1.511.901	-1.506.108	-1.509.690
1	35046.89	1.37e-37	-5.366.615	-52.97096*	-53.40079*
2	3.142.641	1.25e-37*	-53.75398*	-5.242.153	-5.324.538
3	161.0417*	1.36e-37	-5.367.229	-5.170.259	-5.292.045
4	1.408.036	1.51e-37	-5.356.966	-5.096.270	-5.257.457
			post-Calciocaos		
0	-	1.69e-26	-2.528.695	-2.518.687	-2.524.770
1	16350.28	1.26e-40	-5.781.664	-56.51556*	-57.30641*
2	3.757.876	1.02e-40*	-58.02824*	-5.552.616	-5.704.701
3	245.9051*	1.07e-40	-5.798.339	-5.428.032	-5.653.118
4	1.399.792	1.40e-40	-5.772.098	-5.281.691	-5.579.777

Legend: Likelihood-Ratio (LR); Final Prediction Error (FPE); Akaike Information Criterion (AIC); Schwarz Bayesian Criterion (SBC); and Hannah-Quinn (HQ) Criterion. * Shows the optimal number of lags selected for each criterion.

To determine the existence of co-integration relationships, we used the test procedure proposed by Johansen & Juselius (1990). The principle of maximum likelihood forces us to take into account the values of the trace statistic (λ_{Trace}) and the maximum auto-value statistic (λ_{Max}).

According to the values observed in the first line of the tests presented in Table 4, we reject the first null hypothesis of non-existence of co-integration among variables. For the remaining test lines, we find the values observed are less than the critical values, and therefore the null hypothesis is not rejected. In this way, we see that for both the pre-Calciocaos period and the post-Calciocaos period there is only one co-integration vector, which is considered in estimation of the CVAR model with inclusion of two error correction terms: ECT1 (in the pre-Calciocaos period); and ECT2 (in the post-Calciocaos period).

Table 4 Cointegration relationships: Johansen & Juselius (1990) test

Eigenvalues	*Hypotheses*		λ_{Trace}	
	H_0	H_1	*Observed*	*Critical*
		pre-Calciocaos		
0.0745	r=0	r=1	286.0826*	285.1425
0.0508	r=1	r=2	215.2058	239.2354
0.0430	r=2	r=3	167.4947	197.3709
		post-Calciocaos		
0.166448	r=0	r=1	367.0855*	334.9837
0.126384	r=1	r=2	274.5997	285.1425
0.103018	r=2	r=3	205.9617	239.2354
Eigenvalues	*Hypotheses*		λ_{Max}	
	H_0	H_1	*Observed*	*Critical*
		pre-Calciocaos		
0.0745	r=0	r>0	70.8767*	70.5351
0.0508	r≤1	r>1	47.7111	64.5047
0.0430	r≤2	r>2	40.2686	58.4335
		post-Calciocaos		
0.166448	r=0	r>0	92.4858*	76.5784
0.126384	r≤1	r>1	68.6381	70.5351
0.103018	r≤2	r>2	55.2298	64.5047

Legend: * Shows rejection of the null hypothesis, at 5% significance.

Note: The critical values of the trace and maximum auto-value statistics, which are presented for a level of 5% significance, were taken from Osterwald-Lenum (1992).

4. Results and discussion

In dynamic analysis of the inter-relationships formed between the performance of European listed football club stocks, ECTs are necessarily incorporated.

To investigate the existence of relationships of causality between the variables representing stocks, we use the concept originally proposed by Granger (1969). In the causality tests, we present the results obtained from calculation of the Wald statistics referring to each pair of variables included in the dynamic system of simultaneous equations.

The results are supplied through a dynamic analysis that includes assessment of relationships of causality and analysis of the residuals of each equation of the dynamic system of simultaneous equations.

Dynamic analysis based only on the results obtained from the Granger causality tests may be sufficient. According to Sims (1980), Goux (1996), Lütkepohl (1999, 2004) and Juselius (2007), this type of analysis should be complemented with use of two forecasting techniques: decomposition of the prediction error variance and impulse-response functions.

