UNIVERSITY OF BIRMINGHAM

Essays on Information Arrival and Asset Prices

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Abstract

This thesis consists of three empirical papers focusing on the impact of different types of information on investor behaviour and the consequent influence on stock market performance. The first chapter explores the effect of actions taken by the regulator in relation to firms' law violations on a firm's stock performance. The results of this study suggest that the announcements made by the Capital Markets Authority ("CMA") toward firms violating the law have negative and significant effects on the firms' stock performances. In particular, firms announced to be under investigation experience a more severe impact than those that are the subject of sanction announcements.

The second chapter explores the influence of newspaper article sentiment on investors' trading behaviours. The main results show that financial news articles and their sentiments have significant effects on stock performance indicators. Particularly, *Polarity score* has significant positive effects on stock returns and a significant negative impact on stock volatility. While the *Difficulty* and *Subjectivity* scores have positive and negative impacts on stock returns, respectively, both have a limited impact on stock volatility.

Finally, the third chapter reveals the impact of sports events on the nation's stock market indices. I find that the results of football rivalry matches have a significant impact on the stock market indices of participating countries. Specifically, the result of a national football match positively (negatively) affects the performance of the winning (losing) country's stock market index. Furthermore, the magnitude of the impact also depends on the characteristics of the game. The results of this investigation show that the victories in rival matches have a greater positive impact on stock returns than non-rival matches. Similarly, the stock market of the country which suffers a loss in a rival match often experiences a larger negative effect from the match, compared to that of a country that loses in a non-rival match.

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Introduction

This thesis contains three empirical research papers investigating the effect of certain types of important information on stock market performance, namely the stock market regulator's announcements, media news articles, and the results of sports events. These studies are important for a range of key reasons. Firstly, they help us to understand how investor decisions are affected by several different types of information, providing vital implications for market participants, policymakers, and regulators. Secondly, documenting the reactions of stock markets to different kinds of information offers vital implications for financial market efficiency. For example, according to the efficient market theory, stock prices should reflect all available information, thus, the ability to consistently generate excess returns in the stock markets should not be possible. Therefore, stock performance should not be affected by the way that information is given (news article sentiments), or by the mood of investors which is affected by the results of sporting events. Lastly, there have been several approaches used to investigate the impact on stock market performance in the existing literature and the research papers have often focused on stock returns. This thesis employs and compares the results of various methods used to document the impact, not only on stock returns, but also on other stock performance indicators, such as volatility and traded volume.

The first chapter titled "Regulator's Announcements and Stock Performance: The Case of Kuwait" investigates how the stock market reacts differently to investigation announcements and sanction announcements. This study provides vital implications for regulator institutions by showing the effects of the regulator's actions on the stock of listed firms. By comparing the stock returns of listed companies being penalized with the stock returns of those undergoing investigation due to announcements made by the regulators, this research provides insights into the various effects of regulatory enforcement action. Previous studies have focused mostly on regulatory enforcement in developed countries, such as in the United States and the United Kingdom (Karpoff et al., 2008; Armour et al., 2017). This paper fills a gap in the literature by examining the effect of regulatory enforcement measures on stock returns in the context of a developing market, using Kuwait as a case study.

The data used in my research is collected from two sources. The first data source is the CMA's official website, from which I manually gathered 144 CMA announcements from 2012 to 2018. This data includes the company's name, the announcement's publication date, details relating to the violation announcement, and the regulator's action.

The Thomson Reuters EIKON Datastream is the second data source from which data on firms listed on the Boursa Kuwait was acquired. Firm-specific information includes firm ticker symbols, daily exchange dates, closing prices, the Boursa Kuwait Index, and trading volumes. I also collected data on firm performance, including in relation to firm assets and annual returns on assets. By integrating the two datasets, I produced a dataset comprised of the firm ticker symbols, announcements of violations, company characteristics, stock price, and the stock volume of 86 enterprises listed on the Boursa Kuwait.

The findings of this chapter are interesting for a number of reasons. When estimating the cumulative abnormal returns (CAR) and the cumulative abnormal volatility (CAV) for each announcement using the event study approach, the findings suggest that both *Volume* and *Volatility* are adversely affected by a *Suspected* announcement. This type of announcement has a substantial impact on the stock return (CAR) and volatility (CAV). In addition, several factors have shown significant results using different event windows. My findings suggest that there is a negative correlation between penalisation announcements and CAR and CAV for most event windows.

The second chapter, "Financial News Sentiments and Stock Performance", documents the impact of news article sentiments on a firm's stock performance. This study is closely related to the literature on the impact of media news on financial markets, which has shown conclusively that news and stock market activity are connected. Specifically, macroeconomic firm-specific news may have a substantial impact on the stock market. In addition, this chapter adds to the literature on the sentiment of media content and its impact on the capital market by investigating how the sentiments of news articles referencing a listed firm affect the stock performance of that firm.

The empirical research is conducted using a comprehensive dataset spanning the period between 2014 and 2019 for 83 listed companies on the Boursa Kuwait. The sample data includes firm-specific fundamental information, daily trading data, and news article sentiment. All datasets are combined based on the individual company names to provide a unique and complete panel dataset incorporating firm-level information and the sentiment of financial news. The company characteristics dataset is comprised of yearly firm-level fundamental data (such as total assets, total debt, return on total assets). The daily stock trading dataset includes open/close, high/low, and volume traded information for the Boursa Kuwait stock index and the 83 listed businesses. These two datasets were obtained from the

Thomson Reuters EIKON Datastream. The third dataset contains the sentiment score (*Difficulty*, *Polarity*, and *Subjectivity*) and word count for 3,678 Arab Times news articles published between 2015 and 2019.

As a starting point, our data suggests that news articles and the emotions they evoke may significantly affect stock performance metrics (i.e., returns and volume traded). In particular, the stock return is much lower on the days when the news articles are released, relative to the days when there is no news. When considering how news attitudes affects stock returns, I find that the *Polarity* scores are positively and significantly connected with returns. Thus, the date of publication of news stories with a positive tone is associated with a far larger stock return. Further, the *Difficulty* score has a strongly positive effect on stock return and volume. This suggests that stock returns and volume may be negatively impacted by news articles that contain technical and complex phrases which require readers to have a certain level of knowledge and understanding. Finally, there is a negative correlation between the *Subjectivity* score and stock return, but a positive correlation with *Volume*. According to the data, on days when news stories with a more subjective tone are released, a considerable decrease in stock returns and an increase in trading volume are observed.

The cumulative abnormal returns (CAR) and the cumulative abnormal volatility (CAV) for each news article are also estimated using the event study approach. I find that the news sentiment has a substantial influence on stock returns and volatility when regressing CAR and CAV on news sentiment scores and other control variables for various event windows. In particular, CARs tend to increase when news is reported with a more optimistic tone. Additionally, CARs increase as the complexity of the news story increases. Meanwhile, more subjectivity in the media leads to lower cumulative abnormal returns across many different event windows. My results show that the polarity score has a substantial and negative influence on volatility, indicating that stock volatility is greater around the publication date of news articles with a more negative tone.

The third chapter entitled "The Effect of Football Rivalry on Stock Price" documents the impact of football rivalry match results on stock indices performance. This chapter adds to the body of literature that documents the impact of investor sentiment on asset price in the field of psychology. The event study method and the continuous variables method are two typical ways of investigating the connection between investment results and investor sentiment. Frieder and Subrahmanyam (2004), using the event study method, discovered that some religious holidays, such as Yom Kippur and St. Patrick's Day, were associated with better market returns. To explain why stock returns are greater on the days surrounding a new moon than on the days around a full moon, Yuan et al. (2005) refer to the common belief that lunar phases impact the emotions and behaviour of investors to make their case. Saunders (1993) and Hirshleifer and Shumway (2003) use the continuous variables method to demonstrate that sunny days have a materially favourable impact on stock prices due to an increase in investor confidence. This chapter also has close ties to previously published works on the subject of sporting events and the stock market. The stock market is complex, and a lack of understanding may lead to a catastrophe that has far-reaching effects. It is possible that this research may increase trust in the understanding of market-movements by demonstrating how the outcomes of football matches impact the investment choices of investors.

I utilize the daily data from 15 nations retrieved from the Datastream database covering the period from May 2000 to April 2020 to analyse the effect of football rivalry match outcomes on market returns. Worldfootball.net is scraped for information on all matches in which national teams from these nations competed (including date, time, and score).

My findings suggest that the stock market reacts strongly to the results of football games played between competing teams. The effect on the stock market performance in the nation that loses (or wins) a football match tends to be negative (positive), respectively. As a result, the nature of the game itself determines the extent to which football games resonate with audiences. Stock returns seem to be positively impacted to a greater extent by wins in rivalry matches than in non-rivalry matches. Similarly, when a country loses a rivalry match, its stock market suffers more than when it loses a non-rival match.

Chapter 1. Regulator's Actions and Stock Returns: The Case of Kuwait[1]

1.1 Introduction

Regulatory institutions, the enforcers of security laws and regulations, play a crucial role in improving the informational efficiency of the markets, maintaining market integrity, and protecting investors (La Porta, Lopez-de-Silanes et al., 2000, 2002). With the assumption of an informationally efficient market, regulatory institutions have the ability to further contribute to the maintenance of securities markets' integrity, when their actions lead to the dissemination of information that was not previously accounted for within stock prices. The market may then react to the relevant aspect of the regulators' announcements of law or regulation violations (Nourayi, 1994). The existing literature has investigated the stock market reaction toward announcements of regulators' enforcement actions regarding law violation (Lott et al., 1999; Armour et al., 2017). However, it is unknown as to whether the market reacts differently to different types of regulator actions that are taken to address the potential violation of law by firms (investigation or sanction). This study, hence, sheds light on the issue by addressing the following research question: "What is the difference between the stock returns of firms that receive investigation announcements and those which are subject to sanction announcements?"

Announcements relating to firms' violations of law can provide the market with new information about whether a firm implements the law substantively or not. Such a negative event could damage the value of a firm and negatively affect shareholder returns (Davidson III et al, 1988). Indeed, companies that are announced to have violated the law are found to experience a negative effect on their stock returns as a result of the market reaction. Morris et al. (2019) finds a significant reduction in firm market value following the market's detection of misconduct. Studying the impact of restatement announcements on the stock market, Palmrose et al. (2004) document a significant negative market reaction to restatement involving fraud. More specifically, fraud and restatements attributed to auditors are correlated with a greater number of negative returns. Cox and Weirich (2002) also explore the negative impact of fraudulent financial reporting announcements on capital markets and both Strachan et al. (1983) and Song and Han (2013) find that announcements of corporate illegal acts have an adverse impact on stock returns.

[1] In this chapter, we use material that has been submitted to The Scottish Economics Conference (SEC) is Scotland's 2019.

In addition to the announcement of law violations, the regulators' enforcement process also includes the release of different types of pronouncements regarding actions taken by the regulators when market participants violate laws or regulations. The violation announcements are a response to either investigation violations or sanction violations that are committed by market participants. Announcements of investigation violations reveal that the violation committee is still reviewing the alleged incidents, which indicates that the violation is uncertain. This announcement, thus, provides ambiguous and vague information relating to a firm's violation of the law. In contrast, when sanction violations occur, regulators publish, in great detail, information relating to the law violation of the firms and their sanction actions, such as warnings, fines, and other penalties. Due to the difference between the information certainty of sanction announcements and investigation announcements, the market may react differently to these two types of announcements.

Empirical studies detail the actions taken by the regulators in response to a firm's violation of law, which includes information relating to associated legal investigations or legal sanctions on stock returns. The stock market is found to react negatively to investigation announcements, where investors are informed that a firm is suspected of illegal behaviour. Wu and Zhang (2014) study the impact of regulatory investigation announcements on China's stock market. They find that the average cumulative abnormal return of investigated firms during the investigation announcement period is negative. Howe and Schlarbaum (1986) similarly document negative stock abnormal returns after a firm's suspension period. Furthermore, with respect to the announcement of fines, Davidson et al. (1994) find that the stock market reacts negatively to sanction announcements and Lorraine et al. (2004) find that the stock market responds negatively to announcements stating that companies have been fined for violating regulations.

To capture the effect of enforcement and the information provided by the enforcement process, studies usually measure the market reaction across the enforcement announcement window. More recently, Kouwenberg and Phunnarungsi (2013) test the association between corporate governance and the market response to the announcement of rules and regulations using a 3-day event window study (day -1, 0 and +1 combined). They find a greater negative abnormal return when companies that hold minor past violations violate the rules. In their study of how the stock market reacts to sanction announcements, Kirat and Rezaee (2019) utilize an event starting from day -5 to day +5, either side of the announcement date. Their results report that the stock market reacts negatively when sanctions are announced to the press.

This study builds on the existing literature and employs an event study to investigate the market reaction to different announcements on actions taken by the regulators for firms' law violations. The empirical analyses are conducted using a comprehensive panel dataset on board announcements collected from the CMA's website and firms' stock information retrieved from the Thomson Reuters EIKON Datastream during the period 2010-2018. The results show that the CMA's actions taken in relation to firms' law violations have a significant influence on stock returns. In particular, firms that are subject to announcements of an investigation into a violation suffer a significant and negative impact on their stock's cumulative abnormal returns. Meanwhile, those that are penalized following a long period of investigation experience an insignificant impact on their stock returns.

The results indicate that an announcement stating that a firm is suspected of illicit behaviour (a suspected announcement henceforth) negatively impacts *Volume* and *Volatility*. The event study approach recognises this when estimating the cumulative abnormal returns (CAR) and cumulative abnormal volatility (CAV) for each announcement. Stock returns (CAR) and Volatility (CAV) are significantly influenced by this type of announcement. Additionally, other variables have shown significant results across various event periods. According to the findings of this study, announcements penalising a firm are negatively correlated with CAR and CAV across various event windows.

Kuwait offers an interesting empirical setting for the purpose of this study, both due to the fact that it has been neglected in the existing literature and through the significant effort of the Government to reform regulations in order to enhance the quality of the capital markets. The Capital Market Authority (CMA) represents the effort of the Kuwaiti Government to improve the capital market environment in Kuwait with regard to increasing transparency and compliance using international standards, thus easing the way for new and foreign businesses to emerge and operate in the country. Crucial to the CMA's effectiveness is its ability to enforce regulation. It has been highlighted that the regulations of the CMA were previously ill-considered and were, in general, overly strict. This hampered the attempt to transform a poorly regulated environment into one with immediate compliance with new regulations (Nosova, 2017). The CMA has been working dynamically to enforce regulations and to combat law violations in capital markets for many years, however, the empirical evidence detailing how the stock market reacts to CMA enforcement actions remains limited. This study demonstrates the effect of information provided by the CMA by examining changes to stock returns when information relating to law violation is released.

Moreover, as an emerging market, Kuwait's stock market is characterized by informational imperfection. The stock prices in these markets are likely to be noisy due to the fact that there are fewer trades taking place, limited reporting requirements, as well as information that is less frequently updated than in developed markets (Buckberg, 1995). In this context, the regulatory institution is regarded as an information provider who disseminates information to investors. It is essential that the impact of announcements of law violation is understood, since if the information from such announcements is useful to investors, it may affect investors' trading behaviour, and subsequently the return on stocks (Wu and Lin, 2017).

This study makes several contributions. First, this study provides vital implications for regulatory institutions. The evidence shows that investors of firms announced to be undergoing investigation suffer heavier losses around the time of the announcement event than investors of firms announced to have been sanctioned. Therefore, the CMA should carefully consider their announcement statements, and review the content in detail to ensure that it fully reflects accurate information relating to the event before publishing. The release of investigation violation announcements should be carefully considered since this type of announcement could create uncertainty among investors.

Second, the existing literature has investigated the negative stock reaction to a specific announcement of action taken by the regulators in relation to law violation (investigation or sanction). However, the differences in the impact of each type of regulators' action on the market reaction have remained untouched. By comparing the stock returns of firms announced to have been penalized with those announced to be undergoing investigation, this study offers insight into the varying impact of regulatory enforcement action. Third, prior research has largely investigated regulatory enforcement action in developed markets, such as in the US or UK (Karpoff et al., 2008; Armour et al., 2017). This study, therefore, fills the gap in the literature by investigating the impact of regulatory enforcement actions on stock returns in the context of an emerging market, using Kuwait as its case study.

The rest of this chapter is structured as follows: Section 2 presents the literature review and hypothesis development. Section 3 discusses the Capital Market Authority of Kuwait. Section 4 describes the methodology and data. Section 5 provides the statistical evidence of the impact of violation announcements on stock performance. Finally, Section 6 concludes.

1.2 Literature review and hypothesis development

1.2.1 Stock market reaction to the disclosure of law violation

Several studies have discussed the impact of law violation announcements on the value of a firm. If the misconduct of firms is detected and made public, firms will suffer reputational damage, due to the costs that are incurred by the revelation of misconduct. These include costly operations, the cost of capital and the cost of losing potential clients (see, e.g., Dechow et al., 1996; Karpoff, 2012). Each of these costs would reduce a firm's future cash flow, thus resulting in a reduction of a firm's current value. Other empirical studies support this argument by examining the influence of a firm's misconduct on long-term financial performance. For instance, Baucus and Baucus (1997) reported a negative relationship between corporate illegality and shareholder returns, return on assets (ROA) and return on sales (ROS).

According to the efficient market hypothesis, stock prices reflect all relevant information. In other words, a market's judgement of new information can lead to changes in share prices (Fama et al., 1969). This implies that if investors perceive unanticipated news as positive signals or negative signals for stock returns, they may accordingly react positively or negatively. Thus, the disclosure of law violation activities, which is regarded as negative news (Koppel and Shtrimberg, 2006) may reduce firms' stock prices. In particular, investors may perceive firms to undertake poor accounting practices and board monitoring processes when such announcements are first received (Karpoff and Lott, 1993; Palmrose et al., 2004; Kang, 2008). As long as investors are aware that firms are alleged to have violated the law, they are likely to sell their stock. This creates a surplus supply of stock, leading to lower stock prices in the market (Kirat and Rezaee, 2019).

Several studies affirm this argument in their investigations into the reaction of the stock market to the announcement of firms' law violations issued by regulatory institutions. For example, Feroz et al. (1991) and Karpoff et al. (2008) discover a decrease in the abnormal returns of firms in response to the public disclosure of their misconduct from the Securities and Exchange Commission's (SEC) investigation. Song and Han (2013) also report a negative market reaction to stock prices in the South Korea stock market following the announcement of a corporate crime.

In this chapter, I utilize data from the Kuwait stock market to examine whether the Kuwait stock market follows a similar pattern to other stock markets that have previously been studied. In this context, I expect the market to react negatively to the CMA announcements of law violations. I state the following initial hypothesis:

H1: The announcement of a law violation by the regulator will reduce the firm's stock returns.

1.2.2 Stock market reaction to regulatory actions

Established studies have not only identified the influence of the disclosure of law violations, but also have focused on the different regulatory actions of regulators taken on those firms that are guilty of law violation (e.g., Howe and Schalarbaum, 1986; Morris et al., 2019). In this study, we focus on two primary actions in the enforcement process undertaken by regulators, which are investigation and sanction. The first significant action is the announcement of an investigation informing the public that a firm is suspected of having committed a violation of the law and regulators will proceed to investigate. The sanction following the end of the investigation period is the final step of the enforcement process. Sanction actions may include public admonishment (Chen et al., 2005; Yu and Zheng, 2019), fixed penalties such as a monetary fine, the confiscation of illegal income or the suspension of a firm's securities trading (Jia et al., 2009).

Scholars have investigated the significant effects of regulatory actions on firms' stock prices. The stock prices of an implicated company can be negatively affected by announcements of investigations and sanctions made towards such a company (e.g., Feroz et al., 1991; Lorraine et al., 2004; Narayanan et al., 2006; Jain et al., 2010). A possible explanation is that investigations and sanctions are considered "unfavourable news" with regard to a firm's operational situation, which could have a negative impact upon shareholder wealth. Such announcements can produce signals of a firm's weaknesses in terms of their management and can raise questions among investors regarding a firm's value. Although a number of existing studies emphasize the impact of regulatory actions (i.e., investigation and sanction) on stock returns, little attention is paid to the comparison of the scale of the stock market reaction towards these two actions. While investigation announcements may only provide vague and insufficient information relating to a firm's violation of law, sanction announcements, contrastingly, offer detailed final decisions regarding sanctions measure for firms. Thus, it can be inferred that investigation announcements lead to a higher level of uncertainty with regard to the value of a firm, than sanctions announcements.

Previous studies on behavioural finance have investigated a link between the stock market reaction towards uncertainty relating to a firm's value with investor overconfidence (e.g., Hirshleifer, 2001; Kumar, 2009). It is theorized that overconfident investors are those who overweight their evaluation of a firm's operational and financial performance based on private information and, by contrast, underweight public information. The theory of overconfidence not only explains that investors often overreact to private signals, but also demonstrates that investors are likely to underreact when it comes to public information. If investors are confident as to the accuracy of their private signals, assessments and information, they tend to underestimate their forecasting errors. Overconfidence is considered to be a notable psychological bias and such bias will be greater if significant uncertainty exists in relation to a firm's future value. Specifically, return predictability can be higher due to the fact that investors appear to be more over-confident when businesses are difficult to value (Daniel et al., 1998, 2001). This indicates that greater uncertainty is connected to relatively higher or lower stock return after positive or negative news (Zhang, 2006).

Empirical studies have found evidence that supports the overconfidence and information uncertainty theories. In particular, Jiang and Zhang (2005) examine the theory that the price momentum and earnings momentum effects are stronger with firms whose values are hard to evaluate. Accordingly, the profitability of firms with a higher level of information uncertainty is greater than for firms with a low level of information uncertainty. Such findings are explained by investor overconfidence being exacerbated by a high level of information uncertainty which causes a significant interaction effect with stock price and earnings. In an investigation into the influence of announcements of SEC enforcement actions, Muradoglu (2008) examines the effects of diverse case outcomes on the stock market. The results indicate that pending and partially settled cases (which possess a greater level of information uncertainty) cause greater short-term negative returns, relative to cases with known outcomes. They discover that the size of the average cumulative returns of investigated firms is larger than it is for sanctioned firms around the time of the announcement dates. Overall, these findings highlight that those cases with unknown outcomes trigger uncertainty among investors when estimating a firm's value.

According to the theories and empirical results from extant studies (e.g., Bessière, 2014; Wu and Zhang, 2014), I develop my second hypothesis: If the momentum of stock returns is associated with investors' behavioural biases, then I should observe greater momentum in returns when there exists higher information uncertainty. In the case of regulatory enforcement announcements by the CMA in Kuwait, I expect that announcements of investigation cases should produce a larger variation in stock returns relative to cases with finalized sanctions. This can be explained through the fact that cases with unknown outcomes, i.e., suspected cases, trigger higher information uncertainty, thus causing greater momentum in the market reaction to stock prices.

H2: The announcements of the CMA to the public regarding cases of firms that are undergoing investigation in relation to law violation will produce a greater effect on stock returns compared with cases where sanctions have been imposed.

1.3 Capital Market Authority and the enforcement process

1.3.1 Functions of the CMA

The primary function of the Capital Markets Authority (CMA) (see i.e., Nosova, 2017) is to ensure that every securities undertaking is carried out efficiently, impartially, and transparently. The CMA must improve the protection of investors whilst ensuring that the capital markets expand. Moreover, it ensures that the development of investment instruments, as well as diversification, are in line with best international practice. In addition, the CMA ensures transparency and impartiality by enforcing full disclosure. Their duties include protecting confidential information from being disclosed and ensuring that there are no conflicts of interests. Finally, they ensure adherence to securities behaviours' standards. Their initial key aims were to minimise the trades that are used to manipulate stock prices leading to the creation of illegal profits, to improve the investment environment, and to promote market growth. The CMA of Kuwait was established to enforce the law and to regulate the market, and the CMA Board is required to publish all news of violations on their webpage immediately after every board meeting.

The primary objective of this investigation is to explore how the market maker's behaviours are restricted, as well as to analyse the pattern of market manipulations and the consequences of defaulting. In Kuwait's regulatory environment, every form of market manipulation is deemed to be a criminal offence and must be punished accordingly, in line with Chapter 11 of the company law of Kuwait. Article 118 provides an instance, whereby, an insider trading offender could face a five-year imprisonment, alongside a fine equivalent to the profit made from the offence up to a maximum of three times the amount. Behaviours similar to the ones observed in market makers (such as engaging in transactions that do not encourage actual change in the ownership of a security, making others buy or sell by creating real or fabricated trading) are restricted, according to Article 122. It was not until 2010 that such rules became effective, even though it was stated in the Article that the CMA must clearly explain the rules, and the instances where the two clauses referred to earlier are applied (see Dawd et al., 2018).

1.3.2 Enforcement process of the CMA

The first step in the enforcement process is the disclosure of inappropriate behaviour that is identified through detection. The regulatory procedures are contingent on obtaining sufficient information to permit the financial regulators to decide whether or not an investigation is necessary. In Kuwait, the CMA has the power to request details or to execute an inspection. Any action that the CMA may take would be subject to a judicial review and could influence investor confidence in the market. In other words, the power of the CMA to request information must be transparent and provide a mandate without limitations or specifications.

An inspection is a way of collecting knowledge relating to the inappropriate and non-compliant activities of firms. An administrative inspection from the CMA requires on-site inspectors who have access to the documents of the businesses. The purpose of this step is not to identify specific crimes but is intended as an overall analysis to ensure that firms' operational processes are in line with the law. During the inspection process, the CMA has the right to demand that all authorized firms and other supervised entities provide information or documents required in order for the CMA to accomplish its objectives.

If the CMA performs an on-site inspection, i.e., an informal investigation, and the investigator finds a breach of the rules, the investigator can then proceed with a formal investigation and can request further documents from the corporation. In this case, the firm is not allowed to decline to provide them. The investigator has the right to ask any government agency or entity relevant to the CMA for any records, documentation, or articles. The investigator also has the right to hear all witness statements and has the right to call on whomever it might consider appropriate to provide evidence during the investigation. Furthermore, the investigator has the right to visit the premises of any government agency or organization of interest to the CMA's activities and to inspect any register or records that they hold.

The final stage of the investigation process is a decision taken by the investigator in relation to the firms alleged to have violated the law. If the investigation reveals evidence of a crime having been committed, the investor shall prepare a report to the CMA in order to provide a recommendation to refer the suspect to the Disciplinary Board – a body in the Kuwait regulatory system which is responsible for reviewing Capital Market Law (CML) breaches and related rules, as well as any claims made against the decisions of the Kuwait Stock Exchange (Boursa Kuwait). The Disciplinary Board possesses the authority to rule on sanctions over implicated firms.

As part of the regulatory process, the Disciplinary Board accesses the recorded evidence from the CMA's investigations. The accused firm or individual has the right to be notified of the proposed action and the reason for it. Those parties shall have the right to render written or oral representations to the Disciplinary Board. In addition, in response to a request from the referring person or his or her representative, the Disciplinary Board may hear testimony from any person whom it wishes or demands to hear from. The decision-making process is necessary for promoting the issuance of correct and fitting decisions regarding supervised and related activities. If all evidence confirms that firms have committed a violation of law, the Disciplinary Board may issue sanctions in accordance with each case's severity (e.g., caution, warning, suspension, dismissal of members of Board of Directors, financial penalties). The sanctions are then published by the CMA on its website.

