

UNEXPECTED NATIONAL FOOTBALL RESULTS' INFLUENCE ON NATIONAL STOCK MARKETS

DIFFERENCES IN INTEGRATED AND NON-INTEGRATED MARKET

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Unexpected National Football Results' Influence on National Stock Markets: Differences In Integrated and Non-Integrated Markets

Abstract:

Using an event study approach with panel data, this paper investigates the abnormal stock market returns of national indices following an unexpected international football result. We utilise football results as a mood proxy, to better examine the effects of cognitive biases and emotional biases on the stock market. We report a negative abnormal return of -67.9 basis points following a draw for countries with low stock market integration and high football popularity. For the difference between the win abnormal return and the loss abnormal return, we report a significant positive value of 30.1 basis points for countries with low stock market integration. Finally, we also document these results by accounting for stock market noise where we find an abnormal stock return the day after a win of 29.4 basis points for countries with low stock market integration.

Keywords:

Football, securities, returns, mood, market integration, behavioural finance

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1. Introduction

Football, on a global basis, has for a long time been the most viewed sport, as well as the sport with the most supporters. Not only that, but it is a sport characterised by its highly passionate supporters who attend matches almost religiously. These supporters are known for letting a club or national team's performance dictate their mood. As a result, extensive research has been conducted on this subject; Schwarz, N., Strack, F., Kommer, D., & Wagner, D. (1987) were able to show that outcomes of Germany's FIFA World Cup matches were able to significantly alter a subject's well-being and views on national issues. The research finds "strong mood effects on judgements of satisfaction", which confirmed the hypothesis that "affective states serve informative functions" Thus, football is not simply a sport that is followed on a global scale or used as a source of entertainment, but it is also a source of intense satisfaction and despair within certain fan bases which contribute to general changes in decision-making. We, as football supporters ourselves, feel these intense mood changes following large football events and know how these impact our day-to-day decisions the following day. These two characteristics of football, when combined, could have a strong impact on society. As football is watched by a majority of the population and a large portion of football supporters' moods are heavily influenced by football results, one could speculate that football results could have a quantitatively measurable societal effect.

As Malkiel, B. G., & Fama, E. F. (1970) stated in his book "Efficient Capital Markets: a Review of Theory and Empirical Work," financial markets are "informationally efficient" when equity prices incorporate all possible information that affects future values. Over time, researchers have partially rejected this hypothesis due to the exclusion of behavioural biases which are likely to affect equity prices. Within these biases, there is a distinction to be made between cognitive biases and emotional biases. Cognitive biases involve decision-making based on a deviation in the process of understanding information or facts. On the other hand, emotional biases are based on deviations from the norm based on personal feelings and emotions. The overconfidence bias is an example of an emotional bias that shows how, when investors feel good (worse) and are overconfident (underconfident), they become less (more) risk-averse, and vice-versa. The effect heuristic bias is a cognitive bias that plays a role in decision-making. In this bias, the investor relies on a heuristic heavily influenced by their emotions to process a certain situation instead of a more analytical heuristic.

Furthermore, as globalisation increases, people around the world have become more connected. Consequently, information asymmetry is decreasing and access to investments in foreign markets increasing. In these integrated markets researchers have found a positive effect in decreasing biases associated with local, individual investors, thus promoting market efficiency. Boubakri, N., Cosset, J.-C., Guedhami, O., & Omran, M. (2007) found that socioeconomic variables such as favourable regulatory frameworks, higher investor protection and political stability increase overseas investor participation in a given country's stock exchange. The Organisation of Economic Co-operation and Development (OECD) works to increase these variables, making OECD countries' stock exchanges more integrated than Non-OECD countries.

Football and finance are two environments that are becoming increasingly powered by digitalization and globalisation. As financial markets have evolved over time, with the help of globalisation, barriers to the markets have been loosened and foreign investor participation has increased to a larger extent. We see similar effects within the sport of football as it is becoming a more and more globalised sport with foreign ownership structures throughout the highest level of the sport aided by multinational corporation investments. As foreign investment participation in markets is increasing, so is information symmetry, thus, investors are making more rational investment decisions. With the increased adoption of AI, Machine Learning, robo-advising and AI-assisted investment decisions, market efficiency and information symmetry have increased. In addition to the effects of globalisation on financial markets, football as a sport is also subjected to globalisation where sporting events include countries and participants from all over the world. As a result, the nature of globalisation and its implications on the football and finance environment lead us to motivate the test of whether the prevalence of emotional biases resulting from football results has changed over time and whether these biases differ through a geographic and globalised perspective.

In this paper we aim to identify the two biases mentioned above, using national football team results as a proxy for national investor mood. If these football teams' results are a good proxy for investor mood, we theorise national stock market indices should decrease in value after a national team loses and increase after a national team wins. We, therefore, aim to answer the question: "Do unexpected national football team results influence national stock market indices?" Furthermore, we want to look at how market integration and globalisation can impact biases and investor irrationality in equity markets. In our analysis, our mood variable should only affect national investors who are emotionally attached to football, therefore these biases should be stronger in more closed stock markets, where foreign investor participation is low and weaker in integrated stock markets where foreign investment represents a big percentage of the stock exchange. We present a sub-question in our research: How does stock market integration moderate the effect of a national team's results on stock market performance?

In our paper, we utilise data on match information, historical odds data and historical market index data comprising a total of 658 unexpected outcome observations and 382 expected outcome observations. We utilise a sample of 40 countries spanning all 6 habitable continents. Our selection process for country selection was to utilise countries with more than 10 matches at the World Cup and countries which had a corresponding TOTMK Datastream index, which was used to calculate Market Returns.

We document economically and statistically significant positive abnormal win effects for non-OECD countries of 29.4 basis points in Table 7. Additionally, the largest overall effect observed is an economically and statistically significant negative abnormal draw effect for non-OECD countries where football is popular at 67.9 basis points, illustrated in Table 6. The only significant effect found when considering the popularity proxy is a -21.0 basis point draw effect. Although we can find evidence that the degree of market integration within a country changes the effects on the stock market resulting from unexpected international football

results, we do not find similar evidence when considering the popularity of football within a given country. When comparing our results for unexpected results with the results for expected results, we can see that our initial theories regarding market integration and the popularity of soccer do not hold under the expected result environment. Within the expected results, we see directly opposite results compared to our initial theories as we document a statistically significant loss effect of -32.4 basis points for countries where football is considered to be less popular.

This paper's structure is as follows. A thorough literature review in Section 2, followed by a detailed exploration of data sourcing and processing in Section 3. Section 4 outlines the methodology used, while Section 5 presents the empirical results. The Discussion in Section 6 offers insights and interpretations. In section 7 we present our Limitations and section 8 provides Concluding Remarks. Additional information is provided in the References in Section 9 and the Appendix in Section 10.

2. Literature Review

Based on previous research by Schwarz et. al (1987), there is psychological evidence between international football results and psychological mood changes. In addition to this, Carroll, D., Ebrahim, S., Tilling, K., Macleod, J., & Smith, G. D. (2002) present that heart attack admissions increased by 25% within the three days following the day that England lost on penalties to Argentina in the 1998 FIFA World Cup. Thus, football results do not solely impact those involved but have significant implications for the general population. In a study conducted by Sheppherd & McNulty (2002), they discuss the decision affect theory (DAT) to predict that positive (negative) unexpected outcomes will have a larger psychological effect and thus make the person feel better (worse) compared to expected outcomes. They are also able to show that, as consistency theories propose, people feel worse when their expectations are disconfirmed as it gives the feeling that the person is unable to predict certain outcomes. In order to observe the existence of behavioural biases in financial markets, Edmans, A., García, D., & Norli, Ø. (2007) looked at the market impact of sudden mood changes, by using football outcomes as a mood variable. Their analysis allowed them to reject the null hypothesis that the loss effect after football games is driven by economic factors. However, the paper fails to find evidence of abnormal stock returns after wins, suggesting that football results may only affect investors' mood when the result is negative. In our report, we aim to study the correlation between a national football team's unexpected result and a country's market index excess return for different periods. Thus, our aim with this contribution is to isolate the surprise effect caused by unexpected outcomes and test whether this variable acts as an amplifier to the mood variable. The reference study was conducted before the financial crisis, therefore it was subjected to a largely different financial environment than our analysis. Thus, we conducted our analysis in a different time frame than the previous study and have increased the number of countries in the sample.

Empirical studies have indicated that the decision-making process of an investor can be affected by their emotional state. Therefore, by observing the securities market together with mood-inducing events, we can study how these

events affect an investor's perceptions and risk tolerance. Previous literature has found that mood positively influences the stock price, which is supported by Hirshleifer & Shumway's (2003) study building upon past research by choosing morning sunshine as a mood-affecting variable. During another study by Schwarz (1990), evidence was documented showing that individuals in a good mood use simplifying heuristics to make their investment decisions, whereas those in a bad mood tend to perform more detailed analysis of securities. Furthermore, they also consider literature that suggests that individuals in a bad mood usually find negative information more salient, whilst investors in a good mood find positive material more available. Supportingly, Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015) found that weather-based indicators of mood in major financial centres can influence institutional investors assessment, consequently affecting stock index returns. In another study conducted by García (2013), positive and negative words in the financial columns of the New York Financial Times were used to construct a proxy for investor sentiment and found that "one standard deviation change in our sentiment measure predicts a change in the daily average of the DJIA of 12 basis points during recession". This literature supports the idea that expressions of sentiments and mood-altering information and events tie into changes in investor sentiment which affects the stock market. Investor mood is complex and hard to measure and can be estimated using a series of factors. Previous research quantifies investor mood through the approach of defining a mood variable which alters investor mood and quantifies its effects observed on the stock market. Our research study aims to contribute to this approach by studying a mood variable related to unexpected international football results. We aim to quantify the effect of this mood variable by observing the stock market returns on the first trading day following unexpected football results and comparing our results over different geographies.

