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Marcos Henrique Reichert

SOCCER COUNTRY? SPORTS SENTIMENT IN THE BRAZILIAN STOCK MARKET

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Dissertação apresentada à Escola de Administração da Universidade Federal do Rio Grande do Sul como requisito parcial para obtenção do grau de mestre em Administração.

Supervisor: Prof. Dr. Marcelo Scherer Perlin

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RESUMO

Diferentes estudos empíricos mostram um panorama diferente em relação à suposição de que o investidor é um "maximizador de riqueza racional", mostrando que o sentimento do investidor tem fortes efeitos na precificação de ativos. Dessa maneira, esse trabalho utiliza dos resultados de Futebol e Vôlei como um *proxy* para o sentimento do investidor. Essa dissertação é o primeiro trabalho que utiliza dados de alta frequência no contexto brasileiro para testar o sentimento do investidor. Ela testa os efeitos das vitórias e derrotas das Seleções Brasileiras de Futebol e Vôlei em diferentes competições nos retornos e liquidez da B3, o mercado de ações brasileiros. Os resultados mostram que sentimentos esportivos tem pouquissimo efeito nos retornos enquanto afetam de maneira mais forte a liquidez.

Palavras-chave: HFT; B3; Brasil; Sentimento Esportivo; Futebol; Vôleibol; Retornos; Liquidez.

ABSTRACT

Different empirical studies show a different outlook to the assumption that investors are rational "wealth maximizers", they find that investor sentiment have strong effects on asset prices. Thus, this work uses soccer and volleyball results as a proxy for Investor sentiment. This dissertation is the first to test investor sentiment using High-frequency Trading Data in the Brazilian Market, it analyzes if the Brazilian National Soccer and Volleybal Teams' wins and losses affects the returns and liquidity of B3, the Brazilian Stock Market. The results find that sports sentiment has little to no effect in the returns, while it has a stronger effect in the liquidity.

Keywords: HFT; B3; Brazil; Spors sentiment; Soccer; Volleyball; Returns; Liquidity.

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1 INTRODUCTION

Financial Markets are an important part of the world's financial system. It is through them that individuals have easy access to invest their money in shares. It enables insurance companies to exist, banks to borrow money, and companies, in general, to fund their operations (Bank of England, 2019). This way, Capital Markets are critical to a modern economy. Studies show that developing financial markets is positively associated with economic growth (LEVINE; ZERVOS, 1999).

Despite the assumption in financial theory that investors are rational "wealth maximizers" and that capital markets are efficient, different empirical studies show that investor sentiments have strong effects on asset prices since it affects the evaluation of future prospects. There has been a variety of proposed empirical measures to investors' moods. Some of these are related to weather conditions such as sunshine (SAUNDERS, 1993; HIRSHLEIFER; SHUMWAY, 2003; CHANG et al., 2008), temperature (CAO; WEI, 2005), daylight (KAMSTRA et al., 2000; KAMSTRA et al., 2003), air pollution (LEPORI, 2016) and lunar cycles (YUAN et al., 2006). Others use natural disasters (SHAN; GONG, 2012) to quantify an investor's mood and others even take into consideration TV series finales (LEPORI, 2015).

Edmans et al. (2007) propose that the outcomes of sports events have an influence in the investors' mood. He shows that losses in basketball, cricket, rugby and soccer matches have a negative effect on the index of the losing country's market index. With the implication of investors that are not fully rational, the possibility of market overreaction to stock prices (BONDT; THALER, 1985) due to sentiments caused by events unrelated to itself gives room to arbitrage opportunities and even financial crisis (ZOUAOUI et al., 2011).

Despite the large range of articles in the area (PALOMINO et al., 2009; KAPLANSKI; LEVY, 2010; CHANG et al., 2012; PANTZALIS; PARK, 2014; CURATOLA et al., 2016), few focus on the Brazilian market or use high-frequency trading data. The Brazilian Stock Market, B3, is the largest financial exchange in Latin America and is an interesting source for studies. Edmans et al. (2007) propose that a mood variable must satisfy three key characteristics to rationalize studying its link with stock returns: The given variable must drive mood in a substantial and unambiguous way, so it can be powerful enough to show up in asset prices. The variable must affect the mood of a large part of the population, and last, the effect must be correlated across the majority of individuals within a country. This is definitely the case for sports-related sentiment, especially for soccer sentiment in a country called the "soccer country". This nickname comes from the fact that Brazil is the only country in the world to win the World Cup five times, being largely considered one of the most successful soccer countries in the world. In 2005, at least 30 million people practised soccer in Brazil, with 102 million fans in a population of 170 million people (DACOSTA et al., 2005).

Recently, a record from 2006 for most people watching a soccer match in a single broadcaster was broken during a World Cup 2018 game between Brazil and Costa Rica[1], showing that the sport and the national team is still relevant to the Brazilian population. Research from Nielsen Sports shows that 60% of the Brazilian population is passionate about soccer [2], which may seem low but it is important to remind that this research was made after Brazil's 7-1 loss to Germany in 2014 Brazil's World Cup and it still is the majority of the population. Therefore, the Brazilian market is a prime candidate to investors' mood related to soccer results. Since Edmans et al. (2007) finds that other sports results besides Soccer work as a proxy for sports sentiment, such as Basketball. This raises the question which sports besides Soccer should be tested. Even with the majority having preference for soccer, other sports have plenty of international success, one of them being volleyball. Since 2005, the Brazilian National Teams of volleyball, men's and women's, have won together 3 Volleyball World Cups and 3 Olympic Gold medals, which may help to boost the popularity of the sport in the country. In 1999, at least 15,3 millions of Brazilians practised Volleyball (FILHO; ALBERGARIA, 2006), making it the second most practiced sport in Brazil. So this dissertation also works with sports sentiment related to Volleyball results, to test if sports sentiment in general have effects or not in the Brazilian Stock Market.

There is a large body of literature showing that sporting events can affect human emotions and human behavior as a whole. Wann et al. (1994) shows that fans often experience a strong positive reaction when their team performs well, and a corresponding negative reaction when the team performs badly. This reactions extend to this fans'

[1] https://f5.folha.uol.com.br/televisao/2018/06/com-brasil-e-costa-rica-globo-tem-maior-audiencia-em-partida-de-futebol-em-12-anos.shtml
[2] https://exame.abril.com.br/estilo-de-vida/pesquisa-global-questiona-paixao-do-brasil-por-futebol/

positive or negative feelings about life in general and their self-esteem. Schwarz et al. (1987) documents that the results of two soccer games played by Germany in the 1982 World Cup changed subjects' assessments of their views on national issues and of their own well-being. There is also documentation of mood swings affecting economic behavior such as (ARKES et al., 1988) that finds that according to the outcome of the Ohio State University football team matches, the sales of Ohio State Lottery tickets increased or decreased. The importance of sports is taken further with multiple cases where the outcome of the match impacts the health of the fans and spectators negatively. For instance, Carroll et al. (2002) exhibits that during the 3 day period following a loss from England to Argentina in a World Cup penalty shoot-out, admissions for heart attacks increased 25%.

The most prominent example of a study comparing sports results to investors' sentiment is Edmans et al. (2007), which tests for differences in the return of different countries' markets after basketball, cricket, rugby and soccer results in an interday basis. In a general way, this study finds that losses in these sports affect the returns in the following day. Using High-Frequency Trading (HFT) data, this dissertation can expand its results and pinpoint with accuracy the events that affect the stock markets, focusing on analysing the effects on the middle of the game, that is, the intraday effects of sports sentiment. Thanks to High-Frequency Trading data, we can see what is the exact time interval in which the returns and liquidity fall or rise. This way, it's possible to see what is the exact event during the game that affects investors' sentiment the most, including goals made by the Brazilian National Team, by the adversary and outcome changes. Using daily data for an analysis of an event that occurs after working hours can be misleading. During the end of the shift and the opening of the stock market 17 hours have passed, different events occurred, different stock exchanges around the world have opened and closed and a lot of new information is given to the investor, not only the result of a soccer or volleyball game. This is especially true for weekend games, which will have an impact on Monday, alongside events that happened since Friday night. The effects for this type of problem will be considered for the methodology of this dissertation, as some effects only present in high-frequency data will also be taken. But this is an undeniable advantage that the study with high frequency data has, since during an interval of 15 minutes there are way fewer events that can cloud or alter the supposed effects related to sports sentiment.