Discussion of the results is structured according to the two sub-samples referring to the pre-Calciocaos and post-Calciocaos periods.

4.1. The pre-Calciocaos period

In the pre-Calciocaos period, we find unidirectional and bidirectional relationships of causality (see table 5). Regarding the bidirectional relationships, we detect a pair made up of the JUVE and SCP stocks. The DSJF and FCP stocks are completely exogenous, since they do not present a relationship of causality with other variables. Concerning ECT1, the coefficients referring to TOT, CELT, ROM, SHEF, BMC and SCP are significant, carrying out the adjustment mechanism in relation to the deviations in the long-term balance relationships.

The joint causality of the block is detected for the AJAX and CELT variables, at a level of 5% significance, and for the JUVE and ROM variables, at 10% significance, which confirms the importance of including this block of variables in the model specification.

The importance of SCP should be stressed since it is the origin of causality for the JUVE and BVB stocks for a level of significance of 5%. The lesser importance of the TOT stock is also of note, since it does not originate any relationship of causality, despite being explained by past values of the CELT stock.

Table 5 Granger's Causality contrasts: pre-Calciocaos sub-sample

	$\Delta DJSF$	$\Delta JUVE$	ΔBVB	ΔTOT	$\Delta AJAX$	$\Delta CELT$	ΔROM	$\Delta SHEF$	ΔBMC	ΔFCP	ΔSCP
ΔDJSF	-	1.9386	0.5269	0.4508	1.2072*	1.9922	1.7934	1.5979	0.8268	0.3220	0.5024
ΔJUVE	1.6150	-	3.2713	3.0167	1.0161	5.1347**	2.8825	0.4900	2.2940	1.2602	1.0107*
ΔBVB	1.7331	5.4126**	-	1.2302	3.7609	3.4585	2.0119	0.0950	0.3669	3.1563	3.3396
ΔTOT	0.9129	3.6561	0.6998	-	3.8215	2.7459	2.9313	0.2035	0.0546	0.7116	2.0430
ΔAJAX	1.3003	1.9549	0.4112	0.2065	-	7.9731*	4.2206	1.0916	2.9276	1.0449	1.3173
ΔCELT	4.0403	0.5356	0.2151	5.4646**	0.8448	-	0.4564	1.0007	1.2114	0.6538	1.3828
ΔROM	3.8206	0.7471	4.9200**	1.3315	1.5240	6.1868*	-	2.7034	1.8433	1.5338	0.2751
ΔSHEF	0.5950	1.7218	0.7519	0.9586	0.9160	1.1707*	0.8335	-	0.9395	0.6523	1.4084
ΔBMC	0.0337	0.2534	2.5837	0.1800	3.2507	8.2591*	0.4975	1.7299	-	2.3897	0.1334
ΔFCP	0.9734	4.4967	3.3320	0.5241	0.0166	3.8397	1.0852*	3.1782	1.1122	-	5.1443**
ΔSCP	0.5847	8.8149*	6.4368*	1.9409	1.8336	0.4370	2.2231	0.5873	1.0230	3.0037	-
Block	16.8036	29.1034**	21.4095	15.1021	31.5960*	48.4757*	28.8984**	11.6884	15.7770	14.3919	23.4862
ECT1	0.0000	0.0000	0.0000	-0.0021*	0.0000	-0.0012*	0.0026*	0.0029*	0.0027*	0.0000	-0.0023*

Notes:

- Consider the variable or block expressed in each column as being the independent variable (origin of causality), and the variable presented horizontally as being the dependent variable (destination of causality)

- Causality contrasts of the variables are carried out by applying the χ^2 statistic, with a degree of freedom, while contrasts of the significance of the error correction term (ECT) are carried out by applying the t statistic.

* Level of significance: 5%; ** Level of significance: 10%.

Table 6 presents only the results concerning statistically significant relationships of causality. We use the Cholesky decomposition of the prevision error variance and the coefficients obtained with simulation of impulse-response functions.