French, K. R., & Poterba, J. M. (1991) was referenced in the study by Edmans et. al (2007) to show that there exists a "home bias," where institutional investors tend to overweight domestic stocks in their portfolios. Thus, cognitive biases arise, as a result of information asymmetry along with domestic sentiments, impacting market efficiency. However, in a more modernised time period, Bastidon, C., Bordo, M., Parent, A., & Weidenmier, M. D. (2023) found that global stock market integration has been continuously increasing over time. Thus, we infer that these two bodies of literature can be compared against each other due to the time horizon aspect. This is because global stock market integration has increased, strengthening foreign investor participation in equity markets. Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2012) have been able to show that over time financial markets have become more globalised and integrated. The implications of globalisation and market integration discussed are shown to be different based on geographies as certain countries become more segmented than others. Meng, Y., Xiong, L., Xiao, L., & Bai, M. (2023) have been able to show that over time, overseas investors are becoming more prominent in the Chinese financial markets, with A-shares only becoming open to foreign investors in 2003. As a result of the Chinese financial markets becoming more "open," the paper has been able to show that the market also has been becoming more efficient. In relation to the findings on direct proportionality between foreign investor participation and stock market efficiency, Feng, Q., Wang, Y., Sun, X.,

Li, J., Guo, K., & Chen, J. (2023) find that in an increasingly globalised world, spillovers are highest in stocks indicating that stock markets are closely linked between countries, especially within Europe and developing countries markets that closely follow other, more developed markets. With increasing market integration worldwide, countries have become more intertwined and dependent on each other over time, thus it becomes interesting to analyse stock market effects resulting from behavioural biases within subsample country groupings of different levels of market integration in a modernised time. Because we increase the geographic locations in our study and work with a different timeline, we also consider differences in market integration between our study and the referenced literature. As mentioned before, markets have become more integrated over time due to decreases in information asymmetry and increasing levels of globalisation. We want to contribute to past literature, by analysing whether there is a difference in these biases between integrated and non-integrated markets. Furthermore, we also report statistics for all countries combined as well as expected match results, to test if the values found by previous literature remain true today in a more integrated and globalised world. Finally, we further look at whether the popularity of football in the respective countries of analysis has an impact on the magnitude of the mood effect. Although popularity is rather subjective, we believe that by developing a proxy for the “popularity of football” in our analysed countries, we may observe differing stock market effects attributed to football results in those countries classified as “Popular.”

3. Data

3.1. Data Sourcing

Gathering of results and odds data

We collect international football results spanning from the 25th of January 1931 to the 11th of February 2024. The dataset was downloaded from Kaggle and provides information for each game on the date, team playing at home, team playing away, result, location where the game was played, and whether the match was played at a neutral venue or not. To find which of these football results were unexpected we used betting odds of football games to calculate the predicted outcome. We gathered information on the betting odds of the main intercontinental and intracontinental competitions from the website SofaScore. This information was then compared to the observed outcome of the game and the unexpected and expected results were determined.

To make sure the games have a considerable level of importance, only games from the biggest tournament were considered and no qualifying matches were taken into account. In total, we looked at 22 editions from the following tournaments: AFC Asian Cup, AFCON, Copa America, Euro, Gold Cup, Nations League, and World Cup. The first tournament edition is in 2015 and the last tournament edition is in 2024. We gathered a total of 722 game observations where at least one of the countries we analysed was present. Out of these, 437 represented unexpected game results and 285 represented expected game results. Note that sometimes, game observations in our dataset are between two countries that are both part of our sample. Therefore, they count as two return observations, one for each team, within our sample, leading us to a total number

of 658 single unexpected observations and 382 expected outcomes. These unexpected observations were split into three groups, one group for “Win” with 187 observations, one group for “Draw” with 266 observations and one group for “Loss” with 205 observations. Although the general expectation would be that the total number of expected results would outweigh the number of unexpected results, the truth is that modern football is highly unpredictable, especially national football games where the team is constantly changing its players and the time between games can be up to four months. We find evidence of the dynamism in football by analysing the individual tournaments, for example, we see 83% of results in the AFCON 2024 edition being unexpected, but only 18% of unexpected results in the Gold Cup 2019 edition. This displays the unexpected nature of the sport as well as the geographical differences. In the North American Gold Cup, matches are less balanced as the top teams, such as the United States and Mexico significantly outperform weaker and smaller nations, whilst in the African Cup of Nations, teams are more evenly balanced and have similar resource levels.

In our study, we only consider data from 2015 to find the correlation between unexpected results and the resulting following-trading day market index returns. As a benchmark for a level of observations, we refer to the reference paper by Edmans et. al (2007) that makes use of 1162 total observations within football, while we use a total of 1040. The difference in the number of observations is quite small and arises from the change in the analysed time series and the selection of analysed tournaments. The referenced literature conducts the study over an extended time period with a more limited selection of tournaments, while we use a shorter total time series of around 9 years, but we have incorporated a larger amount of tournaments for analysis. Our reasoning for having a rather recent time series is that we aim to contribute to past research by changing the time series of the analysis to a more recent time period when the world has experienced higher levels of globalisation. We also wish to analyse market integration, thus leading us to focus on a larger geographical reach by including the main tournaments for each continent.

Market index returns data

We collect the daily total return index values, for each country, from Refinitiv Eikon Datastream. In contrast to the traditional price return index, the TRI considers both changes in the price of the stocks, as well as the dividends paid by them. Therefore, we justify that the TRI provides a more complete picture of the country's investor's overall return. The time series for country_{*i*} market index starts two working days before their first recorded match within the dataset. This is done to ensure we can account for the lagged world market and country index returns when running regressions. The total return indices used can be found in Refinitiv Eikon Datastream through the mnemonic “TOTMK”, to ensure homogeneity in our study we exclude all countries where information on “TOTMK” is not available, as well as countries where the index regularly has extended periods of inactivity. The majority of the time series begins somewhere between 2015 and 2016. The earliest time series begins on the 11th of June 2015, and the latest time series begins on the 1st of June 2022.

Initially, we started our analysis with a larger sample size of countries, where we analysed all countries with more than 10 World Cup games played as well as adding certain teams that were used in the study conducted by Edmans et. al (2007). Following this, we found that certain countries did not have a corresponding TOTMK dataset, or had a dataset where the data stopped being measured during the time series or the country did not have more than 3 observations of unexpected results. This led us to exclude certain countries such as Costa Rica, Iran, Uruguay, Bulgaria, Ecuador and Indonesia. Consequently, the final countries used in our analysis include 40 different countries from all 6 habitable continents, so that we could observe a holistic view of the correlation between unexpected football results and following trading-day market returns through a wide geographical scope.

The countries included in our analysis include the following; Argentina, Australia, Austria, Belgium, Brazil, Chile, Colombia, Croatia, Czech Republic, Denmark, Egypt, England, France, Germany, Ghana, Hungary, Italy, Ivory Coast, Japan, Mexico, Morocco, the Netherlands, Nigeria, Norway, Peru, Poland, Portugal, Republic of Ireland, Romania, Russia, Saudi Arabia, Slovenia, South Korea, South Africa, Spain, Sweden, Switzerland, Tunisia, Türkiye and the United States of America.

3.2. Data Processing

Once we collected the data on football match results, the historical odds and market returns, we created an integrated Excel sheet to process the data such that it could be compatible with the programming software R to analyse the data. To do this, we collected, for each country, the market index daily values starting from 2 trading days before the earliest match in our dataset was played, so that we could account for lagged returns. We conducted the same process for the world market index. Note that we use the trading day following the date of the match for our analysis because matches often start after markets are closed. Even though there are rare occurrences when the game occurs during trading hours, we ensure a homogeneous analysis by using the following trading day to ensure that each observation is realised after the knowledge of the match result has been completed. Following this, we used Excel to calculate the log returns for each trading day and reported the following values (both for country returns and world market index returns) for each single unexpected and expected observation:

- **Lagged Returns:** Market returns on the day that the match was played since the market closes before the match starts. If the date of the game occurred on a weekend or non-weekend holiday, alternatively we use the trading day before the match was played, (0-2 days before the game was played.)
- **Current Returns:** Market returns for the first trading day following the date that the match was played. If the date of the game occurred on a weekend or non-weekend holiday, alternatively we use the next trading day following the game (1-3 days following the date when the game was played.)

- Future Returns (only for world market index returns): Market returns for the second trading day following the date that the match was played (2-4 days following the game.)
- Day: Day of the week in which the first trading day following the date that the match was played occurred
- Result: The result of the match in the participating country's perspective, classified as "Win", "Loss" or "Draw"

Following the organisation and processing of data into different columns corresponding to each match played, documents were sorted into different classification measures containing the data for countries within the subsample.

