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GOOGLE TRENDS AS AN EXPLANATORY VARIABLE OF THE FOOTBALL STOCKS INDEX

Google trends como variable explicativa del Football Stocks Index

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ABSTRACT: Investment in football has been considered as an alternative investment as it is de-correlated with the evolution of the main stock market indices. This may be caused by the emotional nature of these investments. In this article we aim to measure the impact of emotions on the profitability of football clubs listed in the stock market. For this, we use Google Trends as an indicator of sentiment (explanatory variables) and the FCTP index as a reference for the profitability of football clubs (endogenous variable). We apply an econometric linear regression model, and we find that this sentiment metric is statistically significant for explaining the evolution of the FCTP, both on economic issues and on exclusively soccer issues.

KEY WORDS: FCTP, Google Trends,

RESUMEN: La inversión en fútbol ha sido considerada como una inversión alternativa, ya que está descorrelacionada con la evolución de los principales índices bursátiles. Esto puede deberse a la naturaleza emocional de estas inversiones. En este artículo pretendemos medir el impacto de las emociones en la rentabilidad de los clubes de fútbol que cotizan en bolsa. Para ello, utilizamos Google Trends como indicador del sentimiento (variables explicativas) y el índice FCTP como referencia de la rentabilidad de los clubes de fútbol (variable endógena). Aplicamos un modelo de regresión lineal econométrica y encontramos que esta métrica de sentimiento es estadísticamente significativa para explicar la evolución del FCTP, tanto en temas económicos como en temas exclusivamente futbolísticos.

PALABRAS CLAVE: FCTP, Google trends, estado de ánimo de los inversores, finanzas conductuales

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1. Introduction

The efficient market hypothesis assumes that the investors are rational and therefore the theoretical price of the shares coincides with their market price (Fama, 1970). Nevertheless behavioral finance has shown that emotions have an important role in investment decisions, there are numerous studies that demonstrate that investor mood is affected by multiple factors, changes over time and may be conditioned by experience or training (Cohen & Kudryavtsev, 2012). These changes in mood provide evidence of anomalies in the behavior of stock markets (Nofsinguer, 2005). Corredor, Ferrer and Santamaría (2013) claim that investor mood has a significant effect on stock performance. Some examples of this relationship are the following ones. We find that weather affect to the stock market returns (Hirshleifer & Shumway, 2003, Jacobsen and Marquering, 2008) as sunny climates are associated with an optimistic mood and then positive returns. Seasonal patterns like vacations that implies the effect of “sell in May and go away” or the “Halloween” effect (Bouman & Jacobsen, 2002; Marshall 2010) means that securities market yield should be greater from November to April than from May to October. Even the Moon (Yuan, Zheng, & Zhu, 2006) implies different returns according to the different phases of the moon observing differences from 3% to 5% in yield from one phase to another.

The sports results are another item that modifies investors mood. Edmans, García and Norli (2007) studied the results of football, cricket, rugby and basketball and others have focused on the NFL (Chang, Chen, Chou, & Lin, 2012), football (Berument, Ceylan, & Gozpinar, 2006; Kaplanski & Levy, 2010) and on cricket (Mishra & Smyth, 2010). Gómez and Prado (2014) performed a statistical analysis of the following stock markets session return after national team football matches. The results obtained show that after a defeat of the national team, we should expect negative and lower than average prices on the country's stock market, the opposite occurring in the case of a victory.

In this paper we try to test if Investors’ Mood affect the investments in Football, so we need to measure this investment. The STOXX Europe Football Index (FCTP) covers all football clubs that are listed on a stock exchange in Europe or Eastern Europe, Turkey, or the EU-Enlarged region. The index accurately represents the breadth and depth of the European football industry. The components of this index are the shares of this European football teams are shown in Table 1. As Gómez, Prado and Menéndez (2017) demonstrated, the evolution of this index can be considered as an alternative investment. They used two different approaches, a Bayesian network and a correlation matrix. On the other hand, sports can be considered as an item that affects to investors sentiment, then, a measure of investors sentiment could mean a good predictor of the evolution of the index.

Therefore, if this index is an alternative investment and is not correlated with the main equity markets, then its evolution could be marked by emotional factors. To measure investors sentiment, the new approach focuses on Big Data. Wu et al. (2013) use big data to predict market volatility, Moat et al. (2013) use the frequency of use of Wikipedia to determine investor feelings, whereas Gómez (2013) elaborated a "Risk Aversion Index" based on the stats of Google Trends for certain economic and financial terms that relate to market growth. Through an econometric model, he shows that Google Trends provide relevant information on the growth of financial markets and may generate investment signs that can be used to predict the growth of major European stock markets. According to this approach, we could create an algorithmic trading system that issues buy and sell orders by measuring the level of aversion to risk, if an increase in tolerance towards risk implies a bull market and an increase in aversion to risk a bear market.

Google Trends is becoming a metric for several issues in finance. For example, it was used as a measure of risk factors (Gomes & Taamouti, 2016). On the other hand, Google Trends is proposed as a novel and improved proxy for overreaction as selling winner stocks after they enjoyed a substantial surge in search volume is found to be profitable (Heyman, Lescrauwaet, & Stieperaere, 2019). Another utility is to evaluate the impact of information demand and supply on French (Moussa, Delhoumi, & Ouda, 2017) and Brazilian (Rodolfo, Barbedo, & Val, 2017) stock market return and volatility.