Seeing the evidence of investor's sentiment affecting the stock market returns, how soccer changes the meaning of life of its fans and the importance of soccer in Brazilians' daily life, the general objective of this dissertation is to define whether investors' sentiments related to sports events affect the returns and liquidity of the Brazilian Stock Market or not.

The specific objectives of this dissertation are: If sports sentiment affects the Brazilian Stock Market, identify which sport has a bigger impact, identify with the use of HFT data if the effects are stronger or weaker during the events themselves, if sports-related sentiments have the same effect on both HFT data and on daily data and distinguish which competitions have the most impact on the stock market.

This dissertation tests if sports sentiment affects the returns and liquidity of the Brazilian stock market. The null hypothesis is that B3 is unaffected by the results of sporting events. This hypothesis follows the idea that investors are rational wealth maximizers, the market is efficient and that the economic benefits associated with a win in a sports events are too small to affect the national stock market index and the stock trading volume. The alternative hypothesis is that wins lead to a positive stock market reaction and losses lead to a negative reaction, that is, both during and after victories from the Brazilian national teams the returns and liquidity from B3 will be higher, and both during and after losses of the national teams. the returns and liquidity will be lower. This is motivated by the findings that investors are affected by their sentiments, arbitrageurs' effects aren't nullified by rational investors and the evidence that sports results affect the optimism and pessimism about life in general of sports fans, thus affecting investor's views on future stock prices.

First, we analyse the impact of the Brazilian Soccer National Team's matches on the returns. We also use variables related to the significance of a match to evince the important ones, such as it being an elimination match or the confronting team being either a rival or a strong team. Using ELO rankings based on the match's date, we define whether the adversary is a threat or not to the Brazilian National Team. Changes in the score will be used to evaluate any kind of instantaneous impact on the stock returns. Then, we shift focus to the liquidity. Using the same variables, we the effects of the sentiments due to the game's outcomes in the stock trading. Also, with some reservations, the same will be applied to Volleyball.

Past literature directs to the following expected results: First, as shown in Edmans et al. (2007), Chang et al. (2012), Gallagher e O'Sullivan (2011), Klein et al. (2009) and Gerlach (2011), there will be no effects during or after wins of the Brazilian National Teams. In fact, it's expected that only losses have some kind of impact on B3 (EDMANS et al., 2007; KAPLANSKI; LEVY, 2010; CHANG et al., 2012). Contrary to Edmans paper, Gerlach (2011), Klein et al. (2009), Gallagher e O'Sullivan (2011) find no effects on the stock market caused by the outcomes of sporting events. However, as we follow similar models to Edmans et al. (2007), we expect to find that sporting events affect the stock market, even accounting for the extended CAPM and with a better market index than Edmans, as criticized by Klein et al. (2009).

In Brazil, soccer is by far the most popular sport. This corroborates to the outcomes of the matches causing any type of impact in the returns and liquidity. Still, this works against the notion of Volleyball having any kind of impact. But volleyball is the most popular sport besides soccer, but when the Volleyball World Cup is occurring, the matches are transmitted only by cable TV [3]. The Olympics have way more traction since there is a lot of media coverage, but until the medal matches, Volleyball has to compete for screen time against individual sports, which have earlier medals and thus steal the spotlight from the early stages of the Olympic volleyball tournament, and soccer, that until the Olympics of Rio 2016 had the stigma of never winning a gold medal. While soccer is expected to have effects on B3, especially on losses, the same can't be said about Volleyball. Though Edmans et al. (2007) says that losses on basketball have a bigger effect than losses in soccer, even though Basketball is a much less popular sport than Volleyball[4], their study has other countries mixed in, which may have influenced the results.

About the use of High-Frequency Trading, it is unusual to think that investors will sell everything during a loss from Brazil. First, for weekend games and non-working hours games, few happen on Sunday night, then even if after a moment of fury an investor decides to sell everything, he has until the opening of the market to calm down

3 https://www.esportudo.com/opiniao-a-popularidade-do-voleibol
4 http://www.iboperepucom.com/br/noticias/ibope-repucom-atualiza-o-ranking-anual-das-principais-confederacoes-esportivas-brasileiras-no-mundo-digital/

and change his mind. For working hours games, if an investor is so involved with a match, he probably will focus on it and not worry about his or her stocks until the end of the match, which may cause in a liquidity fall, notably during elimination games.

For liquidity, Edmans et al. (2007) finds no changes in trading volume related to sports events. We expect the same for non-working hour and weekend games, both should have no impact in the liquidity of B3. But during working hours soccer games in the World Cup's knockout stages we can expect a drop in the trading volume because the attention of the investor will be directed for the occurring match. To the other working hour games, there will be no changes in the trading volume.

But, contrary to the expected according to the literature, the Brazilian Stock Market returns do not react to soccer results, both with and without using high-frequency trading data, and only has a weak negative reactions to volleyball results, notably in daily data. Also contrary to the previous works in the area, during soccer games the liquidity falls and during volleyball games the liquidity rises, unless there is a turnaround or someone finishes a set, which may imply that investors stop to watch the Soccer National Team and only watches the volleyball team in the important moments. Interday results for liquidity shows that after soccer game days, the liquidity rises independently of the result. The same happens to Volleyball with the exception that before losses the liquidity falls.

This dissertation is separated into six sections, with this being the first one, which presents the theme, context and objectives of the topics presented next. Section 2 reports the background of behavioral finance and asset pricing, section 3 discusses the data used for this project, section 4 discusses the method used, section 5 discusses the results and section 6 is the conclusion.

2 LITERATURE REVIEW

One of the most important hypothesis in finance is the Efficient Market Hypothesis (EMH) (MALKIEL; FAMA, 1970), which defines that investors are assumed to be rational, valuing the securities rationally and incorporating all the available information. It defines that irrational investors, if present, trade randomly and therefore their trades cancel each other out without affecting the prices and the effect of irrational investors on prices is also eliminated by the trading activities of arbitrageurs. Also according to the EMH, stock market prices are most driven by new information, rather than present and past prices. Because there is no way to predict the news, stock market prices would follow a random walk pattern and cannot be fully predicted (FAMA, 1965; FAMA et al., 1969).

Another pillar of finance that complemented the Efficient Market Hypothesis is the Capital Asset Pricing Model (CAPM) (TREYNOR, 1961), (TREYNOR, 1962), (SHARPE, 1964) , (LINTNER, 1965), (MOSSIN, 1966). By the CAPM formula, the risk measure known as β is the only variable necessary to explain the return. The β and CAPM formula are the following:

$$\beta = cov(R_m, R_i)/var(R_m), \tag{2.1}$$

$$R_i - R_f = \alpha + \beta(R_m - R_f), \tag{2.2}$$

where R_i is the return of an asset, R_f is the return of a risk-free asset, R_m is the return of the market and α is the a measure of the active return of the investment, although in the CAPM it is equal to 0, otherwise it would lead to Arbitrage opportunities.

Further testing started to question the validity of the market β, so other variables were used to complement the original market β. Fama e French (1992) examined the most prominent ones to test their redundancy and then formulated a new model with three factors. These factors were the original β, size and book to market (FAMA; FRENCH, 1993). Later, Carhart (1997) expands this model with a fourth factor, momentum. Carhart's model uses the following formula:

$$R_i - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2 HML + \beta_2 SMB + \beta_3 WML, \tag{2.3}$$

where HML is the return of a theoretical portfolio buying stocks with a high ratio of book value/price and selling the ones with a low ratio, SMB is a theoretical portfolio buying stocks of firms with low capitalization and selling ones with high and WML is another theoretical portfolio, this time, buying with higher past returns and selling the ones with lower past returns.