1.4 Methodology and data

1.4.1 Event study

In order to estimate cumulative abnormal returns (CAR) and cumulative abnormal volatility (CAV), three major elements are identified: event days, event windows, and estimation windows. There are several methods that researchers can use to estimate normal performance, and then to calculate abnormal returns, including the use of the constant mean return model, the market model, the factor model, and the economic model.

This research uses event study to document the potential effects of the regulation's violation announcements on stock returns. In this study, the market model (see MacKinlay, 1997) was used to estimate stock price returns in relation to market index returns. Following this, for each firm, I computed the abnormal return (AR) for each day within the event window. Abnormal returns of stock 'i' at time 't' are measured as the difference between the realised return and an estimate of its expected return in the absence of the event. The calculation is specified as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \ (1)$$

where $AR_{i,t}$ is the abnormal returns of stock *i* on day *t*. $R_{i,t}$ is the realized return of stock *i* on day t. To estimate the expected returns $E(R_{i,t})$, my calculations were based on the market model for the 220 days prior to the start of the event window. The CMA announcement dates are referred to in this study as event days.

Cumulative abnormal returns during the event window $[t_1, t_2]$ are calculated as follows:

$$CAR_{i,t_1} = \sum_{-t_1}^{t_1} AR_{i,t} \ (2)$$

To measure the effect of the CMA announcements, which might influence the stock performance before and after the announcements, I computed cumulative abnormal returns (CAR) and cumulative abnormal volatility (CAV) over four different event windows [-1,1]; [-3,3]; [-5;5]; [-7;7] (3, 7, 11, and 15 days, respectively). It is worth to mention that the presence of more than one event within the same event window was noticeable. To resolve this problem, all events occurring within the same event window were eliminated except for the first event.

1.4.2 Data

The data used in this study is collected from two main sources. The first data source is the official website of the CMA, where I manually collected 144 CMA announcements relating to a period of six years from 2012 to 2018. I then extracted detailed information from the CMA announcements, including the company name, the release date, details about the violation, and the regulator's action. The second data source is the Thomson Reuters EIKON Datastream, from which data on companies listed on Boursa Kuwait was collected. The financial and utility industries are excluded from the study. Data on firms including company ticker, daily exchange dates, closing prices, Boursa Kuwait Index, and trading volumes. Furthermore, information on the firm's assets and return on assets on a yearly basis was included. By combining the two datasets, I obtained a final dataset containing information on the unique identification numbers, violation announcements, firm's characteristics, and the stock price and volume of 86 firms listed on Boursa Kuwait.

During the data quality check process, I find that there are outliers in the sample data (e.g., *TA*; *ROA*; *TL_TA*; and *Volume*). As a first attempt, I replaced the values exceeding the 99th percentile with the value of the 99th percentile. In a similar manner, values below the 1st percentile are replaced with the value of the 1st percentile. As a second approach, I removed observations that fell within 1% of both the top and bottom. The results of the second attempt were similar to those of the first attempt. Therefore, I only report the results using the first attempt in this chapter.

1.4.3 Descriptive Statistics for CARs

The *CAR* of each company was estimated individually for different event windows. It is important to note that all announcements of the same company which have overlapping event windows with each other were dropped. After dropping events with overlapping event windows, the dataset still contained a number of companies with more than one announcement. This indicates that a company could have more than one *CAR* within the sample period.

The results shown in Table 1.1 are cumulative abnormal returns (*CAR*s) for various event windows. For the identified 144 announcements, *CAR*s were calculated for 3, 7, 11, and 15-day event windows. In general, *CAR*s were negative for all intervals, confirming that law violation announcements reduce stock returns. This result is consistent with prior studies investigating the impact of law violation announcements on stock markets (i.e., Armour et al., 2017). Moreover, *CAR*s tend to be negative and greater when the interval of the event window is longer. This suggests that the negative impact of violation announcements on stock performance may not diminish over time.

[Table 1.1]

To compare the impacts of two types of violation announcement on *CAR*, I compute the average *CAR* across all events for each event day by announcement type. Figure 1.1 shows the average *CAR* for *Fined* and *Suspected* announcements, which help to demonstrates the market reaction to *Fined* and *Suspected* announcements during the period of 20 days before and after the event day. The results of this show clearly that the average *CAR* fluctuated around a stable level before the announcement. Meanwhile, a decrease trend is observed after the event date. The negative effect of *Fined* announcements on average *CAR* is greater and lasts longer than that of *Suspected* announcements. The chart showed that the average *CAR* of *Suspected* announcements started recovering after seven days, while the statistics of *Fined* announcements did not.

[Figure 1.1]

Based on the types of announcements, two distinct approaches were used to test the significance of *CAR*s. The first approach is Patell's (1976) "standardized-residual method", shown in Table 1.2 as (t-stat 1). Estimating (t-stat 1) is done by dividing the standard abnormal returns of each stock time-series by the standard deviation of that period. To calculate the t-stat for each event day, it is necessary to divide the sum of standardized abnormal returns across the stocks in the portfolio by the square root of the portfolio's number.

A second approach was used to test the significance level of *CAR*s, which is the "standardized cross-sectional" test from Boehmer et al. (1991), reflected in Table 1.2 as (t-stat 2). The "standardized cross-sectional method" differs from the "standardized-residual method" in that the estimation is made based on a given period, rather than daily. In order to calculate the test statistic, it was necessary to divide the average standardized abnormal return by the standard deviation of the estimate period in the event period. According to Boehmer et al. (1991), abnormal returns are accounted for by cross-sectional variance. It was stated in Kallunki (1995), that the "standardized cross-sectional method" was used to estimate missing prices as a result of thin trading, since it is capable of controlling for cross-sectional variance increases due to autocorrelation.

In Table 1.2, the *CAR* is shown for different event windows ranging from 3 to 21 days, covering a time span of -10 days to 10 days from the event date (violation announcements). On the left-hand column, *CAR* and 1-stats are based on *Suspected* announcement violations, while on the right-hand column, estimations are based on *Fined* announcement violations. It appears that both *CAR*s for *Fined* and *Suspected* announcements are significant following the event day, and both *CAR*s are statistically significant. *Suspected* announcements show the effect in the 0,3 window, but lose significance in the -10,10 window. Meanwhile, *Fined* announcement *CARs* are significantly positive in the range of 0,5 to -10,10. In both cases, the results are similar for the standardised residual method (Patell, 1976) and the standardized cross-sectional method (Boehmer et al., 1991). Although *Suspected* announcements can be observed earlier on *CARs*, *Fined* announcements can last longer. Furthermore, *Fined* announcements produce more significant results than *Suspected* announcements.

[Table 1.2]

1.5 The impact of a violation announcement on stock performance indicators

1.5.1 Stock return, volatility, and volume traded

The impact of announcement violation types on stock performance was investigated using the panel data multi-way fixed-effect model to regress stock returns, volatility, and volume on the type of violation and market index returns (FTSE15 market index returns). The model is specified as follows:

$$Stock\ Performance_{i,t} = \beta_1 Fined_{i,t} + \beta_2 \text{Suspected}_{i,t} + \beta_3 Market\ return_{i,t-1} + \beta_4 Stock\ return_{i,t-1} + \beta_5 Volume_{i,t-1} + \beta_6 Volatility_{i,t-1} + \psi_i + \tau_t + \varepsilon^1_{i,t} \quad (3)$$

where $Stock\ Performance_{i,t}$ is the mean-adjusted return, market-model return, volatility, or volume of stock i on day t. The mean-adjusted return is calculated based on a 220-day estimation period starting 10 days prior to the relevant event day. I employ 220-day estimation period to estimate abnormal returns since this is the most popular approach in the existing literature (see e.g., Caton et al. 2003; Sorescu et al. 2017; Fan et al. 2020). Meanwhile, the market model return is computed using the Kuwait FTSE 15 index return. $Fined_{i,t}$ is a dummy variable equal to 1 if the violation announcement is "fined" for firm *i* on day *t*. $Suspected_{i,t}$ is a dummy variable equal to 1 if the violation announcement type is "suspected" for firm *i* on day *t*. $\psi_i$and τ_t are firm and time fixed effects. $\varepsilon^1_{i,t}$ is the error term.

Based on the results in Table 1.3, most of the control variables have significant predictive power. First, there is a positive correlation between market return and stock return. In other words, the firm's stock returns are positively correlated with the market index returns. Second, lag stock returns are negatively correlated with mean adjusted returns and positively correlated with volume. This means that a firm's stock returns are likely to increase, and volume traded tends to decrease if the stock returns on the previous trading day drop. Third, all regressions show positive significance for lag volume. This suggests that the higher the volume traded on the previous trading day, the higher the stock returns, the higher the volatility, and the larger the volume. Lastly, lag volatility is positively correlated with volatility and negatively correlated with volume. According to this correlation pattern, the higher the volatility on the previous trading day, the higher the volatility and the lower the trading volume.

Regarding violation announcements and stock performance indicators, all regressions found significant and negative coefficients of suspected announcements (see columns 1-4).

Accordingly, stock returns, volatility, and volume are lower on days that have suspected announcements, than on days without announcements. All regressions found that *Fined* announcements had no significant effect on stock performance. This suggests that stock performance on days with *Fined* announcements is not significantly different from stock performance on days without fined announcements.

[Table 1.3]

1.5.2 Violation announcements and CAR

In terms of the impact of CMA announcements on stock returns in the short run, investigation announcements and sanction announcements are expected to have different effects. Several studies (e.g., Daniel and Titman, 1999; Hong et al., 2000; Gleason and Lee, 2003) have examined how the market reacts to news and information relating to firms' operations. These studies suggest that investors are more likely to overreact or underreact in cases of information uncertainty. There was also evidence that the stock market reacts in a more volatile manner when the future value of a firm is unclear. Compared with a finalized sanction announcement, the stock returns of companies alleged to have violated the law will show greater fluctuations after investigation announcements. Investigations into companies may produce greater uncertainty among investors, which can be attributed to the fact that investigations are conducted on the investors themselves, as well as the companies. Thus, the impact of a suspected announcement on stock performance is expected to be greater than the impact of a penalised one.

The model included three control variables relating to firm characteristics, as well as one control variable relating to stock performance that may affect market reactions to violations. The three control variables for firm characteristics are: the natural logarithm of total assets (TA), return on assets (ROA), and leverage ratio (TL_TA), whereas the control variable for stock performance is $Volume$. It has been shown in previous studies that the response to announcements is influenced by a firm's size, profitability, solvency, and stability. Research (e.g., Bhushan, 1989; El-Gazzar, 1998) has shown that small firms are more likely than large firms to experience market reactions to earnings announcements. As a result, investors are more likely to have access to information relating to larger companies (Palmrose et al., 2004). For this reason, I used TA (a natural logarithm of market total assets) as a proxy for firm size. Additionally, I included return on assets (ROA), which is an indicator of profitability and can be positively correlated with the market reaction (Kouwenberg and Phunnarungsi, 2013). Companies that fail to comply with the law when their ROA is low are more likely to experience a negative reaction from the market. Businesses with poor profitability have a greater incentive for expropriation (Durnev and Kim, 2005; Takeda et al. 2020), and the market tends to take this into account when companies commit violations.

For businesses with high debt levels, disclosing more financial information is essential for providing creditors with assurances and for bolstering public trust (Kothari et al., 2009; Godlewski et al., 2013). The relationship between leverage and *CAR* appears to be positive (Wu and Zhang, 2014; Zamroni and Aryani, 2018). In my model, I also included TL_TA (a natural logarithm of the ratio of total liabilities to total assets) as a proxy for leverage. Researchers have also incorporated stock liquidity within the model based on previous studies. As Campbell et al. (1993) point out, stock prices tend to rise on low-volume days and fall on high-volume days depending on trading volume. Consequently, I also include a final control variable, which is $Volume$.

The regression equation below is used to examine the impact of violation announcement type on *CAR*:

$$CAR_{i,k} = \beta_1 TA_{i,y-1} + \beta_2\, ROA_{i,y-1} + \beta_3 TL\_TA_{i,y-1} + \beta_4 Volume_{i,k-1} + \beta_5 Announcement\_type_{i,k} + \phi_t + \varepsilon^2_{i,k} \quad (4)$$

where $CAR_{i,k}$ is the cumulative abnormal return of firm *i* during the event window of event *k*. $TA_{i,y-1}$, $ROA_{i,y-1}$, and $TL\_TA_{i,y-1}$ are total assets, return on asset ratio, and debt to capital ratio of firm i in the previous year to the year of the event. $Volume_{i,k-1}$ is the total value traded of firm *i* on the day before the event date *k*. *Announcement_type* is a dummy variable that equals 1 if the violation investigation has been conducted, and 0 otherwise. ϕ_t is time fixed effects. $\varepsilon^2_{i,k}$ is the error term. More details on variable descriptions and data sources are available in Table A1.1.

Table 1.4 presents the descriptive statistics of all variables *TA, Lag ROA* and *Lag TL_TA*. *TA* refers to the lagged total assets of all firms with an event where this was retained from the annual DataStream of 141 observations. *Lag ROA* is lagged return on assets where *Lag TL_TA* is calculated as lagged total liabilities divided by lagged total assets. Taken from DataStream, I calculated *Lag Volume* as lagged total value that is traded daily within the event window. *Announcement_type* is a dummy variable that equals 1 if the violation is penalised by a warning, fined, or suspended, and equals 0 otherwise (i.e., announcements with suspected violations).

The *Fined* announcements has a mean of 0.54, showing that 54% of the regulator's actions against firms that violate the law are sanction announcements. Regarding variables for firm characteristics, the mean of total assets of all firms is 11.14 and its standard deviation is 1.40. This implies that most firms in my data set have total assets of 11 million Kuwaiti Dinar (KD), which could classify them as small-medium sized companies. *ROA* has a mean of 0.38 and a standard deviation of 0.41, which implies that firms perform well over the period studied. The mean and standard deviation of total liabilities to total assets (*TL_TA*) are 0.39 and 0.24, respectively. This means that most companies in my data set have a relatively healthy leverage ratio. The descriptive statistic for other control variables in relation to stock performance indicates that the mean and standard deviation of *Volume* are 1.121 and 0.339, respectively. This indicates that most companies are liquid, as the amount of volume traded is around 1.1 million KD.

[Table 1.4]

Table 1.5 documents the correlation matrix between the variables in the analysis providing a preliminary overview of the relationship between variables. Initial evidence indicates that *CAR* is negatively correlated with the *Announcement_type* variable, implying that firms undergoing investigation for a violation have a higher value of cumulative abnormal returns when compared with those that are the subject of sanction announcements. Furthermore, other variables were found to be marginally correlated with the *CAR*. This table also shows that none of the correlation coefficients are higher than 0.65, thus confirming that the multicollinearity problem in regression models is not significant.

[Table 1.5]

Table 1.6 presents the results of the regression (4) examining the impact of announcement type on the cumulative abnormal returns (*CAR*). The results of CARs (columns 1-4) in four different event windows are regressed on announcement types and other control variables, including TA, ROA, TA_TL, and Volume. Results show that the estimated coefficients on *Announcement_type* are negative and significant for three event windows: [-3;3]; [-5;5]; [-7;7]. This implies that firms which are the subject of CMA announcements which state that they are undergoing investigation in relation to a violation have higher *CARs* than firms that are fined or suspended. For robustness check, I include the square of TA, ROA, TA_TL, and Volume in the regression to control for nonlinearity and find consistent results (see Appendix Table A1.2).

This finding aligns with previous studies relating to overconfidence, information uncertainty and stock returns. This can be understood through psychological biases (investor overconfidence), which increases in response to increasing levels of information uncertainty relating to firm value (e.g., Hirshleifer, 2001; Kumar, 2009). Due to the fact that investors appear to be more over-confident when companies are difficult to value, return predictability can be greater (Daniel et al., 1998, 2001). It is important to indicate that, following positive or negative news, greater uncertainty is associated with relatively higher or lower stock returns (Zhang, 2006). Findings also show that the degree to which a market responds to new information is positively linked to levels of uncertainty. According to the principle of information uncertainty, it was argued that investigation announcements made by the CMA are considered first time news which create uncertainty for investors. However, sanction announcements only occur in relation to firms that had previously been announced to be undergoing inspection and the market is already prepared for the shock. Thus, a stronger market reaction is caused by CMA investigation announcements.

The estimated coefficient on *Announcement_type* is not statistically significant in the [-1;1] event windows. This result indicates a slower market response to investigation announcements relative to sanction announcements. This finding is consistent with earlier studies (Chan et al., 1996; Barberis, et al., 1998) that focused on price continuation where such studies posit that the market response to the latest released information is gradual. A possible explanation is that investors tend to underreact to new public signals due to psychological biases (investor overconfidence). Stock price responses can be considerably slower when there is high information uncertainty in connection with a firm's value (i.e., cases where firms are in the investigation period). Hence, there is a difference between the market reaction to the CMA's investigation and sanction announcements in the later event windows.

In general, all of the variables (*TA, ROA* and *TL_TA*) display signs of coefficients that are in line with expectations. In particular, *TA* showed statistically significant results in two event windows [-1,1] and [-3,3] with significance levels of 1% and 10%, respectively. *Total Assets* was found to be negatively associated with the *CAR*, indicating that around the time of the announcement event, the stock returns of larger firms are less affected by the regulator's actions relative to smaller firms. This is consistent with the findings of earlier studies (e.g., Chang and Wong, 2010; Paulraj and De Jong, 2011) which indicated that the market reaction around the time of the announcement events is considerably lower for larger firms. The coefficient of *Volume* is negatively significant in two event windows ([-1;1]; [-5;5]). This finding aligns with previous evidence from the empirical research conducted by Arya and Zhang (2009).

In terms of *TL_TA, ROA,* and *Volume* and their relationship with *CAR*, the results were considerably inconclusive. In particular, *TL_TA* and *ROA* are insignificant for all event windows illustrating its negligible impact on stock price. The coefficient of *Volume* is negatively significant in two event windows ([-5;5]; [-7;7]). This result is consistent with the finding of Arya and Zhang (2009).

As part of the investigation, I also run the regression equation (4) controlling for nonlinearity. The results when controlling for nonlinearity were qualitatively the same (see Appendix Table A1.2). I also re-estimated the model controlling for the interaction terms of *Fined* announcement with firm/stock characteristics where the results, in terms of their implication, aligned with the results reported in Table 1.6 (see Appendix Table A1.3).

[Table 1.6]

1.5.3 Violation announcements and CAV

Applying a similar method to equation (4), I examine the impacts of the type of violation announcements on the cumulative abnormal volatility. Specifically, the regression equation is as follows:

$$CAV_{i,k} = \beta_1 TA_{i,y-1} + \beta_2\, ROA_{i,y-1} + \beta_3 TL\_TA_{i,y-1} + \beta_4 Volume_{i,k-1} + \beta_5 Announcement\_type_{\,i,k} + \gamma_t + \varepsilon^3_{i,k} \qquad (5)$$

where $CAV_{i,k}$ is the cumulative abnormal volatility of firm *i* during the event window of event *k*.

γ_t is time fixed effects. $\varepsilon^3_{i,k}$ is the error term.

Table 1.7 illustrates the findings of regression (5), which investigated the impact of the announcement type on the cumulative abnormal volatility (*CAV*), as well as controlling for the control variables (i.e., *TA*; *ROA*; *TL_TA*; and *Volume*). The first column includes the (*Announcement_type*) as a dummy variable as well as other control variables in the regression, whereas the remaining columns reflect the results of different event windows [-1;1], [-3;3], [-5;5], and [-7;7]. *Announcement_type* is a dummy variable that equals 1 if the violation is penalised by a warning, fined, or suspended, and equals 0 otherwise. The results show that the estimated coefficient of *Announcement_type* is negatively and significant over 3-day event windows regression. This imply that suspected announcement has higher volatility than fined announcement. For example, violation announcements for firms with sanctions that are certain to have breached the law, trade with lower *CAV* than those that are undergoing investigation due to the uncertainty.

Regarding firm's characteristics, the coefficient of *Total Assets* was found to be negatively significant for all event windows (3-day, 5-day, 11-days, and 15-days). This indicates that, following violation announcements, the stock performance of a smaller firm is more volatile than a larger firm in terms of *Total Assets*. Meanwhile, the results in Table 1.7 show a limited impact of return on assets and total liability to total assets on the volatility of firm stock after an announcement.

[Table 1.7]

In addition, the model controlling for nonlinearity has been investigated in existing literature (see e.g., Freeman and Tse, 1992; Lipe et al., 1998). Since firm's stock performance could potentially have nonlinear relationship with firm's characteristics (e.g., size, profitability, and leverage), I account for this possibility in the model. Particularly, I employ the baseline model of regression equation (5) and controlling for nonlinearity by adding the squared terms of total asset, ROA, and total liability over total asset ratio. I found that the results controlling for nonlinearity generate the same implications with the results presented in Table 1.7 (see Appendix Table A1.4).

Moreover, existing research has found that the impact of an event, such as, earnings news (Mian and Sankaraguruswamy, 2012), restatement announcements (Palmrose et al., 2004), media news (Chan, 2003; Carretta et al., 2011; Hao et al., 2011) on firms' stock performance could potentially vary with firm's characteristics (e.g., size and profitability). To control for this possibility, the regression equation (5) was re-estimated adding the interaction terms between Announcement_type and total asset, ROA, and total liability over total asset ratio. The results controlling for interaction terms are presented in Appendix Table A1.5, which suggest the same implication with our main results.

1.6 Conclusion

This study provides a deeper examination of the impact of regulator's enforcement actions on the market reaction than has previously been carried out. While some academic scholars (Song and Han, 2013; Morris et al., 2019; Lorraine et al., 2004) have investigated the negative market reaction relating to the regulator's announcements of law violations and their actions towards firms found to violate law, there remain concerns over how the market reacts differently to different types of regulator's actions taken in response to law violations. The purpose of this study is, therefore, to examine the difference in the stock returns of investigated and penalized firms on the Boursa Kuwait.

To summarize, all available data was collected from CMA announcements relating to the actions taken against firms which were found to have violated the law. The results demonstrated that the actions taken by the regulator against firms that violate the law significantly influence the stock market in Kuwait. In particular, changes to the stock returns of investigated firms were found to be greater than for those firms that are penalised during the [-3;3]; [-5,5] and [-7,7] announcement windows. My results suggest that the type of action taken by the regulator regarding law violation is critical in determining the market response. It is important to highlight that investors are more concerned by investigation announcements that carry an uncertain outcome, than sanction announcements which inform investors that firms are to be fined or penalised due to a law violation.

This reaction of the market is consistent with the theoretical framework of Daniel et al. (1998, 2001), which implies that greater informational uncertainty is associated with relatively lower stock returns following negative news. The results also contribute to the existing empirical studies on how the market reacts to information relating to regulators' enforcement actions (Howe and Schalarbaum, 1986; Murphy et al., 2009). They provide supporting evidence to demonstrate the different reactions of the market, dependent upon the type of actions taken by the regulators on firms which violate the law. This study investigates a firm's loss of investors around the time of investigation announcements, relative to sanction announcements, whereas most previous studies only examine the negative market reaction around the day of the law violation announcement (Jain et al., 2010; Kirat and Rezaee, 2019).

This study has implications for a wide range of stakeholders, particularly for regulatory institutions, policymakers and investors. First, it provides important implications through its indication of the association between listed firms' misrepresentation and investor losses.

From the legal perspective, investigation announcements are not officially or legitimately classified as being a misrepresentation of firms. Moreover, this study provides evidence that investors suffer greater losses around the time of investigation announcement events than sanction events. Hence, it is vital for regulatory institutions to clarify the role of investigation announcements in their enforcement action process. Second, this study sheds light on the consequences of regulator's enforcement actions that affect the market reaction, thus, policymakers and regulators can refer to critical aspects of my findings when issuing announcements.

The results from this study point to a number of future research opportunities. First, this study is limited to the context of Kuwait. Therefore, future studies may explore the effect of regulators' enforcement actions in other emerging economies, such as Latin America, Asia, or the African continent, where governments are also attempting to improve capital market environments by enacting capital market laws and regulations. Second, since investors have varying reactions to different types of regulator actions on law violations (investigation or sanction) due to their expectation of firm value to some extent, future studies may wish to consider how other information users (e.g., creditors, analysts, and those responsible for governance) respond to such events. Future research may examine whether the reactions of other information users to an investigation announcement are different from their reactions to a sanction announcement.

Table 1.1. Descriptive Statistics of CAR

CAR Interval	Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	N (8)
[-1; 1]	-1.944	11.606	-16.282	-2.950	-0.213	1.868	9.404	144
[-3; 3]	-3.827	32.605	-27.804	-4.929	-0.354	4.432	19.853	144
[-5; 5]	-5.024	29.346	-37.178	-6.205	-0.766	4.458	23.112	144
[-7; 7]	-4.136	20.392	-45.649	-8.062	-2.048	3.723	23.163	144

Note: CAR Intervals are the cumulative abnormal returns calculated over 3, 7, 11, and 15 day windows centred on the event day (0) and calculated using the closing price of the day (CAR_stats_1 = -1,1; CAR_stats_3 = -3,3; CAR_stats_5 = -5,5; CAR_stats_7 = -7,7). Columns (1) and (2) present the mean and standard deviation of CAR over different windows; columns (4)-(8) present the mean price for each percentile of the CAR; column (10) shows the total number of announcements, N.

Table 1.2. CAR for *Fined* and *Suspected* Announcements

	Suspected Announcements			*Fined* Announcements		
Window	CAR	(t-stat 1)	(t-stat 2)	CAR	(t-stat 1)	(t-stat 2)
-10, 0	0.036	-0.454	-0.390	0.004	-0.609	-0.684
-7, 0	0.041	-0.261	-0.220	-0.008	-1.553	-1.327
-5, 0	0.039	0.102	0.073	-0.005	-0.851	-0.707
-3, 0	-0.009	0.177	0.139	-0.005	-0.913	-0.750
0, 3	-0.009	-1.747*	-2.481**	-0.018	-0.124	-1.173
0, 5	-0.009	-2.384**	-3.136***	-0.025	-2.990***	-2.882***
0, 7	-0.042	-3.684***	-4.176***	-0.058	-3.474***	-2.535**
0, 10	-0.032	-1.982*	-1.633	-0.003	-3.882***	-2.224**
-5, 5	-0.026	-1.825*	-1.226	-0.010	-3.664***	-2.143**
-10, 10	-0.046	-1.002	-0.799	-0.069	-2.755***	-2.097**

Note: Two different kinds of test statistics are applied to test the statistical significance of the cumulative abnormal returns. (t-stat 1) is Patell's (1976) standardized-residual method; (t-stat 2) is the standardized cross-sectional test proposed by Boehmer et al. (1991). Windows are [-10,10] where 0 is the announcement date. CAR is the cumulative abnormal return using the data from the estimation period of 220 days. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 1.3. Regressions of Violation Announcements

	Mean-adj return	Market-model return	Volatility	Volume
Predictors	(1)	(2)	(3)	(4)
Fined	0.010	0.005	-0.001	0.023
	(0.039)	(0.036)	(0.003)	(0.024)
Suspected	-0.116*	-0.132**	-0.008***	-0.084**
	(0.067)	(0.057)	(0.003)	(0.036)
Market return	0.300**		0.023	0.130
	(0.143)		(0.020)	(0.147)
Lag stock return	-0.411***	0.003	0.001	0.103***
	(0.050)	(0.048)	(0.003)	(0.016)
Lag volume	0.019***	0.020***	0.001***	0.447***
	(0.003)	(0.002)	(0.000)	(0.004)
Lag volatility	-0.077	-0.063	0.240***	-0.338***
	(0.051)	(0.043)	(0.008)	(0.041)
R^2	0.218	0.005	0.223	0.605
N	87724	95938	96024	96024

Note: Mean-adjusted return is based on a 220-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using Kuwait FTSE15 index return. Volatility is Parkinson (1980) intraday high-low range. Trading volume is the natural logarithm of the total value traded on that day. The number for each variable is the coefficient of that variable. The numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 1.4. Descriptive Statistics of Predictors

Variables	Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	N (8)
TA	11.144	1.404	8.630	10.394	11.182	12.098	13.387	141
ROA	0.384	0.405	0.004	0.070	0.248	0.504	1.182	141
TL_TA	0.387	0.236	0.064	0.186	0.388	0.549	0.861	141
Volume	1.121	0.339	0.444	0.956	1.144	1.376	1.601	144
Announcement_type	0.542	0.500	0.000	0.000	1.000	1.000	1.000	144

Note: Columns (1) and (2) report the mean and standard deviation of firm characteristics variables [TA (lag total asset); ROA(lag return on assets); TL_TA (lag total liabilities to total assets)]; stock total value traded on that day (Volume); and announcement type (*Announcement_type*) is a dummy variable of all events indicating 1 if the violation is penalized by warning, fined, or suspended. Otherwise, 0 for announcements with suspected violations. All variables are defined in Appendix 1. Columns (3)-(7) report each percentile of the variables; column (8) shows the total number of observations, N.