Table 1. *Components of FCTP index*

TEAM	Country
Galatasaray	TR
Celtic	GB
Fenerbahce sportif hizmet	TR
Olympique lyonnais	FR
Juventus	IT
Besiktas	TR
As roma	IT
Borussia dortmund	DE
Afc ajax	NL
Lazio	IT
Parken sport & entertainment	DK
Brondby if b	DK
Trabzonspor sportif yatir	TR
Teteks ad tetovo	MK
Silkeborg	DK
Agf	DK
Sport lisboa e benfica	PT
Aalborg boldspilklub	DK
Sporting	PT
Aik football	SE
Futebol clube do porto	PT
Ruch chorzow	PL

Source: www.stoxx.com

Scheffer and Weiß (2020) uses Google Trends for analyzing the dependence in investor attention and stock returns for 29 banks, being the investment attention a repeated issue in the literature (Yang., Liu, Yu, & Han, 2017) even in real estate investments (Yung & Nafar, 2017). Tang and Zhu (2017) uses Google Trends to study how security prices respond to a surge in investor attention.

2. Hipothesys and methodology

Following Gómez (2013) methodology, in this paper we describe an econometric linear regression model in which the endogenous variable is FCTP index monthly return while the explanatory variables are not financial variables but the number of searches of different topics measured by Google Trends. In this case, the time series of Google searches will correspond to financial topics, which would measure the financial sentiment, and topics specific to the football world, which would measure the sentiment about football.

In our case, the formulation of the model should be the following one:

$$Y_t = \alpha + \sum_{i=1}^{n} \beta_i x_{i,t} + \varepsilon_t \qquad \text{Model 1}$$

Where:

- Y_t Return of FCTP index in month "t"
- $X_{i,t}$ Searches of term "i" in month "t"

An alternative model searching the predictive power of these variables should be defined in Model 2:

$$Y_t = \alpha + \sum_{i=1}^{n} \beta_i x_{i,t-1} + \varepsilon_t \qquad \text{Model 1}$$

Where:

- Y_t Return of FCTP index in month "t"
- $X_{i,t-1}$ Searches of term "i" in the previous month

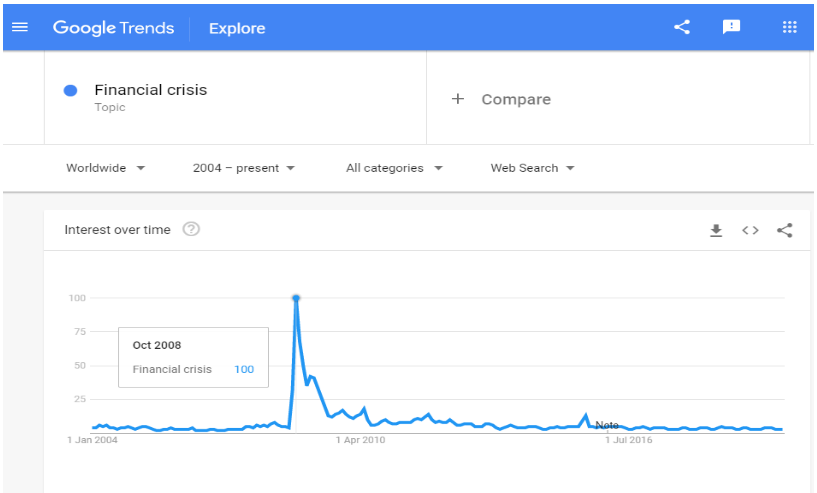


Figure 1. *Google Trends of "Financial Crisis" topic*
Source: Google Trends

The X_i variables have been selected searching a patter in their chart, for example Figure 1 shows how the maximum number of searches made of the topic “Financial Crisis” where made on October 2008, the month when Lehman Brothers crash took place.

If we focus on football topics, for example, we can see a seasonal pattern in “UEFA Champions League” topic, with maximum searches in the month of the final match (Figure 2). Should this patter have any statistical relationship with FCTP index return?