Despite the initial success of this theory with its empirical results, the 90's internet and 2006 real estate and many others crises put the idea that investors are completely rational in check (BAKER; WURGLER, 2007). Alternative theories and models were made following two basics assumptions: Investors are affected by their sentiments (LONG et al., 1990) and betting against sentimental investors is costly and risky (SHLEIFER; VISHNY, 1997), which leaves arbitrageurs afraid to operate against them contrary to the proposed by the EMH (BAKER; WURGLER, 2007). And a growing body of research demonstrate that stock market prices do not follow a random walk and can be predicted to some degree (BUTLER; MALAIKAH, 1992; QIAN; RASHEED, 2007; PERLIN et al., 2017).

Since the investor is not perfectly rational, there is, as extensively reviewed by Hirshleifer (2001), different types of judgement and decision biases that have been documented to impact the actions of investors, such as Heuristic simplifications, Self-Deception, Emotions and Social Interactions. Other studies investigate the role of emotions in human decision making, like (DOLAN, 2002; KAHNEMAN; TVERSKY, 2013). More specifically DellaVigna (2009) also discusses the effect of emotions in the Stock Market, as one aspect that leads to non-standard decision making.

One problem of studying investor emotions and sentiments is how to measure it. Baker e Wurgler (2007) defines different proxies for investor sentiments. The first one is Investor Surveys. Asking investors how optimistic they are, it is possible to gain insight into the marginal irrational investor. In the United States a diverse number of these surveys exists, such as the one that Robert Shiller conducts since 1989, UBS/Gallup surveys that randomly-selected investor households and Investors Intelligence which surveys financial newsletter writers. These surveys were used by different articles as a investor sentiment proxy (BROWN; CLIFF, 2005; QIU; WELCH, 2004; LEMMON; PORTNIAGUINA, 2006).

Another common proxy in the literature is Retail investor trades, according to Baker e Wurgler (2007), the inexperienced retail or individual investor is more likely than the professional to be affected by his sentiment. This proxy had positive results (GREENWOOD; NAGEL, 2009; KUMAR; LEE, 2006). Other proxy is mutual fund flows. Data on how American mutual fund investors allocate across fund categories is easily available, which helps the usage of this proxy. (BROWN et al., 2003) proposed and overall market sentiment measure according to how fund investors are allocating their money, that is, if they allocating their money in "safe" government bond funds and withdrawing from “risky” growth stock funds, the overall market sentiment is negative. But, as asserted by Baker e Wurgler (2007), Mutual fund investors are well-known to chase investments with high recent returns, so whether the causality also goes the other direction, or whether their allocation decisions actually lead to mispricing, is a tricky question.

Trading is also used as a proxy. Liquidity can be viewed an investor sentiment index. Baker e Stein (2004) note that if short-selling is costlier than opening and closing long positions, irrational investors are more likely to trade, when they are optimistic and betting on rising stocks rather than when they are pessimistic and betting on falling stocks. Dividend premium is used as a proxy because Dividend-paying stocks resemble bonds since their predictable income stream represents a salient characteristic of safety, then the dividend premium may be inversely related to sentiment (BAKER; WURGLER, 2004b; BAKER; WURGLER, 2004a). A closed-end fund is a portfolio of pooled assets that issue a fixed number of shares and then lists them for trade on a stock exchange. The closed-end fund “discount”, or premium, is the difference value between the fund’s market price and the net asset value of a fund’s actual security holdings. This premium is also used as a proxy (ZWEIG, 1973; LEE et al., 1991; NEAL; WHEATLEY, 1998; WHALEY, 2000).

Other proxy is the IPO First-Day returns. An IPO is an Initial public offering, that is the event in which a company goes public and sells its shares in the stock market for the first time [5]. Sometimes these events offer a significant return on their first day which is difficult to explain without involving investor enthusiasm. Another IPO related proxy is the IPO volume. As asserted by Baker e Wurgler (2007), the demand for IPOs is said to be

[5] https://web.archive.org/web/20120314134420/http://www.bmfbovespa.com.br/pt-br/educacional/download/BMFBOVESPA-Como-e-por-que-tornar-se-uma-companhia-aberta.pdf

extremely sensitive to investor sentiment, with investment bankers looking for “windows of opportunity” during the IPO which capriciously open and close. These windows of opportunity could explain why IPO volume has wild fluctuations. Another proxy related to new equity issues is the Equity issues over total new issues. It is a broader measure using the equity share of total equity and debt issues by all corporations. This measures all equity offerings, not just IPOs (BAKER; WURGLER, 2000).

Despite legality issues, Insider trading is also considered as a possible proxy. Corporate executives have a better understanding of the price of their firms than outside investors. This way, executives’ personal portfolio decisions may also reveal their views about the mispricing of their firm. If sentiment leads to correlated mispricing across firms, insider trading patterns may contain a systematic sentiment component (BAKER; WURGLER, 2007). Last, Investor Mood. A large part of the literature tries to connect stock prices to exogenous changes in human emotions. As mentioned before, some of these changes include weather, lunar cycles, seasons. And, as the case of this dissertation, sports events. This way, this dissertation will study investor mood as a proxy for investor sentiment.

As shown in the introduction, there is a large body of literature showing that sporting events can affect human emotions and human behavior as a whole and there is significant evidence implying that soccer is an important part of many people lives. For example, in the last four World Cups, the overall viewership of the finals have increased by double digits compared to the previous one[6]. Besides, French e Poterba (1991) shows a “home bias” in which the individuals affected are also likely to be the marginal investors in the domestic stock market. For an extended view in the psychological evidence behind soccer affecting an investor’s mood, Edmans et al. (2007) provides a detailed survey on it.

There is a diverse portfolio of articles and studies following the trend of investor sentiment affecting the market. The next table 2.1 offers a synopsis from some of these articles. The first column highlight the author, the second one details the financial data used and the proxy for investor mood. The last column briefly exhibits the results obtained by the articles.

[6] https://the18.com/soccer-learning/world-cup-final-viewers-tv-ratings

Table 2.1 – Synopsis of the literature

Authors	Study object	Main results
Palomino et al. (2009)	Stocks of British soccer teams. British Soccer Results.	Investors in stocks of British soccer teams tend to overreact to wins of the teams that they are investing. The study shows that the investors don't use or don't have access to all information, since they seem to ignore betting odds, which is shown to be a good predictor of future returns.
Kaplanski e Levy (2010)	US Markets during Soccer World Cups.	Develops a strategy to exploit the effects of investor sentiment in the US Market during World Cups. He finds that during these tournaments the US Market on average has negative returns. Suggests selling stocks and buying short-term Treasury bills during the event, which would theoretically provide higher returns with lower risk.
Chang et al. (2012)	US Markets. NFL Results.	Finds that the outcomes of local NFL sports teams influence investor sentiment, which significantly affects the returns of localized trading stocks. These effects are significantly stronger in surprise losses.
Pantzalis e Park (2014)	Stocks of US Companies with headquarters close to the teams' cities. NFL, NBA, MLB and NHL results.	Verifies the correlation between concurrent local stock returns and local area teams' performance and uses this data to define portfolios based on sports sentiment. The created portfolio obtains abnormal returns of almost 10%.
Curatola et al. (2016)	US Sectoral stocks returns. Soccer World Cups.	Finds that the only sector affected by soccer sentiment is the financial sector. Accordingly, an arbitrageur can build a profitable trading strategy by selling short the financial sector during the FIFA World Cup periods and buying it back afterwards.
Gilbert e Karahalios (2010)	S&P 500 and Monte Carlo Simulations Weblogs.	Shows that by estimating emotions from weblogs, specifically, the site LiveJournal, it is possible to predict future stock market prices. The data showed that increases in expressions of anxiety predicted downward pressure on the SP& 500 index. These results were confirmed via Monte Carlo Simulation.
Bollen et al. (2011)	Dow Jones Industrial Average. Twitter Messages.	Tests if it's possible to predict the stock-market with Twitter messages. They were read by a mood-tracking tool distinguishing them between different moods. This data was used to measure the relationship of the different moods of the general public with the closing values of the Dow Jones Industrial index. It was found that some of the mood intensities can help explain variations in the market index.
Klein et al. (2009)	National Stock Indexes. Soccer results	Finds that with different econometric models using the same data it's possible to obtain results both favorable and against the effect of soccer matches. Ultimately, using the adequate model, there is no effect on the stock market returns, supporting the efficient market hypothesis. Klein et al. (2009) also suggests that favorable results are acquired because they are easier to get published.
Gerlach (2011)	National Stock Indexes Soccer results	Shows that changes in investor sentiment following international sports matches do not have a significant effect on asset prices,. It finds that unusual returns also exist in those countries even though their national teams did not play.