For all of our 658 single observations, we present the raw results as percentages grouped by the unexpected match results; win, draw and loss. These results display the raw return data, thus we are not accounting for the mean log return in Table 1. We report the minimum, maximum, median, and mean as well as the 1st and 3rd quartile of our data for each result. We observe the highest variability within the draw category as the range is 13.06%. Within the draw section, we also document the largest absolute value of mean at 10.2 basis points, while the win and loss categories present mean values close to zero. We can also observe the high variability within the 50th percentile of our data for the loss category as the category reports the lowest (highest) 1st quartile (3rd quartile) results throughout our dataset.

Table 1: Summary statistics for all unexpected observations

Outcome	Min	Q1	Median	Mean	Q3	Max
Win	-3.544	-0.573	0	-0.003	0.474	3.327
Draw	-8.710	-0.588	0	-0.102	0.444	4.356
Loss	-3.430	-0.619	0	0.005	0.668	3.111

The table reports values for the stock market daily change of all countries for the first trading day following a win, draw or loss. Values are in %

3.3. Classification of Subsample Grouping

Classification of integrated markets

To classify the countries in our sample size into 2 groups with different levels of integration and participation of foreign investors in the national market, we use participation in the Organisation of Economic Co-operation and Development (OECD) as a benchmark. Our reasoning stems from a study by Boubakri et. al (2007) that provides criteria and reasoning for OECD countries being able to attract more foreign investors. Through the organisation's existence for over 60

years¹, the countries within the OECD have gained a lot of experience with economic cooperation for the goal of increasing economic and political stability. Additionally, multiple large and developed economies such as the United States, France, Germany etc. are present in the OECD. Thus, we believe that the use of the OECD countries as a classification for integrated markets stems from the fact that these 38 member countries are able to embody high economic and political stability and therefore, these countries are able to attract more overseas investors.

From our classification measure, the countries that we have classified as integrated markets include Australia, Austria, Belgium, Chile, Colombia, Czech Republic, Denmark, England, France, Germany, Hungary, Italy, Japan, Mexico, the Netherlands, Norway, Poland, Portugal, Republic of Ireland, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, United States of America.

Classification of popularity

To test the effects of the increased popularity of football within our chosen countries of analysis, we aimed to develop a popularity index. In order to develop this popularity index, we decided to look at the current Instagram followers of each national team's official account as of April 18th 2024. The reason for choosing this metric is Instagram is a very large social media platform with around 2 billion monthly active followers according to Meta's Q3 report in 2022². Additionally, this measure allows us to access a measure of following in absolute terms for all the selected countries whereas other figures such as viewership or attendance figures do not contain data for all of our countries and thus we would have been forced to make assumptions regarding these figures.

Following the gathering of data for each country, we decided to account for the population size (gathered from the World Bank³ database) of each country to determine popularity relative to size. Further, we developed a median of 3.129% (followers per capita) and we had 20 countries where we consider football to be more popular and 20 countries where it is less popular;

The 20 countries within the upper boundary (in order of highest to lowest) are Portugal, Argentina, France, Croatia, England, Morocco, Netherlands, Chile, Spain, Italy, Belgium, Denmark, Brazil, Colombia, Germany, Norway, Ireland, Mexico, Sweden, Saudi Arabia.

The 20 countries within the lower boundary (in order of highest to lowest): Switzerland, Turkey, Slovenia, Austria, South Korea, Czech Republic, Hungary, Romania, Australia, Peru, Tunisia, Poland, Ivory Coast, United States, Japan, Russia, Egypt, Nigeria, Ghana, South Africa.

Note that although we are classifying countries in terms of popularity, this may not mean that football is not a popular sport in the latter countries, however, it is rather a relative measure within our sample countries. We also acknowledge that this proxy for popularity may not be completely accurate due

¹ "About the OECD - OECD." *OECD*, May 2024, www.oecd.org/about/.

² "Instagram Statistics 2024: Key Demographic and User Numbers." *Backlinko*, 25 Mar. 2024, backlinko.com/instagram-users.

³ "World Bank Group - International Development, Poverty, & Sustainability." *World Bank*, May 2024, www.worldbank.org/en/home.

to the increasing globalisation of the sport of football as a country such as Portugal may have a large portion of their followers stemming from other countries who also display sentiments towards Portugal's national team.

4. Methodology

In this paper, we aim to answer the research question: "Do unexpected national football team results influence national stock market indices?". Consequently, we define our Null Hypothesis (H_0) as: there is no significant influence of unexpected national football team results on national stock market indices. We express this in our analysis as "the mean effect in stock market indices after an unexpected football team results is equal to zero." Under the null hypothesis, football outcomes are uncorrelated with asset prices. This hypothesis stems from the Efficient Market Hypothesis, where securities are priced based on full access and transparency of information and thus, investors are rational in their decision-making and behavioural biases do not exist to distort effective security pricing.

On the other hand, we define our Alternative Hypothesis (H_1) as: There is a significant influence of unexpected national football team results on national stock market indices. We aim to reject the null hypotheses and find supporting evidence for the idea that there is a relationship between a national football team's unexpected results and investor mood so that an effect is realized in the national stock market. Based on the previous literature and investor mood sentiment, we hypothesise that unexpected wins would lead to positive investor sentiments, therefore creating a positive and significant effect in the stock market after a win, whereas an unexpected loss would lead to negative and significant sentiment and a decreasing effect in national indices. With respect to unexpected draws, we theorise that draws lead to negative abnormal returns in the local stock market index. In theory, draws would represent a neutral result. However, in the case of unexpected results, the draw is perceived as a negative result for the odds-favourite. Whereas, for the team with lower odds, the draw is always a two-sided result, since it exceeds expectations, but it is not an optimal result, it represents a small, sometimes unimportant improvement.

In our approach to this study, we aim to find evidence to reject the null hypothesis by segmenting our sample size of 40 countries into subsamples and testing market effects within different groups. Our two groupings as mentioned previously are based on market integration and the popularity of football within countries. We aim to test whether the sample grouping approach can provide more significant evidence to reject the null hypothesis in certain groups compared to others. As we are segmenting the sample countries into groups, we develop two further sub-questions with the aim of utilising these sub-questions to answer our main research question;

- Are there economic indicators, such as market integration, that dampen mood effects?
- Does the popularity of football in a given country influence the effectiveness of the mood proxy?

Classification of unexpected results

In order to classify an unexpected result for our analysis, we create a benchmark where the implied probability of a result is less than 50%. In order to calculate the

implied probability we use the general formula (not accounting for the bookmaker's margin):

- $1 / (\text{Odds of result}) = \text{Implied probability}$

Thus, for example, in the case of a European Championship group-stage game between Germany and Portugal (Germany was considered the home team), the odds for the home win were 3.3, the odds for a draw were 3.4 and the odds for an away win were 2.2. Therefore, following our formula, we see that the implied probability of a German win was around 30.3%. Since they won the game by 4-2, this would be considered an unexpected result. Another example of an unexpected outcome would be the match between Denmark and Finland in the 2021 edition of the European Championship, where a Denmark and Finland win corresponded odds of 1.33 and 12.00 respectively. Thus, Denmark was given a 75.18% probability of winning but ended up losing the match and as such, it is considered an unexpected outcome.

Note that in our classification of unexpected results, there are cases in which the odds are even, for example when Türkiye played against Wales in the 2021 edition of the European Championship, the odds for home win, draw and away win were 2.80, 3.10 & 2.75 respectively. In that case, the implied probability for each result is less than 50%, thus all outcomes of this match would be considered unexpected. The reasoning for this is that this match was considered to be played between two very even teams and there was no general consensus regarding the expected result. Thus we argue that in these cases, when there is no general expected result, we classify all results as unexpected results. An analogy to this methodology would be that of governmental policy where there must be a majority consensus on the policy of above 50%. We also note that when we classify an expected outcome, we observe no draws as an expected outcome. This comes from the fact that in most football matches worldwide, there is an added incentive for one or both of the two partaking teams to win the match and thus, there is always one team that is classified as the odds-based favourite. A draw is often considered a neutral result that is, in most cases, not considered beneficial to both teams and therefore, the odds-makers never put the draw at above 50% implied probability.

Edmans et. al (2007) utilise an ELO-rating system in Section IV of the literature in order to classify important matches, thus allowing them to conduct further analysis on their documented loss effect and whether it is stronger in the cases where a match is considered of high importance. For our analysis, in contrast to this literature, we utilise historical betting odds priced by Bet365 and found on SofaScore. This is motivated by the findings presented by Bunker, R., Yeung, C., Susnjak, T., Espie, C., & Fujii, K. (2023) as they are able to show that, in tennis matches, Alternative Decision Tree models and Logistic Regression models have been historically more accurate at predicting matches compared to ELO systems. Furthermore, they found that these machine learning models have been predicting matches with similar accuracy to betting odds and thus, we justify that betting odds are a more efficient predictor of expected outcomes compared to the ELO system. Since the betting odds are considered the benchmark for accuracy predicting, we argue that, although there is a casino margin

implemented within implied odds, odds-makers are considered to be the most accurate predictor of matches.