Table 1.5. Correlations Matrix

	CAR	TA	ROA	TL_TA	Volume
TA	-0.250				
ROA	0.025	0.040			
TL_TA	0.041	0.350	0.165		
Volume	-0.257	0.396	-0.197	0.199	
Announcement_type	-0.115	-0.008	0.053	0.018	0.009

Note: This table provides the correlations for various measures including stock performance [CAR (cumulative abnormal returns), and Volume]; firm characteristics variables [TA (lag total asset); ROA (lag return on assets); TL_TA (lag total liabilities to total assets)]; and dummy variable indicating type of announcement (*Announcement_type*).

Table 1.6. Regression on CAR with Different Event Windows

Predictors	Event window interval			
	[-1;1]	[-3;3]	[-5;5]	[-7;7]
TA_{y-1}	-0.039***	-0.063**	-0.035*	-0.036
	(0.010)	(0.027)	(0.018)	(0.030)
ROA_{y-1}	0.040	-0.047	-0.085	-0.121
	(0.029)	(0.081)	(0.055)	(0.091)
TL_TA_{y-1}	0.102*	0.052	0.095	0.066
	(0.053)	(0.147)	(0.099)	(0.165)
$Volume_{t-1}$	-0.087**	-0.061	-0.280***	-0.240**
	(0.039)	(0.108)	(0.073)	(0.121)
Announcement_type	0.007	-0.158*	-0.120**	-0.325***
	(0.031)	(0.087)	(0.059)	(0.097)
R^2	0.257	0.171	0.266	0.187
N	141	141	141	141

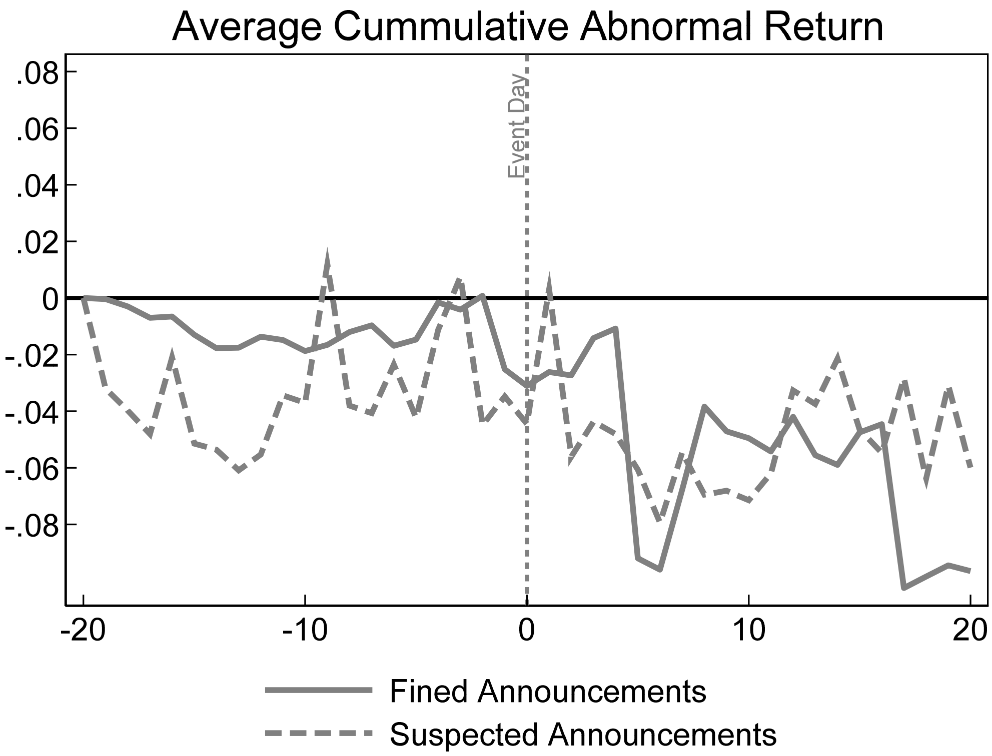
Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 3-day to 15-day windows. The independent variables are Lag Total Assets, Lag ROA, LagTL_TA, Lag total volume, as well as their Squared variable, and Announcement_type. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. The numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 1.7. Regression on CAV with Different Event Windows

Predictors	Event window interval			
	[-1;1]	[-3;3]	[-5;5]	[-7;7]
TA_{y-1}	-0.011***	-0.018***	-0.022***	-0.027***
	(0.003)	(0.005)	(0.008)	(0.010)
ROA_{y-1}	0.000	0.007	-0.013	-0.029
	(0.009)	(0.015)	(0.024)	(0.030)
TL_TA_{y-1}	0.068***	0.078***	0.095**	0.093*
	(0.017)	(0.028)	(0.043)	(0.054)
$Volume_{t-1}$	-0.016	-0.016	-0.087***	-0.152***
	(0.012)	(0.020)	(0.031)	(0.040)
Announcement_type	-0.019*	-0.027	-0.031	-0.020
	(0.010)	(0.017)	(0.025)	(0.032)
R^2	0.279	0.197	0.216	0.265
N	141	141	141	141

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 3-day to 15-day windows. The independent variables are Lag Total Assets, Lag ROA, LagTL_TA, Lag volume, as well as their Squared variables, and *Announcement_type*. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. The numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Figure 1.1. Average CAR before and after event day for *Fined* and *Suspected* announcements



Note: The line chart shows the average CAR for *Fined* announcements and *Suspected* announcements. The horizontal axis represents the event window where 0 is day 0 (the announcement day), -20 is the 20th day before the announcement, and the value 20 is the 20th days after the announcement.

1.7 Appendix

Table A1.1. Description of Variables

Variables	Description
CAR	CAR is the cumulative abnormal returns measured for different intervals over a 15-day, 11-day, 7-day, and 3-day window and centred on the event day. It is calculated using the closing price of each day during the window of all firms with an event, obtained from DataStream daily.
CAV	CAV is the cumulative abnormal volatility measured for different intervals over a 15-day, 11-day, 7-day, and 3-day window and centred on the event day. It is calculated using the closing price of each day during the window of all firms with an event, obtained from DataStream daily.
TA	Computed as the lag total assets of all firms with an event, obtained from DataStream annually.
ROA	Estimated as lag return on assets of all firms with an event, obtained from DataStream annually.
TL_TA	Calculated as lag total liabilities divided by lag total assets of all firms with an event, obtained from DataStream annually.
Volume	Projected as lag of total value traded based on the volume of shares traded daily of all firms with an event, obtained from DataStream daily.
Fined	*Fined* is a dummy variable of all trading days indicating 1 if the violation is penalized by a warning, a fine, or a suspension, otherwise 0 for no violation announcements. Obtained from CMA website. www.cma.gov.kw
Suspected	*Suspected* is a dummy variable of all trading days indicating 1 if the violation announcement mentions a company that is undergoing investigation, otherwise 0 for no violation announcements. Obtained from CMA website. www.cma.gov.kw
Announcement_type	*Announcement_type* is a dummy variable of all events indicating 1 if the violation is penalized by a warning, a fine, or a suspension, otherwise 0 for announcements with investigation violations. Obtained from CMA website. www.cma.gov.kw

Table A1.2. Regression on CAR with Different Event Windows

Predictors	Event window interval			
	[-1;1]	[-3;3]	[-5;5]	[-7;7]
TA_{y-1}	-0.479***	-0.459*	-0.260	0.005
	(0.087)	(0.268)	(0.179)	(0.306)
ROA_{y-1}	-0.061	-0.095	-0.046	0.085
	(0.081)	(0.248)	(0.166)	(0.284)
TL_TA_{y-1}	0.014	0.692	-0.217	0.132
	(0.154)	(0.470)	(0.314)	(0.537)
$Volume_{k-1}$	-0.318**	0.660	-0.855***	-0.231
	(0.148)	(0.453)	(0.303)	(0.517)
Squared TA_{y-1}	0.019***	0.017	0.010	-0.002
	(0.004)	(0.012)	(0.008)	(0.013)
Squared ROA_{y-1}	0.070	-0.000	-0.013	-0.144
	(0.053)	(0.162)	(0.108)	(0.185)
Squared TL_TA_{y-1}	0.173	-0.676	0.373	-0.127
	(0.164)	(0.501)	(0.335)	(0.572)
Squared $Volume_{k-1}$	0.143*	-0.354	0.315**	0.002
	(0.073)	(0.223)	(0.149)	(0.255)
Announcement_type	0.009	-0.163*	-0.117**	-0.329***
	(0.028)	(0.087)	(0.058)	(0.099)
R^2	0.417	0.208	0.310	0.191
N	141	141	141	141

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 3-day to 15-day windows. The independent variables are Lag Total Assets, Lag ROA, LagTL_TA, Lag Volume, and *Fined*. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. The numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A1.3. Regression on CAR with Different Event Windows – Test for Interaction Effect

Predictors	Event window interval			
	[-1;1]	[-3;3]	[-5;5]	[-7;7]
TA_{y-1}	-0.009	-0.046	-0.022	-0.075*
	(0.014)	(0.040)	(0.027)	(0.044)
ROA_{y-1}	0.002	-0.141	-0.169*	-0.269*
	(0.045)	(0.133)	(0.088)	(0.147)
TL_TA_{y-1}	0.023	0.026	0.095	0.116
	(0.077)	(0.226)	(0.151)	(0.251)
$Volume_{t-1}$	-0.047	-0.087	-0.400***	-0.274*
	(0.049)	(0.144)	(0.096)	(0.160)
Fined	0.664***	0.034	-0.214	-1.363**
	(0.193)	(0.567)	(0.377)	(0.627)
TA_{y-1}*Fined*	-0.053***	-0.028	-0.023	0.075
	(0.018)	(0.054)	(0.036)	(0.059)
ROA_{y-1}*Fined*	0.049	0.149	0.145	0.245
	(0.057)	(0.167)	(0.111)	(0.185)
TL_TA_{y-1}*Fined*	0.142	0.038	-0.026	-0.089
	(0.101)	(0.299)	(0.199)	(0.330)
$Volume_{t-1}$*Fined*	-0.112	0.047	0.265*	0.104
	(0.071)	(0.209)	(0.139)	(0.232)
R^2	0.348	0.178	0.291	0.213
N	141	141	141	141

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 3-day to 15-day windows. The independent variables are Lag Total Assets, Lag ROA, LagTL_TA, Lag Volume, as well as their interaction with *Announcement_type* variable, and *Announcement_type*. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. The numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A1.4. Regression on CAV with Different Event Windows

Predictors	Event window interval			
	[-1;1]	[-3;3]	[-5;5]	[-7;7]
TA_{y-1}	-0.038	-0.094*	-0.140*	-0.215**
	(0.031)	(0.050)	(0.077)	(0.092)
ROA_{y-1}	0.050*	0.075	0.060	0.008
	(0.028)	(0.047)	(0.072)	(0.085)
TL_TA_{y-1}	-0.053	-0.064	-0.068	-0.405**
	(0.055)	(0.090)	(0.138)	(0.165)
$Volume_{k-1}$	-0.058	-0.025	-0.279**	-0.571***
	(0.052)	(0.085)	(0.131)	(0.156)
Squared TA_{y-1}	0.001	0.003	0.005	0.008**
	(0.001)	(0.002)	(0.003)	(0.004)
Squared ROA_{y-1}	-0.033*	-0.047	-0.046	-0.012
	(0.018)	(0.031)	(0.047)	(0.056)
Squared TL_TA_{y-1}	0.128**	0.153	0.182	0.580***
	(0.058)	(0.096)	(0.148)	(0.176)
Squared $Volume_{k-1}$	0.027	0.014	0.111*	0.234***
	(0.025)	(0.042)	(0.064)	(0.077)
Announcement_type	-0.020**	-0.030*	-0.032	-0.021
	(0.010)	(0.016)	(0.025)	(0.030)
R^2	0.333	0.246	0.268	0.386
N	141	141	141	141

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 3-day to 15-day windows. The independent variables are Lag Total Assets, Lag ROA, LagTL_TA, Lag Volume, and *Announcement_type*. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. The numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A1.5. Regression on CAV with Different Event Windows–- Test for Interaction Effect

Predictors	Event window interval			
	[-1;1]	[-3;3]	[-5;5]	[-7;7]
TA_{y-1}	-0.013***	-0.013*	-0.020*	-0.038***
	(0.005)	(0.008)	(0.011)	(0.014)
ROA_{y-1}	-0.004	-0.022	-0.057	-0.050
	(0.015)	(0.025)	(0.038)	(0.048)
TL_TA_{y-1}	0.078***	0.052	0.023	0.038
	(0.026)	(0.043)	(0.065)	(0.082)
$Volume_{t-1}$	-0.007	-0.022	-0.090**	-0.105**
	(0.017)	(0.027)	(0.041)	(0.052)
Announcement_type	-0.037	0.016	-0.103	-0.215
	(0.066)	(0.107)	(0.162)	(0.205)
TA_{y-1}**Announcement_type*	0.004	-0.008	-0.001	0.022
	(0.006)	(0.010)	(0.015)	(0.019)
ROA_{y-1}**Announcement_type*	0.007	0.046	0.071	0.029
	(0.019)	(0.031)	(0.048)	(0.061)
TL_TA_{y-1}**Announcement_type*	-0.016	0.044	0.124	0.108
	(0.035)	(0.056)	(0.086)	(0.109)
$Volume_{t-1}$**Announcement_type*	-0.020	0.008	0.004	-0.099
	(0.024)	(0.039)	(0.060)	(0.076)
R^2	0.286	0.219	0.250	0.292
N	141	141	141	141

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 3-day to 15-day windows. The independent variables are Lag Total Assets, Lag ROA, LagTL_TA, Lag Volume, as well as their interaction with *Announcement_type* variables, and *Announcement_type*. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. The numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Chapter 2. Financial News Sentiments and Stock Performance[2]

2.1 Introduction

The securities market is an environment where information is in high demand, and trading is driven by information. An efficient stock market exists when all the relevant information available on the market is incorporated into stock value. Nevertheless, in a stock market characterised by inadequate information, the news media is regarded as an important mechanism that helps investors to acquire information. By releasing timely information, the media (e.g., newspapers) enables investors to determine a firm's fundamental value, particularly when firm disclosures are scant.

When investors recognise a company that appears in the news media, this news can affect their trading behaviour and, subsequently, the stock market. Johnson et al. (2005) investigates publications in the business press that rate US corporations' boards of directors and they conclude that both favourable and unfavourable ratings are significantly associated with positive abnormal returns. Chan (2003) finds that, following pessimistic news in relation to a firm, stocks display a negative drift for up to one year, while stocks linked with optimistic news experience less drift. In addition to headline news, general media coverage also affects stock returns. The returns of stocks without media exposure are higher than those with media exposure (Fang and Peress, 2009). Moreover, individual investors trade more aggressively on stale news and earn significant returns on such days (Tetlock, 2011).

Recently, a growing strand of literature has paid attention to the sentiment analysis of media content and its effect on the capital market. For example, Carretta et al. (2011) analyse how the mass media interacts with the stock market, focusing on the influence that the content of the news and the tone of communication have on abnormal stock returns. They find that both the content (optimistic and pessimistic) and the communication tone of media coverage can impact the behaviour of investors. Garcia (2013) investigates the association between news article sentiment and asset prices by exploring the impact of the media content on stock returns. A high trading volume occurs on days with particularly negative or positive media

[2] In this chapter, we use material that has been submitted to the University of Birmingham for the research proposal of the Advanced Research Methods module.

news. Moreover, Narayan and Bannigidadmath (2015) and Heston and Sinha (2017) indicate that the tone of the news can be used to predict returns on stock.

Given the significant effect of the media in capital markets, this study aims to contribute to this strand of research by examining how news articles about firms influence stock performance in the context of an emerging market, particularly the Kuwaiti stock market. Specifically, I address the following research questions: Do news articles affect stock returns? Do the sentiments of news articles have a significant effect on stock performance indicators?

Kuwait's stock market offers an interesting and unique empirical setting for the purpose of this study, not only due to the shortage of previous studies conducted in this setting, but also because of the specific characteristic of it being an emerging market. Emerging markets are small, and they contain informational imperfections. The stock prices in these markets are likely to be noisy because there are fewer trades taking place and limited reporting requirements, and the information is less up to date than in a developed market (Buckberg, 1995). In this context, news articles could be a vital mechanism for disseminating information to investors. Therefore, understanding the impact of financial news on stock returns is essential as, if the information in news articles is useful to investors, it may affect their trading behaviour and, subsequently, the return on stocks (Wu and Lin, 2017). Moreover, Kuwait is an appropriate location for this study as Kuwaiti newspapers can be freely accessed online, reaching a relatively large number of readers.

The empirical analysis is conducted on a comprehensive dataset covering the period between 2014 and 2019 for 83 listed firms in Kuwait. The sample data contain the firms' fundamental information, their daily trading data, and news story sentiments. All of these datasets were merged in order to create a unique and comprehensive panel dataset containing firm-level information and the sentiment of the financial news relating to the 83 firms listed in Kuwait. The firm fundamentals dataset contains firm-level fundamental information at an annual level (including total assets, total debt, and returns on total assets). The daily stock trading dataset contains the daily open/close, high/low, and volume traded data of the Boursa Kuwait stock index, and the stock of the 83 listed firms. These two datasets were compiled using data from the Thomson Reuters EIKON Datastream.

The third dataset includes sentiment scores for news articles published in the Arab Times newspaper. This was the first English newspaper in Kuwait and is the translated version of Kuwait's most printed Arabic newspaper (Al-Seyassah). Using Python, I collected the news articles that mentioned the listed firms in the finance and economic sections of the Arab Times newspaper. Due to the fact that a news article about a firm would often mention other firms in the same or a related sector, I only chose news articles that were primarily about a specific firm. To this end, I developed Python codes to collect 3,678 news articles in the period from 2015 to 2019 from the website: www.arabtimesonline.com. I then used sentiment analysis packages (i. e., TextBlob and Textstat) on Python to determine the polarity, subjectivity, and difficulty score of each news article.

Our baseline results suggest that news articles and their sentiments have a significant impact on stock performance indicators (i.e., returns and volume traded). Particularly, on days that the news articles are published, the stock return is significantly lower than on days without news articles. Regarding the impact of news sentiments, I find that the *Polarity score* has significant and positive effects on stock returns. This implies that the stock return is significantly higher on dates when news articles with a positive tone are published. Moreover, the *Difficulty score* also has a significantly positive impact on stock returns and volume. This indicates that news articles that use technical and complicated terms, which require readers to have a certain level of education to understand, may increase the stock returns and volume. Lastly, the *Subjectivity score* has a significant negative impact on stock returns and a significant positive effect on volume. This suggests that stock returns are significantly lower, and the trade volume is significantly higher on dates when news articles that contain more personal feelings and opinions are published.

In addition, employing the event study method, I construct cumulative abnormal returns (CAR) and cumulative abnormal volatility (CAV) for each news article. Regressing CAR and CAV on news sentiments scores and other control variables for different event windows, I find that news sentiments have significant effects on stock returns and volatility. Particularly, news with a more positive tone is associated with higher CARs. Similarly, a higher level of difficulty in news articles also leads to higher CARs. Meanwhile, a higher level of subjectivity in news articles reduces the cumulative abnormal returns across several event windows. Regarding the CAV, we find that the *Polarity score* has a significant and negative impact on volatility, suggesting that stock volatility is higher around the published date of news articles with a more negative tone.

The rest of this chapter is constructed as follows. Section 2 presents the literature review on the effect of news articles on the stock market and sentiment analysis in finance research. Section 3 discusses the hypothesis development. Section 4 describes the data, variables and econometrics model used in this study. Section 5 presents the empirical results and Section 6 contains the conclusion.

2.2 Literature review

2.2.1 The influence of media news on the stock market

2.2.1.1 The impact of news publishing event

News regarding macroeconomic and firm-specific factors can have a significant effect on the stock market. Positive news is likely to boost the market, while negative news tends to inhibit the growth of the market (Kauter et al., 2015). Engle and Ng (1993) report that news affects the stock market in an asymmetric way. They indicate that negative news has a greater impact on volatility than positive news. Furthermore, the overall state of the market also affects the association between news and market return. The reaction of investors to positive news in a 'bullish' market may be different to that of investors in a 'bearish' market (Kauter et al., 2015). These studies have clearly provided evidence for the relationship between news and capital markets.

Particularly, a number of researchers have studied how the financial market reacts to macroeconomic news. Pearce and Roley (1985) state that monetary information significantly influences stock prices. Specifically, money stock surprises have a strong impact on stock prices, whereas inflation surprises and discount rates have a weaker impact. Cornell (1983) studies how asset prices react to money supply announcements and also provides evidence supporting the idea that money growth affects stock returns. The conclusion of prior studies regarding monetary policy is confirmed by Flannery and Protopapadakis (2002), who investigate the effect that 17 macro series' announcements in the 1980–1996 period had on aggregate stock returns. More specifically, the authors show that six out of these 17 macro-factors were strong risk determinants affecting the stock market. Inflation (CPI and PPI) only influences the returns of market portfolios. Certain factors, including trade balance, the level of employment and unemployment, and housing starts, merely affect the returns' conditional volatility. Additionally, both the returns and conditional volatility are influenced by money aggregates (generally M1, or money supply, such as physical currency, demand deposits, traveller checks, and other checkable deposits.).

Moreover, other studies have referred to a correlation between reporting on unemployment problems and the price of stock. Boyd et al. (2005) investigated the way that the stock market reacts to unemployment announcement surprises that they considered to be newsworthy. They concluded that news on unemployment rates affects stock prices. These findings are further supported by McQueen and Roley (1993), who find that the stock price has a significant association with fundamental macroeconomic information related to inflation, industrial production, and unemployment rates. For instance, a rise in the rate of employment could be considered an optimistic signal when the economy recovers from a recession, but as a pessimistic signal when near a cyclical peak. McQueen and Roley further state that good news about macroeconomic factors increases stock values during a depressed economy and decreases stock values in a healthy economy. More recently, Birz and Lott Jr (2011) used a technique that chooses newspaper stories as a proxy for news, in order to estimate its effect on stock returns. They document that news about unemployment rates influences stock returns.

Alternatively, the other strand of literature also provides evidence of the influence that firm-specific information exerts on the stock market. Ryan and Taffler (2004) study show how information events influence changes in firm values, as well as trading volume. They show how reported corporate news events affect a considerable percentage of firms' price variations and the volume of trading on stocks. Lee (1992) analyses the intraday directional volume of traded stocks around the publishing dates of different kinds of earnings reports. The author states that, regardless of whether the news is good or bad, small traders purchase unusually large volumes in a determined period. On the other hand, to large traders, 'positive' ('negative') earnings information causes quick but intense purchasing (selling) imbalances. Woolridge and Snow (1990) examine how the stock market responds to public messages of a firm's investment decisions. They report that announcements on strategic investment have a significant effect on stock market valuations.

Traditionally, previous studies have investigated the influence of information events on the value brought to an equity owner by using the variation in stock price around those events.

Nonetheless, this viewpoint does not take into account any potential impact of investors' behavioural biases and how this affects their reaction to the information. To gain a more profound understanding of the factors affecting stock markets, certain researchers incorporate the results of finance behaviour into the literature on capital markets. They argue that 'investor sentiment', beliefs regarding future cash flows and investment risks that are not justified by fundamentals such as macro- or firm-specific factors but are associated with emotional reasoning, is a crucial factor affecting the capital market (Baker and Wurgler 2006; Kaplanski and Levy, 2010b). The impact of this noise trading on the equilibrium price is examined in the notable study of Dejong et al. (1990). High levels of sentiment result in investors overvaluing stocks, thus leading to an excessively positive valuation of future cash flows. By contrast, low levels of sentiment result in an undervaluation of stock (Baker and Wurgler, 2006).

2.2.1.2 The impact of news sentiment

Kaplanski and Levy (2010b) investigate sentiment and stock prices by examining the case of aviation disasters. Based on the hypothesis that an aviation disaster affects the mood of people, which adversely influences their decisions to invest in risky assets, they find that aviation disasters have a detrimental impact on stock values in a short period. Moreover, Mian and Sankaraguruswamy (2012) state that the extent to which the value of stocks is influenced by news varies with investor sentiment. They discover that, in a high sentiment period, stock prices react strongly to good news, and less so in a low sentiment period. Additionally, the response of the market to bad news in a high sentiment period is weaker than in low sentiment ones. Furthermore, sentiment in the context of bad news causes a significantly stronger effect on stock price sensitivity than in the context of good news.

The mass media can play a crucial role during such market noise. It could even be regarded as a key determinant of instability in the capital market, since it is an important source of information that both records and has an effect on public knowledge and people's opinions of firms. Initially, the media helps to diminish the problem of information asymmetry by providing additional information to stakeholders. Owing to their lack of direct experience with a company, some stakeholders rely on the media, which reports the evaluations of other information intermediaries, such as the government and rating agencies, and delivers a consolidated source of information (Deephouse, 2000). Therefore, the mass media can be regarded as providers of information on firm value due to their fulfilment of two criteria in the capital markets. First, they represent an information broker as they help to spread information in a passive way. Second, they are considered to be an active participant, whose comments enable investors to make more precise assessments of their investments (Carretta et al., 2011).

In addition, through either content or presentation style, the media can enrich information with new elements such as 'emotion' or 'suspense'. This procedure alters the information's originality, affecting investors' perceptions. It is certain that the media no longer transmits information in a neutral way, as shown in the abstract world of efficient markets, which subsequently leads to investors' irrational behaviour (Schuster, 2003). Merton (1987) outlines the potentially vital role of media in generating and maintaining speculative sentiment bubbles and fads among market participants, in which the capital market's risk is unnoticed. Additionally, even when no genuine news is provided by the mass media, it is still able to lessen informational frictions and to subsequently influence stock evaluations due to its ability to reach a broad population of investors (Fang and Peress, 2009). Moreover, despite reporting spectacular and exciting 'news', the media news does not only provide new information; information that is already known can be re-packaged by newspaper journalists. However, even if media stories present no new information, they may still have an effect (Tetlock, 2007; Tetlock, 2011).