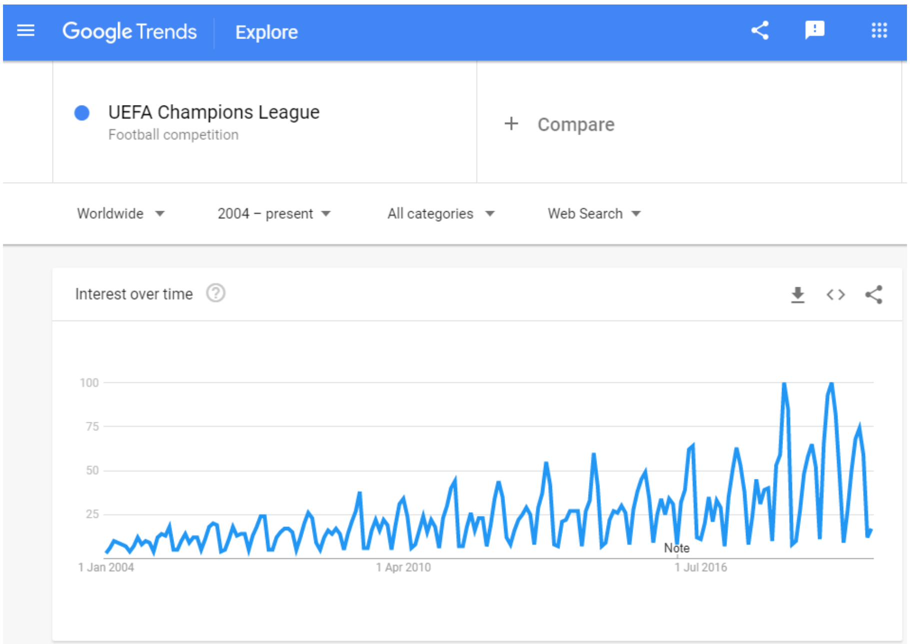


Figure 2. *Google Trends of “UEFA Champions League” topic*

Source: Google Trends

The topics selected for this study are:

- Financial Topics:
  - Dow_Jones
  - Short Selling
  - Volatility
  - Financial Crisis
  - Economic Bubble
  - ETF
  - Derivatives
  - Mutual Funds
  - Debt
  - Investment banking
  - Gold as an investment
  - Brent Oil
  - Fx market
- Football Topics
  - UEFA
  - FIFA
  - Champions league
  - Word cup
  - Lionel Messi
  - Neymar
  - Cristiano Ronaldo
  - Antoine Griezmann
  - Goal

The appendix shows the statistical summary and the correlation matrix of the variables of this study.

According to Gomez (2013), the volume of searches registered in Google on financial terms have explanatory and predictive capacity on the evolution of the markets. Since 2004 in which Google Trends began to publish these statistics, it is observed that bearish markets imply high level of searches of terms such as crash, recession, or short selling, while bull markets imply low levels of this searches. The financial topics used in this study are taken from Gómez, Prado and de la Orden (2018) looking for a graphic evolution in Google Trends that has a certain relationship with the graphic evolution of the market. For the selection of football topics, the same idea is followed, searching for those most representative topics. For example, Google searches for Ronaldo, Messi and Neymar are used because they are the players who have the most followers on social networks as of the date of this study (Mundo Deportivo, 2018).

Form this point, we must test if Google Trends can explain the evolution of FCTP index. Therefore, the hypothesis to test are:

H_1: Google Trends of financial topics explain FCTP return.

H_2: Google Trends of football topics explain FCTP return.

We will validate the hypotheses H_1 and H_2 if we find any estimated b parameter statistically different from cero in the regressions made for Model 1 and 2.

DATA

We use monthly data from January 2004 to December 2019. Google Trends historical series, our predictors, have been downloaded directly from Google webpages (https://trends.google.es/) and FCTP index historical prices have been downloaded from www.stoxx.com. We use data form 2004 because Google do not offer data before that date, and these data are in a monthly base.

The main statistics of the endogenous variable are:

Mean	107,49
Standard deviation	24,82
Return	22,60%
Annualized Return	1,41%

As we can check in Figure 3, from 2004 to 2019, our study period, there is not a clear trend in the evolution of the index.

On the other hand, focusing on the exogenous variables, Google does not give the absolute number of searches. The time series are recalculated on the maximum number of searches registered for the analyzed period. Therefore, all series have a maximum of 100 (in the month that the search record was recorded) and can record a minimum of 0. As time series consider the “topic” instead the “term” all over the world, time series sum up searches made in similar terms of several languages and locations.

Figure 3. *FCTP evolution*

Source: Stoxx.com

RESULTS

The regression of our model has been executed using the GRETL econometric tool. Table 2 shows the main stats of the model:

Table 2. Model 1 regression
Model 1: OLS, using observations 2004:01-2019:12 (T = 192)
Dependent variable: FCTP

	Coefficient	std. error	t-ratio	p-value
Const	17.8315	16.3082	1.093	0.2758
Dow_Jones	0.0156629	0.112575	0.1391	0.8895
Short_Selling	−0.0128927	0.141282	−0.09125	0.9274
Volatility	**−0.474953**	**0.225526**	**−2.106**	**0.0367 ****
Financial_crisis	**−0.821170**	**0.184008**	**−4.463**	**1.47e-05*****
Bubble	**0.126280**	**0.0745937**	**1.693**	**0.0923***
ETF	**0.689444**	**0.134963**	**5.108**	**8.70e-07*****
Derivatives	**−0.480121**	**0.265335**	**−1.809**	**0.0722***
Funds	**0.329861**	**0.136881**	**2.410**	**0.0170 ****
Debt	−0.0358207	0.177627	−0.2017	0.8404
Investment_banki~	**1.03889**	**0.166875**	**6.226**	**3.67e-09 *****
Gold_as_an_inves~	0.0173113	0.0861881	0.2009	0.8411
Brent_Oil	**−0.139870**	**0.0746869**	**−1.873**	**0.0628***
Fx_market	**0.877815**	**0.213933**	**4.103**	**6.33e-05*****
UEFA	**0.225017**	**0.0938666**	**2.397**	**0.0176****
FIFA	0.100872	0.192855	0.5230	0.6016
Champions_league	**0.173379**	**0.0716923**	**2.418**	**0.0167****
World_cup	0.119650	0.216994	0.5514	0.5821
Lionel_Messi	−0.0682492	0.161856	−0.4217	0.6738
Neymar	−0.0698195	0.122035	−0.5721	0.5680