Theoretical approach

We use a single-event study approach to analyse the effects of unexpected international football results on the stock market indices of respective countries. The single-event study approach has disadvantages such as the sample sizing of data and the possible impact of the often noisy financial markets in the short term. However, we argue that it is beneficial to use a single-event study approach in this case because it allows us to isolate an exogenous variable of investor mood. Due to the short time window regarding the mood impact on individuals from football results, this approach allows us to capture immediate and short-term reactions of the stock market to unexpected football results. Large amounts of previous literature use a single-event study approach. Examples of this include Ji, X., Bu, N. (Tom), Zheng, C., Xiao, H., Liu, C., Chen, X., & Wang, K. (2024) studying the announcement of COVID-19 news as a variable impacting the stock market, Berument, M. H., Dogan, N., & Onar, B. (2010) studying daylight saving time changes as a variable impacting the stock market and Zawadzki, K. M., & Potrykus, M. (2023) who study the announcement of hosts of major sporting events as a variable impacting the stock market. The alternative methodology to analyse mood effects would be a continuous mood variable. This, however, would be more applicable to a larger dataset. Although the approach is more efficient at capturing smaller effects and reducing biases, the continuous variable would not be applicable due to the short-term nature of our study. Thus we argue that a single-event study is better suited to capture short-term mood swings caused by football results.

Once data was collected, we organised and imported our dataset into R studio, where each row represented a different single observation and one of the columns showed the country this observation referred to. There we created a new column for our panel data where we included the mean effect defined as the difference between the stock index change the day after and the mean log daily index change for that country (throughout the whole time series). To divide the dataset into different groups we simply created copies of our main dataset and removed the sheets not related to that group's characteristics. Through conducting the analysis in RStudio, the software would then extract data from the sheets we used and create new panel data for that group. For the mean effect of each country and the different groups, we defined the standard deviation and standard error as it is commonly defined in econometrics. In our tests for data significance of the mean effect per subset, we use a two-tailed p-value test. We aim to test whether we can reject the null hypothesis with significance, therefore testing for if there is an effect, rather than the direction of this effect. Therefore, we opt for a two-tailed p-value test rather than a one-tailed test.

Econometric approach

We calculate the win minus loss effect as the difference between the mean win effects and the mean loss effects. We aim to find a positive win-loss difference supporting our theory that wins have a positive effect and losses have a negative effect. We are also interested in the range of this difference as a way to quantify

the overall mood effect per group. To calculate the standard error of this win minus loss effect we use the pooled standard error, which assumes equal variance for both groups, by taking the average variances of both groups, weighted by their respective degrees of freedom and then using the square root operation to convert the pooled variance back to standard error scale.

To further account for stock market noise in the short term and fully isolate the specific effect of a national team's unexpected result on the national stock market we create a market model regression. In this regression, we define our dependent variable as the country_{*i*} stock market return the day after the game was played. For the independent variables in this market model we used the lagged daily stock market return of country_{*i*}, the lagged daily world market return, the day of the game daily world market return and the day after the game world market return. We define the following variables for our econometric approach:

- R_{it-1} : Country_{*i*} returns at time t
- R_{it-1} : Lagged country_{*i*} returns
- R_{mt-1} : Lagged world market returns
- R_{mt} : First trading day following match returns
- R_{mt+1} : Second trading day following match returns
- ϵ_{it} : Residuals for country_{*i*}

This approach is based on the econometric approach used by Edmans et. al (2007), who explains that “if football outcomes are uncorrelated with asset prices. This in turn implies that the effects of football should be consistently estimated with any model of stock returns—even one that is completely misspecified. This follows from the fact that omitted variables do not bias coefficient estimates in a regression when the omitted variable is independent of other regressors.” We then collect all of the residuals for each subset we want to study. Consequently, using Equation 2 we organise them by developing dummy variables for Win, Loss and Draw. Where the dummy variables take on a value of 1 or 0 for the respective match result. Through this approach, we find the betas pertaining to the abnormal returns of that result for each specific subgroup. The two equations mentioned before are as follows:

$$1) R_{it} = \gamma_{0i} + \gamma_{1i}R_{it-1} + \gamma_{2i}R_{mt-1} + \gamma_{3i}R_{mt} + \gamma_{4i}R_{mt+1} + \epsilon_{it},$$

$$2) \hat{\epsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_D D_{it} + \beta_L L_{it} + u_{it},$$

5. Empirical Results

In Table 2 we report the summary statistics for each of the 40 countries in our sample. The summary statistics consist of the number of unexpected wins, draws and losses for each country, the average mean effect for all country's observations in that subset (win, draw or loss) for each result as well as the standard error of each result reported. The mean effect is defined as the subtraction of the stock market return on the following trading day after a match from the daily mean log return of the country market index. In Table 2 we can observe that certain countries experience larger stock market effects compared

to others following an unexpected football result. Between all countries, we report a range of average abnormal win returns from -111.5 to 230.4 basis points, a range for average abnormal draw returns of -160.7 to 78.8 basis points and a range for average abnormal loss returns of -163.3 to 142.8 basis points. The range for the average effect of a win, draw or loss range varies significantly between countries. Argentina represents an example of extreme values, $> \pm 150$ basis points average abnormal effect corresponding to each result. Meanwhile, other countries such as Ghana report average abnormal returns of less than 20 basis points for each result. When analysing the overall maximum and minimum mean effect values for each country, we see a preliminary trend regarding the effects of match results. Losses exhibit the most negative average abnormal return, wins exhibit the most positive average abnormal return and draws have the smallest average range.

One thing to note about the data presented in Table 2 is that certain countries have one or zero unexpected wins. One of these countries is Brazil who don't exhibit any unexpected wins within this time series. The reason that this occurs is that Brazil and other countries such as Germany are very often odds-favorites due to their historical success in the sport. As a result, the predicted outcome of their matches is often in their favour and thus, when they win, it is considered to be highly expected.

Table 2: Summary statistics for each country

Country	Win N°	Win Effect	Draw N°	Draw Effect	Loss N°	Loss Effect	Country	Win N°	Win Effect	Draw N°	Draw Effect	Loss N°	Loss Effect
Argentina	2	2.304 (0.003)	10	-1.607 (0.009)	4	-1.633 (0.008)	Morocco	6	0.138 (0.001)	6	-0.247 (0.002)	6	-0.248 (0.003)
Australia	2	0.275 (0.006)	3	-0.205 (0.002)	4	0.036 (0.004)	Netherlands	7	0.364 (0.004)	6	-1.253 (0.007)	3	-0.146 (0.005)
Austria	4	-0.046 (0.006)	4	0.104 (0.007)	6	0.133 (0.004)	Nigeria	8	0.837 (0.006)	2	0.604 (0.016)	4	-0.572 (0.003)
Belgium	8	0.717 (0.003)	2	-0.244 (0.012)	10	-0.317 (0.002)	Norway	2	0.064 (0.001)	2	-1.60 1(0.005)	3	-0.259 (0.01)
Brazil		NA (NA)	7	-0.528 (0.004)	5	0.23 (0.007)	Peru	7	-0.165 (0.002)	7	0.117 (0.001)	2	-0.073 (0.001)
Chile	2	0.297 (0.003)	6	0.106 (0.004)	4	-0.115 (0.004)	Poland	4	-0.475 (0.01)	9	-0.149 (0.005)	8	0.073 (0.004)
Colombia	8	-0.107 (0.001)	8	0.282 (0.001)	5	-0.093 (0.001)	Portugal	7	0.019 (0.005)	11	0.784 (0.003)	8	-0.085 (0.003)
Croatia	12	-0.314 (0.002)	10	-0.028 (0.001)	5	0.195 (0.003)	Republic of Ireland	2	-0.755 (0.019)	7	-0.488 (0.005)	6	-0.333 (0.003)

Table 2 (Continuation): Summary statistics for each country

Czech Republic	7	-0.479 (0.002)	3	0.407 (0.002)	4	0.107 (0.004)	Romania	2	0.148 (0.002)	4	-0.749 (0.008)	3	0.403 (0.002)
Denmark	8	-0.256 (0.003)	7	0.103 (0.005)	5	0.062 (0.008)	Russia	4	-0.048 (0.002)	6	0.422 (0.005)	6	0.013 (0.005)
Egypt	3	0.113 (0.01)	9	0.693 (0.006)	4	-0.131 (0.004)	Saudi Arabia	2	-0.341 (0.003)	2	-1.106 (0.01)	1	-0.825 (NA)
England	3	-0.062 (0.004)	12	-0.142 (0.002)	12	0.482 (0.003)	Slovenia	1	-2.748 (NA)	3	-1.429 (0.004)	1	0.035 (NA)
France	12	-0.182 (0.003)	10	0.251 (0.005)	6	0.003 (0.005)	South Africa	3	-0.142 (0.003)	4	-0.471 (0.003)	3	-1.117 (0.004)
Germany	1	0.485 (NA)	13	-0.405 (0.003)	10	-0.001 (0.003)	South Korea	3	-1.088 (0.002)	4	-0.097 (0.003)	4	0.281 (0.006)
Ghana	3	-0.022 (0.001)	6	-0.004 (0.001)	6	0.198 (0.006)	Spain	5	-0.018 (0.009)	13	0.025 (0.002)	8	0.328 (0.004)
Hungary	7	0.135 (0.004)	7	-0.287 (0.005)	2	0.207 (0.002)	Sweden	7	-0.155 (0.004)	4	-0.449 (0.005)	5	-0.225 (0.01)
Italy	8	0.21 (0.006)	10	-0.123 (0.006)	3	1.428 (0.009)	Switzerland	5	-1.115 (0.003)	12	-0.06 (0.004)	5	-0.769 (0.004)
Ivory Coast	5	0.106 (0.001)	6	-0.262 (0.002)	4	-0.144 (0.001)	Tunisia	3	0.182 (0.003)	7	0.192 (0.001)	8	0.053 (0.002)
Japan	4	0.014 (0.006)	4	-0.521 (0.003)	5	0.504 (0.003)	Turkey	3	0.136 (0.003)	3	0.788 (0.014)	7	0.098 (0.005)
Mexico	4	0.076 (0.002)	9	0.09 (0.001)	6	0.447 (0.002)	United States	3	-0.382 (0.001)	8	0.024 (0.003)	4	-0.629 (0.005)