Source – Elaborated by the author

Reading table 2.1 we see that the majority of the literature has results that comply with the idea of investor sentiment having an effect in the stock market. Most of the articles shown used sports-related events as proxies for investor mood, but as seen in the same table, the study object is not limited by sports, with the examples of twitter and weblog messages by Bollen et al. (2011) and Gilbert e Karahalios (2010). The overwhelming use of sports results, especially football, shows that the object of this study is relevant in behavioral finance. Although most results show that sports sentiment has an effect on the stock market, Klein et al. (2009) and Gerlach (2011) have different results. This is relevant for the study as both works have a special interest in the work of Edmans et al. (2007). Even though this dissertation follows a similar methodology to Edmans, we strike some of Klein's and Gerlach's criticism by using a better market index, i.e., the Ibovespa instead of the World Market Index - which is not the best to evaluate the studied countries in Edmans et al. (2007) as denoted by Gerlach (2011).

3 DATA

The events of this study consist of all 158 games from the Brazilian's Men and Women Soccer National Team since 2010, including games from 2 World Cups and 2 Olympic games, and 98 Volleyball games of the Men's and Women's National Team in the Volleyball World Cup, World Championship and Olympics. The soccer data is collected from *www.worldfootball.net* and includes the hour of the match, partial scores and final outcome. Volleyball data is gathered using the official reports of the matches from the *Fédération Internationale de Volleyball* (FIVB) on their website[7]. The sample comprises data from 2010-10-01 to 2018-05-29.

The soccer matches dwell of friendly matches, qualifying games for the World Cup, *Copa América*, Confederations Cup, World Cup and the Olympics games. Besides Uruguay and Argentina, Italy, Netherlands and, recently, Germany considered rivals to Brazil. Specifically for soccer, we collect data from *https://www.eloratings.net/* (EDMANS et al., 2007) to determine which games are more important and which losses are more shocking, with the confrontations against the top 15 countries during the period before the next World Cup being elected as the most important matches.

The effect of sporting events on stock prices is measured using the returns of B3's assets that corresponds to 75% of the Brazilian Market liquidity. The liquidity filter is the number of trades that happened during each 15-minute interval. For weekday games in which the market is open while the match is occurring, we'll use HFT data to analyze the effects of every goal in the match for the soccer game and the results of every set in the Volleyball games and for weekend games and games ocurring during the off-hours of the market we use the first trading day after the game. For liquidity we consider the trading volume for the same time frame used in the return analysis. The financial data comes directly from B3 *FTP* as a .txt file with its information extracted using the R package GetHFData (PERLIN; RAMOS, 2016).

The data consists of information about each trade of the day, it includes the following information:

- Session date;

[7] Example: <http://www.fivb.org/vis_web/volley/MWC2007/pdf/P2-023.pdf>

- Instrument identifier;
- Trade number;
- Trade price;
- Traded quantity
- Trade time, with the format HH:MM:SS.NNNNNN;
- Trade indicator, a dummy in which 1 represent a trade and 2 a cancelled trade;
- Buy order date;
- Sequential buy order number;
- Secondary Order ID - Buy Order;
- Aggressor Buy Order Indicator, a dummy in which 0 represents that a order was not executed, 1 when it was an aggressive order and 2 when it was passive order;
- Sell Order Date;
- Sequential Sell Order Number;
- Secondary Order ID - Sell Order;
- Aggressor Sell Order Indicator, a dummy following the Aggressor Buy Order Indicator convention;
- Cross Trade[8] Indicator, which indicate if a cross trade is intentional or not;
- Entering Firm (Buy Side);
- Entering Firm (Sell Side);

this information is then aggregated in 15-minutes intervals by the the same package. The information is filtered using the Trade Indicator, cancelled trades are excluded from the dataset. During this process, the package evaluates the return - how much the price has gone up or down, the volatility of the return and the weighted price of each asset for each interval. The complete aggregated database consists of over 1600

[8] https://www.investopedia.com/terms/c/crosstrade.asp

assets, including the odd lots market, with almost 8 million entries. As mentioned before, the number of trades is used as the liquidity filter. Higher the number of trades, higher the liquidity. After the liquidity filter is done, only 96 assets stay in the database. Using this high-frequency data, we compute the daily data, and the high-frequency portfolios for the Ibovespa and Carhart's four factors.

The process of transformation of the database works in the following way: First, both the financial data from B3'S FTP Website and the sports results from *www.worldfootball.net* and FIVB's official match reports are extracted. The next step is recoding some of B3's ticker symbols. From 2010 to 2018 a few important assets from the Brazilian Market changed its tickers, since this dissertation tests the effects in the Brazilian Market using the assets that correspond for 75% of its liquidity during the 8 years of data, it's necessary to guarantee that a high liquidity asset that changed name doesn't disappear from the financial data.

After the recoding of the ticker symbols, the cleaning of the financial database is done. The package GetHFData (PERLIN; RAMOS, 2016) does most of the work; this way, the cleaning is simply getting rid of data that is not going to be used in this dissertation. Next, we have turning the sports results into High-Frequency data, i.e., turning the match reports into intervals in which there will be an indication if a goal happened, Brazil is winning and other relevant information. The following step is the creation of the High-Frequency version of the Brazilian index, Ibovespa. Using the composition of the index since 2010 provided by B3's Investor relation we create portfolios identical to the index for each quarter and calculate its returns in the High-Frequency Trading Data. A similar process is made for the creation of Carhart's four factor expanded CAPM, but instead of using B3's composition, data from the Economatica software is used. Next, both the sports and financial database are merged, the separation between high-frequency trading data and daily data is made, the log returns are extracted and the CAPM portfolios are merged.

Table 3.1 show the games' results in the sample. Columns *"Wins"* and *"Losses"* shows the results for every game, except for ties, for the specific competition. *"Score Brazil"* consists of the number of goals and sets that happened during the working hours of the B3 and *"Score Adversary"* the goals and sets of the opposition. *"Scoreboard Changes"* has the number of tiebreakers, opening goals and turnarounds for the competition. It's important to emphasize that competitions organized by CONMEBOL don't have games during the stock market working hours. The same happens for Volleyball World Cup games and World Championship Elimination games. Thus, columns Score Brazil, Score Adversary and Scoreboard changes are blank for these competitions, which indicates these competitions are only evaluated with financial daily data.

Table 3.1 – Summary of Soccer and Volley Games

	Wins	Losses	Score Brazil	Score Adversary	Scoreboard Changes
Panel A: Soccer Games					
All games	111	30	113	47	82
International Friendlies	57	19	65	26	50
Qualifying games	13	1			
Copa América Group Stage Games	3	1			
Olympic Games Group Stage Games	8	1	14	3	6
Olympic Games Elimination Games	12	3	10	4	5
World Cup Group Stage Games	10	1	13	3	11
World Cup Elimination Games	3	4	7	10	6
Panel B: Volleyball Games					
World Cup Games	17	5			
Olympic Games Group Stage Games	17	4	2	6	2
Olympic Games Elimination Games	9	2	9	2	3
World Championship Group Stage Games	36	4	41	6	16
World Championship Elimination Games	5	3			

Source – Elaborated by the author

According to Table 3.1, we can see that Brazil has a really strong National Soccer Team, with just 30 losses in the period of 8 years. The difference between goals pro and against Brazil is huge, but the number of Scoreboard changes also suggests that the majority of these goals don't affect the result of the match. It's important to note that the bulk of matches are International friendlies, which in theory should be irrelevant to the average Brazilian, although there is a considerable number of losses in elimination games. The National Volleyball Teams, despite losing relatively more than the soccer team, shows a better performance in elimination matches, barely conceding any sets during those games. Up next, table 3.2 summarizes the return data. Column N denotes the number of observations, Mean and SD shows the average and the standard deviation, min shows the minimum return in the dataset, Max the maximum and % Positive and % Negative gives the percentage of returns that are greater or equal to 0 and less than 0, respectively.