Table 6 Analysis of causality directions: pre-Calciocaos sub-sample

Direction of causality	***Forecasting***	***8 weeks***	***24 weeks***	***40 weeks***	***Sign***
ΔBVB →ΔJUVE	CVD	0.24	0.20	0.19	-
	AIRF	-0.0064	-0.0081	-0.0026	
ΔSCP →ΔJUVE	CVD	0.25	0.09	0.06	-
	AIRF	-0.0109	-0.0017	-0.0112	
ΔROM →ΔBVB	CVD	0.40	0.64	0.69	+
	AIRF	0.0143	0.0114	-0.0067	
ΔSCP →ΔBVB	CVD	1.86	2.83	3.04	-
	AIRF	-0.0011	0.0159	0.0428	
ΔCELT→ΔTOT	CVD	0.01	0.01	0.01	+
	AIRF	0.0016	0.0079	0.0114	
ΔDJSF →ΔAJAX	CVD	0.06	0.06	0.06	-
	AIRF	0.0031	-0.0009	-0.0142	
ΔJUVE →ΔCELT	CVD	0.04	0.05	0.06	+
	AIRF	0.0063	0.0401	0.0847	
ΔAJAX →ΔCELT	CVD	0.00	0.00	0.00	+
	AIRF	0.0010	0.0095	0.0218	

ΔROM $\rightarrow\Delta$CELT	CVD	3.73	5.16	5.47	+
	AIRF	0.0145	0.0944	0.1975	
ΔSHEF $\rightarrow\Delta$CELT	CVD	3.39	4.32	4.51	+
	AIRF	0.0149	0.0919	0.1886	
ΔBMC $\rightarrow\Delta$CELT*	CVD	5.03	6.83	7.19	+
	AIRF	0.0083	0.0717	0.1591	
ΔFCP $\rightarrow\Delta$ROM	CVD	0.41	0.48	0.50	+
	AIRF	0.0053	0.0217	0.0399	
ΔJUVE$\rightarrow\Delta$SCP	CVD	1.03	1.00	0.99	-
	AIRF	-0.0126	-0.0203	-0.0149	
ΔFCP $\rightarrow\Delta$SCP	CVD	0.02	0.01	0.01	+
	AIRF	0.0039	0.0081	0.0100	

Notes: DVC is the Cholesky Variance Decomposition; AIRF is Accumulated Impulse-Response Function.

The causality sign is obtained from the accumulated value of the 10 week coefficients, since from that period coefficients reach the necessary stability (Goux, 1996).

Considering analysis of causality directions based on Cholesky's forecasting technique of decomposition of the forecast error variance, we find the direction of causality ΔBMC $\rightarrow\Delta$CELT is significant, as in a period of eight weeks, the impact of the BMC stock on the CELT stock is around 5%, with a persistent and growing character, reaching around 7% and 7.19%, for periods of 24 and 40 weeks respectively. Making an analysis of the coefficients of the impulse-response functions, we find the sign of causality is positive.

4.2 The post-Calciocaos period

In the post-Calciocaos period, we again find unidirectional and bidirectional causality between stocks and the benchmark index (see Table 7). From the results obtained with the Granger causality contrasts, only the TOT, CELT, SHEF and BMC variables can be considered completely exogenous. We also find feedback relationships between the DJSF and JUVE variables, between DJSF and BVB, between BVB and JUVE, DSJF and SCP, and between DUMMY and JUVE. However, some of these feed-back relationships are detected at different levels of significance. There are bidirectional relationships between the JUVE and BVB, and JUVE and DUMMY variables at a level of 5% statistical significance.

Besides, we observe that the BVB and SCP variables, at a level of 5% statistical significance, determine the behaviour of the DJSF benchmark index. In turn, BVB determines the behaviour of JUVE, which lets us conclude that BVB has enormous importance in determining the performance of the benchmark index (DJSF) and the JUVE stock, associated with the corruption case in the post-Calciocaos period.

The block of variables determines performance of the JUVE, AJAX and FCP stocks; at a level of statistical significance of 10%. This result contributes to confirming the importance of including the variables selected for model specification.