The table reports the number of win, draw and loss observations for each country in our dataset, as well as the average effect of these observation on the countries stock market. Effect = Stock Market Change the Day After the Game – Country_i Mean Log Return

In Table 3, we can see our tentative results of the mean effect, as defined in methodology section, for each of the 658 unexpected observations, split into three groups for wins, draws and losses. We can see that the effect range between the 1st and 3rd quartile is larger following an unexpected loss than an unexpected win or draw. However, when looking at extreme data points, we can see that the effects following a draw are more extreme when compared to the outliers for abnormal loss or win returns. These results could be a consequence of the environment we study our effect in. We choose to study only unexpected games because past literature has shown that unpredictable events have a bigger impact on an individual's mood than predictable events. The highest

stock market abnormal return in our dataset is within the draw subset, - 871.0 basis points, as well as the largest positive effect + 435.6 basis points, once again highlighting the unexpected perception of the draw as a possible outcome. These tentative results do not provide enough evidence to positively answer our research question as we see mean abnormal stock market returns following a win or loss that are statistically not distinguishable from zero. We do see a 12.8 negative abnormal return following a draw, however, this does not provide enough evidence to positively conclude that unexpected football results lead to significant abnormal stock market returns.

Table 3: Summary statistics for all effect observations

Outcome	Min	Q1	Median	Mean	Q3	Max
Win Effect	-3.544	-0.601	-0.026	-0.027	0.461	3.327
Draw Effect	-8.710	-0.644	0.001	-0.128	0.431	4.356
Loss Effect	-3.430	-0.644	-0.016	-0.018	0.644	3.111

The table reports values for the stock market effect of all countries for the first trading day following a win, draw or loss. Effect = Stock Market Change the Day After the Game – Country_i Mean Log Return. Values are in %

Integrated stock markets

We theorise that the difference between the results found in Edmans et. al (2007) and our first analysis could be due to the different time frames and methodology in our analysis. Past literature, as mentioned before, is conducted in a pre-2009 financial crisis, when markets and the world were significantly less integrated and globalised compared to today. More integrated markets lead to an increase in efficiency and a decrease in local investor sentiment biases. So, to better answer our research question, we developed a study sub-question regarding market integration; “Are there economic indicators, such as market integration, that dampen mood effects?”

Table 4 represents the preliminary findings of this paper in relation to market integration. It looks at the sets of the data, “All Countries”, representing all countries in our dataset and “OECD” and “Non-OECD” groups, as defined previously. We observe relatively high standard errors, in comparison to the magnitude of effects, within our results for all data observations. By looking at the p-values derived from a two-tailed p-test for “Total Countries”, we cannot observe statistical significance in any of the values presented apart from the -12.8 basis point abnormal draw effect with significance at the 0.10 level. Thus, we cannot provide statistically significant evidence to reject the null hypothesis for win and loss effects. Concerning draws, we observe an overall economic loss effect, with statistical significance, following a draw throughout the entire sample size, showing that unexpected football result draws have a negative impact on investor

sentiment. The most significant result that we observe is found in column 10, row 3 of Table 4 and relates to the markets classified as non-integrated. It represents the difference between the average win effect and the average loss effect. This win minus loss effect for Non-OECD is 30.1 basis points. We find statistical significance for the positive non-OECD results at the 0.10 significance level, but no statistical significance for OECD countries. Thus, we can tentatively report that the non-OECD countries' win-loss difference presents stronger evidence of investor sentiment changes between wins and losses. Observing the average effects by result, we see economically significant win, draw and loss effects for Non-OECD countries of +12.6, -21.0 and -17.5 basis points respectively. Regarding OECD countries, the average effects for all wins, draws and losses are under 10 basis points, therefore showing a weak economic and statistical effect. Looking at the p-values, we cannot find evidence of our win, loss and draw effects being statistically significant.

Comparing our results with the results documented by Edmans et. al (2007), we see a marginal similarity, in that we document an economically significant loss effect, however, in our study, it arises within the subset of non-OECD countries. In contrast to the literature referenced which did not find a win effect that is distinguishable from zero, we do see an economically significant win effect of 12.6 basis points, as well as a significant draw effect, for which they do not analyse, of -21.0. We cannot observe results for OECD countries that are distinguishable from zero, but we are able to document economically significant effects for non-OECD countries. As mentioned before, OECD countries portray a set of socioeconomic variables that attract more foreign investors which can be justified by Boubakri et. al (2007). By using the OECD classification as a proxy for stock market integration we can test for the effect of market integration on behavioural mood biases. Through our results, we can tentatively defend the idea that increased foreign investor participation dilutes the effects that local investor sentiment, caused by football results, has on the national stock market. On average in non-OECD countries, when a country's national team unexpectedly wins a football game, the respective market index goes up 12.6 basis points higher than the mean, potentially representing a cognitive or behavioural bias related to the mood variable. The same holds true, for draw and loss results, which we theorise would affect the mood proxy negatively. The effect for a draw result within OECD countries is also almost double the basis points of the effect for "Total Countries".

Table 4: Abnormal returns for subgroups “OECD” and “Non OECD”

Win N°	Win Effect	Win p-value	Draw N°	Draw Effect	Draw p-value	Loss N°	Loss Effect	Loss p-value	Win-Loss Effect	Win-Loss Effect p-value	Country
187	-0.0268 (0.078)	0.73	266	-0.1282(0.076)	0.09	205	-0.0183 (0.074)	0.80	-0.0084 (0.107)	0.94	Total Countries
127	-0.0989 (0.1)	0.33	180	-0.0889 (0.087)	0.31	144	0.0483 (0.088)	0.59	-0.1472 (0.134)	0.27	OECD
60	0.1259 (0.118)	0.29	86	-0.2104 (0.151)	0.17	61	-0.1756 (0.132)	0.19	0.3014(0.177)	0.09	Non OECD

The table reports values for the stock market effect the first trading day following a win, draw or loss. Effect = Stock Market Change the Day After the Game – Country_i Mean Log Return. Values are in %

Popularity of football per country

In this section, we aim to answer a second sub-question in relation to our main research question; “Does the popularity of football in a given country influence the effectiveness of the mood proxy.”. We theorise that if the effects previously observed are related to the change in mood of local investors due to national team football's unexpected results, then this effect would be more prominent in countries where football as a sport is more popular and affects the individuals' mood to a larger extent.

In Table 5, we report findings for the countries which are grouped as “Popular” and “Non-Popular” based on our proxy for the popularity of national team football defined in the data section. We once again report values for the number of observations, the mean effect, the win minus loss effect and the standard error and p values. In this table, we report a new statistically and economically significant effect for the subset “Popular”. The mean effect of a draw for this group is -21.0 basis point, with high statistical significance. Besides the values for “Total Countries” and the draw effect which we had already discussed, the only other economically significant value we find is a -11.9 basis point win effect for “Non-Popular” countries, however, it is not statistically significant with a p-value of 0.31. Furthermore, for the win minus loss effect, the value is positive for “Popular” and negative for “Non-Popular”, suggesting that for the first subgroup, there could be an effect stemming from the football mood proxy since wins (losses) should affect the stock market positively (negatively), whereas for the second group, we see the direct opposite so we cannot draw these same conclusions. However, both of these differences have an effect of under 10 basis points and high p values. As a result, we cannot conclude that differing levels of football popularity within countries have a significant influence on the strength of the investor mood variable.

The main takeaway, which we discussed, is the highly significant draw effect for “popular” countries of -21.0 basis points which, once again, shows us that an unexpected draw is perceived as a negative result. We can argue that the reasoning for this comes from the fact that countries in which football is more popular, tend to perform better historically and thus, are more often considered favourites to win matches. Consequently, if these “Popular” teams do not live up to the expectation to win, the supporters following the team will perceive a draw

as a negative result and we theorise that they exhibit negative sentiments the following day. In conjunction with the overall sample size draw effect found in Table 4, we also find evidence to reject the null hypothesis for draw results solely within the “popular” subsample grouping.