Table 3.2 – Descriptive stats of HFT returns.

	N	Mean	SD	Min	Max	% Positive	% Negative
Every observation	2356862	-0.00002756185	0.004526082	-0.1550	0.2728	50,79%	49,21%
No games	2338993	-0.00002663265	0.00453045	-0.1550	0.2728	50,80%	49,20%
Soccer descriptive stats							
	N	Mean	SD	Min	Max	% Positive	% Negative
All game intervals	13762	-0.0001667344	0.02675022	-0.08	0.0435	54,80%	45,20%
Winning	4480	0.00003484457	0.003681847	-0.02	0.027	56,83%	43,17%
Losing	1733	0.0002425428	0.003027186	-0.0139	0.0216	60,36%	39,64%
Volleyball descriptive stats							
	N	Mean	SD	Min	Max	% Positive	% Negative
All game intervals	4107	-0.0008823303	0.03374275	-0.0253	0.0207	55,47%	44,53%
Winning	2310	0.000135682	0.003953802	-0.0179	0.02	57,70%	42,30%
Losing	265	-0.0007541245	0.004748381	-0.0252	0.0198	46,79%	53,21%

Source – Elaborated by the author

Despite many observations, there are few games during the working hours of the Brazilian Stock Market. Sometimes, games begin during the working hours but end after the market is closed. This is especially relevant to Volleyball games and the national teams losses. It's interesting to see that according to the table 3.2, drawing is worse for the returns than losing, since the mean is worse for all intervals in both soccer and volleyball stats than in the losing intervals. Is also worth notice that the minimum return and maximum are outside of sports matches, which could suggest there isn't anything special occurring during the matches. Another interesting fact is the percentage of negative returns during volleyball losses.

Table 3.3 – Descriptive stats of Daily returns.

	N	Mean	SD	Min	Max	% Positive	% Negative
Every observation	86225	0.0003493126	0.05542609	-0.9859	8.7938	50,53%	49,47%
No games	77952	0.000473687	0.05758854	-0.9859	8.7938	50,56%	49,44%
Soccer descriptive stats							
	N	Mean	SD	Min	Max	% Positive	% Negative
All games	5824	0.001330421	0.02675022	-0.2	0.44	53.14%	46.86%
Wins	3821	0.00202064	0.0265855	-0.1904	0.44	54.95%	45.05%
Losses	891	-0.0004143742	0.02828203	-0.138	0.1796	51.52%	48.48%
Volleyball descriptive stats							
	N	Mean	SD	Min	Max	% Positive	% Negative
All games	2827	-0.0008823303	0.03374275	-0.7573	0.1317	51.07%	48.93%
Wins	2427	-0.0006778885	0.0337383	-0.7573	0.1317	51.11%	48.87%
Losses	653	-0.0004702921	0.03271691	-0.4840	0.1317	48.24%	51.76%

Source – Elaborated by the author

For daily data, there is less observations, notably even less losses. The most interesting thing about table 3.3 is that apparently after every volleyball game the returns are lower. The minimum, maximum and the positive and negative columns follow similar patterns to the High-Frequency Trading, except for the huge maximum return and a lesser percentage of positive returns for soccer losses. It's important to remind that sometimes there are wins and losses on the same day since this dissertation works with both the men's and women's national teams, mainly after weekends. But the methodology used by Edmans et al. (2007) accounts for this types of situation by using Gallant et al. (1992) for filtering the data.

4 METHOD

To test the hypothesis, this work applies a similar model to Edmans et al. (2007), but accounting for the extended factor of the CAPM, on the data collected from the B3 ftp website. It estimates the impact of wins and losses on stock returns while controlling for the Monday effect and other confounding effects through a series of panel linear models. First, we estimate the following model:

$$\begin{aligned} R_{it} =& \gamma_0 + \gamma_1 R_{mt} + \gamma_2 R_{it-1} + \gamma_3 HML_t + \\ & \gamma_4 SMB_t + \gamma_5 WML_t + \gamma_6 D_t + \gamma_7 Q_t + \\ & \beta_{Wins} W_{it} + \beta_{Losses} L_{it} + \beta_{Gameday} G_{it} + \\ & \beta_{BeforeWins} BW_{it} + \beta_{BeforeLosses} BL_{it} + \beta_{AfterGameday} AG_{it} + u_t, \end{aligned} \tag{4.1}$$

in which R_{it} is the discretely compounded daily or by each 15-minutes interval nominal return on the asset i on day or hour t, $D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday through Thursday, $Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables for days for which the previous 1 through 5 days are non-weekend holidays. R_{mt} is the 15-minute interval or minutely nominal return of the Ibovespa on day or hour t. The lagged index return, R_{it-1}, is included to account for first-order serial correlation. HML_t, SMB_t, WML_t correspond to the returns of the factor portfolios of Book-to-Market, Size and momentum on the day or hour t. The factor portfolios are constructed with data extracted from the Economatica software. The Ibovespa index is assembled using their historical compositions, making it possible to evaluate its high-frequency returns, since the index isn't present with the high-frequency data.

The βs are the variables related to sports data. $W_t = \{W_{1it}, W_{2it}, ...\}$ are dummies for days after the national team won in different subgroups of matches, i.e., the dummy has a value 1 on the days following Brazil wins and 0 when Brazil lost. $L_t = \{L_{1it}, L_{2it}, ...\}$ are the same but for days in which the National Team lost. The number of different subgroups will vary according to the sport, the subgroups are divided in a subgroup for important matches - matches against rivals and strong opponents - and in a different subgroup for each competition present in table 3.1. $G_t = \{G_{1it}, G_{2it}, ...\}$ are dummies for working days before or with a national team match for the different subgroups of matches, for example, a Friday before a weekend game or a Workday with a soccer game during its

24 hours have a value of 1, otherwise it will be 0. $AG_t = \{AG_{1it}, AG_{2it}, ...\}$ are dummies for the next working day after a match, it comprises Mondays after a weekend game and the next day after a workday game (Thursday for a Wednesday game), this dummy has a value of 1 for those days or 0 for the exceptions and has the same subgroups as the other dummies. $BW_t = \{BW_{1it}, BW_{2it}, ...\}$ and $BL_t = \{BL_{1it}, BL_{2it}, ...\}$ work the same as G_t, representing the business days before wins and losses respectively. This dissertation estimates the model using panel corrected standard errors (PCSE) (BECK; KATZ, 1995) assuming that the error terms u_{it} are uncorrelated and have mean zero but allows for heteroskedacity.

For games during the working hours, the regression uses data for each 15 minutes. Instead of dummies for wins and losses we apply dummies for the current state of the match, that is, if the Brazilian national team is currently winning or losing in that 15 minute interval. This study will also check for effects in the stock market caused by change in the score. So the regression for the working hours games is:

$$\begin{aligned} R_{it} =& \gamma_0 + \gamma_1 R_{mt} + \gamma_2 R_{it-1} + \gamma_3 HML_t + \\ & \gamma_4 SMB_t + \gamma_5 WML_t + \gamma_6 D_t + \gamma_7 Q_t + \\ & \gamma_8 H_t + \beta_{Gametime} Gw_{it} + \beta_{Winning} Ww_{it} + \beta_{Losing} Lw_{it} + \\ & \beta_{ScoreBrazil} SB_{it} + \beta_{ScoreRival} SR_{it} + \beta_{Outcomechange} O_{it} + u_{it}, \end{aligned} \tag{4.2}$$

wherein the $H_t = \{H_{1t}, H_{2t}, ..., H_{7t}\}$ are dummy variables for the hours of the day, which is exclusive for the High-Frequency Trading data. $Ww_t = \{Ww_{1it}, Ww_{2it}, ...\}$ are the dummies for the national team winning in the same different subgroups of matches from equation 4.1, it has a value of 1 if the Brazil National Teams are winning during the 15-minute interval being tested and 0 otherwise. $L_t = \{Lw_{1it}, Lw_{2it}, ...\}$ is the same but for losing. $SB_t = \{SB_{1it}, SB_{2it}, ...\}$ works as a dummy for Brazil scoring during that time period and $SR_t = \{SR_{1it}, SR_{2it}, ...\}$ for the opposing team scoring. This means that if Brazil scores during one of the intervals being studied, the dummy SB_t will have a value of 1 instead of 0, the same applies for scores against Brazil, but in this occasion the dummy SR_t will have the value of 1. $O_t = \{O_{1it}, O_{2it}, ...\}$ are dummies representing a change in the outcome, that is, Brazil started to lose, draw or win because of that score, some of the situations in which this dummy has a value of 1 includes when someone scored first or scored a tiebreaker, scores that extend the lead or "honor goals", such as the 1 in Brazil's 1-7, have a value of 0. Also, $Gw_t = \{Gw_{1it}, Gw_{2it}, ...\}$ is a dummy for every interval where there is a National Team match. SB_{it}, SR_{it},O_{it} and G_{it} have the same subgroups as the other dummies. This study considers a score a goal in soccer and winning a set in volleyball. With this new set of dummies we can confer if a score pro or against Brazil has any impact in the returns of the B3 and differentiate an opener goal or a tiebreaker from goals in the *garbage time*, when the match is already decided and one team is winning by a landslide.