Cristiano_Ronaldo	**−0.344194**	**0.172048**	**−2.001**	**0.0470****
Antoine_Griezmann	0.149200	0.127656	1.169	0.2441
Gol	0.152560	0.206521	0.7387	0.4611

Mean dependent var 107.4929	S.D. dependent var 24.81692
Sum squared resid 26738.03	S.E. of regression 12.57828
R-squared 0.772700	Adjusted R-squared 0.743110
F(22, 169) 26.11407	P-value(F) 3.22e-43
Log-likelihood −746.3255	Akaike criterion 1538.651
Schwarz criterion 1613.573	Hannan-Quinn 1568.995
rho 0.638615	Durbin-Watson 0.723646

* Significant with a 90% confidence interval; ** significant with a 95% CI; *** significant with a 99% Cl

Source: Authors' own research using GRETL

The regression presents a high R^2 statistic and the set of exogenous variables is significant according to the F statistic. However, the Durbin Watson statistic indicates the presence of autocorrelation, so the calculated OLS estimators will not be maximum likelihood, so we will assume they are consistent.

We can check that we found some significant variables in other to explain FCTP return, some of them are the number of searches of financial topics like "volatility", "Financial Crisis", "Bubble", "ETF", "Derivatives", "Mutual Funds", Investment Banking" and "Brent Oil". Figure 3 shows the relationship between these variables.

Table 3. Model 1 regression only with football variables
Model 1: OLS, using observations 2004:01-2019:12 (T = 192)
Dependent variable: FCTP

	coefficient	**std. error**	**t-ratio**	**p-value**
const	104.122	6.50797	16.00	1.52e-036 ***
UEFA	**0.504257**	**0.120435**	**4.187**	**4.40e-05*****
FIFA	−0.0350450	0.307153	−0.1141	0.9093
Champions_league	0.120301	0.0886029	1.358	0.1762
World_cup	0.359097	0.331010	1.085	0.2794
Lionel_Messi	**−0.788956**	**0.234973**	**−3.358**	**0.0010*****
Neymar	−0.0144382	0.186659	−0.07735	0.9384
Cristiano_Ronaldo	−0.361147	0.246556	−1.465	0.1447
Antoine_Griezmann	**0.397927**	**0.198973**	**2.000**	**0.0470****
Gol	0.306446	0.259641	1.180	0.2394

Mean dependent var 107.4929	S.D. dependent var 24.81692
Sum squared resid 78605.54	S.E. of regression 20.78217
R-squared 0.331773	Adjusted R-squared 0.298729
F(9, 182) 10.04028	P-value(F) 1.79e-12
Log-likelihood −849.8476	Akaike criterion 1719.695
Schwarz criterion 1752.270	Hannan-Quinn 1732.888
rho 0.835777	Durbin-Watson 0.338328

* Significant with a 90% confidence interval; ** significant with a 95% CI; *** significant with a 99% Cl

Source: Authors' own research using GRETL

If we split Model 1 using only football variables or financial variables, we also check in Tables 3 and 4 that some of them are statistically significative. The model statistics have changed because variables have been removed but the parameter maintains the same sign and the significance is similar.

TABLE 4. Model 1 regression only with financial variables
Model 1: OLS, using observations 2004:01-2019:12 (T = 192)
Dependent variable: FCTP

Variable	coefficient	std. error	t-ratio	p-value
const	11.3829	14.0429	0.8106	0.4187
Dow_Jones	0.137888	0.106149	1.299	0.1956
Short_Selling	−0.153663	0.134403	−1.143	0.2544
Volatility	**−0.447515**	**0.226134**	**−1.979**	**0.0494****
Financial_crisis	**−0.951683**	**0.180820**	**−5.263**	**4.04e-07 *****
Buble	0.118896	0.0757071	1.570	0.1181
ETF	**0.651840**	**0.133976**	**4.865**	**2.50e-06 *****
Derivatives	−0.319208	0.250476	−1.274	0.2042
Funds	**0.403316**	**0.138788**	**2.906**	**0.0041*****
Debt	0.0591836	0.169822	0.3485	0.7279
Investment_banki~	**0.923297**	**0.164183**	**5.624**	**7.13e-08*****
Gold_as_an_inves~	0.0204566	0.0862755	0.2371	0.8128
Brent_Oil	**−0.181483**	**0.0723964**	**−2.507**	**0.0131****
Fx_market	**1.00557**	**0.181329**	**5.546**	**1.04e-07 *****

Mean dependent var	107.4929	S.D. dependent var	24.81692
Sum squared resid	29997.22	S.E. of regression	12.98167
R-squared	0.744993	Adjusted R-squared	0.726369
F(13, 178)	40.00157	P-value(F)	6.87e-46
Log-likelihood	−757.3672	Akaike criterion	1542.734
Schwarz criterion	1588.339	Hannan-Quinn	1561.205
rho	0.671895	Durbin-Watson	0.658942