Regarding ECT2, the coefficients of the DJSF, JUVE, AJAX, ASR, FCP and SCP stocks ensure operation of the adjustment mechanism related to deviations in long-term balance relationships.

Table 7 Granger's Causality contrasts: post-Calciocaos sub-sample

	$\Delta DJSF$	$\Delta JUVE$	ΔBVB	ΔTOT	$\Delta AJAX$	$\Delta CELT$	ΔROM	$\Delta SHEF$	ΔBMC	ΔFCP	ΔSCP	$\Delta DUMMY$
ΔDJSF	-	5.2457**	9.6184*	1.2727	0.0037	0.0305	0.0541	1.077	3.0846	1.4124	8.4413*	1.5714
ΔJUVE	6.1997*	-	8.6377*	0.1355	0.3538	0.0923	4.8821**	0.1623	0.2273	2.619	4.5294	6.8448*
ΔBVB	6.1137*	4.6388**	-	0.3657	2.2791	1.5776	0.1861	3.8773	4.4608	1.9418	1.1755	6.2922*
ΔTOT	6.1731	0.1025	0.9378	-	2.7636	1.0126	1.0133	0.9767	1.9683	0.9878	0.2274	0.0246
ΔAJAX	1.7527	1.1362	0.2693	3.3482	-	0.0889	3.3341*	7.3071	2.2105	0.2328	6.3751	0.0178
ΔCELT	1.2682	0.2458	0.5399	2.7894	0.4522	-	0.5059	0.1842	2.5724	1.3774	1.0487	0.0135
ΔROM	3.6031	3.8333	1.6868	2.5144	0.9548	0.0519	-	1.6143	2.2082	1.6545	4.1768	0.0112
ΔSHEF	1.0513	2.1143	2.4682	2.4251	4.1535	0.3353	0.8356	-	0.5025	2.0048	1.2183	0.0482
ΔBMC	8.8051*	4.433	3.3775	3.978	6.8228*	4.5897	0.0468	1.0358	-	5.7897*	0.4605	0.0529
ΔFCP	1.5544	0.2915	0.9591	2.8044	5.5822	0.8816	0.3137	1.549	2.2435	-	2.777	0.1658
ΔSCP	5.7161**	2.1794	0.3588	2.3442	6.2895	1.3556	0.3595	3.0147	0.6331	1.0395**	-	0.0882
$\Delta DUMMY$	3.7798	1.0105*	1.0945	0.2286	2.9977*	2.7944	0.2599	1.5229	0.0631	0.1763	1.9693	-
Block	42.9643	32.1512**	24.038	21.6017	32.2662**	12.5752	20.8897	21.502	18.4467	32.3984**	24.5193	14.4354
ECT1	-0.0133*	-0.0286*	-0.007	-0.005	-0.0205*	-0.0079	-0.0777*	-0.017	-0.0131	-0.0251*	0.0290*	-0.011393

Notes: * Level of significance: 5%; ** Level of significance: 10%.

As in the procedure followed before, the results of the analysis of causality directions in Table 8 presented below show statistically significant causality relationships.