There is an assumption that stock returns have constant volatility, but French et al. (1987) and others show that stock index returns have time-varying volatility. To solve this problem we model stock return volatility using General Autoregressive Conditional Heteroskedasticity (GARCH) which was developed by Engle (1982) and generalized by Bollerslev (1986). After modeling the stock returns using equation 4.1, we model the volatility of the error following the GARCH(1,1) process in similar way to Edmans et al. (2007), $\sigma_{it}^2 = \lambda_{0i} + \lambda_{1i}\epsilon_{it-1}^2 + \lambda_{2i}\sigma_{it-1}^2$ where σ_{it}^2 is the volatility of the returns for day or minute t. We apply this to the entire sample. Then we form the normalized stocks returns of the new time series following this equation: $R_{it}^0 = a_i + b_i(1/\hat{\sigma}_{it}^2)R_{it}$, where a and b are chosen so the mean is zero and the deviation is one. The normalized returns are then used in equation 4.1 that obtains normalized residuals denoted as $\tilde{\epsilon}_{it}$. This study work both with the normalized and abnormal residuals.

For Liquidity, this dissertation follows a similar method to Edmans et al. (2007). We use a filter procedure similar to Gallant et al. (1992), with V_{it} being the aggregate volume of the 15-minute interval or day, we filter using the following equation: $V_{it} = \gamma_0 x_{it} + u_{it},$ where x_{it} is a set with the dummies for seasonality as day of the week and month and two lags of volume. Then we estimate the variance running the following regression $\log \hat{u}_{it}^2 = \gamma_1 y_{it} + \epsilon_{it}$ where y_{it} is a set of variables containing the same dummies as x_{it} except for the two lags of volume. Lastly we model $\hat{w}_{it} = a_i + b_i\hat{u}_{it}^2/\exp(\hat{\gamma}y_{it}/2)$ with a_i and b_i being chosen as $\hat{w}_{it}$ having a mean equal to zero and volatility equals to one. This way, we guarantee constant volatility. We then estimate the impact of sporting events outcomes on weekends and non-working hours games with the equation:

$$\begin{aligned}\hat{w}_{it} =& \beta_0 + \beta_{Wins}W_{it} + \beta_{Losses}L_{it} + \beta_{Gameday}G_{it} + \\ & \beta_{BeforeWins}BW_{it} + \beta_{BeforeLosses}BL_{it} + \beta_{AfterGameday}AG_{it} + u_{it},\end{aligned} \tag{4.3}$$

with the dummies working as the same as equation 4.1. However, for working hours we use the following equation:

$$\begin{aligned}\hat{w}_{it} =& \beta_0 + \beta_{Gametime} Gw_{it} + \beta_{Winning} Ww_{it} + \beta_{Losing} Lw_{it} + \\ & \beta_{ScoreBrazil} SB_{it} + \beta_{ScoreRival} SR_{it} + \beta_{Outcomechange} O_{it} + u_{it},\end{aligned} \tag{4.4}$$

where the dummies are the same as equation 4.2. For volleyball games, we remove the dummies $Gw_{it}, G_{it}, BG_{it}, AG_{it}$ from every equation because they are redundant since there is no way for a volleyball match to end in a tie. This way, the dummies covering for wins and losses are enough.

For the estimation and diagnostics, we use the statistic software R (R Development Core Team, 2009) with the package rugarch (GHALANOS, 2018) for the normalization process with GARCH and the packages PLM (CROISSANT; MILLO, 2008) and Sandwich(ZEILEIS, 2004) for the Panel Correlated Square Errors method used in daily data. The comparisons, descriptive statistics and analysis of the regressions and its coefficients will also be done with the same software. With the method we presented in this section, this study can analyze the immediate effects of scores and the matches' outcomes for the Brazilian national teams of Volleyball and Soccer for both the returns and liquidity of B3.

Finally, it's time to do the linear model. First, we estimate the returns regression for the abnormal returns, both the daily and the high frequency. Afterwards, the GARCH normalization is done for the return data, which permits the estimation for the normal returns. Last, it is applied the PCSE method in the daily data for both the normal and abnormal regressions. Hereafter this process is repeated for each subgroup, for important games and for the log returns, which are used as a robustness test for the results. Finally, it's time for the liquidity. The process is very similar, except the filter procedure (GALLANT et al., 1992) mentioned beforehand is done before the regressions.

This dissertation's test expects according to the alternative hypothesis that the coefficients related to Brazil losses will be negative and the ones related to Brazil wins will be positive, whereas in the null hypothesis it won't, but given the results of the literature, we elaborate a table with a summary of the expected result for each coefficient:

Table 4.1 – Hypothesis for the coefficients

Coefficient	Literature	Relevance for returns	Coefficient sign for returns	Relevance for liquidity	Coefficient sign for liquidity
β_{Wins} (4.1, 4.3)	Yes	No	Not relevant	No	Not relevant
β_{Losses} (4.1, 4.3)	Yes	Yes	Negative	No	Not relevant
$\beta_{Gameday}$ (4.1, 4.3)	Yes	Yes	Negative	No	Not relevant
$\beta_{BeforeWins}$ (4.1, 4.3)	No	No	Not relevant	No	Not relevant
$\beta_{BeforeLosses}$ (4.1, 4.3)	No	No	Not relevant	No	Not relevant
$\beta_{AfterGameday}$ (4.1, 4.3)	Yes	Yes	Negative	No	Not relevant
$\beta_{Gametime}$ (4.2, 4.4)	No	Yes	Negative	No	Not relevant
$\beta_{Winning}$ (4.2, 4.4)	No	No	Not relevant	No	Not relevant
β_{Losing} (4.2, 4.4)	No	Yes	Negative	No	Not relevant
$\beta_{ScoreBrazil}$ (4.2, 4.4)	No	No	Not relevant	No	Not relevant
$\beta_{ScoreRival}$ (4.2, 4.4)	No	Yes	Negative	No	Not relevant
$\beta_{Outcome}$ (4.2, 4.4)	No	No	Not relevant	No	Not relevant

Source – Elaborated by the author

Every coefficient in table 4.1 which have a "Yes" in the column literature was already tested in a previous study. Wins and losses are both used by Edmans et al. (2007) and Chang et al. (2012) to account for the effects of sports sentiment in the returns of stock market, and in both cases, the results found are that only losses have significant impact and that is a negative one. Edmans et al. (2007) also tests both coefficients for market liquidity though it doesn't find any sign of effects on it. For the coefficients related to gamedays, Kaplanski e Levy (2010) finds that, during the World Cup, stocks, in general, have lower returns in the USA. Considering the fact that this work pioneers the use of high-frequency trading data to analyse the effects of sports sentiment in the stock market, the coefficients related to it were never used before in the literature. Helped by the past literature using interday data, we can trace parallels between it and High-Frequency Trading data and expect that only coefficients related to losses will have any effect in the returns, and they will be negative. Although former studies with interday data show that sports sentiment doesn't affect the liquidity, the different nature of HFT data can entail different results. But it will still be expected to not have any relevance.