A number of researchers have discovered the crucial role of media news in capital markets. Tetlock (2007) studies the impact of the media on the stock market by utilising the daily content from a popular Wall Street Journal column. The author classifies each column according to its degree of pessimism in relation to the stock market, and reports that downward pressure on market prices is forecasted by high levels of media pessimism. In addition, a remarkably high or low degree of media pessimism predicts a high volume of trading. These findings are supported by further research by Tetlock (2011) that examines the reaction of investors to old news. He concludes that individual investors trade aggressively on stale news, and stocks and less-informed investors experience a high return on days with old news.

In addition, Johnson et al. (2005) study the influence of the business press publications that rate US corporations' boards of directors on stockholder wealth. After controlling for market effects and confounding events, they find that both unfavourable and favourable ratings lead to significant positive abnormal returns. Furthermore, Antweiler and Frank (2004) examine the effect of stock message boards on the stock market. The authors present three main findings: 1) negative returns are forecasted by an optimistic shock on a message board posting; 2) the amount of message posting, as well as inconsistency among messages, assist the project trading volume; and 3) message posting supports forecast volatility both at daily frequencies and within the trading day.

Moreover, firm-specific news in the media makes a difference to stock market reactions. Hamilton (1993) states that stockholders in companies reporting Toxic Release Inventory (TRI) pollution data experience significant adverse abnormal returns when they first release such information. Chan (2003) investigates the reaction of stock values to news headlines about an individual company by comparing monthly returns following public news with stock that has similar returns, but without being associated with any recognisable public news. Chan explores the variation between the two sets and finds significant drifts after negative news. Furthermore, investors seem to react slowly to this news.

Different from Chan (2003), who focuses on headline news, Fang and Peress (2009) count articles (not necessarily headlines) in newspapers attracting a high number of readers and concentrate on media coverage to study how the media coverage affects expected stock returns. They discover that the stock of firms appearing in the news media has lower returns than those without media coverage. Their findings are also robust among small-sized stocks and stocks that features relatively higher individual ownership than others, a low analyst following, and high idiosyncratic volatility.

Although the previous studies provide important evidence for the theory that news significantly affects stock markets, only a handful of recent studies take into account how the communication of the news influences stocks. Researchers of financial economics have investigated traditional quantitative factors and their effects on the evaluation of stock, but it is argued that information presented by a quantitative factor alone may not be sufficient to clarify the stock price movement (Feldman et al., 2009). Therefore, quantifying text in order to investigate how the stock market is affected by news is essential.

2.2.2 Sentiment analysis in finance research

2.2.2.1 Sentiment analysis methods

Sentiment analysis is a popular methodology used to examine the effect of news text. It focuses on the examination of direction-based text, and it attempts to examine if the text is objective or subjective, and if the subjective parts comprise positive or negative opinions. There are two approaches that are employed in autodetection and sentiment analysis: lexicon-based and machine learning approaches.

First, lexicon-based approaches determine the orientation of textual content by considering it as a group of words and relating the words to the semantic orientation of each of those words. Specifically, the sentiment value of each word within the textual content is identified by a dictionary and a combination function is then used to predict the sentiment of the textual content as a whole. For instance, while 'wonderful' demonstrates a positive point of view, 'detrimental' is considered to be a negative sentiment word. There are two ways to build subjectivity lexicons: manually (Mohammad and Turney, 2010) and semi-automatically (Ding et al., 2008; Esuli and Sebastiani, 2006). Most studies concentrate on English, however, less spoken languages, such as Dutch, can also use sentiment lexicons (DeSmedt and Daelemans, 2012; Jijkoun and Hofmann, 2009).

Second, the machine learning method takes advantage of categorisation algorithms based on an identified dataset (Pang et al., 2002). This dataset could be created through extraction from prevailing sources, such as user assessments determined by a star rating (Dave et al., 2003; Pang et al., 2002; Turney, 2002) or constructed manually using explanatory notes (Boldrini et al., 2012; Wiebe et al., 2005). These two methods mentioned above are used in sentiment analysis on a number of levels, such as on the document (Pang et al., 2002), paragraph (O'Hare et al., 2009), or word level (Hatzivassiloglou and McKeown, 1997).

2.2.2.2 The use of sentiment analysis in financial markets

In the field of finance, there has been extensive use of sentiment analysis within the past decade. Nassirtoussi et al. (2014) show how the predictability of capital markets can be determined by the quality of the sentiment in the information published on social media and online news. This study is further supported by the research of Nassirtoussi et al. (2015), which analyses breaking news headlines to forecast currency-pair movement in the foreign exchange market (FOREX) within a day. By using the text mining method, they find the predictive effect of news articles on the FOREX market.

In the same vein, recognising that microblogging forums (e.g., Twitter) have developed into popular online platforms that enable individuals to share information on stocks, Sprenger et al. (2014) examine how microblog content on stock information affects the stock market.

They explore how stock returns, trading volume, and volatility are influenced by tweet sentiment, message volume, and disagreement, respectively. More specifically, it is indicated that quality and content are more influential than quantity, because the relationship between bullishness and returns is stronger than its relationship with message volume.

In addition to social media and online news, the existing literature indicates that the information in firm reports also affects the stock market. The first type of information identified as being important is the management discussion and analysis (MN&A) in 10-Q reports, which are reports on performance that all public companies must submit to the US Securities and Exchange Commission (SEC) on a quarterly basis. The second source of important information are the 10-K reports, another report that the SEC requires firms to provide. It is an annual report that provides an overview of a company's financial outcomes. Feldman et al. (2009) analyse whether these reports contain information besides financial measures that could potentially influence the stock market. Their findings show that around the SEC filing date, the change in tone of the MD&A section significantly impacts the market within a short window of time. Changes in management tone have a significant effect on portfolio drift returns during the 2-day window after the SEC filing date and during the 1-day window after the following quarter's initial announcement on earnings.

Additionally, Loughran and McDonald (2011) study whether the stock market is affected by the tone expressed in corporate 10-K reports. By constructing a unique list of negative words to measure the tone of financial reports instead of employing the widely-used list of negative words provided by the Harvard Dictionary, they document a significant relationship between the report tones and returns on filing dates, volume of trades, the subsequent volatility of returns and standardised earnings surprises. Similarly, Jegadeesh and Wu (2013) provide a new method to analyse content and to quantify a document's tone. They examine the reaction of the market to their measure of the 10-K report tones for both negative and positive words. For both positive and negative words, they discover that the tone in 10-K reports has an effect on stock returns for up to two weeks. The generalizability of this method is analysed in a different economic setting when Jegadeesh and Wu (2013) investigate the effect that the tone of IPO (Initial Public Offering) prospectuses exerts on IPO undervaluation. They report that the tone is adversely associated with undervaluation, as predicted by a number of models in the literature.

Markets always crave new information and constantly want updates on the information. By providing new information, media (e. g., television and social media) can affect stock prices; it is considered that financial news articles are trustworthy information providers (Schumaker et al., 2012).

Many studies employing information retrieval approaches have investigated the use of textual analysis for news articles. When analysing a financial article, a number of these types of methodologies can be useful. They can help to investigate the impact of the article on markets, through, for example, the textual representation, style of writing, or sentiment of the writer. However, sentiment analysis is a conventional technique that is used to examine the effect that financial news articles have on the stock market. Tetlock et al. (2008) study whether quantifying language can help to forecast the accounting incomes of companies and the return on stocks. The study provides a number of findings. First, low firm earnings are predicted by the proportion of negative words in news stories about firms. Second, there is a brief underreaction of firm stock value to information rooted in negative words. Third, the ability of negative words to forecast the earnings and returns is most accurate for the news that concentrates on fundamentals.

Carretta et al. (2011) investigate the way that stock markets react to press news on corporate governance. Their study presents findings consistent with previous studies, indicating that press news exerts a significant impact on investor expectations about the future value of firms. More specifically, the news content, as well as the communication tone, significantly affects investor trading behaviour, and thereby stock returns.

Boudoukh et al. (2012) examine the impact that news has on stock prices by using advanced textual analysis. This enables them to determine which news is relevant by utilising categories and tone in a more efficient way than is done in previous studies. The authors find that the degree of stock volatility on no-news days is similar to that on unidentified news days, which is in line with the view that there is no difference in the effect of the amount or importance of information arriving during these days. Adversely, the volatility level of stock values on a day with news is more than twice the level observed on other days. Furthermore, when examining article tone, the authors find that different topics affect stock price differently.

Garcia (2013) investigates the impact of sentiment upon the value of assets and reveals that media content significantly influences the returns of the Dow Jones Industrial Average (DJIA) during times of adversity. Additionally, they report that media content issued on a particular afternoon is strongly correlated with the stock returns on that day. This effect is even stronger during weekends. More specifically, news that is released on Saturdays and Sundays has a significant effect on Monday's stock returns. Finally, media content is also found to affect trading volume. Days with positive or negative media content have high volumes of trading.

Ammann et al. (2014) examine whether the aggregate return on stocks can be predicted by language quantification. In general, their results show that newspapers contain important information that is useful for forecasting the development of the stock market in the future. Word-count indicators have a significant association with the return on stocks. Moreover, newspaper articles have provided a more precise explanation of the trend in future stock markets than traditional forecaster variables. Notably, the predictive ability of quantitative newspaper language has improved over time.

In the same vein, Narayan and Bannigidadmath (2015) examine whether returns on Islamic and non-Islamic stocks are predicted differently by financial news. Their findings show that, while returns on these two types of stock are forecasted by both positive and negative words contained in news, the returns are more influenced by positive words than by negative ones. In addition, only certain stocks experience a decline in the shock to returns originating from financial news. The profit of mean-variance investors when they invest in Islamic stocks is higher than the profit that stems from corresponding non-Islamic stocks.

Ahmad et al. (2015) investigate whether the tone of firm-specific media news has a relationship with stock returns. Employing vector autoregressive models, they demonstrate that the negative tone of media news results in lower returns on stock on the next day. Moreover, their findings indicate that the tone of media news in relation to a particular firm consists of value-relevant information about that firm.

Heston and Sinha (2017) examine whether the return on stocks could be forecasted using news stories. Utilising the Thomson Reuters neural network to measure sentiment, they find that news released on a daily basis is capable of predicting the return on stocks for several days. Nonetheless, news released on a weekly basis possesses the ability to forecast stock returns over a longer period of time, up to three months. Furthermore, the market reacts to good news swiftly, whereas bad news experiences a postponed response. Surrounding the day of an earnings announcement, there is a significant delay in the market's reaction to news.

Boudoukh et al. (2018) investigate the influence that firm-specific news exerts on firms' stock. They employ the approach of textual analysis used in the existing literature, however, their focus is quite different. They do not identify the sentiment of the salient news, but rather they use textual analysis to detect events related to firms, for example, the introduction of new products, litigation, analyst coverage, the disclosure of financial outcomes, or mergers. Their findings indicate that public news about a specific firm is a meaningful explanation for its stock return variance.

2.3 Hypothesis development

2.3.1 Subjectivity and stock return

Subjective information provided by other investors, experts, or decision makers on social networks or in newspaper reports could influence the investment decisions of market participants (Figlewski, 1979) and, subsequently, the returns of stocks. Intermediaries (e.g., analysts, the business press, financial advisors) provide information to investors, delivering value-relevant information related to a stock's potential growth. Moreover, Bartov (2017) finds that the internet advancement allows investors to take advantage of peer-to-peer information through posts on internet forums (e.g., Yahoo! Finance) or social media platforms, such as Twitter and Facebook.

Stickel (1995) and Womack (1996), who study the impact of security analysts on stocks, suggest that positive (negative) adjustments in the recommendations of an individual analyst lead to higher (lower) returns on stocks at the point that their statements are released. More recently, Jiang et al. (2014) also investigated the Chinese stock market's reaction to analyst recommendation revisions. They report a significant relationship between market reactions, which are measured by abnormal stock returns and analyst recommendation revisions (both upgrades and downgrades). More specifically, the market reaction is weaker in relation to downgrades than to upgrades.

Another strand of literature analysing posts in internet financial forums also shows that stock returns are affected by these postings. Antweiler and Frank (2004) investigate the impact that stock message boards have on the stock market by examining postings on Yahoo! Finance and RagingBull. Their findings indicate that stock messages have a significant influence on the return on stocks. Furthermore, Tumarkin and Whitelaw (2001) study whether internet message board activity on RagingBull.com, a popular discussion forum, is associated with abnormal returns on stocks and the volume of trading. It is found that, on days when there is abnormally high message activity, there is a correlation between changes in investor opinions and abnormal returns.

Regarding investor opinions posted on social networks, Sul et al. (2017) investigate whether emotional content social media, particularly Twitter, can be utilised to predict returns on stocks. The author states that the sentiment (pessimistic and optimistic) expressed in users' Twitter postings about a specific firm significantly influences the return on stocks the next day, 10 days later, and 20 days later. This study is further supported by Bartov et al. (2018), who examine whether the opinions within individuals' tweets directly before the earnings announcement of a company can be used to predict its stock return. They indicate that the tweets of individuals successfully forecast a company's stock return. The research of Siganos et al. (2014) analyses the impact of the daily sentiment of Facebook status updates on investor trading behaviour in 20 international markets. They find that sentiment is positively associated with the return on stocks. Notably, sentiment on Sundays influences stock returns on Mondays.

The foregoing discussions lead me to my first hypothesis as follows:

H1: The subjectivity in financial news exerts a significant influence on the performance of stocks.

2.3.2 Polarity and stock return

Previous studies analysing the tone of qualitative information suggest that a negative (positive) tone reflects negative (positive) information relating to a firm's performance that has not been incorporated into the stock price, which could therefore lead to lower (higher) stock returns. For example, Sadique et al. (2008) examine the tone expressed in earning reports by using the number of times that positive and negative words appear in the reports as a measure of tone. They find that a negative tone decreases the return on stocks, whereas a positive tone leads to an increase in stock returns. Loughran and McDonald (2011), who investigate the tone of 10-K reports, suggest that a stronger negative tone results in lower returns.

In addition to firm reports, a broad stream of research, which utilises different text corpora and text analysis approaches, shows that the tone expressed in media news has a significant influence on stock returns (Heston and Sinha, 2015; Chen et al., 2014; Ferguson et al., 2013). Tetlock (2007) finds that the media tone is connected to investor sentiment and that a pessimistic tone is linked with lower returns. Tetlock et al. (2008) report that news stories' negative words convey significant qualitative information that is not presented in firm fundamentals and stock prices. They find that a negative tone in news stories relating to a specific company forecast lowers the returns on that company's stock on the next day of trading. This result is supported by Ahmad et al. (2016), who analyse the tone of news articles related to 20 large-sized US companies. They find that an increase in negative media tone results in a decrease in the return on stocks one day later.

Dzielinski (2011) examines whether there is a difference between the return on stocks on days with news and the average daily returns on stocks of representative US companies. The author indicates that returns on days with good (bad) news are higher (lower) than the average returns. Ferguson et al. (2015) state that an optimistic tone expressed in news stories about a particular firm significantly predicts greater returns, whereas a pessimistic tone forecasts lower returns in the following period of trading. Likewise, Narayan and Bannigidadmath (2015) find that negative news leads to lower returns for all stock, irrespective of whether they are conventional or Islamic stocks. The recent study of Heston and Sinha (2017) further confirms the results of previous studies by showing that daily news enables the prediction of stock returns. Positive news stories increase stock returns rapidly, while negative news stories experience a delayed reaction.

In formulating my second hypothesis, I follow the conventional view of the impact that the negative (positive) tone of news has on the return on stocks.

H2: The negative (positive) tone in financial news exerts a negative (positive) influence on the performance of stocks.

2.3.3 Difficulty and stock returns

The difficulty of information (a difficult articles being one that uses technical and complicated terms, which require readers to have a certain level of education to understand) might affect stock returns due to its impact on investor decisions (De Fraco et al., 2015). Kennekamp (2012), who analyses the reaction of investors to firm disclosure difficulty, reports that small investors have a strong response to the disclosures which are easier to comprehend. Hence, changes in investors' valuation assessments are more optimistic for positive news and more pessimistic for negative news. De Fraco et al. (2015) examine the need for the technical information published in analysts' reports and they state that a higher level of difficulty suggests more accurate information signals, which could be useful to investors. Therefore, a higher report difficulty level leads to a rise in the volume of trading. In the same vein, Boubaker et al. (2019) provide evidence that corporate annual reports with a low difficulty score negatively affect investors' information-processing and analysing ability. This subsequently reduces the trading motivation of investors.

Numerous studies have shown that the difficulty level of information significantly affects the stock market. For example, the research of Hsieh et al. (2016) investigates how markets respond to analysts' reports on firms in a high-tech industry. They find that the equity market responds positively to analysts' reports that have a higher level of difficulty. More specifically, the results of this research further indicate that the return on stocks at the time that an analyst report is released is more positive for companies possessing analyst reports with a high level of difficulty. Kim et al. (2019) finds that 10-K reports with a low difficulty level led to a greater risk of a stock price crash as managers are able to conceal negative information through difficult-to-read annual reports.

The above arguments lead me to my third hypothesis:

H3: The difficulty degree of financial news exerts a positive and significant influence on the performance of stocks.

2.4 Data description

2.4.1 Data collection

The sample comprises all the Kuwaiti listed companies on Boursa Kuwait (excluding the auction market securities) over the period of six years from 2014 to 2019. The data are taken from three main datasets. The first dataset has the open/close, high/low, and volume traded data of the Boursa Kuwait stock index and the stock of 83 firms at a daily level. The second dataset contains firm-level fundamental information (such as total assets, total debt, returns on total assets) at an annual level. These two datasets are comprised of data from the Thomson Reuters EIKON Datastream. The third dataset relates to financial news. The data collected are news articles by firm from the economic articles section of the Arab Times newspaper. There are three main reasons for choosing the Arab Times newspaper for this research. The first reason is the data availability. The news articles archive of the Arab Times newspaper is available online for the five years period from 2015 to 2019. Second, this was the first English newspaper to be established in Kuwait, as well as being the translated version of Kuwait's most printed Arabic newspaper (Al-Seyassah). Finally, the Arab Times has a high circulation compared to other newspapers. In 2001, the circulation of the Arab Times newspaper was reported to be 48,000, in comparison with the Kuwait Times, which reports 28,000 circulations for the same period. In a more recent report, in 2017, the circulation of Arab Times was reported to be 55,000.

In order to collect news articles by firm, I systematically searched for articles published in newspapers which refer to the companies in the sample. Due to the fact that a news article about a firm may mention other firms in the same or related sector, I only chose news articles whose contents were primarily about a specific firm. To this end, I developed Python codes to collect 3,678 news articles in the period from 2015 to 2019 from the website: www.arabtimesonline.com. I then used the sentiment analysis package (i.e., TextBlob and Textstat) on Python to determine the polarity, subjectivity, and difficulty score of each news article, which will be discussed in more detail in the next section.

All the datasets were merged based on each company's unique name in order to create a unique and comprehensive panel dataset containing firm-level information and the sentiment of the financial news of 83 listed firms in Kuwait.

As a first attempt, after collecting the data. I found that there are outliers in the data, i.e., total assets, the return on assets ratio, and debt to capital ratio. Using Stata code "winsor" I cleaned the data by replacing the values exceeding the 99th percentile with the value of the 99th percentile for the collected variables. In a similar manner, values below the 1st percentile are replaced with the value of the 1st percentile.

2.4.2 Sentiment analysis

The Python packages that I used to extract the sentiments of financial news are TextBlob and Textstat, which are popular Python libraries used to process textual data. Running sentiment analysis on the text, TextBlob provides the scores of the polarity and subjectivity level, while Textstat produces the score of the difficulty level.

Regarding the scores produced by TextBlob, the polarity score refers to a float whose value is within the range [-1,1], where 0 indicates a neutral tone, 1 indicates the most positive tone and -1 indicates the most negative tone. Subjectivity generally implies a personal point of view, feelings, or judgement, while objectivity implies neutral information based on facts. The value of the subjectivity score is within the range [0,1], where 0 is the most objective and 1 is the most subjective.

To measure the difficulty level of financial news, I used Textstat, a Python package that helps to identify the difficulty, complication and grade level required to understand a particular corpus. There are two indexes that can be used to determine the difficulty level. The first index is the Dale-Chall Readability Score. The classification of each score range is shown in the following table:

Score	**Understood by**
4.9 or lower	Student in grade 4 or lower
5.0–5.9	Student in grade five or six
6.0–6.9	Student in grade seven or eight
7.0–7.9	Student in grade nine or ten
8.0–8.9	Student in grade eleven or twelve
9.0–9.9	Student in grade thirteen to college student

The second index is the Flesch Reading Ease Score. The maximum score is 100 and the lowest score is 0. There are seven score ranges that help to determine the difficulty level in the text: [90–100], [80–89], [70–79], [60–69], [50–59], [30–49], and [0–29]. These identify the difficulty levels of Very Easy, Easy, Fairly Easy, Standard, Fairly Difficult, Difficult, and Very Confusing, respectively. To save space, I only present the results of the Dale-Chall

Readability Score in this chapter. The results when using the Flesch Reading Ease Score generate similar implications and are available upon request.

2.4.3 Stock performance indicators

In this study, the trading volume ($\text{Volume Traded}_{i,t}$) is computed as the logarithm of the number of shares of company *i* traded on day *t*. Following Parkinson (1980), I also compute the indicator of the stock volatility level for company *i* on day *t* using the intra-day high/low prices as below.

$$\text{Stock Volatility}_{i,t} = \ln\,(High_{i,t} - Low_{i,t})/(2\sqrt{ln2})$$

Furthermore, I use the log of the daily returns to compute the abnormal returns. In particular, the abnormal returns are calculated by subtracting the expected return when no event (no article related to the firm published) occurs from the realised return.

$$A_{i,t} = R_{i,t} - E(R_{i,t})\ (1)$$

where $A_{i,t}$ is the abnormal returns of stock *i* on day *t* based on an event window of one day. $R_{i,t}$ is the realised return of stock *i* on day *t*. To estimate the expected returns $E(R_{i,t})$, I use the market model to calculate the returns using the trading data from 220 days prior to the news article publication day (event day).

Cumulative abnormal returns in the event window $[t_1, t_2]$ are calculated by:

$$CAR_{i,t} = \sum_{t_2}^{t_1} A_{i,t}\ \ (2)$$

In this study, I investigate the impact of the financial news sentiments on stock market performance, which can only have impact after the publication date of the article (the event date). Therefore, I calculate the cumulative abnormal returns (CAR) over the event windows of [0,1], [0,3], [0,5], and [0,7]. Therefore, if there is an event within seven days of another event of the same firm, both will be dropped. Employing the same event study method to compute the cumulative abnormal returns, I also estimate the cumulative abnormal volatility (CAV) over the same event windows.

[Table 2.1]

Table 2.1 presents the average, standard deviation, and each percentile of the CAR and CAV distributions for different event windows across 1,204 events within the sample. Overall, the mean values of CAR range between 0.2% and 0.3%, and the median is close to 0. The top 25% of the returns range from 0.5% to 2.1% and the lowest 25% lies between -0.5% and -2.3% across different windows. The 5th percentile of CARs ranges from -5.3% to -13 % depending on the event windows interval. On the other hand, the 95th percentile of CARs ranges from 7.7% to 14.5% depending on the event windows interval. Additionally, the larger the window interval, the larger the standard deviation of CAR.

Regarding the CAV, the medians values across different event windows are negative ranging from -0.3% to -0.1%. The lowest 25% varying between the values of -0.8% and -0.4%, and the top 25% being around 0.3%. The 5th percentile of CAVs range from -2% to -1 % depending on the event windows interval. On the other hand, the 95th percentile of CAVs range from 3% to 1% depending on the event windows interval. Unlike CAR, the larger the window interval, the smaller the CAV standard deviation.

2.4.4 Sample overview

Table 2.2 presents the descriptive statistics of all the variables. As can be seen from Table 2.2, the logarithm of firm stock returns and the FTSE 15 index return have the same mean of 0 and a standard deviation of 0.06 and 0.01, respectively. Meanwhile, the mean of stock volatility is 0.02 with a standard deviation of 0.07; and the mean of the FTSE 15 volatility is 0.01 with a standard deviation of 0.01.

On average, a firm listed on Boursa Kuwait has a volume traded per day of around 1.2 million stocks. Firms in the top 5% of traded stocks have volume traded per day of nearly 5.5 million stocks, while firms in the bottom 5% of traded stocks have volume traded per day of 500 stocks. The median firm has a volume traded of around 203,000 shares per day, suggesting that half of the firms in my dataset trade less than 203,000 shares per day.

With regard to firm characteristics, Table 2.2 shows that the average total assets across all firms is around 774 million KWD, and the standard deviation is nearly 2,830. Firms in the top 5% of total assets have a value of around 3.8 billion KWD, and the firms in the bottom 5% of total assets have a value of around 15 million KWD.

Furthermore, the means of ROA (return on assets) and Debt to Capital are 24% and 27%, respectively. The top 5% most profitable firms have a ROA of 99%, while the least profitable firm has 0% returns. As for the highest and lowest 5% Debt to Capital ratios, the values are 71% and 0%, respectively.

In terms of the sentiment scores of the news articles, the average score of *Polarity* is 0.05 and the standard deviation is 0.04, suggesting that the news articles usually have a positive rather than a negative tone. *Subjectivity* has the average value of 0.28 and a standard deviation of 0.05, implying that the news articles in the sample tend to be more objective than subjective. The mean and standard deviation of *Difficulty* are 3.94 and 0.36, respectively. This means that most of the news articles are very easy to understand.

[Table 2.2]

Moreover, to understand the general correlations between market index, firm stock, and news article features, the Pearson's correlation test is employed. The test results are presented in Table 2.3 below.

Table 2.3 describes the correlation between the various measures of market data variables and text sentiment variables. In general, FTSE 15 indexes are found to be positively correlated with stock characteristics. The table shows that the FTSE 15 return has a positive correlation with stock returns, with a correlation coefficient of 0.05. This suggests that a firm's stock returns tend to move in the same direction as the stock index returns. Similarly, FTSE 15 volatility and stock volatility are positively correlated with a correlation coefficient of 0.028, which implies that the stock volatility and market volatility share the same trends.

Regarding the correlation between stock performance (i.e., stock return and stock volatility) and text sentiments, the results are diverse. Firstly, there is a positive correlation between stock returns and text sentiment variables. *Stock return* is positively correlated with *Polarity*, *Subjectivity*, and *Difficulty*, with correlation coefficients of 0.004, 0.002, and 0.001, respectively. In contrast, stock *Volatility* is negatively correlated with the same text sentiment variables, with a correlation coefficient of -0.029 for *Polarity* and -0.035 for both *Subjectivity* and *Difficulty*. This indicates that stock returns move in the same direction as text sentiment, while *Volatility* moves in the opposite direction, meaning that when sentiments are positive, returns increase and the volatility level decreases, and vice versa. This implies that the sentiments of the news mentioning a firm have potential impacts on the firm's stock performance, which is consistent with my expectation and hypotheses presented in section 2.3.