Comparing the last two tables together we see stronger effects in Table 4 for “Non-OECD” countries compared with the results for “Popular” countries. A possible reason for this could be that market integration as a statistic is more objective and justified through previous literature, while, on the other hand, popularity is a subjective measure. Popularity can be measured in multiple ways and popularity may also vary over time as different generations of people may care more about the sport than another generation. Thus, we can conclude that objective measures regarding the stock market such as the presence of foreign investors are better proxies to compare how different groups' characteristics affect the stock market in comparison to subjective measures such as popularity.

Table 5: Abnormal returns for subgroups “Popular” and “Non Popular”

Win N°	Win Effect	Win p-value	Draw N°	Draw Effect	Draw p-value	Loss N°	Loss Effect	Loss p-value	Win-Loss Effect	Win-Loss Effect p-value	Country
187	-0.0268 (0.078)	0.73	266	-0.1282(0.076)	0.09	205	-0.0183 (0.074)	0.80	-0.0084 (0.107)	0.94	Total Countries
106	0.0438 (0.106)	0.68	155	-0.2097(0.107)	0.05	115	-0.0012 (0.106)	0.99	0.045 (0.15)	0.76	Popular
81	-0.1191 (0.116)	0.31	111	-0.0143 (0.106)	0.89	90	-0.0402 (0.099)	0.69	-0.0789 (0.153)	0.61	Non Popular

The table reports values for the stock market effect the first trading day following a win, draw or loss. Effect = Stock Market Change the Day After the Game – Country_i Mean Log Return. Values are in %

Combined grouping characteristics

Previously we looked at popularity and market integration in different subsets to try to understand if these variables had any impact on the significance of the effect of the national team’s football results on the stock market. We now conduct further analysis regarding the intersection between these two grouping metrics. As we looked at popularity and market integration in two separate groups, an interesting point of analysis was to isolate the subsets further by grouping them based on individual characteristics related to both of these proxies. In Table 6, we report these statistics for each of the results; win, draw, loss, the number of observations, the mean effect, the win minus loss effect and the standard error and p values.

The most significant observation that we find in Table 6 is a -67.9 basis point effect following an unexpected draw which is highly significant, with a corresponding p-value of 0.03 for Non-OECD countries where football is popular. This documented result presents a larger effect than the loss effect of -49.4 basis points following a loss in World Cup elimination games documented by Edmans et. al (2007). Even though we use different approaches to our analysis, the biggest effect found in the previously mentioned literature is lower than the draw effect from “Non-OECD + Popular” countries. This can be due to a lot of things,

one of these reasons could be that our dataset only contains unexpected results, which, as previously mentioned, tend to have a higher impact on an individual's moods. Another reason for this can be related to the subset we have created, as in this subgroup we only consider markets with low stock market integration and where the popularity of football is high. In our previous findings, we have been able to report that both of these characteristics have increased our draw effect. Then it follows that combining these two metrics would, in theory, increase the significance of the effect even further. We, however, must emphasise that due to subsampling, this sample only includes 5 countries and 78 total observations. The only positive win effect that is economically distinguishable from zero is the one observed for “Non-OECD + Non-Popular” countries of 17.3 basis points. We also see for “OECD + Non-Popular” a negative result for the win effect of -37.7 basis points. In theory, based on our assumptions, higher levels of market integration and low popularity of football should correspond with a non-significant economic stock market effect. However, we report a highly statistically significant negative win effect for this group. Because football popularity is low and the levels of market integration are assumed to be high in the country we do not attribute this win effect to investor sentiment that comes from unexpected football results, but rather to other economic factors such as short-term market noise. Furthermore, as we can see in Table 11 in the Appendix, when we observe the effects of this group, accounting for market noise, we can see that the result decreases by around 20 basis points to show that at least more than half of this observed result stems from market noise. Additionally, the number of observations within this group is quite low with 43 total win observations thus affecting the reliability of the estimate.

For Table 6 we focus our analysis on the win minus loss effect for each category. In the “Non OECD + Popular” category we report an economically significant win-loss effect of 36.5 basis points. For the opposite category, “OECD + Non Popular” we observe a win-loss win minus loss effect of -38.4 basis points with high statistical significance. When comparing these two groupings, we note that the “Non-OECD + Popular” category doesn’t report results with statistical significance in the win minus loss effect, whereas the “OECD + Non-Popular” group does. The effects presented for these two groups are almost direct opposites around zero of each other.

The first group has two characteristics that we predict will increase the positive impact of wins and the negative impact of draws and losses, whereas the second group has characteristics that we believe will dampen these effects. Thus for the first group “Non-OECD + Popular” even though we fail to statistically reject our null hypothesis within the subset, we do see strong economic effects that would support our theory. Whereas for the second group “OECD + Non-Popular” shows significant evidence that OECD countries where football is a less popular experience, do not follow our hypothesis. We theorise the reported results may have been affected by market noise and other biases or events.

Table 6: Abnormal returns for subgroups with combined characteristics

Win N°	Win Effect	Win p-value	Draw N°	Draw Effect	Draw p-value	Loss N°	Loss Effect	Loss p-value	Win-Loss Effect	Win-Loss Effect p-value	Country
187	-0.0268 (0.078)	0.73	266	-0.1282 (0.076)	0.09	205	-0.0183 (0.074)	0.80	-0.0084 (0.107)	0.94	Total Countries
84	0.0435 (0.125)	0.73	120	-0.073 (0.107)	0.50	94	0.07 (0.113)	0.54	-0.0266 (0.169)	0.87	OECD + Popular
43	-0.377 (0.163)	0.03	60	-0.1208 (0.15)	0.42	50	0.0074 (0.14)	0.96	-0.3843 (0.215)	0.08	OECD + Non Popular
22	0.0449 (0.186)	0.81	35	-0.6785 (0.29)	0.03	21	-0.3201 (0.279)	0.27	0.3649 (0.336)	0.28	Non OECD + Popular
38	0.1727 (0.153)	0.27	51	0.1109 (0.146)	0.45	40	-0.0997 (0.14)	0.48	0.2724 (0.207)	0.19	Non OECD + Non Popular

The table reports values for the stock market effect the first trading day following a win, draw or loss. Effect = Stock Market Change the Day After the Game – Country_i Mean Log Return. Values are in %

Controlling for stock market noise

In past literature, Edmans et. al (2007), take a different econometric approach to the analysis of mood variables, in order to account for the noise of the stock markets. This approach, which has been previously explained in the Methodology section, aims to fully isolate the effect of a national team's result on the national stock market. In order to holistically compare our results with past literature we also report T-values for each calculated Beta. Table 7 demonstrates the results of this analysis. Looking at the entire sample size of unexpected games from the 40 countries in our analysis we can see that although the values are not highly significant, we do report a positive win effect and loss effect of 5.9 and 2.1 basis points respectively and a negative draw effect of -5.8 basis points.

For “Non OECD” countries we see an increase in all effects. The win effect becomes 29.4 win basis points, with high significance. The draw and loss effect, although not statistically significant, also increased to -12.1 and -11.9 basis points, respectively. On the other hand, for the subgroup “OECD” we document no economically or statistically significant stock market effect corresponding to any of the results. We conclude that generally, OECD countries experience a minimal effect if any at all from unexpected football results. Comparingly, “Non-OECD” countries exhibit evidence to reject, under the assumption that the country is not a member of the OECD, the null hypothesis which states: “There is no significant influence of unexpected national football team results on national stock market indices”. Non-integrated markets report stock market effects that can be linked to behavioural and cognitive-emotional biases, whilst integrated markets do not report any of these effects. These indicative results can help us answer the sub-questions: “Are there economic indicators, such as market integration, that dampen mood effects?”. Following this, we analyse our second sub-question, whether the popularity of football within a country could strengthen the effect of mood variables in the stock market. We report the following values; for the “Popular” sub-group we see no significant changes, nor economically significant effects. The win draw and loss effects are 7.5, -6.2 and 2.1 basis points, respectively. The same trend continues in the sub-group “Non Popular”, although for this group, the effects are generally smaller. Overall, we do not find

any significant effects within either of these subgroups and thus, we are not able to support the idea that the popularity of football can increase the strength of mood effects on stock markets following unexpected football games.

Overall, by factoring in local lagged market returns and world market returns we can reject the null hypothesis for the subgroup “Non OECD”. Within this group, we observe an economically and statistically significant win effect, while the draw and loss effects also contain economic significance. We attribute our different results compared to Edmans et. al (2007) for three reasons. Firstly, we only consider unexpected football results. Secondly, we conduct our analysis in a different time frame and through a slightly wider geographical perspective. Finally, we also believe these differences arise due to differing time periods of analysis. Nowadays, markets are becoming consistently more integrated and emotional biases become harder to quantify. This conclusion is supported by the fact that we only find a strong effect in the sub-group “Non-OECD”

Table 7: OLS regression of abnormal returns for each subgroup and result

Category	Win N°	Win β Effect	Win T-Value	Draw N°	Draw β Effect	Draw T-Value	Loss N°	Loss β Effect	Loss T-Value
All Countries	187	0.059	0.879	266	-0.058	-1.017	205	0.021	0.320
OECD	127	-0.082	-1.180	180	-0.014	-0.241	144	0.090	1.378
Non OECD	60	0.294	2.039	86	-0.121	-1.000	61	-0.119	-0.834
Popular	106	0.075	0.819	155	-0.062	-0.810	115	0.014	0.154
Non Popular	81	0.020	0.201	111	-0.031	-0.367	90	0.020	0.217

The table reports the ordinary least square estimates of β_W , β_D , β_L from equation 2). Values are in %

Expected results

In our study, we study our hypothesis under the assumption that the game result of each observation is unexpected. We do this because past literature conducted by Sheppherd & McNulty (2002) shows that unexpected outcomes tend to have a larger psychological effect than expected outcomes. As such, we attempt to isolate the surprise effect caused by unexpected outcomes and test whether this variable acts as an amplifier to our mood variable. We compare our two datasets containing unexpected results and the expected results (occurring with >50% implied probability). We report the same time series, starting from 2015, as we do in the unexpected results section. As we see from the bookmaker's classification and within our data processing, games that end in a draw are always unexpected, therefore draws are excluded from Table 8.