5 RESULTS

The coefficient values in this section are obtained multiplying the dependent variable by 10.000. The objective of this process is to give an easier understanding of the results. First, the results for the High-Frequency Trading Data were the following:

Table 5.1 – Soccer sentiments results for HFT Data

	Abnormals	Normals
γ_{Mt}	9308.7294^{***}	207.5138^{***}
	(13.2775)	(0.2953)
γ_{Lag}	-172.9418^{***}	-2.2236^{***}
	(5.8947)	(0.1308)
γ_{HmL}	78.5922^{***}	-1.1365^{***}
	(11.5532)	(0.2573)
γ_{SmB}	-102.2983^{***}	-3.1922^{***}
	(8.5749)	(0.1912)
γ_{WmL}	-163.4295^{***}	-4.6307^{***}
	(19.4481)	(0.4332)
$\beta_{Gametime}$	-0.2154	-0.0055
	(0.4743)	(0.0106)
$\beta_{Winning}$	0.3578	0.0255
	(0.9665)	(0.0216)
β_{Losing}	1.2688	0.0400
	(1.2957)	(0.0289)
$\beta_{Outcomechange}$	0.2123	-0.0178
	(1.2753)	(0.0285)
$\beta_{ScoreBrazil}$	-0.1924	-0.0250
	(1.2936)	(0.0289)
$\beta_{ScoreRival}$	-1.7150	-0.0089
	(1.7859)	(0.0399)
R^2	0.18	0.20
Adj. R^2	0.18	0.20
Num. obs.	2356762	2331196

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

The column Abnormals represents the results obtained using the raw returns and the Normals column represents the results obtained with the normalized returns obtained after the GARCH(1,1) process.

Contrary to the liquidity that coming up next, the R^2 for the returns also includes the other gamma coefficients shown in the equation 4.1 and equation **??**. As table 5.1 shows, sports sentiment related to soccer results doesn't have any effect on the returns of the Brazilian stock market using High-Frequency Trading Data. This result contradicts the findings of Edmans et al. (2007), who shows that losses have a negative effect on the returns of the stock market, although in daily data. The results for Volleyball sentiment in the Stock market are the following:

Table 5.2 – Volleyball sentiments results for HFT Data returns

	Abnormals	Normals
γ_{Mt}	9308.9373^{***}	207.5185^{***}
	(13.2780)	(0.2954)
γ_{Lag}	-172.9205^{***}	-2.2237^{***}
	(5.8946)	(0.1308)
γ_{HmL}	78.6919^{***}	-1.1311^{***}
	(11.5534)	(0.2573)
γ_{SmB}	-102.1694^{***}	-3.1888^{***}
	(8.5748)	(0.1912)
γ_{WmL}	-163.3137^{***}	-4.6200^{***}
	(19.4479)	(0.4332)
$\beta_{Gametime}$	0.2317	0.0024
	(1.0467)	(0.0234)
$\beta_{Winning}$	-1.3153	-0.0416
	(1.6758)	(0.0376)
β_{Losing}	0.6618	-0.0246
	(3.4699)	(0.0775)
$\beta_{Outcomechange}$	-2.1870	-0.1280^{*}
	(2.2216)	(0.0498)
$\beta_{ScoreBrazil}$	2.0692	0.0869^{*}
	(1.8993)	(0.0427)
$\beta_{ScoreRival}$	-3.2892	0.0682
	(5.7445)	(0.1285)
R^2	0.18	0.20
Adj. R^2	0.18	0.20
Num. obs.	2356762	2331196

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

The column Abnormals represents the results obtained using the raw returns and the Normals column represents the results obtained with the normalized returns obtained after the GARCH(1,1) process.

Table 5.2 has similar results to table 5.1, except for a weak relevance for Sets that result in an outcome change. These results also differ from previous literature. This shows that at least using High-Frequency Data, sports sentiment doesn't affect the Brazilian Stock Market. The results for the Soccer sentiment effects on the daily returns are in the next table:

Table 5.3 – Soccer sentiments results for daily data returns

	Abnormal	Normal
γ_{Mt}	9178.0030^{***}	24.3335^{***}
	(242.3702)	(0.4948)
γ_{Lag}	50.1500^{**}	0.1039^{**}
	(18.4304)	(0.0396)
γ_{HmL}	470.9853^{*}	0.4198
	(186.2942)	(0.3162)
γ_{SmB}	-190.1855	-0.5991^{**}
	(107.1153)	(0.2166)
γ_{WmL}	-845.6813^{**}	-1.4494^{**}
	(274.3847)	(0.4597)
$\beta_{Gameday}$	4.1836	0.0110
	(7.0938)	(0.0170)
β_{Losses}	14.8192	0.0768
	(34.5572)	(0.0564)
β_{Wins}	-3.7991	0.0210
	(38.3962)	(0.0588)
$\beta_{BeforeLosses}$	-8.0843	-0.0075
	(10.7854)	(0.0253)
$\beta_{BeforeWins}$	-4.1420	0.0018
	(9.1586)	(0.0204)
$\beta_{AfterGameday}$	-3.5259	-0.0340
	(35.5551)	(0.0546)
R^2	0.06	0.12
Adj. R^2	0.06	0.12
Num. obs.	83272	83272

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

The column Abnormals represents the results obtained using the raw returns and the Normals column represents the results obtained with the normalized returns obtained after the GARCH(1,1) process.

As table 5.3 shows, the results using daily returns are the same as the results using high-frequency trading data. They show that soccer sentiment has no relation to the returns using both PCSE, also used by Edmans et al. (2007), and using a normal panel linear model. These results differ greatly from the expected according to the previous body of work in the area. Up next, we have the results related to Volleyball sentiment in Daily data.

Table 5.4 – Volleyball sentiments results for daily data returns

	Abnormal	Normal
γ_{Mt}	9172.1128^{***}	24.3132^{***}
	(242.4990)	(0.4957)
γ_{Lag}	49.9688^{**}	0.1035^{**}
	(18.4122)	(0.0396)
γ_{HmL}	475.6165^{**}	0.4638
	(183.4866)	(0.3102)
γ_{SmB}	-204.0507	-0.6307^{**}
	(110.8203)	(0.2219)
γ_{WmL}	-847.8703^{**}	-1.4344^{**}
	(274.0743)	(0.4580)
β_{Losses}	-31.2596^{**}	-0.1104^{**}
	(12.0639)	(0.0386)
β_{Wins}	-14.4325^{*}	-0.0395^{*}
	(6.8525)	(0.0170)
$\beta_{BeforeLosses}$	3.7749	0.0184
	(9.5462)	(0.0259)
$\beta_{BeforeWins}$	-4.6999	-0.0178
	(6.8086)	(0.0206)
R^2	0.06	0.12
Adj. R^2	0.06	0.12
Num. obs.	83272	83272

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

The column Abnormals represents the results obtained using the raw returns and the Normals column represents the results obtained with the normalized returns obtained after the GARCH(1,1) process.

Sports sentiment related to volleyball, surprisingly, has the strongest relation to the returns of the Brazilian market using daily data. Even though the results differ from the expected, since the relation is mostly weak and even the wins of the Brazilian Volleyball National teams results in losses for the returns. With these results we can define that sports sentiment related to Soccer and Volleyball doesn't have a strong effect on the returns of the Brazilian Stock Market. The results of this dissertation differed greatly from the expected. Contrary to the previous literature, soccer sentiment had almost no effect on the returns of the Brazilian Stock Market.

Contrary to the returns, sports sentiment had a bigger effect on the liquidity of the Brazilian Stock Market. Table 5.5 shows the results for sports sentiment related to soccer results using daily data.

Table 5.5 – Soccer sentiments results for daily data liquidity

	Normal
$\beta_{Gameday}$	-0.01
	(0.03)
β_{Losses}	-0.07^{*}
	(0.03)
β_{Wins}	-0.05
	(0.03)
$\beta_{BeforeLosses}$	-0.08^{*}
	(0.04)
$\beta_{BeforeWins}$	-0.06^{*}
	(0.03)
$\beta_{AfterGameday}$	0.19^{***}
	(0.03)
R^2	0.00
Adj. R^2	0.00
Num. obs.	83272

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

Analysing the results is possible to see there is a weak relation to sports sentiment related to soccer, since after gamedays, the liquidity rises. Even though this could mean that the liquidity isn't affected by the result of the match, losses have a better p-value and a higher negative effect than the victories. As reminded in the beginning in the chapter, this and the rest of the liquidity tables' R^2 is accounting only the liquidity betas. The next table shows the results for volleyball sports sentiment in daily data.