[Table 2.3]

2.5 Impact of news article sentiments

2.5.1 News article features and stock performance

In order to examine the main research question on the impact of financial news sentiments on stock performance, I employ the panel data multi-way fixed-effect model to regress the stock returns, volatility and volume on the sentiment of financial news, as well as market index returns (*FTSE15 market index returns*), respectively. The model is specified as follows:

$$Stock\ Performance_{i,t} = \beta_1 \text{FTSE15 Index Return}_t + \beta_2 \text{Stock Return}_{i,t-1} +$$

$$+ \beta_3 Volume_{i,t-1} + \beta_4 Volatility_{i,t-1} + \beta_5 News_{i,t} + \beta_6 News * Word\ Count_{i,t} +$$

$$+\beta_7 News{*}Polarity_{i,t} + \beta_8 News{*}Subjectivity_{i,t} + \beta_9 News{*}Difficulty_{i,t} + \psi_i + \tau_t + \varepsilon^3_{i,t} \ (3)$$

where $Stock\ Performance_{i,t}$ is the mean-adjusted return, market-model return, volatility, or volume of stock *i* on day *t*. The mean-adjusted return is calculated based on a 220-day estimation period starting 10 days prior to the relevant event day. I employ 220-day estimation period to estimate abnormal returns since this is the most popular approach in the existing literature (see e.g., Caton et al. 2003; Sorescu et al. 2017; Fan et al. 2020). Meanwhile, the market-model return is computed using the Kuwait FTSE 15 index return. $News_{i,t}$ is a dummy variable that equals 1 if there is news about firm *i* on day *t,* and 0 otherwise. *Word count* is the number of words included in the news article. *Polarity*, *Subjectivity*, and *Difficulty* are scores that measure news article sentiments produced by TexBlob and Textstat. $\psi_i$and τ_t are firm and time-fixed effects. $\varepsilon^1_{i,t}$ is the error term.

[Table 2.4]

The results in Table 2.4 show that all the explanatory factors have some meaningful predictive power. First, the higher the stock return on the previous trading day, the lower the mean-adjusted return and volatility level, and the higher the volume traded. This implies that, on days after a bear market, the returns and volatility decrease, whereas the trading volume increases. This result is consistent with the finding of De Jong et al. (1992) in that successive returns on individual stocks are often negatively correlated. This relationship is possibly due to measurement errors or infrequent trading.

Second, the higher the volume on the previous trading day, the higher the stock returns and volume traded, and the lower the volatility level. This indicates that on days after a high volume of trading, the market return and volume increase, while volatility is relatively lower. For example, a study by Darrat et al. (2007) examined the relationship between trading volume and the volatility of large and small firms, including and excluding news. They concluded that, on days when investors trade excessively, volatility is higher the day after.

Third, the higher the stock volatility on the previous trading day, the lower the mean-adjusted return, market-model return, and volume traded, and the higher the volatility. This suggests that returns and volume are lower the day after a highly volatile market, but the volatility lessens. Connolly (1989) studied the weekend effect in US markets and reported that the effect on stock returns and volatility is significant and negative.

Fourth, news has a significant and negative impact on stock returns (columns (1) and (2)). This implies that, on days that news articles are published, the stock return is lower than those on which no news articles are published. A possible explanation for this result is that financial news is an important factor that affects the stability of the capital market (Kauter et al., 2015). It could be considered to be a decisive source of information that contains public knowledge and opinions relating to companies, as well as affecting the public's viewpoint of a company. Moreover, financial news could affect "investor mood", which refers to the belief that future cash flow and investment risk are justified by emotional reasoning through its content or presentation style, including new elements such as "emotion" or "suspense" (Schuster, 2003). As a result, financial news about a company could have a significant impact on the stock return by alleviating the problem of information asymmetry and enabling investors to make an accurate assessment of a firm's value (Carretta et al., 2011).

Likewise, through the sentiment expressed within it, financial news content generates and maintains speculative sentiment bubbles and fads among market participants (Merton, 1987), which subsequently leads to significant variations in stock returns. My finding is consistent with existing studies on media news and the stock market (see e. g., Tetlock, 2007; Fang and Peress, 2009; Tetlock, 2011). I also find that news article sentiments have a significant impact on stock returns, as well as the volume traded.

In particular, *Polarity* has significant and positive effects on stock returns, but an insignificant impact on volatility and volume. This implies that when news articles provide good news, the stock return increases. Prior studies (e. g., Sadique et al., 2008; Loughran and Mcdonald, 2011) suggest that the tone of qualitative information (positive or negative) could provide (optimistic or pessimistic) information regarding a firm's operating outcomes. This could affect investor sentiment and assessment of a company, which results in lower or higher stock returns. Consequently, the stock return of a company on days with positive firm-specific financial news would increase, since investors may hold an optimistic view about a company's performance. This finding is supported by other studies that also indicate that a positive tone expressed in media news has a positive effect on the return of stocks (e.g., Tetlock et al., 2008; Narayan and Bannigidadmath, 2015; Heston and Sinha, 2017).

Additionally, *Difficulty* also has a significantly positive impact on stock return and volume. This indicates that news articles that use technical and complicated terms, which require readers to have a certain level of education to understand, may increase the stock returns and volume. A feasible explanation for this finding is that firm disclosures with a low readability level could reduce investors' information-processing and analysis ability (Boubaker et al., 2019). Therefore, investors are discouraged from investing in firms with less readable disclosures (Lawrence, 2013), which subsequently affects stock return volatility. Moreover, it is argued that firms providing less readable annual reports experience more negatively skewed returns, and a higher stock crash risk, since firms can withhold adverse information by filing complex reports (Kim et al., 2019). Given that firm-specific financial news with a low level of readability may increase investors' uncertainty about a firm's future performance, these firms could suffer a high variation in stock returns.

Moreover, *Subjectivity* has a significant negative impact on stock returns and a significant positive effect on volume. This means that when news articles contain subjective feelings and opinions, stock returns decrease but trading volume increases, whereas when news articles contain objective facts, stock returns increase and the trading volume lessens. Studies have shown that market participants rely mainly on facts, rather than personal opinions, as facts are more trusted and truthful than personal opinions. Such action increases volume and decreases stock returns. Darrat et al. (2007) concluded that traders are highly dependent on private news, which results in a high trading volume. Similarly, Blume et al. (1994) mentioned that investor beliefs encourage market participants to take action, which, in turn, increases the trading volume. In addition, Yu et al. (2012) supports our findings as they found that both conventional and social media news have a strong effect on stock performance. Although the effect of social media news is greater than that of conventional news, they found that trading volume is higher with social media news, than with conventional news. These findings imply that subjective news has a stronger effect than conventional news.

Furthermore, *Word count* has a significant positive effect on stock returns and a significant negative impact on volume. This illustrates that when news articles comprise a longer text, stock returns rise but volume drops. One can say that a longer text has more information about the firm than a shorter text, which may be the reason why returns are higher. Additionally, people prefer reading a shorter text, which drives a higher stock volume.

2.5.2 News article features and cumulative abnormal returns

One may argue that the model specification in equation (3) is rather simple, and that 1,204 events is small compared to the large sample, and that it cannot, therefore, fully reflect the impact of news article features on stock returns. To further investigate the impact of news article sentiments on stock returns, I conducted the regression analysis on CAR across all events. Following the literature, I control for the main features of a firm that might affect stock returns (see i.e., Chen and Zhang, 2007; Price et al., 2012; Hsieh et al., 2016).

Besides the indicators of market performance, the features of a firm may also influence its stock performance. Specifically, *Total Asset* is the variable indicating the size of a firm and it is measured as its total assets. *ROA* represents the profitability of a company, and it is calculated as equity scaled by total assets. *Debt to Capital,* indicating financial leverage, is measured as total debt divided by total capital ratio. Thus, the regression equation is specified as follows:

$$CAR_{i,k} = \beta_1 Lag\,TA_i + \beta_2 Lag\,ROA_i + \beta_3 Lag\,Debt\ to\ Capital_i + \beta_4 Word\ Count_{i,k} + \\ + \beta_5 Polarity_{i,k} + \beta_6 Subjectivity_{i,k} + \beta_7 Difficulty_{i,k} + \psi_i + \varepsilon^4_{i,t} \quad (4)$$

where $CAR_{i,k}$ is the cumulative abnormal return of firm *i* during the event window of event *k*. $Lag\,TA_i$, $Lag\,ROA_i$, and $Lag\,Debt\ to\ Capital_i$ are total assets, the return on assets ratio, and debt to capital ratio of firm *i* in the previous year of the event day. *Word count* is the number of words contained in the published news article. *Polarity*, *Subjectivity*, and *Difficulty* are scores that measure news article sentiments. ψ_i is firm fixed effects. $\varepsilon^2_{i,t}$ is the error term.

The results in Table 2.5 suggest that a firm's characteristics have some predictive power. In particular, total asset is significantly and positively associated with CAR. This indicates that the larger the firm size, the larger the CAR. Additionally, the results show that debt to capital ratio is statistically significant in all event windows, and it is negatively associated with the value of CAR. This suggests that stock returns are higher for firms with a lower debt to capital ratio. Regarding news article sentiments, the coefficients of *Polarity* score are positively and statistically significant in all event windows. It suggests that the more positive the tone, the higher the CAR. Similarly, the coefficients of *Difficulty* score are positively and statistically significant in all event windows which implies that the more difficult the article is to read, the larger the return. Meanwhile, *Subjectivity* score has significant and negative coefficients in up to a 5-day event window. This finding suggests that articles that are more subjective lead to lower returns and that the negative effect vanishes after five days.

[Table 2.5]

In addition, the model controlling for nonlinearity has been investigated in existing literature (see e.g., Freeman and Tse, 1992; Lipe et al., 1998). Since firm's stock performance could potentially have nonlinear relationship with firm's characteristics (e.g., size, profitability, and leverage), I account for this possibility in the model. Particularly, I employ the baseline model of regression equation (4) and controlling for nonlinearity by adding the squared terms of total asset, ROA, and total liability over total asset ratio. I found that the results controlling for nonlinearity generate the same implications with the results presented in Table 2.5 (see Appendix Table A2.2).

For further robustness test, I replace the *Polarity* score with negative news – a dummy variable that equals 1 if the news article has a negative tone (polarity score < 0), and 0 otherwise. Most of the results remain qualitatively the same. I find that news articles with a negative tone have a significant and negative impact on the CAR of every event window. However, *Word count, Difficulty* and *Subjectivity* have limited impacts on CAR (see Appendix, Table A2.3).

Next, I investigate the interaction effects between news articles with a negative tone and other sentiments of the article. Applying a similar setting to that in equation (4), I added the interaction terms between *Polarity* with *Word count*, *Difficulty*, and *Subjectivity*. In particular, the regression equation is as follows:

$$CAR_{i,k} = \beta_1 Lag\,TA_i + \beta_2 Lag\,ROA_i + \beta_3 Lag\,Debt\ to\ Capital_i + \beta_4 Polarity_{i,k} +$$

$$+ \beta_5\, Word\ Count_{i,k} + \beta_6 Subjectivity_{i,k} + \beta_7 Difficulty_{i,k} +$$

$$+ \beta_8 Polarity{*}Word\ Count_{i,k} + \beta_9 Polarity{*}Subjectivity_{i,k} +$$

$$+\beta_{10} Polarity{*}Difficulty_{i,k} + \psi_i + \varepsilon^5_{i,t}\ (5)$$

The results in Table 2.6 imply that the more negative the tone of news articles, the lower the CAR, vice versa. Nevertheless, the coefficients of the interaction term between *Polarity* and *Subjectivity* score are significant and positive across all event windows. This suggests that the negative effect of the negative tone in news articles on returns is lessened when the article is more subjective (influenced by personal points of view, feelings, or judgement). One possible explanation for this result is that negative tone has negative impact on stock returns. However, the more subjective the news is, the less reliable, therefore, the smaller the impact that it has on stock returns. Regarding the interaction terms between *Polarity* and *Word Count* as well as *Difficulty*, their coefficients are insignificant across all event windows. It suggests that the impact of the negative tone in news articles on stock returns does not correlate with the length of the news or the difficulty score of the text.

[Table 2.6]

For further robustness test, I use negative news – a dummy variable instead of Polarity score in equation (5). Most of the results remain qualitatively the same (see Appendix, Table A2.4).

2.5.3 News article features and cumulative abnormal volatility

Applying the same setting as equation (4), I investigate the impacts of news article sentiments on the CAV. Specifically, the regression equation is as follows:

$$CAV_{i,k} = \beta_1 Lag\,TA_i + \beta_2 Lag\,ROA_i + \beta_3 Lag\,Debt\ to\ Capital_i + \beta_4\, Word\ Count_{i,k} +$$

$$+ \beta_5 Polarity_{i,k} + \beta_6 Subjectivity_{i,k} + \beta_7 Difficulty_{i,k} + \psi_i + \varepsilon^6_{i,t}\ (6)$$

where $CAV_{i,k}$ is the cumulative abnormal volatility of firm *i* during the event window of event k. $\varepsilon^4_{i,t}$ is the error term.

The results in Table 2.7 suggest that the debt to capital ratio is statistically significant for up to a 3-day event window, and it is positively associated with the value of CAV. This implies that a bigger debt to capital ratio of a firm leads to a larger CAV. Regarding news article sentiments, *Polarity* is negative and statistically significant for up to a 5-day event window in relation to CAV. This implies that a more negative tone is associated with higher CAV. This is because negative tone mostly worries investors and creates uncertainty, which increases the volatility of the stock. However, the length of the article, as well as its *Difficulty* and *Subjectivity* scores, have insignificant impacts on CAV.

[Table 2.7]

Similar to the analysis on CAR, I conduct further robustness tests by controlling for nonlinearity (see Table A2.5) and using negative news dummy instead of using polarity score (see Table A2.6). Most of the results remain qualitatively the same with results presented in Table 2.7.

Then, I applied the same setting as in equation (6) and added the interaction effects between *Polarity* and other sentiments of the article. Specifically, the regression equation is as below:

$$CAV_{i,k} = \beta_1 Lag\,TA_i + \beta_2 Lag\,ROA_i + \beta_3 Lag\,Debt\ to\ Capital_i + \beta_4 Polarity_{i,k} +$$

$$+ \beta_5\, Word\ Count_{i,k} + \beta_6 Subjectivity_{i,k} + \beta_7 Difficulty_{i,k} +$$

$$+ \beta_8 Polarity{*}Word\ Count_{i,k} + \beta_9 Polarity{*}Subjectivity_{i,k} +$$

$$+\beta_{10} Polarity{*}Difficulty_{i,k} + \psi_i + \varepsilon^7_{i,t} \quad (7)$$

The results in Table 2.8 show that news articles with a more negative tone lead to a significantly higher CAV in all event windows. In addition, the coefficients of the interaction term between *Polarity* and *Subjectivity* are significant and negative across all event windows. This means that the positive impact of negative tone articles on CAV is lessened when the article is more subjective. Regarding the interaction term between *Polarity* and *Word Count* as well as *Difficulty*, their coefficients are insignificant across all event windows. It implies that the impact of the negative tone in news articles on stock volatility is not correlated with the length of the news or difficulty score of the text.

[Table 2.8]

2.6 Conclusion

This study provides an investigation into how firm-specific financial news influences stock performance. More specifically, I employ sentiment analysis to construct the polarity, subjectivity, and difficulty scores for each news article. I then examine the impact of financial news sentiments on firms' stock returns, volatility, and volume using a comprehensive dataset covering firm-level fundamental information, daily stock trading data, and the sentiments scores of financial news articles for 83 firms listed in Kuwait from 2014 to 2019.

After conducting this research, our main findings indicate that news article sentiments considerably impact stock returns and volume traded. The stock return is found to be considerably lower on days when newspaper articles are published, than on days when no news is released. In terms of the influence of news sentiments on stock returns, I find that the *Polarity* score has a significant and positive impact on returns. This indicates that when news articles with a positive tone are published, the stock return is significantly higher. Additionally, my research outcome indicates that the *Difficulty* score has a significant positive influence on stock returns and volume. This suggests that newspaper articles that employ technical and complex phrases when reporting on a firm may lead to higher stock returns and volume for that firm. Finally, *Subjectivity* has a significantly negative influence on stock returns, yet a significantly positive impact on volume. This shows that on the day of publication of news stories containing more personal views and opinions, stock returns are considerably lower, and volume traded is significantly higher.

To determine the influence of news articles on stock returns and volatility, I utilise the event study approach to create the CAR and CAV for each news article. My findings suggest that news sentiments significantly influence stock returns and volatility when I regress CAR and CAV on news sentiment scores and other control variables for different event windows. News with a more optimistic tone results in larger CARs. Similarly, larger CARs are associated with higher difficulty levels in news stories. Meanwhile, newspaper articles with a higher level of subjectivity had lower CARs across many event intervals. In terms of CAV, we observed that the polarity score has a significant and negative influence on volatility, implying that stock volatility is higher around the publication date of a newspaper article with a more negative tone.

This study makes several contributions to the literature. First, a large body of literature in finance research investigates the influence of quantitative stock data. Nonetheless, in addition to the quantitative data, compulsory reports are frequently published by firms and financial articles reporting firm-specific information appear in the news media. Moreover, most firm reports and news are presented in a textual format, rather than in a numerical format. As a result, it is important for research practitioners and policy makers to investigate how financial news affects investor behaviour and thereby the stock market. A number of studies examine how the market responds to quantitative information; however, relatively few investigate the reaction of investors to firm-specific information spread by financial articles. This study, thus, makes specific contributions by investigating how the subjectivity, polarity, and difficulty level of financial news affect investor decisions, and, subsequently, stock performance indicators.

Additionally, previous research has investigated how firm-specific media news affects the stock market. However, most of them focus on the developed markets, such as the US or UK (Garcia, 2013; Boudoukh et al., 2018; Turner et al., 2018). This study, therefore, fills the research gap by investigating how financial news affects the stock market in the context of an emerging market, specifically Kuwait, by focusing on the subjectivity, polarity, and difficulty level of the content of financial news. Our results suggest that, not only the information, but also the way that the information is presented, has a significant impact on investor decisions and, therefore, stock performance.

Table 2.1. Summary Statistics of CAR & CAV

		Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	N (8)
CAR	[0;1]	0. 003	0. 045	-0. 053	-0. 005	0. 000	0. 005	0. 077	1204
	[0;3]	0. 002	0. 058	-0. 091	-0. 011	0. 000	0. 011	0. 095	1204
	[0;5]	0. 003	0. 066	-0. 102	-0. 015	0. 001	0. 016	0. 121	1204
	[0;7]	0. 002	0. 077	-0. 130	-0. 023	0. 000	0. 021	0. 145	1204
CAV	[0;1]	0. 000	0. 016	-0. 018	-0. 008	-0. 003	0. 004	0. 032	1204
	[0;3]	-0. 000	0. 011	-0. 013	-0. 005	-0. 002	0. 003	0. 019	1204
	[0;5]	-0. 000	0. 009	-0. 012	-0. 004	-0. 001	0. 002	0. 015	1204
	[0;7]	-0. 000	0. 008	-0. 011	-0. 004	-0. 001	0. 002	0. 014	1204

Note: CAR Intervals are the cumulative abnormal returns calculated over 1, 3, 5, and 7-day windows where 0 is the event day and is calculated using the closing price of the day (CAR_stats_1 = 0,1; CAR_stats_3 = 0,3; CAR_stats_5 = 0,5; CAR_stats_7 = 0,7). Similar to CAR, CAV Intervals are the cumulative abnormal volatility over the same day windows and are estimated using Parkinson's (1980) intraday high-low range (CAV_stats_1 = 0,1; CAV_stats_3 = 0,3; CAV_stats_5 = 0,5; CAV_stats_7 = 0,7). Columns (1) and (2) present the mean and standard deviations of CAR and CAV over different windows; columns (3)–(7) present the mean price for each percentile of the CAR and CAV; column (8) shows the total number of articles, N.

Table 2.2. Summary Statistics

Variables	Mean (1)	SD (2)	5% (3)	50% (4)	95% (5)	N (6)
Log FTSE15 Return	0.000	0.011	-0.015	0.000	0.015	125,536
Volatility FTSE15	0.009	0.006	0.003	0.008	0.019	100,634
Log Stock Return	0.001	0.058	-0.057	0.000	0.058	125,536
Stock Volatility	0.024	0.067	0.000	0.000	0.132	125,882
Volume Traded	1199.503	3484.163	0.500	202.800	5466.400	125,872
Total Assets	774.059	2829.942	15.307	87.841	3790.043	83
ROA	0.236	0.348	0.002	0.079	0.987	83
Debt to Capital Ratio	0.269	0.241	0.000	0.204	0.711	83
Polarity Score	0.047	0.038	-0.001	0.042	0.467	6,848
Subjectivity Score	0.278	0.048	0.212	0.274	0.362	6,848
Difficulty Score	3.938	0.359	3.455	4.001	4.290	6,744
Number of Words	1,024	210.772	623	1,122	1,149	6,848

Note: Columns (1) and (2) report the mean and standard deviation of market data variables (Log FTSE15 Return; Volatility FTSE15; Log Stock Return; Stock Volatility; Volume Traded), firm characteristics variables (Total Assets; ROA; Debt to Capital Ratio), and text sentiment variables (Polarity Score; Subjectivity Score; Difficulty Score; Number of Words). Columns (3)– (5) report each percentile of the variables; column (6) shows the total number of observations, N.

Table 2.3. Correlation between Market, Stock, and News Article Features

Variables	FTSE15 Return	Volatility FTSE15	Stock Return	Stock Volatility	Volume Traded	Polarity	Subjectivity	Difficulty
Volatility FTSE15	-0. 067							
Stock Return	0. 050	-0. 017						
Stock Volatility	-0. 002	0. 028	0. 066					
Volume Traded	0. 024	0. 068	0. 041	0. 076				
Polarity	0. 034	0. 020	0. 004	-0. 029	0. 008			
Subjectivity	0. 001	0. 037	0. 002	-0. 035	0. 005	0. 819		
Difficulty	-0. 003	0. 040	0. 001	-0. 035	0. 002	0. 738	0. 970	
No of Words	0. 030	0. 002	0. 002	0. 007	-0. 088	-0. 216	-0. 394	0. 368

Note: This table provides the correlations for various measures of market, stock, and news article characteristics including market data variables (Log FTSE15 Return; Volatility FTSE15; Log Stock Return; Stock Volatility; Volume Traded), and text sentiment variables (Polarity Score; Subjectivity Score; Difficulty Score; Number of Words).

Table 2.4. Predictors of Stock Performance

Predictors	Mean-adj return (1)	Market-model return (2)	Volatility (3)	Volume (4)
FTSE15 Index Return	-0. 026		-0. 002	-0. 029
	(0. 063)	()	(0. 033)	(0. 089)
Lag Stock Return	-0. 320***	0. 001	-0. 015***	0. 084***
	(0. 007)	(0. 007)	(0. 005)	(0. 008)
Lag Volume	0. 009***	0. 011***	-0. 016***	0. 469***
	(0. 001)	(0. 001)	(0. 001)	(0. 003)
Lag Stock Volatility	-0. 028***	-0. 028***	0. 634***	-0. 063***
	(0. 005)	(0. 005)	(0. 006)	(0. 007)
News	-0. 194***	-0. 193***	-0. 001	0. 059
	(0. 027)	(0. 027)	(0. 009)	(0. 042)
Word Count	0. 027***	0. 027***	0. 001	-0. 017***
	(0. 004)	(0. 004)	(0. 001)	(0. 006)
Difficulty Score	0. 010***	0. 010***	-0. 001	0. 005*
	(0. 002)	(0. 002)	(0. 000)	(0. 003)
Polarity Score	0. 113***	0. 113***	0. 001	-0. 009
	(0. 005)	(0. 005)	(0. 001)	(0. 006)
Subjectivity Score	-0. 041***	-0. 041***	-0. 001	0. 018***
	(0. 004)	(0. 004)	(0. 001)	(0. 005)
R^2	0. 152	0. 038	0. 478	0. 602
N	111656	124905	125206	125199

Note: Mean-adjusted return is based on a 220-day estimation period starting 10 days prior to the relevant date; market-model abnormal return is calculated using Kuwait FTSE15 index return. Volatility is Parkinson's (1980) intraday high-low range. Trading volume is the natural logarithm of the number of shares traded. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 2.5. Regression on CAR with Different Event Windows

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	0. 080**	0. 038	0. 086*	0. 100**
	(0. 040)	(0. 043)	(0. 047)	(0. 048)
Lag ROA	0. 026	0. 007	-0. 016	-0. 045
	(0. 047)	(0. 052)	(0. 054)	(0. 058)
Lag Debt to Capital	-0. 143**	-0. 177***	-0. 196***	-0. 233***
	(0. 062)	(0. 067)	(0. 074)	(0. 079)
Word Count	0. 011	0. 013	0. 015	0. 019*
	(0. 009)	(0. 010)	(0. 010)	(0. 011)
Difficulty Score	0. 015***	0. 016***	0. 016***	0. 016***
	(0. 004)	(0. 004)	(0. 004)	(0. 004)
Polarity Score	0. 089***	0. 089***	0. 091***	0. 091***
	(0. 011)	(0. 011)	(0. 011)	(0. 013)
Subjectivity Score	-0. 022**	-0. 023**	-0. 025**	-0. 023
	(0. 010)	(0. 011)	(0. 011)	(0. 014)
R^2	0. 222	0. 198	0. 199	0. 188
N	926	926	926	926

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, Polarity Score, and Subjectivity Score. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 2.6. Regression on CAR with Different Event Windows (Interaction Terms)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	0.006	-0.030	0.003	-0.002
	(0.038)	(0.042)	(0.051)	(0.055)
Lag ROA	-0.044	-0.051	-0.043	-0.039
	(0.046)	(0.050)	(0.054)	(0.064)
Lag Debt to Capital	-0.094**	-0.141**	-0.132**	-0.186***
	(0.047)	(0.060)	(0.065)	(0.070)
Polarity Score	0.044***	0.045***	0.043***	0.046***
	(0.002)	(0.002)	(0.003)	(0.003)
Word Count	0.021	0.030	0.032	0.024
	(0.013)	(0.019)	(0.021)	(0.028)
Difficulty Score	0.009	0.018	0.026*	0.017
	(0.010)	(0.015)	(0.014)	(0.018)
Subjectivity Score	-0.049***	-0.043***	-0.045***	-0.041***
	(0.009)	(0.003)	(0.005)	(0.004)
Polarity Score*Word Count	-0.018	-0.013	-0.008	0.001
	(0.023)	(0.012)	(0.014)	(0.016)
Polarity Score*Difficulty	0.010	0.019	0.016	0.013
	(0.008)	(0.012)	(0.028)	(0.016)
Polarity Score*Subjectivity	0.022*	0.023	0.018**	0.029**
	(0.012)	(0.018)	(0.008)	(0.012)
R^2	0.906	0.871	0.848	0.798
N	778	778	778	778

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, and Subjectivity Score, and Polarity Score. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 2.7. Regression on CAV with Different Event Windows

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	-0.050	-0.095*	-0.083	-0.097
	(0.034)	(0.056)	(0.067)	(0.085)
Lag ROA	0.008	-0.007	-0.029	-0.011
	(0.035)	(0.052)	(0.061)	(0.081)
Lag Debt to Capital	0.124***	0.200***	0.100	0.092
	(0.043)	(0.064)	(0.074)	(0.092)
Word Count	-0.013	-0.009	-0.012	-0.001
	(0.019)	(0.023)	(0.024)	(0.028)
Difficulty Score	0.003	0.005	0.005	0.005
	(0.005)	(0.006)	(0.008)	(0.009)
Polarity Score	-0.033**	-0.035*	-0.041*	-0.029
	(0.016)	(0.019)	(0.021)	(0.023)
Subjectivity Score	0.020	0.028	0.027	0.029
	(0.022)	(0.028)	(0.034)	(0.036)
R^2	0.788	0.678	0.642	0.596
N	778	778	778	778

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, Polarity Score, and Subjectivity Score. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 2.8. Regression on CAV with Different Event Windows (Interaction Terms)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	-0.032	-0.076	-0.066	-0.082
	(0.030)	(0.053)	(0.065)	(0.081)
Lag ROA	-0.002	-0.018	-0.039	-0.022
	(0.029)	(0.048)	(0.058)	(0.079)
Lag Debt to Capital	0.115***	0.191***	0.089	0.082
	(0.035)	(0.059)	(0.070)	(0.087)
Polarity Score	-0.024***	-0.025***	-0.026***	-0.023***
	(0.007)	(0.008)	(0.006)	(0.008)
Word Count	-0.005	0.001	0.007	0.024
	(0.014)	(0.019)	(0.024)	(0.031)
Difficulty Score	0.011	0.013	0.009	0.012
	(0.008)	(0.011)	(0.014)	(0.018)
Subjectivity Score	0.001	0.003	-0.010	-0.026
	(0.019)	(0.030)	(0.039)	(0.046)
Polarity*Word Count	0.000	-0.004	-0.014	-0.023
	(0.007)	(0.011)	(0.014)	(0.019)
Polarity*Difficulty	-0.006	-0.007	-0.004	-0.007
	(0.007)	(0.010)	(0.013)	(0.016)
Polarity*Subjectivity	-0.064***	-0.065***	-0.064***	-0.064***
	(0.002)	(0.002)	(0.003)	(0.003)
R^2	0.959	0.904	0.864	0.810
N	778	778	778	778

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, Subjectivity Score, and Polarity Score. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

2.7 Appendix

Table A2.1. Variable Definitions

Variables	Description
CAR	Cumulative abnormal returns.
CAV	Cumulative abnormal volatility.
Log FTSE15 Return	Logarithm of Kuwait FTSE15 index return is the abnormal returns using the market-model of the Kuwait FTSE15 index on day *t* based on an event window of one day.
Volatility FTSE15	Following Parkinson (1980) to compute the indicator of the Kuwait FTSE15 index volatility level using the intra-day high/low prices.
Log Stock Return	Logarithm of Stock Return is the abnormal returns of stock using the market model of stock i on day t based on an event window of one day.
Stock Volatility	Following Parkinson (1980) to compute the indicator of stock volatility level using the intra-day high/low prices.
Volume Traded	The natural logarithm of the number of shares traded of company i traded on day t.
Total Asset	Indicates the size of a firm. It is measured as the total assets of a firm.
ROA	Return on assets represents the profitability of a company and is calculated as equity scaled by total assets.
Debt to Capital Ratio	Indicates the financial leverage and is measured as total debt divided by total capital ratio.
Polarity Score	The value of the polarity score is within the range [-1,1], in which 0 indicates a neutral tone, 1 indicates the most positive tone and -1 indicates the most negative tone. Generated using TextBlob.
Subjectivity Score	The value of the subjectivity score is within the range [0,1] where 0 is the most objective and 1 is the most subjective. Generated using TextBlob.
Difficulty Score	Using the Flesch Reading Ease Score, the value of difficulty score is within the range [100,0] where 0 is the most difficult and 100 is the easiest. Generated using Textstat.
Number of Words	Number of words is the word count included in the news article.
Negative News	A dummy variable, which equals 1 if the news article has a negative tone (polarity score < 0) and 0 otherwise.
News	A dummy variable that equals 1 if there is news about firm i on day t and 0 otherwise.
Mean-adj return	Mean-adjusted return is based on a 220-day estimation period starting 10 days prior to the relevant date.
Market-model return	Market-model abnormal return is calculated using Kuwait FTSE15 index return.