Table 8 Analysis of causality directions: post-Calciocaos sub-sample

Direction of causality	***Forecasting***	***8 weeks***	***24 weeks***	***40 weeks***	***Sign***
ΔJUVE →ΔDJSF*	CVD	25.01	24.9	24.88	+
	AIRF	0.1326	0.398	0.6629	
ΔBVB − ΔDJSF	CVD	1.79	1.8	1.8	+
	AIRF	0.02	0.0605	0.1009	
ΔTOT − ΔDJSF	CVD	2.99	2.93	2.92	+
	AIRF	0.0349	0.1051	0.1748	
ΔBMC →ΔDJSF	CVD	3.08	3.09	3.09	+
	AIRF	0.0497	0.1581	0.2663	
ΔSCP→ΔDJSF*	CVD	10.19	10.97	11.13	+
	AIRF	0.0205	0.0703	0.1203	
ΔDJSF →ΔJUVE	CVD	1.05	1.04	1.04	+
	AIRF	0.0074	0.0244	0.0414	
ΔBVB →ΔJUVE	CVD	0.02	0.01	0.01	-
	AIRF	-0.0008	-0.0027	-0.0047	
ΔDUMMY →ΔJUVE*	CVD	7.36	7.44	7.45	+
	AIRF	0.1294	0.4083	0.6872	
ΔDJSF →ΔBVB	CVD	0.2	0.19	0.18	+
	AIRF	0.0074	0.0113	0.0184	
ΔJUVE→ΔBVB	CVD	0.32	0.33	0.33	-
	AIRF	-0.0085	-0.0391	-0.0698	
ΔBMC →ΔAJAX	CVD	2.52	2.62	2.63	-
	AIRF	-0.0353	-0.0841	-0.2349	
ΔDUMMY →ΔAJAX	CVD	0.34	0.35	0.35	-
	AIRF	-0.0235	-0.0841	-0.1449	
ΔJUVE→ΔROM	CVD	1.17	1.21	1.21	-
	AIRF	-0.0224	-0.0809	-0.1397	
ΔAJAX →ΔROM	CVD	0.01	0.01	0.01	+
	AIRF	0.0006	-0.0006	-0.0019	

ΔBMC→ΔFCP	CVD	0.01	0.01	0.01	+
	AIRF	0.0088	0.0476	0.0878	
ΔSCP →ΔFCP*	CVD	22.66	23.94	24.2	+
	AIRF	0.0349	0.1082	0.1817	
ΔDJSF →ΔSCP*	CVD	11.32	12.12	12.28	+
	AIRF	0.0133	0.0706	0.1296	
ΔJUVE → ΔDUMMY	CVD	1.98	1.94	1.94	-
	AIRF	-0.0361	-0.1107	-0.1844	

Notes:

DVC is the Cholesky Variance Decomposition; AIRF is Accumulated Impulse Response Function. The causality sign is obtained from the accumulated value of the 10 week coefficients, since from that period coefficients reach the necessary stability (Goux, 1996).

*Shows that the direction of causality analysed presents a significant impact, i.e. over 5% after 8 weeks (Goux, 1996).

Analysis of causality directions shows that five causality relationships indicate the existence of direct significant impacts, namely: ΔSCP→ΔDJSF; ΔJUVE →ΔDJSF; ΔSCP →ΔFCP; ΔDJSF →ΔSCP; and ΔDUMMY→ΔJUVE. For these same relationships of causality, bidirectional directions of causality are detected in the cases: ΔSCP→ΔDJSF and ΔDJSF →ΔSCP, i.e. SCP determines the performance of the DJSF benchmark index, and in turn the DJSF determines performance of the SCP stock. According to the results obtained from the Cholesky variance decomposition, concerning the causality relationship ΔSCP→ΔDJSF, the explanatory weight in decomposition of the prediction error is around 11%, while for the causality relationship ΔDJSF →ΔSCP it reaches 12%, in the three forecast periods (8, 24 and 40 weeks). According to the coefficients obtained for the impulse-response functions, both causality relationships have a positive sign.

Performance of the SCP stock also has a positive and significant impact on the performance of the FCP stock. The first explains 23% of the prediction error variance of the FCP stock after 8 weeks, and around 24%, after 24 and 40 weeks.

Regarding the causality direction ΔJUVE →ΔDJSF, for the three forecast periods, the explanatory weight is around 25%, the causality sign being positive. Therefore, despite expecting a negative impact arising from the corruption episode, this does not happen, the JUVE stock having a direct and significant impact of 25% on performance of the DJSF benchmark index.

5. Conclusions

This paper analysed the impact of the Calciocaos corruption episode on the performance of European listed football clubs and the Dow Jones Stoxx Football index benchmark. In addition, it analysed in dynamic terms the relationships of causality between stocks in two distinct periods: pre-Calciocaos and post-Calciocaos; finding significant differences in the pattern of these relationships.

In this context, we underline that, despite the Italian JUVE stock being directly involved in the corruption episode, besides continuing to contribute substantially to the composition of the DJSF, it began to determine positively, in causal terms, the performance of the benchmark index.