When we compare the unexpected results with the expected results, we find, within the expected results, a loss effect which is significant at the 0.10 significance level. The effect of each of the expected game results is also stronger with a -11.3 basis points for the win effect and -24.7 basis points for the loss effect. Furthermore, the win minus loss effect between the two results, although statistically not significant, is positive at 13.3 basis points. This loss effect which we document is interestingly similar to the -21.2 basis points presented by Edmans et. al (2007). Although the referenced literature uses a different econometric approach, it is still interesting to note that in both our analysis of expected games and the referenced study, the loss effect is still prominent almost 2 decades later.

To further our analysis, we do the same subgrouping as we did for unexpected for expected results, aiming to understand if the strong results supporting our hypothesis remain in this different environment. However, we found opposite results in regard to our expectations, the sub-group "OECD" showed a stronger negative loss effect of -29.9 basis points compared to the effect shown by the sub-group "Non-OECD" of -16.3 basis points. We note, however, that we do not find statistical significance for the first group, whereas for the latter results are significant at a p-value of 0.07. We continue to not record any positive or statistically significant values for the win effect for both groups.

For our other sub-question, we test whether the popularity of football in different countries has different impacts on stock markets following a football result. Once again, we look at the sample of expected results to test whether the prior results still hold. For expected results, we also see the direct opposite of what we saw for unexpected results. We register the only positive win effect, at 4.8 basis points on our table for the sub-group "Non-Popular", whereas the "Popular" group registers a -18.5 basis points win effect with significance at a p-value of 0.07. Regarding the loss effect, even though we do register two negative effects after losses, once again the results contradict our expectation that popular countries would have a bigger effect. For "Non Popular" the effect is -32.4 basis points with a p-value of 0.02, whereas for "Popular" the effect is only -13.1 basis points with no statistical significance. Consequently, we find the only statistical significance for the win minus loss effect within this table for the sub-group "Non Popular". The value is 37.2 basis points with a p-value of 0.04.

In conclusion, we can see that for all expected national results, there is a strong loss effect in national stock markets with high significance. This reconfirms the findings by Edmans et. al (2007) but within a different geographical horizon and time series. However, under the expected results assumptions, neither of our sub-hypotheses holds true. In fact, instead of finding an increase in the resulting impact for either "Popular" or "Non-OECD" countries, we find the complete opposite.

Table 8: Abnormal returns for expected results

Win N°	Win Effect	Win p-value	Loss N°	Loss Effect	Loss p-value	Win-Loss Effect	Win-Loss Effect p-value	Country
187	-0.0268 (0.078)	0.73	205	-0.0183 (0.074)	0.80	-0.0084 (0.107)	0.94	All Unexpected
276	-0.1137 (0.079)	0.15	106	-0.2472 (0.151)	0.10	0.1335 (0.17)	0.43	All Expected
196	-0.1044 (0.088)	0.24	67	-0.296 (0.233)	0.21	0.1917 (0.249)	0.44	Expected OECD
80	-0.1365 (0.17)	0.42	39	-0.1633 (0.089)	0.07	0.0269 (0.192)	0.89	Expected Non OECD
191	-0.1858 (0.103)	0.07	42	-0.1305 (0.323)	0.69	-0.0554 (0.339)	0.87	Expected Popular
85	0.0485 (0.114)	0.67	64	-0.3238 (0.133)	0.02	0.3723 (0.175)	0.04	Expected Non Popular

The table reports values for the stock market effect the first trading day following a win, draw or loss. Effect = Stock Market Change the Day After the Game – Country_i Mean Log Return. Values are in %

6. Discussion:

When comparing the total effects seen for the group “Total Countries” we are not able to find similar effects as the ones found by Edmans et. al (2007). When accounting for stock market noise we cannot find economic or statistical significance in any of the results. When we do not account for short-term market noise in Table 7, we do observe a statistically and economically significant negative draw effect as documented not only, but also, in table 4. As a result we do find a significant effect that allows us to reject the null hypothesis for draw results. We cannot, however, for “Total Countries” find an abnormal economic effect following a given unexpected win or loss in national football, which can be attributed to behavioural biases that arise from this result. However, when we create subsamples within the countries of analysis, we can observe further effects that can provide evidence to reject the null hypothesis within those specific subgroups.

Win effect disparities

What was largely interesting regarding the results in the earlier parts of the study was that we could never document an economically and statistically significant positive win effect. These results were consistent with the findings presented by Edmans et. al (2007) as they could not document any positive abnormal returns associated with wins. However, when we proceed with the market model regression defined in Section 4 to account for stock market noise, we actually document a statistically and economically significant win effect of 29.4 basis points for Non-OECD countries. This poses a further point of discussion. When we do not factor in lagged and world market returns, our results are consistent with the findings by Edmans et. al (2007), we do not report any statistically significant win effect. However, when we utilise a similar econometric

approach to the referenced paper, we find contrasting results and document a win effect. By following the same econometric model under different datasets and assumptions, contrasting effects on stock market returns can be found. This shows us the importance of proceeding with caution when drawing conclusions from a study. Even though our study of the past 10 years has found a positive win effect, it does not necessarily entail that in the future these results will stay consistent. The contrasting effects allow us to compare the two different methodologies that we used and the respective results. Our first methodology used provides us with findings that are consistent with evidence found in previous literature by Baker and Wurgler (2006) that illustrates that positive sentiments do not necessarily lead to any significant positive stock market returns. However, Shepherd and McNulty (2002) show that unrelated to the stock market, positive unexpected outcomes lead to more significant, positive general emotions. When we change our approach to account for market noise we are able to quantify this idea with statistical significance.

Data subsets - OECD and Popularity

As justified previously we use OECD and Non-OECD countries as a proxy for the level of integration in a country's stock market. We want to be able to distinguish between integrated and non-integrated markets to analyse whether the effects of globalisation and increased information transparency can be observed in abnormal market returns. In Table 7 we found economically and statistically significant positive abnormal returns following an unexpected win for Non-OECD countries, whereas the effects for OECD countries were almost non-existent. Moreover, by referencing the figures presented in Table 4 and Table 7, we find that for both of our approaches, Non-OECD countries exhibit positive abnormal win returns as well as negative abnormal loss and draw returns. Whereas the direct reverse effect is exhibited by OECD countries. We, therefore, provide evidence that non-integrated markets, assumed to be highly composed of local investors, are more vulnerable to behavioural biases in relation to changes in mood after unexpected football results. This ties into the literature presented by Meng et. al (2023) and Boubakri et. al (2007). Regarding our popularity proxy, in general, we don't find economically and statistically significant effects in any of the tables for our subsets "Popular" and "Non Popular", except for in Table 5, where we report a -20.9 basis point significant negative abnormal draw effect for "Popular" countries. We justify the lack of documented effects for our different subsets with two possible reasons. Firstly, our proxy for football popularity within a country could be improved. As mentioned before, popularity is a very subjective measure and quantifying it can be ambiguous. Secondly, if our proxy were to be an accurate approximation of football popularity, we have failed to reject our null hypothesis, and consequently, we fail to find evidence that popularity can impact the strength of mood effect on behavioural biases.

Significance in a global context

The most significant effect that we see throughout our analysis is the -67.9 basis point effect documented following an unexpected draw for the sub-samples "Non OECD + Popular". As discussed, this result is highly statistically significant at both the 0.10 and 0.05 significance levels. We attribute this result to both lower levels

of stock market integration as well as a high level of popularity for football within these countries. The following countries were part of this subsample; Argentina, Brazil, Croatia, Morocco and Saudi Arabia. To better understand the magnitude of this impact we take the Brazilian market as a reference point. The market capitalization of the Brazilian stock exchange for March 2024 was 920.47⁴ billion USD. Consequently, a -67.9 basis point loss in the Brazilian stock exchange would represent a loss of around 6.24 billion USD in market capitalization on one day following an unexpected draw. With statistical significance, these results show that behavioural biases play an important role in security pricing and can lead to significant absolute changes.