Table A2.2. Regression on CAR with Different Event Windows (Nonlinearity)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	-0.523*	-0.578*	-0.704**	-0.866**
	(0.284)	(0.301)	(0.327)	(0.404)
Squared Lag Total Asset	0.021**	0.022**	0.028**	0.034**
	(0.010)	(0.011)	(0.012)	(0.015)
Lag ROA	0.143	0.150	0.186	0.008
	(0.154)	(0.162)	(0.172)	(0.191)
Squared Lag ROA	-0.059	-0.063	-0.072	-0.013
	(0.044)	(0.045)	(0.048)	(0.054)
Lag Debt to Capital	-0.002	-0.232*	-0.187	-0.297*
	(0.110)	(0.139)	(0.138)	(0.170)
Squared Lag Debt to Capital	-0.093	0.148	0.110	0.173
	(0.139)	(0.175)	(0.197)	(0.231)
Word Count	0.001	0.012	0.014	0.019
	(0.007)	(0.012)	(0.015)	(0.021)
Difficulty Score	0.052***	0.051***	0.053***	0.047***
	(0.003)	(0.005)	(0.006)	(0.007)
Polarity Score	0.085***	0.085***	0.084***	0.102***
	(0.009)	(0.012)	(0.015)	(0.018)
Subjectivity Score	-0.045***	-0.044***	-0.051**	-0.062**
	(0.011)	(0.017)	(0.022)	(0.027)
R^2	0.700	0.656	0.644	0.602
N	778	778	778	778

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Squared Lag Total Assets, Lag ROA, Squared Lag ROA, Lag Debt to Capital Ratio, Squared Lag Debt to Capital Ratio, Word Count, Difficulty Score, Polarity Score, and Subjectivity Score. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A2.3. Regression on CAR with Different Event Windows (Negative Dummy)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	0.030	-0.014	0.036	0.051
	(0.023)	(0.026)	(0.033)	(0.035)
Lag ROA	-0.007	-0.027	-0.050	-0.079*
	(0.029)	(0.033)	(0.037)	(0.045)
Lag Debt to Capital	-0.082**	-0.114***	-0.133**	-0.171***
	(0.033)	(0.043)	(0.054)	(0.061)
Negative News	-0.302***	-0.311***	-0.310***	-0.301***
	(0.005)	(0.006)	(0.007)	(0.009)
Word Count	0.002	0.004	0.006	0.010*
	(0.003)	(0.004)	(0.005)	(0.006)
Difficulty Score	0.001	0.003	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.002)
Subjectivity Score	-0.000	-0.002	-0.003	-0.000
	(0.003)	(0.004)	(0.005)	(0.007)
R^2	0.739	0.663	0.596	0.506
N	926	926	926	926

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, and Subjectivity Score. Negative News is a dummy variable, which equals 1 if the news article has a negative tone (polarity score < 0) and 0 otherwise. All variables are defined in Appendix Table A1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A2.4. Regression on CAR with Different Event Windows (Interaction Terms)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	0.007	-0.031	0.001	-0.005
	(0.038)	(0.042)	(0.051)	(0.055)
Lag ROA	-0.043	-0.054	-0.049	-0.047
	(0.046)	(0.050)	(0.054)	(0.063)
Lag Debt to Capital	-0.084*	-0.128**	-0.117*	-0.176**
	(0.045)	(0.058)	(0.065)	(0.070)
Negative News	-0.529***	-0.366*	-0.348	-0.567*
	(0.159)	(0.202)	(0.253)	(0.324)
Word Count	0.007	0.022*	0.023	0.023
	(0.008)	(0.013)	(0.016)	(0.023)
Difficulty Score	0.002	0.000	0.002	-0.005
	(0.004)	(0.005)	(0.006)	(0.007)
Subjectivity Score	-0.003	-0.002	-0.009	-0.014
	(0.011)	(0.017)	(0.021)	(0.024)
Negative News*Word Count	0.043	-0.004	0.016	-0.041
	(0.038)	(0.045)	(0.052)	(0.076)
Negative News*Difficulty	-0.099	-0.074	-0.102	0.028
	(0.064)	(0.075)	(0.081)	(0.135)
Negative News*Subjectivity	0.072***	0.100***	0.083**	0.125***
	(0.024)	(0.031)	(0.041)	(0.046)
R^2	0.906	0.871	0.847	0.799
N	778	778	778	778

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, and Subjectivity Score. Negative News is a dummy variable, which equals 1 if the news article has a negative tone (polarity score < 0) and 0 otherwise. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A2.5. Regression on CAV with Different Event Windows (Nonlinearity)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	-0. 166	-0. 210	-0. 255	-0. 118
	(0. 219)	(0. 366)	(0. 438)	(0. 535)
Squared Lag Total Asset	0. 005	0. 005	0. 007	0. 001
	(0. 008)	(0. 014)	(0. 017)	(0. 021)
Lag ROA	-0. 159*	-0. 341**	-0. 345*	-0. 458*
	(0. 094)	(0. 160)	(0. 198)	(0. 265)
Squared Lag ROA	0. 051**	0. 104**	0. 098*	0. 139**
	(0. 025)	(0. 042)	(0. 053)	(0. 070)
Lag Debt to Capital	0. 197*	0. 279*	0. 212	0. 140
	(0. 108)	(0. 157)	(0. 212)	(0. 254)
Squared Lag Debt to Capital	-0. 118	-0. 130	-0. 172	-0. 095
	(0. 130)	(0. 187)	(0. 252)	(0. 318)
Word Count	-0. 005	-0. 001	-0. 004	0. 007
	(0. 009)	(0. 015)	(0. 019)	(0. 023)
Difficulty Score	0. 055***	0. 057***	0. 057***	0. 057***
	(0. 003)	(0. 005)	(0. 007)	(0. 009)
Polarity Score	0. 101***	0. 099***	0. 093***	0. 105***
	(0. 008)	(0. 012)	(0. 016)	(0. 017)
Subjectivity Score	-0. 035***	-0. 028	-0. 028	-0. 027
	(0. 012)	(0. 022)	(0. 029)	(0. 032)
R^2	0. 752	0. 632	0. 595	0. 556
N	778	778	778	778

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Squared Lag Total Assets, Lag ROA, Squared Lag ROA, Lag Debt to Capital Ratio, Squared Lag Debt to Capital Ratio, Word Count, Difficulty Score, Polarity Score, and Subjectivity Score. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A2.6. Regression on CAV with Different Event Windows (Negative Dummy)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	-0.029	-0.073	-0.061	-0.076
	(0.030)	(0.053)	(0.065)	(0.082)
Lag ROA	0.001	-0.015	-0.035	-0.020
	(0.028)	(0.047)	(0.057)	(0.078)
Lag Debt to Capital	0.107***	0.182***	0.083	0.074
	(0.036)	(0.061)	(0.070)	(0.086)
Negative News	0.312***	0.321***	0.316***	0.315***
	(0.010)	(0.017)	(0.021)	(0.028)
Word Count	-0.004	-0.000	-0.002	0.006
	(0.008)	(0.014)	(0.018)	(0.022)
Difficulty Score	0.005	0.007	0.007	0.007
	(0.003)	(0.005)	(0.007)	(0.008)
Subjectivity Score	0.014	0.022	0.019	0.025
	(0.011)	(0.020)	(0.028)	(0.031)
R^2	0.860	0.735	0.683	0.626
N	778	778	778	778

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, and Subjectivity Score. Negative News is a dummy variable, which equals 1 if the news article has a negative tone (polarity score < 0) and 0 otherwise. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A2.7. Regression on CAV with Different Event Windows (Interaction Terms)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Lag Total Asset	-0.029	-0.074	-0.062	-0.077
	(0.030)	(0.054)	(0.065)	(0.082)
Lag ROA	0.002	-0.015	-0.036	-0.020
	(0.028)	(0.048)	(0.058)	(0.079)
Lag Debt to Capital	0.107***	0.183***	0.084	0.075
	(0.036)	(0.061)	(0.070)	(0.087)
Negative News	0.665***	0.635***	0.638**	0.533
	(0.160)	(0.240)	(0.309)	(0.394)
Word Count	-0.008	-0.004	-0.005	0.001
	(0.010)	(0.017)	(0.022)	(0.026)
Difficulty Score	0.005*	0.007	0.007	0.007
	(0.003)	(0.005)	(0.007)	(0.008)
Subjectivity Score	0.013	0.021	0.018	0.025
	(0.011)	(0.021)	(0.029)	(0.032)
Negative News*Word Count	0.026	0.009	-0.012	-0.010
	(0.027)	(0.041)	(0.053)	(0.074)
Negative News*Difficulty	0.009	0.043	0.073	0.104
	(0.033)	(0.051)	(0.065)	(0.110)
Negative News*Subjectivity	-0.104***	-0.092***	-0.079**	-0.091*
	(0.021)	(0.033)	(0.039)	(0.053)
R^2	0.959	0.904	0.864	0.809
N	778	778	778	778

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 1-day to 7-day windows. The independent variables are Lag Total Assets, Lag ROA, Lag Debt to Capital Ratio, Word Count, Difficulty Score, and Subjectivity Score. Negative News is a dummy variable, which equals 1 if the news article has a negative tone (polarity score < 0) and 0 otherwise. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Chapter 3. The Effect of Football Rivalry on Stock Price

3.1 Introduction

The extant literature on behavioural finance suggests that investors routinely and systematically make irrational decisions due to psychological biases, which subsequently lead to asset prices that deviate from the fundamental value stated by the efficient market hypothesis (Statman,1999; Thaler, 1999). It is argued that events affecting investor mood, temper, confidence, or the physical, mental, or emotional state of investors can significantly affect asset prices, regardless of their impact on the asset fundamentals (Boyle and Walter, 2003). In this study, I examine the impact of investor mood and behavioural biases on asset pricing in the stock market by using data on international football rivalry matches. More specifically, I study how international football match outcomes (win/loss) affect stock returns.

The impact of international football results on stock price fluctuations could be explained by the well-documented link between investor mood/emotional state and stock market performance (Bell et al., 2012; Demir and Rigoni, 2017). A number of studies on investor psychology show that sporting results exert a substantial influence on the mood of investors. For instance, Wann et al. (1994) find that the performance of a sports team strongly affects its fans' reactions. Specifically, fans react positively (negatively) when their team has a good (bad) performance. More importantly, such positive (negative) reactions of fans relate to an increase (decrease) in self-esteem and optimistic (pessimistic) feelings about their life in general. Hirt et al. (1992) show that the performance of college students at Indiana University is estimated to be substantially better after watching a basketball match that their college team wins, rather than after watching a match that they lose. Arkes et al. (1988) indicate that there is a rise in the sales of Ohio State lottery tickets on the day after a victory by the Ohio State University football team. Consequently, sporting outcomes could result in investors feeling optimistic (pessimistic) about the future, as well as increasing their confidence in their chances of making good investment decisions. Such optimism and pessimism about, not only their own ability, but also life in general, is reflected in investor views on future stock prices, and this thereby has an impact on the stock market (Mishra and Smyth, 2010; Wann and Dolan, 2004).

Stock price reactions to international football results provide an interesting setting in which to investigate the determinant of stock price fluctuations. Football is the most popular sport in the world and plays an important role in many people's lives (Hudson, 2006).It can, therefore, exert a more profound impact on investor sentiment than any other sport. Undoubtedly, the popularity of football is shown by the intensive media coverage, TV audiences, and political involvement (Kaplanski and Levy, 2010a). FIFA estimated that a record of nearly 3.6 billion people worldwide, which is more half of the world population, watched the 2018 FIFA World Cup via official broadcast. Furthermore, international football results can be considered an appropriate proxy for capturing mood changes among investors, since they produce substantial and correlated mood swings in a large portion of a nations population (Edmans et al., 2007).

To investigate the impact of football rivalry match results on stock returns, I use the daily data of 15 countries for the period between May 2000 to April 2020, collected from the Datastream database. Additionally, information (i.e., date and time, scores) on all football matches in which the national team of these countries has participated is scraped from the website: Worldfootball.net. According to my findings, the outcomes of football rivalry matches have a significant impact on the stock market. Particularly, losses (wins) in football matches negatively (positively) influence the performance of the losing (winning) country's stock market. Moreover, the magnitude of the impact of football matches also depends on the characteristics of the game. I find that a victory in playoffs and rival matches has a greater positive impact on stock returns than non-playoffs and non-rival matches. Likewise, the stock markets of countries which lose in playoffs and rival matches react more negatively than those of countries which lose in non-playoffs and non-rival matches.

This study contributes to the strand of literature that examines the asset pricing effect of investor mood documented in psychology research. There are two common approaches to studying the relationship between returns and the mood of investors, which are: the event study approach and the continuous variables approach. An example of event study methodology is Frieder and Subrahmanyam (2004), who found higher stock returns around certain religious holidays, such as Yom Kippur and St. Patrick's Day. Yuan et al. (2005) establish the link between lunar phrases and stock market movements by using the popular perception that lunar phases affect mood and the behaviour of investors to explicate why stock returns are higher on the days around a new moon, than they are on the days around a full moon. A more recent study by Bialkowski et al., (2012) found that that stock returns during Ramadan are significantly higher and less volatile than during the rest of the year. Also, Bergsma and Jiang (2016) found that stock markets outperform in days surrounding "cultural New Year" or that do not occur on January 1. Regarding the continuous variables approach, which is less common. Saunders (1993) and Hirshleifer and Shumway (2003) show that sunshine has a significantly positive effect on stock prices as a result of upbeat moods or investor optimism encouraged by the good weather. In addition to sunshine, other weather conditions are also investigated. A significant and pervasive effect of strong wind on stock returns was found by Shu and Hung (2009). They argue that strong wind can negatively influence human mood.

My study employs the most common approach in existing literature - event study. However, unlike previous work on football match type which often focuses on the relationship between club football match type and the stock performance of the football club, in this chapter, I attempt to investigate the different reactions of the market index following decisive and non-decisive national football matches which often attract more attention than matches at club level. Particularly, I aim to provide new evidence by document the stock performance response to different types of national football match: rival and non-rival; playoff and non-playoff. The stock market is challenging to comprehend and a lack of insights into it can result in a crisis, which negatively influences a wide range of people. My findings with more generalized implications than existing papers can enhance the understanding of the way that the stock market works. Particularly, how football match affects investor mood and investment decisions, which help to increase our comprehension of market-movements and its relation to human mass-psychology.

The structure of this study is as follows. Section 2 provides a literature review on event studies as a transformative methodology in financial research. This includes the daily news and stock market volatility, as well as both football match results and different types of football rivalry and their relation to the stock market. Section 3 discusses the hypothesis development. Section 4 presents the data and methodology. Section 5 provides the main results and additional analysis. Finally, Section 6 concludes.

3.2 Literature review

3.2.1 Sport event and stock return

It is widely acknowledged that humankind has limited information processing abilities (Simon, 1978). As a consequence of this restricted processing ability, investors may devote their time and attention to highly visible and easy-to-process information. In other words, a limited processing ability may generate limited attention. As a result, in financial markets, investor responses to public news depend on the relative salience of the news: the higher the information salience (i.e. media coverage), the faster the public information will be processed by investors and reflected in the stock prices (Palomino et al., 2009).

In recent decades, several studies have reported empirical evidence on asset price reactions to public news, consistent with the salience theory of information processing activities. For example, Klibanoff et al. (1998) show that country-specific information which does not receive widespread media coverage is incorporated only gradually into the share prices. In a case study, Huberman and Regev (2001) document the substantial and permanent stock price rise of a pharmacy company after an article on new cancer-curing drugs was published on the front page of the Sunday edition of the New York Times. However, this article did not contain any new information; this news had already been reported five months earlier in the scientific press and in the popular press (including the New York Times itself, but the article was short, and its position was not prominent).

A large body of literature employs sporting events as an exogenous and salient source of information to test stock market reactions to new information (Benkraiem et al., 2009; Floros, 2010; Mishra and Smyth, 2010). The media coverage of sport has grown exponentially over recent decades (Pilar et al., 2019). Hence the popularity of sport, as well as its importance and impact in people's lives, is increasingly significant. Moreover, sporting news is publicly available information which is immediately and widely accessible to investors. In addition, sport information (such as game results) is usually known to insiders before it is published, meaning there is no informed trading before public release.

Numerous types of sporting events are employed in the literature. Some studies focus on the announcement of hosting of mega-sport events. For instance, Berman et al. (2000) found a significant positive reaction of Australian stocks in certain industries to the announcement of hosting the Sydney 2000 Olympic Games. Similarly, hosting the Rugby World Cup, the Cricket World Cup, and the FIFA World Cup are shown to have positive impacts on host countries' stock performance (see Gospan and Mmotla, 2019; Ramdas et al., 2015).

Since hosting mega-sports events tends to occur infrequently, many other studies use sports match results as a more regular alternative source of sporting events that can affect the financial market (see Kaplanski and Levy, 2010a; Palomino et al., 2009). For example, Brown and Hartzell (2001) analyze the effect of the basketball game performances of the

Boston Celtics, a leading basketball team in the USA, on its stock price. Mishra and Smyth (2010) find a significant link between the national Indian cricket team's performance in international cricket matches and stock returns on the Indian stock market.

An explanation for such market reaction has been widely discussed in several studies. For example, Boyle and Walter (2003) finds reason that sport match results may not only influence investor fans' self-confidence, but also their assessments of potential investments. If their favourite team wins a match, both their self-esteem and beliefs on the prospect of achieving positive earnings increase. However, contrasting feelings occur when there is a loss by their team. Specifically, football performances can significantly affect tickets, advertising, licensing revenue, a team's reputation (Brown and Hartzell, 2001), and investors' attempts to estimate the value of players (Hickman et al., 2008). Therefore, a strong performance implies a positive future cash flow to the team which leads to an increase in the stock prices. In contrast, losses can cause a negative reaction from the stock market.

Among various sport games, a large number of studies choose football as the primary sport for their analysis. The reason for this is that football is the most important sport globally and plays a vital role in many people's lives (Hudson, 2006), and, hence, can affect investor sentiment far beyond other sports. Indeed, the importance of football can be seen in the intensive media coverage, TV audience, and politicians' involvement (Kaplanski and Levy, 2010a). For instance, the total number of worldwide TV viewers of the 2002 World Cup reached 25 billion with the final match between Brazil and Germany being watched by over 1 billion viewers. Moreover, Edmans et al. (2007) argue that national football results can affect the mood of the whole country (both fans and non-fans), while other favoured sports, i.e., American football or baseball, can only affect the mood of fans, rather than the entire country.

3.2.2 Sport events and stock volatility

Besides evidence of the impact on stock return, existing research also finds significant responses of stock volatility following new information. Engle and Ng (1993) investigated how news about stock prices—either positive or negative—causally contributes to either increased future volatility predictions (in the event of negative news) or decreases volatility predictions (in the event of positive news). These findings were affirmed in a study by Chen and Ghysels (2010).

Throughout most studies focusing on how news impacts stock price volatility, two common threads seem to be the certainties that intra-daily news has a stronger effect on volatility than older news, and that negative news has a stronger effect than positive news. For example, recent research from Iqbal et al. (2021) confirmed the asymmetry of news impact curves (i.e., the likelihood that negative news is more damaging than positive news is beneficial) by investigating how news related to COVID-19 affected stock returns in Australia. They empirically confirmed that negative news (proxied as news related to the spread of the virus and the closure of economies) was significantly more negatively impactful than positive news (proxied as news related to government stimulus packages and efforts to combat the pandemic) was positively impactful. Umar et al. (2021) also conducted similar research focused on the prices of commodity markets and reached similar conclusions.

A potential explanation for this lies in the relationship between investor mood/emotional state and financial market performance (De Long et al., 1990; Edmans et al., 2007; Bell et al., 2012; Demir and Rigoni, 2017). Previous studies have used events, e.g., sport event to capture investor mood (see i.e. Edmans et al., 2007; Allmers and Maennig, 2009; Kaplanski and Levy, 2010a; Martins and Serra, 2011; Payne et al., 2018). In particular, Edmans et al. (2007) indicate that sports results affect the mood of investors in a significant and unambiguous way, hence, its effect is strong enough to influence investors' views on future asset prices. Additionally, sports results are able to drive the mood of a large proportion of the population, meaning that it can influence a large number of investors' optimism/pessimism in relation to their ability and confidence when making investment decisions.

In this regard, the psychology literature has reported that there are significant differences in the behaviour of investors following a win, loss or draw by their favourite team. For instance, Renneboog and Vanbrabant (2000) document the impact of the football team's weekly performance on its share price. They find that a win can be rewarded by a positive abnormal return. However, a loss/draw can be penalised by a larger size of negative abnormal return. Scholtens and Peenstra (2009) investigate the effect of football match scores on the football team's stock market performance from 2000 to 2004. Their find that the stock market reacts significantly and positively following a win, nevertheless drop more severely following a loss.

3.2.3 Types of football matches and stock performance

In addition, prior studies even discover that investor emotions are strongly affected by, not only the performance of their favorite team, but also their rival team's performances in matches with other opponents (Hareli and Weiner, 2002; Leach et al., 2003). Particularly, people can derive pleasure from a loss by their rival team (Zillmann et al., 2012). Such an effect, which is known as "schadenfreude", could be explained by the feeling derived from justice being served and envy. Fans may not only obtain utility when their favorite team wins a match, but also when their team's rival performs poorly (Koyama and Reade, 2009). The pleasure of being on the winning side is associated with the feeling of having a superior performance (Smith et al., 2006). In other words, a social comparison is made between either side (Festinger, 1954). Thus, the failure or success of rival teams can foster the "schadenfreude" emotions of investor fans.

In this regard, researchers have documented how the results of a match between football rivals can drive investor mood significantly (Leach et al., 2003). Bell et al. (2009) show that the magnitude of the effect of football results on the stock market depends on the importance of the game. Stadtmann (2006), while analysing the influence of match results of Borussia Dortmund – a German football club–- on its stock price, also unexpectedly discovered that a match won by Bayern Munich – the rival of Borussia Dortmund–- could lead to a fall in Borussia Dortmund's share price. Furthermore, Leach et al. (2003) document that, in the Netherlands, football fans were delighted with Germany's surprise defeat to Croatia, even though Germany was put in a separate group of teams and excluded from the competition earlier than the Netherlands. The magnitude of the stock market reaction to football match results can be influenced by the significance of the football matches. This assumption has been clarified in several pieces of empirical research (e.g., Aston et al., 2003). For example, in their study on the causal link between the World Cup or continental cups and investor fan behaviours, Edmans et al. (2007) found that stock market reactions are more prominent in nations where the football taking place is particularly important, such as during World Cup matches and elimination matches. It is likely that these decisive encounters have the greatest impact upon people's mood. Bell et al. (2011) measures the importance of football games based on the rivalry levels of competitors or the closeness of the games to the end of season. They posit that stock price changes following a result of a relegation match are more significant, since this type of match is considered to be pivotal, and its result can directly affect the rank and revenue of the football club. Important matches can greatly affect the mood of sport fans, thus, this equates to strong reactions in the stock market. This assumption implies that the market reactions can be diverse depending on the importance of the match and the expectations associated with the results.

Moreover, Scholtens and Peenstra (2009) point out that the response of the stock market to football results is stronger for games in European competitions than for those in national competitions, since a European competition is perceived as a more important and more popular competition. Ashton et al. (2003) find that the stock market responds more strongly to qualifying and finals games than friendly games. Brown and Hartzell (2001) show that playoff matches usually have a stronger effect on the stock market than regular season matches. It is expected that stronger stock market reactions will be observed in relation to international and playoff matches than in friendlies and national competitions.