* Significant with a 90% confidence interval; ** significant with a 95% CI; *** significant with a 99% Cl
Source: Authors' own research using GRETL

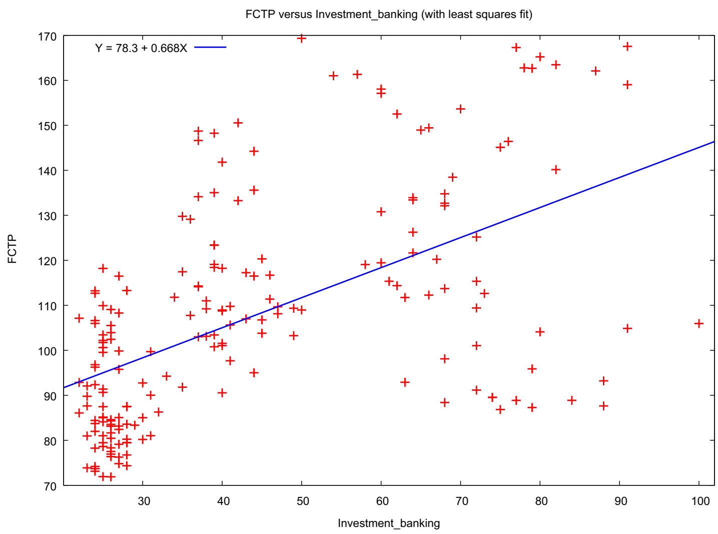


Figure 3. X-Y scatter FCTP vs "Investment Banking" topic
Source: Authors' own research using GRETL

How should we interpret these estimated parameters? If we observe that Google searches for topics such as "bubble", "ETF", "funds", "investment banking" or "fx market" are increasing, we should observe in parallel that the FCTP index appreciates. On the other hand, if we see an increase in searches for topics such as "volatility", "financial crisis", "derivatives" or "petroleum Brent", we should expect the FCTP to depreciate.

Moreover, we also found football topics like "Champions League" and "Cristiano Ronaldo" are significant. Based on the estimated parameters, if we observe in Google that interest in UEFA or the Champions League is increasing, this will be accompanied by a similarity in the FCTP index, while an increase in interest in Cristiano Ronaldo would not be good for investors. It could be also shown graphically in Figure 4.

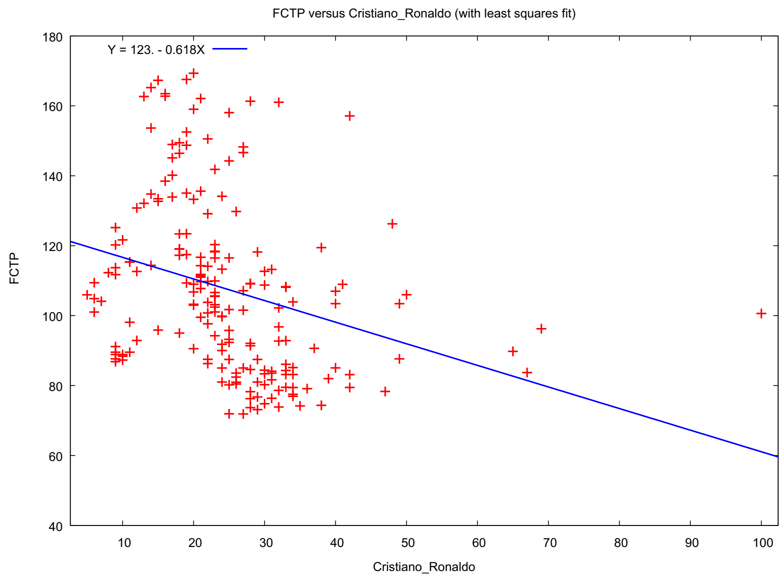


Figure 4. X-Y scatter FCTP vs "Cristiano Ronaldo" topic

Source: Authors' own research using GRETL

Following these results, hypothesis 1 and 2 are validated and Model 1 have certain explanatory capacity over FCTP index returns (Figure 5).

If we repeat the regression using one lag in the exogenous variables, we record the results of Table 5.

Table 5. Model 2 regression
Model 2: OLS, using observations 2004:02-2019:12 (T = 191)
Dependent variable: FCTP