Moreover, dynamic analysis of Calciocaos showed that corruption episodes involving listed football clubs may stimulate emotional behaviour by investors who are simultaneously supporters, since in fact they do not sell their participations. Furthermore, investor reaction is characterized by a substantial increase in the explanatory power of the JUVE stock on the performance of the DJSF. Nevertheless, this positive impact may also be related to substantial amounts of money obtained at the time from selling important international players to other leading European football clubs, such as Real Madrid F.C. and F.C. Internazionale Milano.

In addition, and somewhat surprisingly, we found that the explanatory power of the Portuguese SCP stock on performance of the benchmark index increased substantially, after transmission of the shock generated by the Calciocaos corruption episode. However, this may be justified by the fact that SCP has been capitalizing its image and international prestige in recent years, through developing young talent which is later sold to clubs in the elite of European football.

From comparative analysis of the results obtained for the two sub-samples, it is possible to produce two fundamental insights. Firstly, in the pre-Calciocaos period, relationships as a whole between stocks are not statistically significant, except for the relationship between BMC and CELT. However, there is a relationship of interdependence between JUVE and SCP, since these stocks present a relationship of bidirectional causality. Nevertheless, the DJSF index is completely exogenous, being self-explanatory, i.e. no stock has a significant impact on performance of the index.

Secondly, in the post-Calciocaos period, there was an increase in the number of bidirectional causality relationships between the stocks with the greatest weighting in composition of the benchmark index, as well as between the index and those same stocks. The public announcement of the corruption episode in the Italian A Series, which involved Juventus directly, had an impact on stock performance, since we find that JUVE and SCP stocks began to determine strongly performance of the benchmark index.

Faced with these results, we see that the Calciocaos corruption case had an impact on the stock performance of listed European football clubs, as well as on a new composition of causality relationships and causal determination of shock transmission mechanisms, from the time the corruption case, the subject of this study, went public.

As the main limitation of this study, we point to the impossibility of obtaining more information about other stocks included in the DJSF reference index, in order to increase the size of the sample and its representative character, and then we could have checked for the existence of contagion and the type of contagion (for example, shift contagion), through alternative tests that use, for example, correlation coefficients and other estimation methods: ARCH, GARCH, Probit and Copula Distributions.

In terms of implications for policy-makers, we suggest they prepare new regulatory actions that allow anticipation and warning of new corruption episodes involving listed football clubs. In our opinion, one of the proposed innovations concerning regulation could be based on intensive use of new technology in the activity of refereeing and supervising sporting competitions held in Europe.

For practitioners and managers interested in the continuous improvement of listed football clubs' performance, we warn of the need to guarantee a critical mass of young investors/fans, as it is they who stimulate sustainable success in sporting companies, from a longitudinal and inter-generational perspective.

It is suggested that future investigations explore the issue of sentimental behaviour by investors, following a behavioural approach, which would allow exploration through recourse to experimental methods and individual data, of a better understanding of supporters' investment strategies, when faced with anomalous situations such as cases of corruption or even situations of announced insolvency of listed football clubs.

Finally, we suggest carrying out an empirical study of contagion channels between stocks quoted on the DJSF benchmark index, having as common denominator the comparative analysis of other corruption episodes in Europe and South America (for example, Argentina and Brazil) with the aim of contrasting the respective impacts on performance of the DJSF index and on a new composition of shock propagation mechanisms between the different stocks of main listed football clubs in the continents of Europe and America.

References

Ahlin, C. and Pang, J. (2008). Are financial development and corruption control in promoting growth?. *Journal of Development Economics*, 86, 414-433.

Ascari, G. and Gagnepain P. (2006). Spanish football. *Journal of Sports Economics*, Vol.7 No.1:76-89.

Baig, T. and Goldfajn, I. (2000). The Russian default and the contagion to Brazil. *IMF Working paper*, Working paper No.00/160.

Barajas, A.; Fernández-cardón, C.; and Crolley, L. (2005). Does sports performance influence revenues and economic results in Spanish football?. *MPRA Paper*, No. 3234, posted November 2007.