Unlike existing research which often focuses on the relationship between club football match type and the stock performance of the football club, in this chapter, I attempt to investigate the different reactions of the market index following decisive and non-decisive national football matches which attract more attention. Particularly, I aim to provide new evidence by document the stock performance response to different types of national football match: rival and non-rival; playoff and non-playoff. The stock market is challenging to comprehend and a lack of insights into it can result in a crisis, which negatively influences a wide range of people. My findings with more generalized implications than existing literature can enhance the understanding of the way that the stock market works. Particularly, how football match affects investor mood and investment decisions, which help to increase our comprehension of market-movements and its relation to human mass-psychology. In order to identify the differences, I utilize the data of playoffs and rival games between the countries, since these matches all require a greater focus and are considered to be more important compared to regular matches played throughout the season.

3.3 Hypothesis development

3.3.1 Impact of football match results on stock performance

It is well-documented that the performance of a football club can affect the club's own share price. For example, Stadtmann (2006) examines 97 matches played by Borussia Dortmund, a leading German football club, over the period from 2000 to 2002. He found a close link between unexpected results in national and international matches and subsequent changes in the club's share price. Palomino et al. (2009) study news about the game results of 16 listed football clubs on the London Stock Exchange between 1999 to 2002. They revealed that the stock prices of football clubs react strongly to news about their performance, resulting in considerable abnormal returns and trading volumes in the subsequent days following a match.

The literature does not restrict itself to the effect of an individual sports team's performance on its own stock price. Some recent studies also investigate the performance of the national team on the country's stock market as a whole. Particularly, Ashton et al. (2003) find a significant association between the international match results of the English national football team and subsequent daily share index movements on the London stock exchange. Furthermore, Kaplanski and Levy (2010a) document the link between sporting events and financial behaviour at an even more aggregate level than the national level. They show that the US stock market returns significantly declined during World Cup tournaments, which is explained by the aggregate spill-over effect of many non-US investors experiencing feelings of sadness from football losses.

To document the impact of the football match results between national teams on the stock market performance of participated countries, I test the following hypothesis:

H1: A win/loss of national football match has a significant impact on the market index performance.

Furthermore, some studies suggest that the type of results can have asymmetric impacts on investor behaviour. In other words, the impact of a loss on the stock market is shown to be larger than the impact of a win or a draw (see e.g., Edmans et al., 2007). Researchers explain such asymmetry through the differences in investor mood changes following wins and losses. For example, while a rise in heart attacks, crimes, and suicides is shown to be associated with sporting losses, there is no evidence of improvements in mood being of an equal magnitude following victories. Another alternative explanation for the asymmetric response to wins and losses, especially in elimination matches, is the asymmetry in the importance of wins and losses in the competition. That is, while a win can only advance a football team to the next round, a loss will immediately eliminate them from the competition.

Another potential reason for the asymmetric effects of wins and losses lies in the prospect theory developed by Kahneman and Tversky (1979). This behavioural economics theory is based on the concept of loss aversion in which people evaluate their loss and gain in an asymmetric manner. More specifically, individuals react and make decisions differently between potential losses and potential gains based on a reference point. For instance, for some people, the pain from losing $100 could only be compensated by the pleasure of earning $300. The reference point in the case of sport game results is a fan's pre-match expectations for the performance of their favorite team. Additionally, it is documented that football fans psychologically invest in a desired outcome then generate biased predictions, which is called "allegiance bias" (Markman and Hirt, 2002). The term "Allegiance bias" in psychotherapy means the outcome studies refers to the results being contaminated or distorted by the investigators' theoretical or treatment preferences in psychotherapy (Luborsky, Singer, & Luborsky, 1975). Hence, if the expectation of fans is that their favorite team will win, we can expect a stronger stock price reaction following losses than following wins.

Investor fans might react more aggressively when their team performs badly than when a win occurs. I incorporate this assumption into the following hypothesis:

H2: The effect on market index performance of losing a national match is stronger than that of winning a national match .

3.3.2 Impact of rivalry matches on stock performance

The existing literature has also documented the relationship between football rivalry and different investor fans' reaction levels. For example, Demir and Rigoni (2017) document that the magnitude of the effect of football results on the stock market is correlated with the wins or losses of both investors' favorite teams and their rival teams. They found that a loss by a favorite team combined with an unexpected, good result achieved by the rival can result in a strong negative market reaction. On the other hand, another result shows that when the favorite team performs well, stock prices are unlikely to be affected, regardless of the win or loss by its rival. Such empirical results are in accordance with the theory of the hedonic editing rule (Thaler, 1999) which assumes that the happiness of people is determined by a combination of events. Accordingly, football fans experience extreme positive feelings when their favorite team wins a match and, thus, they are likely to be ignorant of the performance of the rival. However, if there is a loss from the team and they are simultaneously aware of their competitor's unexpected success, it is likely that they would be prone to negative emotions.

Empirical literature has illustrated the magnitude of stock market reactions in response to different football match results of, not only a particular team, but also its rivals. I test a further hypothesis to compare the magnitude of the impact on stock market performance between rival matches and non-rival matches as bellow:

H3: The effect on the stock market performance of a rival match is stronger than that of a non-rival match.

3.4 Data and Methodology

3.4.1 Data

In this study, in order to investigate the impacts of football match results on stock market reactions, I collect data on the stock market indices of fifteen (15) countries from Datastream over the period from May 2000 to April 2020. Datastream is a platform providing international financial data relating to the stock market, currencies, fixed securities and other economic indices for many nations and markets. Moreover, I also utilize another dataset, which is scraped from Worldfootball.net using Python, containing the data of 1,258 matches played by the national team of those 15 countries. The 15 countries in my data set were chosen from the list in the article "The 10 greatest rivals in international football" by Nick Miller on ESPN.com. The list included the rivalry between the following national teams: Brazil vs. Argentina; USA vs. Mexico; England vs. Scotland; Egypt vs. Algeria; Serbia vs. Croatia; Japan vs. South Korea; Germany vs. Netherlands; Denmark vs. Sweden; Chile vs. Peru; France vs. Italy. The list of rival countries covers the world demographically including North and South America, Africa, Europe, and Asia. This dataset contains comprehensive information regarding the date and time, tournament, location and the score of football matches. Finally, I merge the two datasets by aligning the code of the matches with the stock market data.

To minimize the effects of extreme values in our data, I treat those extreme values by replacing them. I do this by applying a winsorized code on STATA to all variables at both the top and the bottom one percent of their distributions.

3.4.2 Descriptive statistics

Table 3.1 provides information on the number of football games included in the sample, as well as the mean daily log stock market returns on the days following the match day. In general, we can see that the daily returns on the first trading day after a match are often close to zero, which suggest that H1 might not hold. We do not observe significant differences between the returns of playoff and non-playoff matches, or on rival and non-rival matches on the first trading day after the match, which suggest that H2 and H3 might not hold. The average daily returns on the first trading day after a match is won is often positive (20 basis points for Euro Cup, Asian Cup, and Confederation). Although we observe that the daily returns on the first trading day after a match win in the Africa Cup is negative (50 basis points), the number of observations for this tournament is only nine. Meanwhile, the daily returns on the first trading day after a match defeat are similar to those after a match win. However, the mean daily return after match defeats is negative in the Asian Cup and Africa Cup, -170 and -60 basis points, respectively. The standard deviation of returns is usually similar or slightly higher after match defeats than for match wins, except for the World Cup, the Copa America, and the Africa Cup. In addition, we observe minor differences between the standard deviation of returns after playoff and non-playoff match wins, as well as for rival and non-rival match wins. The standard deviation of returns after rival and non-rival match defeats is also similar, while the statistics after playoff match defeats is greater than for non-playoff matches.

The descriptive statistics for volatility and volume are presented in Table A3.2. As can be seen from the table, the average daily change in volatility on the first trading day after match wins is -0.000 for the World Cup, Euro Cup, the Copa America, and the Gold Cup tournaments. The average daily change in volatility on the first trading day after match wins is -0.001 for the Asian Cup, Confederation cup, and the Friendlies. Meanwhile, the Nation League has a mean of -0.002, and the Africa Cup, 0.001. In addition, the average daily change in volume on the first trading day after match wins are positive for the World Cup, Gold Cup, Africa Cup, and the Friendlies tournaments (0.001, 0.002, 0.020, and 0.002 respectively). On the other hand, for the other tournaments the average daily changes in volume are negative -0.015 for Euro Cup, -0.001 Asian Cup, -0.012 Confederation cup, -0.011 Copa America, and -0.028 for Nation League. As can be seen from the table, the average daily change in volatility on the first trading day after match wins is -0.000 for the World Cup, Euro Cup, the Copa America, and the Gold Cup tournaments. Also, the average daily change in volatility on the first trading day after match loss is 0.000 for World Cup; -0.000 for Europe Cup, Friendlies and Confederation cup; -0.002 for Gold Cup and Africa Cup; 0.001 for Copa America and National League; -0.004 for Asian Cup. Meanwhile, the average daily change in volume on the first trading day after match loss are positive for the World Cup, Asian Cup, Copa America, Africa Cup and Nation League tournaments (0.008, 0.055, 0.012, 0.034 and 0.005 respectively). While for the other tournaments the average daily changes in volume after loss are negative -0.011 for Euro Cup, -0.018 Confederation Cup, -0.001 Gold Cup, and -0.010 for Friendlies.

[Table 3.1]

3.4.3 Methodology (event study, market model)

For the past three decades, the methodology of event study has seen significant theoretical and empirical development. It has become widely used in regulatory financial studies and, when combined with multivariate regression analyses, it allows for the testing of multiple hypotheses simultaneously, which greatly benefits the empirical study of a wide variety of subfields, both within and without the corpus of financial literature (Binder, 1998). For example, financial researchers have attempted to uncover links between various aspects of individuals' daily lives, their environments, and documented the pricing of assets listed on the stock market (Campbell and Hentschel, 1991; Engle and Ng, 1993; Olsen, 1998; Sayim et al., 2013; Shiller, 2003; Shu and Chang, 2015). Also, event studies analysis is qualified as admissible evidence in insider trading cases by the US Supreme Court's (Mitchell and Netter, 1994).

This research uses event study method to document the potential effects of the regulation's violation announcements on stock returns. In particular, to estimate the abnormal returns (AR) and abnormal volatility (AV), I use the event study market model approach following MacKinlay, (1997). Then, I calculate the cumulative abnormal return (CAR) and the cumulative abnormal volatility (CAV) for different event windows.

The abnormal returns of country *c* at time *t* is measured as the difference between the realized return and an estimate of its expected return in the absence of the event. The calculation is specified as follows:

$$R_{c,t} = r_{c,t} - E(r_{c,t}) \ (1)$$

where $R_{c,t}$ is the abnormal returns of country *c* on day *t*. $r_{c,t}$ is the realized return of country *c* on day *t*. To estimate the expected returns $E(r_{c,t})$, I use the market model to calculate the returns over the 220 days prior to the day before the event window starts. It should be noted that the event days in this study are the football match dates.

Cumulative abnormal returns during the event window $[t_1, t_2]$ are calculated by:

$$CAR_{c,t_1} = \sum_{-t_1}^{t_1} R_{c,t} \ (2)$$

I investigate the impact of the investor mood after a football match on stock index performance, which can only have impact after the event. Therefore, I compute the cumulative abnormal returns (CAR) and the cumulative abnormal volatility (CAV) over four different event windows [0,1]; [0,3]; [0;5]; [0;7] (1, 3, 5, and 7-day, respectively). Events are dropped when more than one event falls within the same event window.

3.5 Empirical results

3.5.1 Impact on market index performance indicators

In order to investigate the impact of football match types on market performance, I apply the panel data multi-way fixed-effect model to regress the market returns, volatility, and volume and world index return on the type of football match. The model is specified as follows:

$Market\ Performance_{c,t} = \beta_1 IndexR_{c,t-1} + \beta_2 \text{Volume}_{c,t-1} + \beta_3 \text{Volatility}_{c,t-1} + \beta_4 \text{World indexR}_t + \beta_5 \text{Win}_{c,t} + \beta_6 Loss_{c,t} + \beta_7 Playoff_{c,t} + \beta_8 Rival_{c,t} + \beta_4 \text{Win}_{c,t} * Playoff_{c,t} + \beta_5 Loss_{c,t} * Playoff_{c,t} + \beta_4 \text{Win}_{c,t} * Rival_{c,t} + \beta_5 Loss_{c,t} * Rival_{c,t} + \phi_t + \theta_c + \varepsilon_{i,t}^1$ (3)

where $Market\ Performance_{i,t}$ is the mean-adjusted return, market-model return, volatility, or volume of the market index of country *c* on day *t.* The mean-adjusted return is calculated based on a 220-day estimation period starting 10 days prior to the relevant event day. I employ 220-day estimation period to estimate abnormal returns since this is the most popular approach in the existing literature (see e.g., Caton et al. 2003; Sorescu et al. 2017; Fan et al. 2020). Meanwhile, the market model return is computed using each country index return. Following Parkinson (1980), I also compute the indicator of stock volatility level for country *c* on day *t* using the intra-day high/low prices. Volume is computed as the natural logarithm of the total shares traded of the market index of country *c* on day *t*.

Our controlling variables are for market characteristics and match type. The variables are explained as follows. $IndexR_{C,t-1}$ is the index return of country *c* on the previous day. I include this variable to account for first-order serial correlation. $Volume_{C,t-1}$ is the index volume of country *c* on the previous day. $volatility_{C,t-1}$ is market index volatility of country

c on the previous day. Following Curatola et al. (2016), I control for the continuously compounded daily U.S. dollar return on Datastream's World Market Index on the event day, which is $World\ indexR_t$. Furthermore, for the predictors of the match type, we use $Win_{C,t}$ which is a dummy variable equal to 1 if the match is "won" by country c on day t. $Loss_{c,t}$ is a dummy variable equal to 1 if the match is "lost" by country c on day t. $Playoff_{C,t}$ is a dummy variable equal to 1 if the match is "qualifying, final, semi-final, and so on" for country c on day t. $Rival_{C,t}$ is a dummy variable equal to 1 if the match is "against a rival team" for country c on day t. $\phi_t$and θ_c are time and country fixed effects. $\varepsilon^1_{i,t}$ is the error term.

[Table 3.2]

The Table 3.2 findings have many significant results across most control variables. First, the lagged index return is negatively and significantly correlated with volatility and volume of the market index. This implies that the lower the lagged market index return, the higher the volatility and volume. Second, the lag market volume is positive and significantly correlated with the volatility level and the volume. This means that the market volume on the day before the event is positively correlated with volatility and volume. For instance, when volume is high on the previous day, match day volume and volatility are also high. Third, lag volatility is positive and significantly correlated with mean return, market return, and volatility. This suggests that when volatility is low on the event day, the market returns, and volatility are low. Finally, world index is positive and significantly correlated with adjusted return, but negative and significantly correlated with volatility and volume. This indicates that when the world index is low, volatility and volume are high on event day.

With regards to the variables controlling for match results, in general, the results show that national football match result have a significant impact on market index performance. Particularly, a win is positive and significantly correlated with adjusted returns, market return, and volatility, while a loss is negative and significantly correlated with adjusted returns and market return, and positive and significantly correlated with volatility. These findings suggest that match wins lead to higher returns and matches lost lead to lower returns, and both wins and losses lead to high volatility. According to Edmans et al. (2007), the effect of sporting results on stock market returns is much higher after losses than after wins. Additionally, the *Playoff* variable for both *Volume* and *Volatility* are negative and significant. This implies that playoff games are negatively correlated with volume and volatility. For example, playing in the games of world cup finals, or in the qualifying games, will lead to lower trading volumes and volatility than would be seen on a regular day. The *Rival* variable is negative and significantly correlated with market returns and positive and significantly correlated with *Volatility*. This suggests that playing in a rival match leads to lower returns and higher volatility.

Table 3.2 also shows the interaction term of *Rivals* and *Playoff* on the *Win*/*Loss* variables. The *Win**Rival* interaction term is positive and significantly correlated with the mean adjusted return. The coefficient of *Win**Rival* is larger than for *Win* itself (0.019 and 0.038 respectively). This implies that, although a win has a strong positive effect on the market, a win in a rival match has an even stronger impact. The results relating to the mean adjusted return are consistent with the market model return. Table 3.2 also shows that *Win**Rival* interaction is negative and significantly correlated with *Volatility*. This implies that a win in a rival match leads to lower volatility. The finding of the *Loss**Rival* interaction term with the mean adjusted return is negatively significant. This implies that match defeats have a negative impact on the market return and losing in a rival match has an even greater negative impact on the market. Both the *Win**Playoff* and *Loss**Playoff* variables are positive and significantly correlated with *Volatility* and *Volume*. This implies that competing in playoff matches increases volatility and volume, regardless of whether the matches are lost or won.

Playoffs are considered important games in the football season, as they determine the rank of football teams. Although the playoffs are less frequent than the regular matches, they are typically intended to promote economic interests during primetime (Fan and Wang, 2018). Any arrangements relating to the playoffs seldom overlap so that the influence of competitive matches can be concentrated. The playoffs are also the most important matches of the season that affect the public more significantly. Thus, playoff games have a significant, incremental impact on returns. Furthermore, the playoffs represent a large (and immediate) variable source of revenue that depends on winning games. Given the importance of playoffs matches, this type of game has the potential to impact significantly on investor fans' emotions, and to thereby trigger stronger stock reactions than following regular games in the football season. My results are consistent with the findings of the Edmans et al. (2007) and Brown and Hartzell (2001) studies, which show that playoff matches usually have a stronger effect on the stock market than regular matches played throughout the season.

International football performances have especially effective properties when used as a mood indicator (Edmans et al., 2007). Though detailed psychological research suggests that sports, in general, have a significant impact on mood (which we discuss below), TV viewership rates, media attention, and retail sales indicate that football, in particular, is of “national interest” in many of the countries we study. Other frequent occurrences that cause such significant and associated mood changes in a large proportion of a country’s population are difficult to conceive. These features offer clear a priori motivation for using game results to monitor investor mood shifts.

The market's reaction to game results may be a fair response to reports about these listed football club companies' potential cash flows or the quality of their football players. For example, wins (losses) can have a significant financial effect on a club in terms of increased (decreased) sales of associated goods and advertisements, as well as the distribution of television rights. Higher revenues could boost a club's profitability, resulting in higher (expected) dividend payments. Consequently, high dividends being paid will lead to an increase in the stock price. These results are consistent with previous studies on sports game results and investor sentiments (e.g., Renneboog and Vanbrabant, 2000; Palomino et al., 2005, 2009). These studies also show that wins have a positive impact on a club's share price, while defeats have a negative effect, and losses have a greater absolute effect.

Investor fans' self-confidence, as well as their evaluations of future investments, can be influenced by sports match outcomes (Boyle and Walter, 2003). When their favorite team plays a game, their self-esteem and confidence in the possibility of healthy returns both rise. When their team loses, on the other hand, contrasting emotions arise. Football success, in particular, has a significant impact on ticket sales, sponsorship revenue, licensing revenue, a team's prestige (Brown and Hartzell, 2001), and investors' attempts to assess a team’s valuation (Hickman et al., 2008).

Furthermore, existing literature has found empirical evidence of the influence of financial development on the market index return (e.g., Beck, et al., 2001; Bacchetta and Caminal 2000) as well as volatility (e.g., Dellas and Hess, 2005). To control for this element, the regression equation (3) was re-estimated controlling for two financial development indices: Financial Development Index, and Financial Market Access Index. The results controlling for financial development are presented in Appendix Table A3.5, which suggest the same implications with my main results.

3.5.2 Impact of CAR on market index

To investigate the impact of football matches on CAR, we employ the regression equation below:

$$CAR_{c,t} = \beta_1 Win_{c,t} + \beta_2\, Loss_{c,t} + \beta_3 Playoff_{c,t} + \beta_4 Rival_{c,t} + \phi_t + \theta_c + \varepsilon_{i,k}^2 \quad (4)$$

where $CAR_{c,t}$ is the cumulative abnormal return of country *c* during the event window of the event at time *t*. $Win_{c,t}$, $Loss_{c,t}$, and $Playoff_{c,t}$ are dummy variables for matches won, matches lost, playoff matches, and rival matches of country *c* on the event day *t*. ϕ_t is time fixed effects. θ_c is country fixed effect. $\varepsilon_{i,k}^2$ is the error term. More details on variable descriptions and data sources are available in Appendix Table A3.1.

From the regression on the CAR with different event windows (see Appendix Table A3.3), the graph below was produced. Figure 3.1 shows that the estimated coefficients of *Win* are positive and significant for the 1-, 2-, and 3-day event windows, while the coefficients of *Loss* are significant over all windows. This implies that matches won result in higher CAR, while matches lost result in lower CAR. I found that the effect lasts longer for games lost than for those of games won.

[Figure 3.1]

To control for financial development level, the regression equation (4) was re-estimated controlling for Financial Development Index, and Financial Market Access Index. The results controlling for financial development are presented in Appendix Table A3.4, and Figure A3.1, which suggest the same implications with my main results.

To investigate the impact of match type on CAR we employ the regression equation below:

$$CAR_{c,t} = \beta_1 Win_{c,t} + \beta_2\, Loss_{c,t} + \beta_3 Playoff_{c,t} + \beta_4 Rival_{c,t} + \beta_5 Win{*}Playoff_{c,k} + \beta_6 Loss{*}Playoff_{c,k} + \beta_7 Win{*}Rival_{c,k} + \beta_8 Loss{*}Rival_{c,k} + \phi_t + \theta_c + \varepsilon_{i,k}^2 \quad (5)$$

Table 3.3 presents the descriptive statistics of the CAR over four windows. Each football match is matched to its country during the sample period. We estimate the CAR of each country individually for four event windows. If a football match relating to a country is in the same window as another match of that country, then both events are dropped. Each CAR is an independent observation for each one of a country's football matches. Table 3.3 shows the descriptive statistics for various intervals of the CAR, which is calculated over four windows ranging from 1 to 7-day event windows. The total number of observations is indicated in column (8) where 1,106 observations are football matches played over the period 2000 to 2020 in the World Cup, Euro Cup, Asian Cup, Confederation Cup, Copa America, Gold Cup, Africa Cup, the National League, and Friendlies. The mean value of CAR is positive in the [0:1] and [0;3] windows, while its negative for event windows that have longer period. This suggests that win matches may increase market return immediately after the match, while loss matches may have a negative impact on market return that is delayed and last longer compared to positive impact of win matches. The standard deviation is shown in column (2); the value increases from 1.3 [0;1] to 2.46 [0;7].

[Table 3.3]

Table 3.4 presents the results of the regression (4) examining the impact that football games have on the cumulative abnormal returns (*CAR*). Columns 1-4 provide the results of the CARs in four different event windows that are regressed on won and lost games, as well as the type of game (*Playoff, Rivals*) and controlling for the interaction term. Results show that the estimated coefficients on *Win* are positive and significant for the 1-day and 3-day event windows, while they are negative for *Loss* over all windows. This implies that matches won result in higher CARs, while matches lost result in lower CARs. Additionally, the effect lasts longer for *Loss* games than for *Win* games. The results are also significant for *Rival* matches. *Win*Rival* matches are positively and significantly correlated with CAR for up to 5-day event windows, while *Loss*Rival* matches are negatively and significantly correlated with CAR for up to 3-day event window. This implies that a win (loss) rival match has stronger positive (negative) impact on CAR than a win (loss) non-rival match during the first 5 (3) days after the match.

Rival games are also considered to be essential games as they determine the rank of football clubs, and the potential for glory. Hence, investors could experience strong feelings (optimism/pessimism) upon discovering the outcome of such games (Kim and Mao, 2021). This can lead to a significant reaction in the stock market. Moreover, rival matches could attract large audiences (Baimbridge et al., 1996; Allan and Roy, 2008). Fans prefer watching a rival match, rather than the safe play experienced when competing with a weaker team. This is because watching players fighting with a fierce rival provides more suspense and enjoyment (Buraimo and Simmons, 2009). Thus, such matches have the potential to influence the mood of an entire country more significantly, compared to non-rival matches, and this can thereby influence the national stock price indices. Consequently, due to the importance and appeal of rival matches, the stock market may react more strongly to the outcomes of rival matches than to non-rival matches. These findings are further supported by the study of Bell et al. (2011), who examine the magnitude of the stock reaction to the level of importance of football games, this being measured as the rivalry levels of competitors.

[Table 3.4]

To control for financial development level, the regression equation (5) was re-estimated controlling for Financial Development Index, and Financial Market Access Index. The results controlling for financial development are presented in Appendix Table A3.6, which imply the same implications with my main results.

3.5.3 Impact of CAV on market index.

Applying a similar method to equation (4), I examine the impacts of football matches on CAV by employing the regression equation below:

$$CAV_{c,t} = \beta_1 Win_{c,t} + \beta_2\, Loss_{c,t} + \beta_3 Playoff_{c,t} + \beta_4 Rival_{c,t} + \phi_t + \theta_c + \varepsilon^2_{i,k} \quad (6)$$

where $CAV_{c,t}$ is the cumulative abnormal volatility of country *c* during the event window of event *t*. ϕ_t is time fixed effects, θ_c is the country fixed effect, and $\varepsilon^2_{i,k}$ is the error term.

Table 3.5 presents the descriptive statistics of CAV over four windows. The mean of CAV is presented in column 1 and the standard deviation is detailed in column 2. The mean of the CAV is negative across all event windows, while the standard deviation is positive. The longer the window span, the higher the value of both the mean and standard deviation. The number of observations is reflected in column 8.

[Table 3.5]

Next, to investigate the impact of match type on CAV we employ the regression equation below:

$$CAV_{c,t} = \beta_1 Win_{c,t} + \beta_2\, Loss_{c,t} + \beta_3 Playoff_{c,t} + \beta_4 Rival_{c,t} + \beta_5 Win{*}Playoff_{c,k} + \beta_6 Loss{*}Playoff_{c,k} + \beta_7 Win{*}Rival_{c,k} + \beta_8 Loss{*}Rival_{c,k} + \phi_t + \theta_c + \varepsilon^2_{i,k} \quad (7)$$

Table 3.6 illustrates the findings of regression (5) which investigates the impact of matches won and lost on the cumulative abnormal volatility (CAV) whilst controlling for the interaction terms *Playoff*, and *Rivals*. After the predictors column, the table displays the results of different event windows: [0;1], [0;3], [0;5], and [0;7]. The findings suggest that the estimated coefficient on *Win* is positive and significant over a 1-day event window at a 5% significance level. The estimated coefficient on *Win*Rival* is not statistically significant in any event windows. These results indicate that winning a national match have significant and positive effect on CAV. On the first trading day after the match. However, the impact on CAV of winning a rival match is not significantly different from winning a non-rival match. Meanwhile, the result of the *Loss* variable is positive and significant over most event windows. The results imply that after losing a national football match, the CAV is expected to be higher, and this positive effect on CAV lasts longer compared to the similar impact on CAV of winning a match. In addition, the interaction term *Loss*Rival* is positive and statistically significant in the [0,1] and [0,3] event windows. This finding suggests that the effect of a loss is robust for games lost against rivals.

[Table 3.6]

To control for financial development level, the regression equation (7) was re-estimated controlling for Financial Development Index, and Financial Market Access Index. The results controlling for financial development are presented in Appendix Table A3.7, which suggest the same implications with my main results.