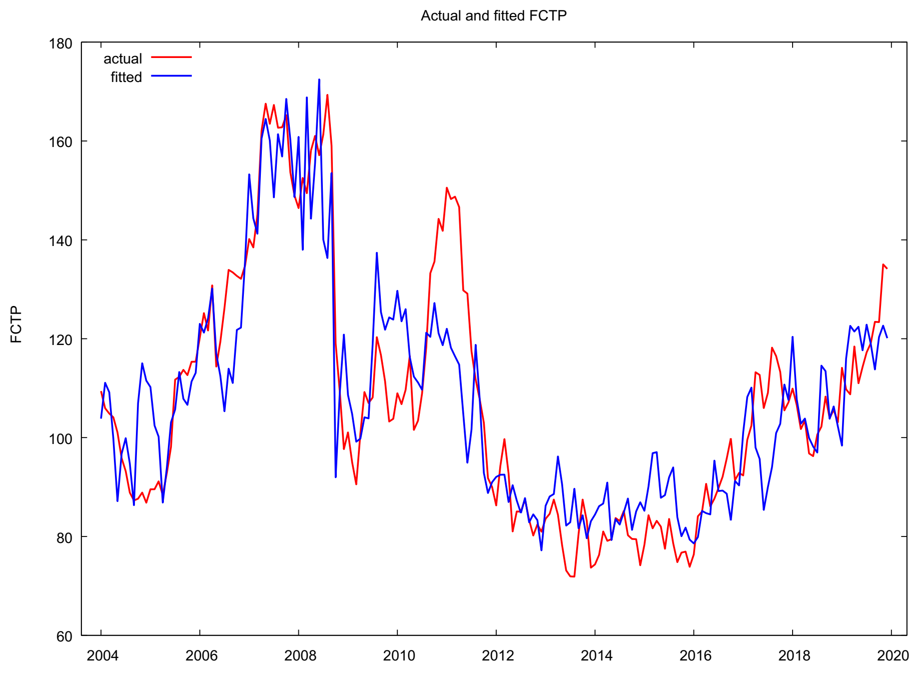
	coefficient	std. error	t-ratio	p-value
const	41.1054	18.3773	2.237	0.0266**
Dow_Jones_1	0.294461	0.213670	1.378	0.1700
SP_500_1	−0.332567	0.272068	−1.222	0.2233
NASDAQ_1	−0.191955	0.138875	−1.382	0.1688
IBEX_35_1	**0.230951**	**0.121163**	**1.906**	**0.0584***
Short_Selling_1	**−0.327825**	**0.139760**	**−2.346**	**0.0202****
Volatility_1	−0.243637	0.231354	−1.053	0.2938

Financial_cris~_1	**−1.00095**	**0.193964**	**−5.160**	**7.00e-07 *****
Buble_1	**0.146340**	**0.0742735**	**1.970**	**0.0505***
ETF_1	**0.589790**	**0.137489**	**4.290**	**3.04e-05*****
Derivatives_1	**−0.549110**	**0.270076**	**−2.033**	**0.0436****
Funds_1	**0.475516**	**0.138371**	**3.437**	**0.0007*****
Debt_1	−0.0484584	0.178313	−0.2718	0.7861
Investment_ban~_1	**0.838050**	**0.166126**	**5.045**	**1.19e-06*****
Gold_as_an_inv~_1	−0.0809083	0.0846815	−0.9554	0.3408
Brent_Oil_1	−0.105317	0.0818681	−1.286	0.2001
Fx_market_1	**0.937697**	**0.225087**	**4.166**	**4.99e-05*****
UEFA_1	**0.223546**	**0.0921759**	**2.425**	**0.0164****
FIFA_1	0.215121	0.191055	1.126	0.2618
Champions_leag~_1	0.0854087	0.0721555	1.184	0.2382
World_cup_1	0.0802498	0.215639	0.3721	0.7103
Lionel_Messi_1	−0.219662	0.161833	−1.357	0.1765
Neymar_1	−0.0167524	0.123138	−0.1360	0.8920
Cristiano_Rona~_1	**−0.316521**	**0.170209**	**−1.860**	**0.0647***
Antoine_Griezm~_1	0.184393	0.131674	1.400	0.1633
Gol_1	0.0339191	0.216928	0.1564	0.8759

Mean dependent var	107.4829	S.D. dependent var	24.88175
Sum squared resid	24873.95	S.E. of regression	12.27808
R-squared	0.788540	Adjusted R-squared	0.756500
F(25, 165)	24.61151	P-value(F)	2.66e-43
Log-likelihood	−736.0357	Akaike criterion	1524.071
Schwarz criterion	1608.630	Hannan-Quinn	1558.322
rho	0.639186	Durbin-Watson	0.722463

* Significant with a 90% confidence interval; ** significant with a 95% CI; *** significant with a 99% Cl
Source: Authors' own research using GRETL

Figure 5. Actual and fitted FCTP



Source: Authors' own research using GRETL

Model 2 regression shows that some Google searches of financial and football topics in the previous month are significantly different form cero, so we validate Hypothesis 1 and 2 as Google Trends could have certain predictive power over FCTP index. In this case, if we observe an increase in Google searches for topics such as "Ibex 35", "bubble", "ETF", "funds", "investment banking", "FX market" or "UEFA" we should take an early indicator of a bullish trend in the FCTP index. But, an increase in searches for "short selling", "financial crisis", "derivatives" or "Cristiano Ronaldo" would anticipate a downturn in the FCTP index for next month.

Conclusion

In this article we have studied the emotional character of investment in football using the FCPT index. With this purpose, we have proposed a linear regression model in which the endogenous value is the profitability of this index while the explanatory variables measure interest in financial and football issues according to Google Trends.

The results show that Investors' Mood measured through the interest of these topics is statistically significant, therefore the investment in football has a clear emotional bias, not only observable on financial topics but also on football topics.

These results question the suspicions of the efficient market theory that assumes the total rationality of investors.