Compared with the referenced literature, it is interesting to note that this draw effect is nearly 20 basis points stronger than the observed loss effect found in previous literature. We can attribute this largely negative abnormal draw effect not only to the grouping measures used but also to the unexpected nature of the draw as a result overall. The draw result presenting the most significant effect can be a result of its inherent unexpected nature. We can also attribute these results to supporter mood, as the draw is often an anticlimactic result. As we conduct the analysis on a different set of observations in comparison with the referenced literature, it is not surprising that we observe significantly different results. Thus, we can theorise that when a draw occurs as an unexpected result, supporters and viewers will be disappointed with the overall match and that it ended in a neutral result. Therefore, in accordance with this theory, it can be inferred that the pronounced negative draw effect may not exclusively stem from pessimistic investor sentiments regarding unfavourable outcomes, it may also be linked to feelings of disillusionment.

7. Limitations

Within our empirical results, we struggle with a lack of significance in a majority of the results we observe. This can be due to two main reasons. Firstly, by using a single-event study approach, our results could be impacted by short-term market noise, increasing the difficulty in identifying patterns. In our last subsection, we aim to control for market noise in our study, but it could stem from the fact we are not able to capture all market noise in its entirety. Secondly, it could come from sampling deficiencies and that our dataset is not large enough to detect meaningful differences. For a large portion of our results, the effects follow the directions that support our theory, positive for the win effect and negative for the draw and loss effect. However, most of the time these results present either low economic significance or low statistical significance. Thus, a bigger dataset could possibly better represent these differences.

Another limitation of our study arises from the popularity proxy that we developed. The popularity of a sport, as mentioned, is a very subjective variable to measure and it is a challenge to quantify this variable. Because of existing economic and technological inequalities worldwide, football within certain countries is less developed, even though supporters' passion can be large. Therefore, we developed a popularity proxy based on a national team's social

⁴ “Brazil Market Capitalization.” *Brazil Market Capitalization, 1995 – 2024 | CEIC Data*, May 2024, www.ceicdata.com/en/indicator/brazil/market-capitalization.

media following, which, in principle, should not be affected by socioeconomic inequalities. There are two main limitations to this proxy. Instagram as a social media platform, has different adoption levels around the world, so the values to indicate supporter levels could be underreported for some countries. Secondly, the national team's following could be influenced by external supporters. That is because the quality and the popularity of certain countries' players, can amass a higher amount of followers coming from foreign countries, therefore affecting how well our proxy incorporates the passion for the national team's results within the country. For example, Cristiano Ronaldo has an Instagram following of 629 million⁵ and he plays for the Portuguese national team. We saw in our study that Portugal was classified as the most popular country. Although we cannot deny the significance of football within Portugal, it is highly possible that Portugal's huge national team following may come from international fans of Cristiano Ronaldo. For the market integration proxy, we also find a possible limitation. Within our 40 chosen countries of analysis, we find that a majority of these countries are members of the OECD, thus reducing our subsample of Non-OECD countries. We therefore have a total of 451 single observations for OECD countries and 207 single observations for Non OECD countries. This is in part, due to the higher popularity of football in OECD countries and the lack of stock market information for most Non-OECD countries. We believe that our study would benefit from further increasing the amounts of countries analysed. This would add a further geographical perspective and propose further, additional perspectives regarding market integration.

Finally, we also need to consider that our observations are clustered around the months of January, June and July since most significant international tournaments in football are either played in this timeframe. However, the mean log return considered for our analysis incorporates the changes for the whole year. Although this could present a limitation to our analysis, it cannot be improved since the majority of significant football matches are expected to continue being played in this time frame for the foreseeable future.

8. Concluding Remarks

For future research into this subject, we believe it would be insightful to combine the time horizon studied by Edmans et. al (2007) with the one analysed in this study. By conducting this analysis, observing the change of effects over time and accounting for levels of stock market integration, one could give an improved image of the effect of globalisation on cognitive biases and emotional biases in the stock market. Another potential extension to our analysis could be to look at the results by trimming our datasets and removing the extreme outliers. This could help us reduce the impact of extreme values and improve the accuracy of our analysis.

Another further point of development would be to create sub-samples that divide our Non-OECD countries into different portfolios with stocks of different sizes. This stock size segmentation was done by Edmans et. al (2007) since small-size stocks are predominantly owned by local investors. Therefore, this segmentation process could further aid in understanding how the level of

⁵ Instagram, May 2024, www.instagram.com/.

integration of countries' stock markets can impact the effect of cognitive biases and emotional biases in the stock market. Finally, one could redefine what an unexpected result is. To do this, researchers could lower the threshold for unexpected results. In our study, we classify unexpected results as any results that had a lower implied probability than 50%. But by lowering the threshold to less than 25% one could isolate the shock factor even further by only considering results that were highly unexpected. This would reduce the sample size by a large margin thus requiring an extension of the time horizon, analysis of more tournaments or increases in the country sample size. Consequently, a study of this approach could better test whether the psychological effects presented by Sheppherd and McNulty (2002) hold in this context when only highly unexpected outcomes are considered.

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10. Appendix

Table 9: Tournaments Analysed and Number of Unexpected and Expected Results

Tournament	Year	Nº Games	Unexpected Results	Expected Results	% of Unexpected Games
Gold Cup	2015	12	5	7	0.42
Copa America	2015	23	13	10	0.57
Euro	2016	48	33	15	0.69
Copa America	2016	26	14	12	0.54
AFCON	2017	20	16	4	0.80
Gold Cup	2017	11	3	8	0.27
Nations league	2018	48	35	13	0.73
World Cup	2018	63	39	24	0.62
AFCON	2019	28	18	10	0.64
Copa America	2019	22	12	10	0.55
Gold Cup	2019	11	2	9	0.18
AFC Asian Cup	2019	22	7	15	0.32
Nations league	2020	88	54	34	0.61
Euro	2021	49	28	21	0.57
Copa America	2021	25	15	10	0.60
Gold Cup	2021	11	3	8	0.27
Nations League	2022	70	50	20	0.71
AFCON	2022	22	15	7	0.68
World Cup	2022	61	34	27	0.56
Gold Cup	2023	11	5	6	0.45
AFCON	2024	29	24	5	0.83
AFC Asian Cup	2024	22	12	10	0.55
Total	NA	722	437	285	0.61

Table 10: Mean Daily Percent National Index Returns and Number of Wins, Draws and Losses in International Unexpected Football Matches

Results by Country					
country	Win	Draw	Loss	Time Series Begins	Mean Log Return
Argentina	2	10	4	2015-06-11	0.188
Australia	2	3	4	2018-06-20	0.015
Austria	4	4	6	2016-06-13	0.020
Belgium	8	2	10	2016-06-10	-0.007
Brazil	0	7	5	2015-06-16	0.021
Chile	2	6	4	2015-06-12	-0.001
Colombia	8	8	5	2015-06-11	-0.001
Croatia	12	10	5	2016-06-09	0.027
Czech Republic	7	3	4	2016-06-16	0.023
Denmark	8	7	5	2018-06-14	0.052
Egypt	3	9	4	2017-01-16	0.027
England	3	12	12	2016-06-09	0.010
France	12	10	6	2016-06-16	0.035
Germany	1	13	10	2016-06-15	0.015
Ghana	3	6	6	2017-01-19	0.024
Hungary	7	7	2	2016-06-13	0.038
Italy	8	10	3	2016-06-10	0.026
Ivory Coast	5	6	4	2017-01-13	-0.017
Japan	4	4	5	2018-06-18	0.027
Mexico	4	9	6	2015-06-11	0.013
Morocco	6	6	6	2017-01-13	0.000
Netherlands	7	6	3	2018-10-11	0.035
Nigeria	8	2	4	2018-06-21	0.054
Norway	2	2	3	2020-09-03	0.028
Peru	7	7	2	2015-06-17	0.009
Poland	4	9	8	2016-06-15	0.017
Portugal	7	11	8	2016-06-13	0.009
Republic of Ireland	2	7	6	2016-06-10	0.014
Romania	2	4	3	2016-06-14	0.045
Russia	4	6	6	2016-06-09	0.009
Saudi Arabia	2	2	1	2018-06-22	0.004
Slovenia	1	3	1	2022-06-01	0.053
South Africa	3	4	3	2019-06-28	0.006
South Korea	3	4	4	2018-06-15	0.008
Spain	5	13	8	2016-06-20	0.011
Sweden	7	4	5	2016-06-10	0.033
Switzerland	5	12	5	2016-06-14	0.018
Tunisia	3	7	8	2017-01-12	0.008
Turkey	3	3	7	2016-06-09	0.126
United States	3	8	4	2015-07-10	0.036
Total	187	266	205	NA	0.026

Table 11: Regression table for 4 groups combined

Category	Win N°	Win Effect	Win T-Value	Draw N°	Draw Effect	Draw T-Value	Loss N°	Loss Effect	Loss T-Value
All Countries	187	0.059	0.879	266	-0.058	-1.017	205	0.021	0.320
OECD + Popular	84	-0.042	-0.498	120	0.018	0.256	94	0.014	0.181
OECD + Non Popular	43	-0.176	-1.429	60	-0.057	-0.545	50	0.220	1.923
Non OECD + Popular	22	0.457	1.606	35	-0.303	-1.344	21	0.027	0.091
Non OECD + Non Popular	38	0.211	1.439	51	0.008	0.065	40	-0.211	-1.475

Figure 1: Boxplot diagram of all stock market effect observations after an unexpected outcome