Baroncelli, A. and Lago, U. (2006). Italian football. *Journal of Sports Economics*, Vol.7, N.º1, 13-28.

Barros, C. (2006). Portuguese football. *Journal of Sports Economics*, Vol. 7, N.º 1, 96-104.

Batyrberkov, K. (2007). *Soccer stocks: market reaction to game results of professional soccer franchises*. Undergraduate thesis, Harvard College, Harvard.

Berument, H; Ceylan, N.; and Gozpinar, E. (2006). Performance of soccer on the stock market: evidence from Turkey. *The Social Science Journal*, 43, 695-699.

Boido, C. and Fasano, A. (2007). Football and mood in Italian Stock Exchange. *The Journal of Behavioral Finance*, Vol. 4, N.º 4, 32-50.

Buraimo, B.; Simmons, R.; and Szymansky, S. (2006). English football. *Journal of Sports Economics*, Vol. 7 N.º 1, 29-46.

Chakravorti, S. and Lall, S. (2004). Managerial incentives and financial contagion. *IMF Working Paper*, WP/04/199.

Chiang, T.; Jeon, N.; and Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian Markets. *Journal of International Money and Finance*, 26, 1206-1228.

Ciocchini, F; Durbin, E.; and David, T. (2003). Does corruption increase emerging market bond spreads?. *Journal of Economics and Business*, 55, 503-528.

Corsetti, G.; Pericoli, M.; and Sbracia, M. (2005). Some contagion, some interdependence: More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, 24, 1177-1199.

Dickey, D. and Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74, 427-431.

Didier, T.; Mauro P.; and Schumkler, S. (2007). Vanishing Financial Contagion?. *Journal of Policy Modeling*, 30(5), 775-791.

Dornbusch, R.; Park, Y.; and Claessens, S. (2000). Contagion: Understanding how it spreads. *The World Bank Research Observer*, Vol. 15, N.º 2, 177-197.

Eun, C. and Shim, S. (1989). International transmission of stock market movements. *Journal Financial and Quantitative Analysis*, 24, 241–256.

Fazio, G. (2007). Extreme interdependence and extreme contagion between emerging markets. *Journal of International Money and Finance*, 31, 1261-1291.

Forbes, K. and Rigobon (2000). Contagion in Latin America: Definitions, Measurement and Policy Implications. *NBER Working Paper Series*, Working Paper 7885.

Forbes, K. and Rigobon (2001). Measuring Contagion: Conceptual and Empirical issues. In Stijn Claessens and Kristin Forbes (Eds.), *International Financial Contagion*, Kluwer Academic Publishers: 1-27.

Frick, B. and Prinz, J. (2006). Crisis? What Crisis? Football in Germany. *Journal of Sports Economics*, Vol. 7 No. 1, 60-75.

Goel, R. and Nelson, M. (2007). Are corrupt acts contagious? Evidence from the United States. *Journal of Policy Modeling*, 29, 839-850.

Goux, J. (1996). Le canal étroit du crédit en France. *Revue D'Économie Politique*, 106(4), Juillet-Août, 1996, 655-681.

Granger, W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37, 424-438.

Gropp, R.; Lo Duca, M.; and Vesala, J. (2009). Cross-Border Bank contagion in Europe. *International Journal of Central Banking*, March 2009 Issue: 97-139.

Guégan, D. (2008). Contagion between the financial sphere and real economy. Parametric and non-parametric tools: A comparison. In , NY, (Ed.), *Progress in Financial Market Analysis*, NOVA publishers, 25-45.

Haan, M.; Koning, R.; and Witteloostuijn, A. (2002). Market forces in European Soccer, *Research Report 02F18, SOM, University of Groningen*, 2002:1-29. http://irs.ub.rug.nl/ppn/241199409 [Accessed in 08/12/02]

Haile, F. and Pozo, S. (2007). Currency Crisis contagion and the identification of transmission channels. *International Review of Economics and Finance*, 17, 1-17.

Hon. T.; Strauss, J.; and Yong, S. (2007). Deconstructing the Nasdaq bubble: A look at contagion across international stock markets. *Journal of International Financial Markets, Institutions and Money*, 17, 213-230.