Discussion limitations and forthecoming investigation

Taking these results into account, the main contribution of this paper should be that there is an econometric evidence that investing in football is an emotional decision. The debate is opened on what criteria should be followed when deciding to invest by buying shares of football teams. Should an analysis be made based on financial or sports results? Would the technical analysis be efficient, or should it be better to measure the perception of the fans about footballers and the coaching staff?

The main practical implication of this paper should be useful for investors, the investment decision of buying shares of a football club is different form buying shares of a bank or telco, in this case the investors' mood is more important. A new investigation line that should be explored, covering the shortcomings of this study. For example, the explanatory variables have been selected under different criteria of relevance and a graphic analysis of the time series that shows a certain correlation with the market. A machine learning study selecting the most relevant "topics" could be an important improvement.

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APPENDIX

Table 4. Summary statistics

	Mean	Median	Minimum	Maximum
FCTP	107.49	103.87	71.880	169.33
Dow_Jones	22.958	15.000	8.0000	100.00
Volatility	56.339	52.000	38.000	100.00
Financial_crisis	6.4896	4.0000	1.0000	100.00
Buble	40.536	35.000	15.000	100.00
ETF	55.302	54.500	24.000	100.00
Derivatives	48.938	43.000	24.000	100.00
Funds	46.010	40.000	12.000	100.00
Debt	75.802	74.000	56.000	100.00
Investment_banki~	43.703	38.000	22.000	100.00
Gold_as_an_inves~	32.682	32.500	9.0000	100.00
Brent_Oil	22.536	16.000	7.0000	100.00
Fx_market	45.823	44.000	27.000	100.00
UEFA	25.135	22.000	4.0000	100.00
FIFA	7.1406	4.0000	2.0000	100.00
Champions_league	24.870	20.000	3.0000	100.00
World_cup	3.7448	1.0000	1.0000	100.00
Lionel_Messi	22.188	25.000	1.0000	100.00
Neymar	9.5885	9.5000	1.0000	100.00
Cristiano_Ronaldo	24.844	23.000	5.0000	100.00
Antoine_Griezmann	5.4115	1.0000	1.0000	100.00
Gol	36.130	38.000	10.000	100.00

	Std. Dev.	C.V.	Skewness	Ex. kurtosis
FCTP	24.817	0.23087	0.75440	-0.24615
Dow_Jones	18.384	0.80075	2.1462	4.3409
Volatility	13.590	0.24122	0.97418	0.27403
Financial_crisis	10.844	1.6711	5.4420	35.772
Buble	17.030	0.42011	1.4545	1.9389
ETF	15.600	0.28210	0.22061	-0.63865
Derivatives	19.082	0.38993	0.65363	-0.77434
Funds	19.320	0.41990	0.72687	0.12685
Debt	10.505	0.13858	0.53230	-0.52762
Investment_banki~	20.368	0.46605	0.82207	-0.60189
Gold_as_an_inves~	15.562	0.47617	1.4834	4.2283
Brent_Oil	16.155	0.71682	1.9519	4.3098
Fx_market	10.512	0.22939	1.9810	7.0361
UEFA	14.183	0.56424	1.4734	4.0399
FIFA	12.245	1.7148	5.5338	32.703
Champions_league	19.527	0.78517	1.5324	2.4860
World_cup	11.880	3.1724	5.9361	36.908
Lionel_Messi	16.851	0.75948	0.95670	2.3115
Neymar	12.258	1.2784	3.4762	18.052
Cristiano_Ronaldo	12.002	0.48310	1.9632	8.5949
Antoine_Griezmann	11.290	2.0863	5.4366	36.685
Gol	13.806	0.38211	0.45566	1.8132

	5% perc.	95% perc.	IQ range	Missing obs.
FCTP	76.335	161.12	31.745	0
Dow_Jones	9.0000	68.350	12.750	0
Volatility	40.000	82.700	20.000	0
Financial_crisis	2.0000	23.450	2.0000	0
Buble	22.000	79.050	17.750	0
ETF	30.000	81.700	25.750	0
Derivatives	27.000	83.000	32.750	0

Funds	14.000	84.700	26.500	0
Debt	61.650	97.350	14.000	0
Investment_banki~	24.000	82.000	36.000	0
Gold_as_an_inves~	11.000	59.000	14.000	0
Brent_Oil	8.0000	57.700	17.750	0
Fx_market	33.000	62.400	10.000	0
UEFA	8.0000	49.000	18.750	0
FIFA	2.0000	16.350	2.0000	0
Champions_league	5.0000	65.000	23.500	0
World_cup	1.0000	10.700	1.0000	0
Lionel_Messi	1.0000	44.350	27.000	0
Neymar	1.0000	29.050	12.000	0
Cristiano_Ronaldo	9.0000	43.750	12.000	0
Antoine_Griezmann	1.0000	17.700	4.7500	0
Gol	13.000	54.350	18.000	0

Table 5. Correlation Matrix
Correlation Coefficients, using the observations 2004:01 - 2019:12
5% critical value (two-tailed) = 0.1417 for n = 192

FCTP	Dow_Jones	Short_Selling	Volatility	
1.0000	0.0018	-0.1601	0.3212	FCTP
	1.0000	-0.0525	-0.2296	Dow_Jones
		1.0000	-0.1046	Short_Selling
			1.0000	Volatility