Table 5.6 – Volleyball sentiments results for daily data liquidity.

	Normal
β_{Losses}	0.19^{***}
	(0.04)
β_{Wins}	0.18^{***}
	(0.02)
$\beta_{BeforeLosses}$	-0.14^{**}
	(0.05)
$\beta_{BeforeWins}$	-0.03
	(0.03)
R^2	0.00
Adj. R^2	0.00
Num. obs.	83272

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

The results in table 5.6 are somewhat the equal to the soccer's sports sentiment except for $\beta_{BeforeLosses}$. $\beta_{BeforeLosses}$ has a strong negative reaction and p-value, which could mean that the stock market can predict losses from the Brazilian National Volleyball teams. But, wins and losses have a positive impact on the liquidity,so the result is not very important, especially if the fact that losses have a higher positive impact than wins. Next, we discuss the results for High-Frequency Trading Data.

Table 5.7 – Soccer sentiments results for HFT data liquidity.

	Normal
$\beta_{Gametime}$	-0.13^{***}
	(0.01)
$\beta_{Winning}$	-0.03
	(0.02)
β_{Losing}	-0.09^{**}
	(0.03)
$\beta_{Outcomechange}$	-0.03
	(0.03)
$\beta_{ScoreBrazil}$	-0.01
	(0.03)
$\beta_{ScoreRival}$	0.11^{**}
	(0.04)
R^2	0.00
Adj. R^2	0.00
Num. obs.	2331196

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

Table 5.7 shows that the variable that has the most effect in the liquidity of the Brazilian Stock Market is the gametime, i.e. Brazilian National Soccer Team's matches during the working hours negatively affect the liquidity of the stock market. It is possible to rationalize that $\beta_{Gametime}$ reducing liquidity means that the investor trades less during Brazilian Soccer games, but the fact that losing affects negatively the liquidity goes against that, unless the investor likes to see Brazil losing. This hypothesis would make sense if the rival scoring didn't have a positive effect in the Stock Market.

Table 5.8 – Volleyball sentiments results for HFT data liquidity.

	Normal
$\beta_{Gametime}$	0.14^{***}
	(0.02)
$\beta_{Winning}$	-0.12^{**}
	(0.04)
β_{Losing}	-0.19^{*}
	(0.08)
$\beta_{Outcomechange}$	-0.25^{***}
	(0.05)
$\beta_{ScoreBrazil}$	0.14^{**}
	(0.04)
$\beta_{ScoreRival}$	0.34^{*}
	(0.13)
R^2	0.00
Adj. R^2	0.00
Num. obs.	2331196

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Source – Elaborated by the author

Last, the results for sports sentiment related to volleyball in HFT data follow the same pattern as the results in daily data in a way that $\beta_{Gametime}$ has a positive relation to liquidity, the opposite of the results for Soccer's sentiment. Also different to the soccer results is that every variable has at least a weak correlation.

Both the results for liquidity and returns are very similar to every competition and rival matches, except for World Cup games for soccer matches and Olympic Games for Volleyball games. The results using log returns were also very similar, remarkably, there is no effect in High-Frequency data too. Although the effects present in the nominal returns were stronger. Focusing only in the important matches, again there wasn't any effect in the High-Frequency Trading Data returns. For daily data, the effects had a stronger p-value but they were still weak, except for a positive effect in the returns before games, not dependent of the result. Against rivals, the coefficients in the liquidity also had stronger relation.

After all, it's possible to partially discard the alternative hypothesis of this dissertation, since wins did not lead to a positive reaction in Stock Market Returns and losses did not lead to a negative one. Basically, we can definitely guarantee that the Brazilian Stock Market returns aren't affected by sports sentiment, specially football related and in High-Frequency Trading Data. For liquidity, it appears in the daily data that after the Brazilian National Soccer and Volleyball Teams game day, independent of the result, the liquidity rises, but in the game day has no strong effect. This is unexpected, since the liquidity rises during the volleyball games and falls during Soccer games, according to the High-Frequency Trading Data. Analysing both the returns results and the liquidity results as a whole, it is possible to imply that the investor's mood is not affected by sports results, but their activities are. If this is correct, it would mean that investors have less interest in Volleyball.

6 CONCLUSION

This dissertation analysed the effects of the investor's sentiment related to sports in the Brazilian Stock Market using High-Frequency Trading Data. Even with the majority of the previous literature indicating that sports sentiment affect the Stock Market negatively after losses of the national teams and using the methodology of one of the most prominent works in the area, this dissertation found no effect of the sports sentiment in the Brazilian Stock Market's returns. Moreover, a surprising result found that sports sentiment affects the Brazilian Stock Market liquidity. This dissertation shows that daily data and high-frequency trading data have different results, usually weaker in the High-frequency Trading data. This means that using soccer and volleyball results as a proxy for investor mood in daily data can be incorrect since during the game, the stock market isn't affected. Even though the vast majority of the Brazilian population prefers soccer, volley had bigger effects, so if Brazil is the soccer country, at least its Stock Market isn't.

The results of this dissertation implies that sports sentiment related to both Volleyball and Soccer have no effect in the Brazilian Stock Market returns. This follows the results from Klein et al. (2009) and Gerlach (2011), however, contrary to the previous studies, this dissertation tries to follow to the letter Edmans et al. (2007)' methodology. This dissertation is the only known work in the literature to use High-frequency Trading data to analyse the effects of investor's sports sentiment, especially in the Brazilian Stock Market. This work is also one of the few studies to use the CAPM and the extended CAPM in High-frequency Trading Data.

This dissertation serves as a starting point for the study of investor and sports sentiment effects in the returns and liquidity of the Brazilian Stock Market using High-frequency Trading Data. It can be expanded by focusing in the Brazilian National Teams' sponsors or by using different methods as, for an example, Events Study or using a different econometric model, as the ones suggested by Gerlach (2011).

This dissertation could be improved by using a bigger dataset, in a way that it has more games to be studied using High-frequency Trading Data, i.e., more games during the working hours. It could also have used the Panel Corrected Square Errors for the High-frequency Trading Data but the dataset was too big, which prevented the methods use due to the lack of computational capacity. Anyway, the daily data with the method had less sports sentiment effects than the daily data without using PCSE. Last, other improvements for this dissertation would be a bigger focus in the liquidity, especially considering that, contrary to the seminal work of Edmans et al. (2007), sports sentiment had an effect in it and expanding the object of the study to the post-game too.

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APPENDIX A – THE STRUCTURE OF SOCCER AND VOLLEYBALL COMPETITIONS

In soccer, the national teams are divided into federations based on their continents, with the federation in which a country is allocated delineating the adversaries in the qualifying games and the continental cup. This way, Brazil is part of CONMEBOL, having its main rivals in Argentina and Uruguay. During South America's World Cup Qualification, teams face each other at home and away. Depending on the performance in the qualification, a national team is selected to the World Cup, with South America having four direct spots and another in which the representative of South America has to face the representative of another continent to decide who will play the World Cup.

However, as the fact of calling itself the "Soccer country" suggests, Brazil has never been left out of a World Cup. The basic structure of a soccer tournament is the following: first, countries are split into groups of four where a team in a group face each other team in it - this is called "the group stage". After it's done, the two best-placed teams in every group go into the next stage, called "the knockout stage". In this stage, no ties are allowed and the team that loses the match is eliminated from the competition. The team that survives at the end is crowned as the champion. This is the format used in the World Cup, Copa América, Confederations Cup and Olympic tournament.

The Volley Olympic tournament and World Championship follow a very similar format to the one mentioned before - the difference is that the group is formed by five teams instead of four. On the other way, the Volleyball World Cup follows its own structure, where every team plays eleven matches and the one with the best results in the end is the World Champion.