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregression Models. *Econometrica*, 59, 1551-1580.

Johansen, S. and Juselius, K. (1990). Maximum Likelihood Estimation and Inference on Cointegration with Applications to Money Demand. *Oxford Bulletin of Economics and Statistics*, 52, 169-210.

Jokipii, T. and Lucey, B. (2007). Contagion and interdependence: Measuring CEE banking sector co-movements. *Economic Systems*, 31, 71-96.

Juselius, K. (2007). *The Co-integrated VAR Model – Methodology and Applications*, Oxford University Press.

Kasa, K. (1992). Common Stochastic Trends in International Stock Markets. *Journal of Monetary Economics*, 29: 95-124.

Khalid, A. and Kawai, M. (2003). Was financial Market contagion the source of economic crisis in Asia? Evidence using a multivariate VAR model. *Journal of Asian Economics*, 14, 131-156.

Koch, P. and Koch, T., (1991). Evolution in dynamic linkages across daily national stock indexes. *Journal of International Money and Finance*, 10, 231–251.

Kumar, M. and Persaud, A. (2002). Pure contagion and investors shifting risk appetite: Analytical issues and empirical evidence. *International Finance*, 5(3), 431-436.

Kwiatkowski, D.; Phillips, P.; Schmidt, P.; and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. *Journal of Econometrics*, 54, 159-178.

Lee, H.; Wu, H.; and Wang, Y. (2007). Contagion effect in financial markets after South-East Asian Tsunami. *Research in International Business and Finance*, 21, 281-296.

Leitão, J. and Oliveira, C. (2007). The Puzzling effect of September Eleven on interdependences of international stock markets. *ICFAI Journal of Applied Economics*, Vol. 6(4), 35-51.

Leitão, J. (2008). The Taylor Effect on the Performance of the Red Devils' Football Brand. In Helmut D.; E. Franck; and H. Kempf (Eds.), *Football – Economics of a Passion*. Hofmann-Verlag, Sportökonomie, 10, 289-307.

Lütkepohl, H. (1999). Vector Autoregressions. *Working Paper of Institut für Statistik und Ökonometrie*, Humboldt, Universitat, Berlin.

Lütkepohl, H. (2004). Recent advances in cointegration analysis. *European University Institute - Economics Working Papers*, ECO2004/12, Florence.

Miralles, J. and Miralles, J. (2003). Relações Dinâmicas entre as principais bolsas de valores: Os efeitos sobre a Euronext Lisboa. *Revista de Gestão e Economia*, 5, 8-20.

Morrow, S. (2006). Scottish football: it´s a funny old business. *Journal of Sports Economics*, vol. 7 No. 1, 90-95.

Osterwald-Lenun, M. (1992). A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Economics and Statistics*, 54, 461-471.

Phillips, P. and Perron, P. (1988). Testing for unit root in time series regression. *Biometrika*, 75, 335–346.

Schoenmaker, D. (1996). Contagion risk in banking. *London School of Economics, Financial Markets Group, Publications - Working Papers*, 86-103.

Sims, C. (1980). Macroeconomics and reality. *Econometrica*, Vol.48, Nº.1, 1-49.

Treisman, D. (2000). The causes of corruption: a cross-national study. *Journal of Publics Economics*, 76, 3, 399-457.

Vinod, H. (2003). Open economy and financial burden of corruption: theory and application to Asia. *Journal of Asian Economics*, 13, 873-890.

Watson, M. (1994). Vector Autoregressions and Cointegration. In Engle, R.; Mcfadden, D. (Eds), *Handbook of Econometrics*, Vol IV, Chapter 47, 2844 – 2915.

Yang, J. and Bessler, D. (2008). Contagion around the October 1987 stock market crash. *European Journal of Operational Research*, 184, 291-310.

Ziglydoupolos, S.; Fleming, P.; and Rothenberg, S. (2008). Rationalization, overcompensation and the escalation of corruption in organizations. *Journal of Business Ethics*, 84(1), 65-73.