Financial_cris~	Buble	ETF	Derivatives	
-0.0139	0.3313	0.3910	0.3611	FCTP
0.2105	-0.2931	0.6238	-0.4063	Dow_Jones
0.3717	0.0336	0.1256	-0.1354	Short_Selling
0.1841	0.6272	-0.2272	0.9201	Volatility
1.0000	0.1193	0.3500	0.2386	Financial_cris~
	1.0000	-0.1151	0.6015	Buble
		1.0000	-0.2945	ETF
			1.0000	Derivatives

Funds	Debt	Investment_ban~	Gold_as_an_inv~	
0.5481	0.1456	0.5482	-0.1835	FCTP
-0.4392	0.6047	-0.2859	0.4570	Dow_Jones
0.0479	0.0122	-0.3417	0.0478	Short_Selling
0.7675	-0.3471	0.8385	-0.5228	Volatility
0.0531	0.3127	0.0022	0.1310	Financial_cris~
0.6177	-0.3144	0.5349	-0.3627	Buble
-0.1345	0.7565	-0.2112	0.3868	ETF
0.8059	-0.3757	0.8950	-0.5702	Derivatives
1.0000	-0.4185	0.8073	-0.6214	Funds
	1.0000	-0.3219	0.4371	Debt
		1.0000	-0.5562	Investment_ban~
			1.0000	Gold_as_an_inv~

Brent_Oil	Fx_market	UEFA	FIFA	
-0.2547	0.2092	0.4331	-0.0449	FCTP
0.4248	-0.0481	-0.2270	-0.0791	Dow_Jones
0.2032	0.5251	-0.0568	0.0278	Short_Selling
-0.2775	0.0775	0.4463	-0.0157	Volatility
-0.0661	0.7544	0.1742	-0.0253	Financial_cris~
-0.2418	0.1521	0.3318	-0.0414	Buble
0.2050	0.3659	-0.0651	-0.1184	ETF
-0.4245	0.1649	0.5206	0.0099	Derivatives

-0.3374	0.1454	0.4740	0.0140	Funds
0.2072	0.2872	-0.1864	-0.0207	Debt
-0.3743	-0.0418	0.4792	-0.0284	Investment_ban~
0.1842	0.1061	-0.2326	-0.0562	Gold_as_an_inv~
1.0000	-0.1119	-0.2868	-0.1488	Brent_Oil
	1.0000	0.3351	0.0174	Fx_market
		1.0000	-0.1172	UEFA
			1.0000	FIFA

Champions_leag~	World_cup	Lionel_Messi	Neymar	
-0.1112	-0.0672	-0.4750	-0.3494	FCTP
0.5164	0.0336	0.2068	0.2694	Dow_Jones
-0.0771	0.0631	0.2910	0.0877	Short_Selling
-0.3715	-0.0771	-0.7126	-0.5252	Volatility
-0.0989	-0.0520	-0.1501	-0.1821	Financial_cris~
-0.3636	-0.0916	-0.5010	-0.3781	Buble
0.2992	-0.0503	0.0494	0.0365	ETF
-0.5071	-0.0799	-0.7788	-0.5981	Derivatives
-0.4843	-0.0365	-0.6485	-0.4941	Funds
0.3828	-0.0002	0.1725	0.0871	Debt
-0.4370	-0.0962	-0.7924	-0.5312	Investment_ban~
0.3249	-0.0284	0.4231	0.3567	Gold_as_an_inv~
0.3226	-0.0619	0.3698	0.2227	Brent_Oil
-0.2328	-0.0439	-0.1145	-0.2408	Fx_market
-0.1810	-0.1759	-0.4316	-0.3938	UEFA
-0.2284	0.8968	0.2624	0.2504	FIFA
1.0000	-0.1551	0.3335	0.1663	Champions_leag~
	1.0000	0.3648	0.3624	World_cup
		1.0000	0.7122	Lionel_Messi
			1.0000	Neymar

Cristiano_Rona~	Antoine_Griezm~	Gol	
-0.2987	-0.1160	-0.3510	FCTP
0.1443	0.3442	0.0978	Dow_Jones
0.3764	0.0867	0.3927	Short_Selling
-0.5673	-0.3170	-0.6834	Volatility
-0.0487	-0.1315	0.0334	Financial_cris~
-0.3985	-0.2530	-0.4615	Buble
0.1127	0.1767	0.1178	ETF
-0.5946	-0.3924	-0.6791	Derivatives
-0.4314	-0.2902	-0.5623	Funds
0.1595	0.1975	0.2673	Debt
-0.6154	-0.3086	-0.7657	Investment_ban~
0.2352	0.1449	0.3994	Gold_as_an_inv~
0.2786	0.3064	0.1757	Brent_Oil
0.0915	-0.1607	0.1792	Fx_market
-0.2486	-0.2143	-0.2837	UEFA
0.4572	0.1440	0.4091	FIFA
0.1548	0.1646	0.2705	Champions_leag~
0.5576	0.3353	0.4485	World_cup
0.7143	0.4564	0.8364	Lionel_Messi
0.4843	0.4242	0.5091	Neymar
1.0000	0.5806	0.7394	Cristiano_Rona~
	1.0000	0.2515	Antoine_Griezm~
		1.0000	Gol