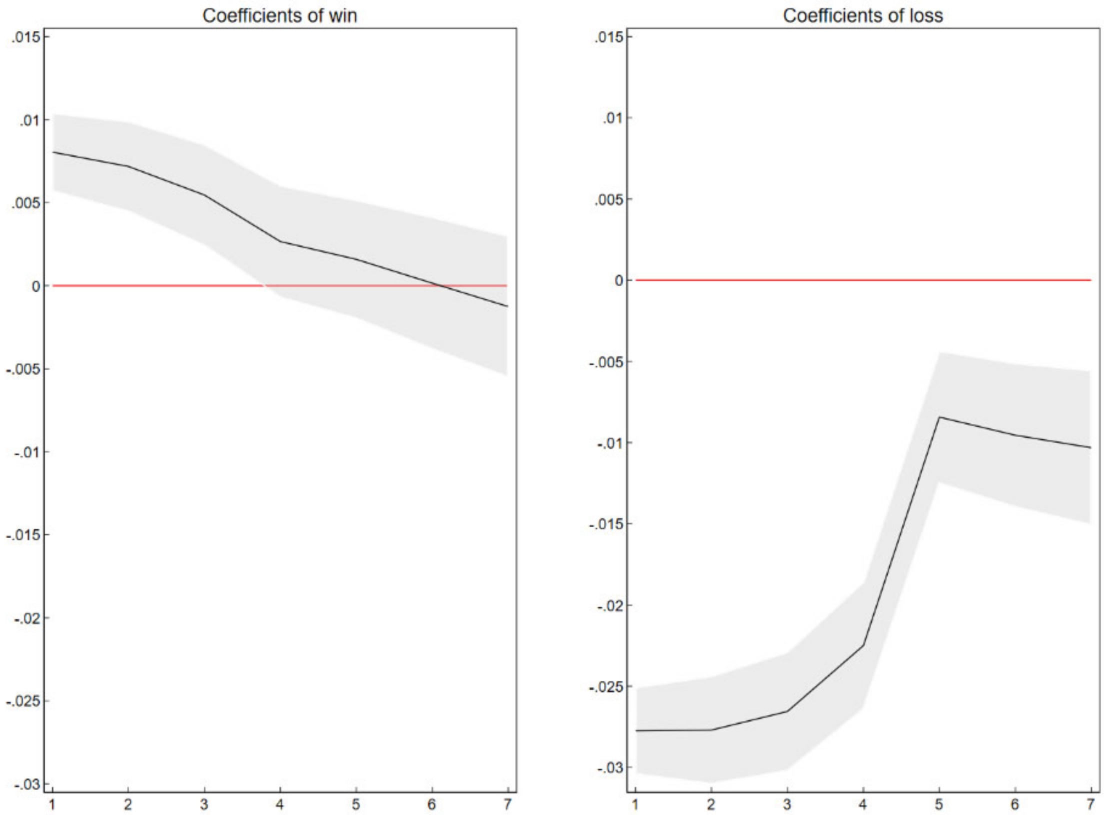
3.6 Conclusion

Motivated by the psychological evidence indicating that investor mood is strongly affected by sports results, this study investigates how the stock market reacts to international rivalry football match results. To conduct the empirical analysis, I use a comprehensive dataset covering information on fifteen countries' stock market indices and international football matches in the period between May 2000 and April 2020. To this end, I find a strong positive (negative) stock market reaction to wins (losses) by national football teams. In particular, compared to days with no matches, the abnormal stock return is higher on days with winning matches, and lower on days with losing matches. Moreover, the effect of sport results on the stock market is more pronounced for particularly important matches, these being playoff matches and rival matches. My findings suggest that investors may be able to attain greater excess returns by making transactions based on such mood events. For example, they can short futures on both countries' stock indices before an important football match in order to take advantage of the asymmetry of the impact.

I relate my findings to previous studies. First, my findings are consistent with Brown and Hartzell (2001) and Scholtens and Peenstra (2009), as I discover that the outcomes of football matches do indeed directly influence stock returns and that there is an asymmetric reaction to matches won and lost. Such asymmetry is to be expected as per the conclusions of Engle and Ng (1993). Second, in line with Renneboog and Vanbrabant (2000), Palomino et al. (2005), and Ashton et al. (2003), we also determine that the stock markets react positively to a national victory, whereas defeats are associated with a negative stock market reaction. Furthermore, my study is also complemented by the studies of Bell et al. (2011) and Edmans et al. (2007), who find that the magnitude of the effect of sporting results on the stock market is more significant with respect to decisive matches, such as playoffs and rival matches.

My study contributes to our understanding of the impact of investor emotions and behaviour in financial decisions, by demonstrating that international football results are a determinant of stock market reactions. This conclusion provides additional validation to the research of Engle and Ng (1993), while also giving credence to the wider shift toward: a) qualitative research in finance, and b) the shift over the past thirty years toward the incorporation of behaviourism into financial research. Humans are inherently irrational and can never achieve a theoretically optimal level of intelligence and information regarding the decisions they make, and are, thus, heavily influenced by the subjective nature of mood, emotion, and other non-quantifiable variables. These elements of human nature must still be factored into models empirically if such models are to be accurate or predictive. Moreover, the findings of my study contain important implications, not only for academics, but also for practitioners and the wider investment community.

Figure 3.1. Regression on CAR for Win/Loss with Different Event Windows



Note: Figure 3.1 is the illustration of the regression on CAR for Win and Loss with different event windows (Table A1). The x-axis represents the event window, and the y-axis corresponds to the number of the coefficient for Win and Loss.

Table 3.1. Number of Wins/Losses and Percent of Mean Daily Returns on the First Trading Day after the Match

	Wins			Losses		
	N (4)	Mean (5)	SD (6)	N (7)	Mean (8)	SD (9)
Tournament						
World Cup	369	0.001	0.023	135	0.000	0.020
Euro Cup	132	0.002	0.017	43	0.005	0.016
Asian Cup	46	0.002	0.017	10	-0.017	0.025
Confederation Cup	79	0.002	0.017	26	0.003	0.023
Copa America	39	0.001	0.017	27	0.000	0.012
Gold Cup	65	0.001	0.008	16	0.004	0.009
Africa Cup	9	-0.005	0.016	5	-0.006	0.010
Nation League	10	0.003	0.009	7	0.003	0.006
Friendlies	587	-0.000	0.019	309	0.001	0.016
Match Type						
Playoff	82	0.002	0.020	37	-0.000	0.021
Non-playoff	1217	0.000	0.019	540	0.001	0.017
Rival vs non-rival						
Rival	227	-0.001	0.019	213	0.001	0.016
Non-rival	1072	0.001	0.019	364	0.000	0.018

Note: The table reports the number of wins and losses in national football matches. The football matches are played over the period 2000 to 2020 in the World Cup, Euro Cup, Asian Cup, Confederation Cup, Copa America, Gold Cup, Africa Cup, National League, and Friendlies. The mean returns reported in the table are computed from the log daily return on national stock market indices (from Datastream) on the first trading day after wins and losses. The Appendix details the country selection and rivals. Playoff matches are matches in which the loser is eliminated from the tournament.

Table 3.2. Match Interactions

Predictors	Mean-adj return (1)	Market-model return (2)	Volatility (3)	Volume (4)
Lag index return	-0.126***	0.033***	-0.033***	-0.008***
	(0.007)	(0.012)	(0.004)	(0.002)
Lag volume	-0.005	0.001	0.046***	0.592***
	(0.008)	(0.008)	(0.006)	(0.008)
Lag volatility	0.058***	0.057***	0.216***	-0.007
	(0.016)	(0.018)	(0.026)	(0.006)
World index return	0.118***		-0.008***	-0.003***
	(0.001)		(0.001)	(0.000)
Win	0.019***	0.013***	0.080***	0.004
	(0.005)	(0.005)	(0.003)	(0.002)
Loss	-0.035***	-0.045***	0.198***	-0.007
	(0.006)	(0.006)	(0.004)	(0.010)
Playoff	-0.003	0.001	-0.005***	-0.002**
	(0.003)	(0.003)	(0.002)	(0.001)
Rival	-0.003***	-0.005***	0.020***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Win*Playoff	0.034	-0.007	0.049**	0.032***
	(0.038)	(0.034)	(0.021)	(0.012)
Loss*Playoff	-0.031	-0.062	0.047*	0.030*
	(0.047)	(0.046)	(0.028)	(0.016)
Win*Rival	0.038***	0.057***	-0.203***	-0.002
	(0.015)	(0.014)	(0.009)	(0.013)
Loss*Rival	-0.031**	-0.015	-0.013*	-0.010
	(0.016)	(0.015)	(0.008)	(0.009)
R^2	0.571	0.196	0.579	0.956
N	40867	42295	42314	42314

Note: This table shows associations between football match results and stock performance. Mean-adjusted return is based on a 220-day estimation period starting 10 days prior to the relevant date Market-model abnormal return is calculated using world index return. Volatility is the Parkinson (1980) intraday high-low range. Trading volume is the natural logarithm of the number of shares traded. Control variables include world index return, lagged market return, day effects and individual effects. *, **, *** denote significance at 10%, 5% and 1%, respectively.

Table 3.3. Descriptive Statistics of CAR

CAR Interval	Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	N (8)
[0;1]	0.08	1.30	-2.06	-0.58	0.06	0.76	2.25	1106
[0;3]	0.05	1.76	-2.81	-0.88	0.03	1.00	2.99	1106
[0;5]	-0.08	2.05	-3.62	-1.23	0.01	1.05	3.29	1106
[0;7]	-0.12	2.46	-4.29	-1.52	-0.09	1.37	3.76	1106

Note: CAR Intervals are the cumulative abnormal returns calculated over 1, 3, 5, and 7-day windows on the event day and they are calculated using the closing price of the day (CAR_stats_1 = 0,1; CAR_stats_3 = 0,3 ; CAR_stats_5 = 0,5 ; CAR_stats_7 = 0,7). The number of events totals 1,106 events (1,106 observations are football matches played over the period 2000 to 2020 in the World Cup, Euro Cup, Asian Cup, Confederation Cup, Copa America, Gold Cup, Africa Cup, National League, and Friendlies).

Table 3.4. Regression on CAR with Different Event Windows Controlling for Interaction Terms

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Win	0.007***	0.004*	-0.001	-0.004
	(0.001)	(0.002)	(0.002)	(0.003)
Loss	-0.023***	-0.023***	-0.010***	-0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Playoff	-0.004	-0.004	-0.006	-0.009
	(0.003)	(0.005)	(0.005)	(0.008)
Rival	0.001	-0.002	-0.003	-0.004
	(0.002)	(0.003)	(0.003)	(0.004)
Win*Playoff	0.005	0.005	0.007	0.015
	(0.004)	(0.007)	(0.007)	(0.009)
Loss*Playoff	0.005	0.006	0.011	0.017
	(0.005)	(0.007)	(0.009)	(0.011)
Win*Rival	0.005*	0.010***	0.009**	0.008
	(0.003)	(0.003)	(0.004)	(0.005)
Loss*Rival	-0.014***	-0.010***	0.005	0.007
	(0.003)	(0.004)	(0.004)	(0.005)
R^2	0.610	0.421	0.176	0.179
N	1094	1094	1094	1094

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Win, Loss, Playoff, Rival, as well as the interaction term. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 3.5. Descriptive Statistics for CAV

CAV Interval	Mean (1)	SD (2)	5% (3)	25% (4)	50% (5)	75% (6)	95% (7)	N (8)
[0;1]	-0.01	1.37	-1.83	-0.60	-0.20	0.31	2.14	1106
[0;3]	-0.10	2.58	-3.43	-1.13	-0.45	0.41	3.49	1106
[0;5]	-0.18	3.39	-4.60	-1.63	-0.64	0.56	5.41	1106
[0;7]	-0.26	4.41	-5.78	-2.16	-0.86	0.77	7.58	1106

Note: CAV Intervals are the cumulative abnormal volatility calculated over 1, 3, 5, and 7-day windows on the event day and they are calculated using the closing price of the day (CAV_stats_1 = 0,1 ; CAV_stats_3 = 0,3 ; CAV_stats_5 = 0,5 ; CAV_stats_7 = 0,7). The number of events totals 1,106 events (1,106 observations are football matches played over the period 2000 to 2020 in the World Cup, Euro Cup, Asian Cup, Confederation Cup, Copa America, Gold Cup, Africa Cup, National League, and Friendlies).

Table 3.6. Regression on CAV with Different Event Windows Controlling for Interaction Terms

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Win	0.002**	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Loss	0.006***	0.005***	0.004**	0.004
	(0.001)	(0.001)	(0.002)	(0.003)
Playoff	0.001	-0.006	-0.007	-0.005
	(0.003)	(0.008)	(0.008)	(0.009)
Rival	-0.002	-0.001	-0.000	-0.000
	(0.001)	(0.002)	(0.003)	(0.003)
Win*Playoff	0.005	0.012	0.013	0.002
	(0.004)	(0.009)	(0.010)	(0.012)
Loss*Playoff	-0.001	0.006	0.007	0.002
	(0.005)	(0.010)	(0.011)	(0.013)
Win*Rival	0.001	0.002	0.000	0.000
	(0.002)	(0.003)	(0.004)	(0.004)
Loss*Rival	0.004***	0.004*	0.002	0.001
	(0.002)	(0.003)	(0.003)	(0.004)
R^2	0.730	0.760	0.758	0.778
N	1094	1094	1094	1094

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 1-day to 7-day windows. The independent variables are Win, Loss, Playoff, Rival, as well as the interaction term. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

3.7 Appendix

Table A3.1. Variable Descriptions

Variables	Description
CAR	CAR is the cumulative abnormal returns measured for different intervals over a 15-day, 11-day, 7-day, and 3-day window and centred on the event day. It is calculated using the closing price of each day during the window of all firms with an event, retained from DataStream daily.
CAV	CAV is the cumulative abnormal volatility measured for different intervals over a 15-day, 11-day, 7-day, and 3-day window and centred on the event day. It is calculated using the closing price of each day during the window of all firms with an event, retained from DataStream daily.
Win	Win is a dummy variable of all games indicating 1 if the match is won. Otherwise, 0 for matches lost.
Loss	Loss is a dummy variable of all games indicating 1 if the match is lost. Otherwise, 0 for non-loss matches.
Playoff	Playoff is a dummy variable of all games indicating 1 if the match is a qualifier. Otherwise, 0 for nonplayoff matches.
Rival	Rival is a dummy variable of all games indicating 1 if the match is between rivals. Otherwise, 0 for nonrival matches.

Table A3.2. Percentage Change of Daily Mean in Volatility and Volume on the First Trading Day after the Match

	Win		Loss	
	Volatility (1)	Volume (2)	Volatility (3)	Volume (4)
Tournament				
World Cup	-0.000	0.001	0.000	0.008
Euro Cup	-0.000	-0.015	-0.000	-0.011
Asian Cup	-0.001	-0.001	0.004	0.055
Confederation Cup	-0.001	-0.012	-0.000	-0.018
Copa America	-0.000	-0.011	0.001	0.012
Gold Cup	-0.000	0.002	-0.002	-0.001
Africa Cup	0.001	0.020	-0.002	0.034
Nation League	-0.002	-0.028	0.001	0.005
Friendlies	-0.001	0.002	-0.000	-0.010
Match Type				
Playoff	-0.000	-0.009	-0.000	0.013
Non-playoff	-0.000	-0.001	0.000	-0.003
Rival vs non-rival				
Rival	-0.000	0.003	0.000	-0.006
Non-rival	-0.000	-0.002	-0.000	-0.000

Note: The table reports the percentage change of the daily mean in Volatility and Volume on the first trading day after national football matches. The football matches are played over the period 2000 to 2020 in the World Cup, Euro Cup, Asian Cup, Confederation Cup, Copa America, Gold Cup, Africa Cup, National League, and Friendlies. The mean returns reported in the table are computed from the log of daily volume and volatility on national stock market indices (from Datastream) on the first trading day after wins and losses. The Appendix details the country selection and rivals. Playoff matches are matches in which the loser is eliminated from the tournament.

Table A3.3. Regression on CAR with Different Event Windows (Figure 3.1)

Predictors	Event window interval						
	[0;1]	[0;2]	[0;3]	[0;4]	[0;5]	[0;6]	[0;7]
Win	0.008***	0.007***	0.005***	0.003	0.002	0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Loss	-0.028***	-0.028***	-0.027***	-0.022***	-0.008***	-0.010***	-0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Playoff	0.000	0.001	0.001	0.002	0.001	0.004	0.003
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Rival	-0.002	-0.002	-0.001	0.003	0.002	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.581	0.503	0.400	0.296	0.172	0.174	0.176
N	1094	1094	1094	1094	1094	1094	1094

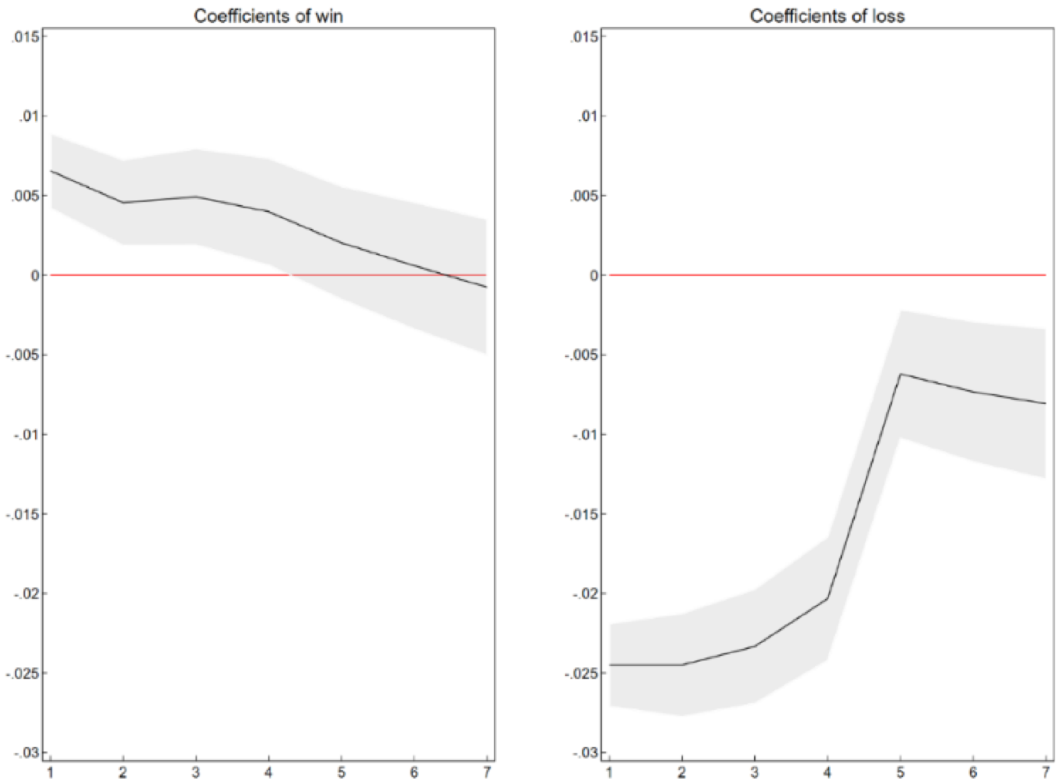
Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Win, Loss, Playoff, and Rival. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A3.4. Regression on CAR (Financial Development Index – Figure A3.1)

Predictors	Event window interval						
	[0;1]	[0;2]	[0;3]	[0;4]	[0;5]	[0;6]	[0;7]
Financial Development Index	-0.007**	-0.006*	-0.005	-0.006	-0.003	0.001	0.003
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Financial Markets Access Index	0.002	-0.001	-0.006	-0.004	-0.001	-0.007	-0.011
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Win	0.007***	0.005***	0.005***	0.004***	0.002	0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Loss	-0.024***	-0.024***	-0.023***	-0.020***	-0.006***	-0.007***	-0.008***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Playoff	0.001	0.001	0.002	0.002	0.003	0.006	0.005
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Rival	-0.002**	-0.002*	-0.002	0.001	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.528	0.436	0.355	0.283	0.159	0.161	0.163
N	1094	1094	1094	1094	1094	1094	1094

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Financial Development Index, Financial Markets Access Index, Win, Loss, Playoff, and Rival. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Figure A3.1. (Financial Development Index)



Note: Figure A3.1 is the illustration of the regression on CAR for Win and Loss with different event windows controlling for financial development index (Table A3.3). The x-axis represents the event window, and the y-axis corresponds to the number of the coefficient for Win and Loss.

Table A3.5. Match Interactions (Financial Development Index)

Predictors	Mean-adj return (1)	Market-model return (2)	Volatility (3)	Volume (4)
Financial Development Index	0.005	-0.020	-0.056***	0.005
	(0.004)	(0.023)	(0.003)	(0.003)
Financial Markets Access Index	0.001	0.010	-0.019***	0.025***
	(0.006)	(0.009)	(0.003)	(0.004)
Lag index return	-0.136***	0.053***	-0.033***	-0.005**
	(0.007)	(0.011)	(0.004)	(0.002)
Lag volume	-0.001	-0.000	0.008***	0.979***
	(0.002)	(0.008)	(0.001)	(0.001)
Lag volatility	0.053***	0.058***	0.271***	-0.085***
	(0.014)	(0.017)	(0.030)	(0.010)
World index return	0.123***		-0.007***	-0.003***
	(0.001)		(0.001)	(0.000)
Win	0.018***	0.013***	0.080***	0.005*
	(0.005)	(0.005)	(0.003)	(0.003)
Loss	-0.035***	-0.045***	0.196***	-0.009
	(0.006)	(0.006)	(0.004)	(0.010)
Playoff	-0.003	0.001	-0.006***	-0.002*
	(0.004)	(0.003)	(0.002)	(0.001)
Rival	-0.003***	-0.005***	0.020***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Win*Playoff	0.030	-0.009	0.045**	0.030**
	(0.041)	(0.034)	(0.023)	(0.012)
Loss*Playoff	-0.037	-0.064	0.050*	0.025
	(0.049)	(0.046)	(0.030)	(0.017)
Win*Rival	0.039***	0.057***	-0.203***	0.004
	(0.015)	(0.014)	(0.009)	(0.014)
Loss*Rival	-0.031*	-0.015	-0.007	-0.006
	(0.016)	(0.015)	(0.008)	(0.009)
R^2	0.555	0.192	0.538	0.948
N	39756	41049	41068	41068

Note: This table shows associations between football match results and stock performance. Mean-adjusted return is based on a 220-day estimation period starting 10 days prior to the relevant date. Market-model abnormal return is calculated using world index return. Volatility is the Parkinson (1980) intraday high-low range. Trading volume is the natural logarithm of the number of shares traded. Control variables include Financial Development Index, Financial Markets Access Index, world index return, lagged market return, day effects and individual effects. *, **, *** denote significance at 10%, 5% and 1%, respectively.

Table A3.6. Regression on CAR Controlling for Interaction Terms (Financial Development Index)

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Financial Development Index	-0.007**	-0.005	-0.003	0.004
	(0.003)	(0.004)	(0.005)	(0.005)
Financial Markets Access Index	0.002	-0.006	-0.001	-0.011
	(0.005)	(0.006)	(0.007)	(0.009)
Win	0.006***	0.004**	0.001	-0.002
	(0.001)	(0.002)	(0.002)	(0.003)
Loss	-0.020***	-0.020***	-0.008***	-0.011***
	(0.002)	(0.002)	(0.003)	(0.003)
Playoff	-0.004	-0.003	-0.004	-0.008
	(0.003)	(0.005)	(0.006)	(0.008)
Rival	0.001	-0.002	-0.002	-0.003
	(0.002)	(0.003)	(0.003)	(0.004)
Win*Playoff	0.005	0.005	0.008	0.015*
	(0.004)	(0.007)	(0.007)	(0.009)
Loss*Playoff	0.004	0.006	0.012	0.018
	(0.005)	(0.007)	(0.010)	(0.011)
Win*Rival	0.002	0.006*	0.005	0.004
	(0.003)	(0.003)	(0.004)	(0.005)
Loss*Rival	-0.012***	-0.007**	0.004	0.007
	(0.003)	(0.004)	(0.004)	(0.005)
R^2	0.545	0.366	0.161	0.166
N	1094	1094	1094	1094

Note: In the regression, the CAR is the dependent variable. Each CAR represents its unique window, varying from 1-day to 7-day windows. The independent variables are Financial Development Index, Financial Market Access Index, Win, Loss, Playoff, Rival, as well as the interaction terms. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table A3.7. Regression on CAV with Different Event Windows Controlling for Interaction Terms

Predictors	Event window interval			
	[0;1]	[0;3]	[0;5]	[0;7]
Financial Development Index	-0.011***	-0.011***	-0.009**	-0.010**
	(0.002)	(0.003)	(0.004)	(0.005)
Financial Markets Access Index	-0.008***	-0.008*	-0.008	-0.006
	(0.003)	(0.004)	(0.006)	(0.007)
Win	0.002***	0.002	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Loss	0.007***	0.006***	0.006***	0.005**
	(0.001)	(0.001)	(0.002)	(0.003)
Playoff	-0.000	-0.007	-0.008	-0.006
	(0.003)	(0.008)	(0.008)	(0.010)
Rival	-0.001	-0.001	-0.000	-0.001
	(0.001)	(0.002)	(0.003)	(0.003)
Win*Playoff	0.005	0.011	0.012	0.002
	(0.004)	(0.009)	(0.010)	(0.012)
Loss*Playoff	-0.002	0.005	0.005	0.001
	(0.005)	(0.010)	(0.011)	(0.013)
Win*Rival	0.001	0.002	0.000	0.000
	(0.002)	(0.003)	(0.004)	(0.004)
Loss*Rival	0.005***	0.005*	0.002	0.002
	(0.002)	(0.003)	(0.003)	(0.004)
R^2	0.734	0.759	0.758	0.778
N	1094	1094	1094	1094

Note: In the regression, the CAV is the dependent variable. Each CAV represents its unique window, varying from 1-day to 7-day windows. The independent variables are Financial Development Index, Financial Market Access Index, Win, Loss, Playoff, Rival, as well as interaction terms. All variables are defined in Appendix 1. The number for each variable is the coefficient of that variable. Numbers in parentheses are standard errors. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

CONCLUSION

This thesis studies several important types of information affecting stock performance that has, to date, received limited attention from the existing literature. In the first chapter, I distinguish between the impacts of suspected crimes and sanction announcements on firm stock performance. This chapter expands on earlier works by applying an event analysis to the study of how markets respond to news of regulatory actions being taken against corporations that have broken the law. The empirical studies use panel datasets, including board announcements from the CMA's website and stock data from the Thomson Reuters EIKON Datastream for the years from 2010 to 2018.

To begin, the regression findings for the whole sample demonstrate that the CMA's responses to violation announcements significantly impact stock returns. Particularly, companies that have *Suspected* violation announcements experience greater negative effects on their stock returns. Meanwhile, there is no significant difference in stock returns on the day that a *Fined* violation is announced, compared to a day when no violation announcements are reported. In addition, I have observed that the *Volume* and *Volatility* of the market are adversely affected by a *Suspected* announcement. For this second part, I use the event study method to determine the cumulative abnormal returns (CAR) and the cumulative abnormal volatility (CAV) of each announcement. Specifically, my findings indicate that CAR and CAV are significantly affected by the type of announcement.

This finding is consistent with research related to overconfidence, information uncertainty, and stock returns. Investor overconfidence is one example of a cognitive bias that becomes more pronounced when the amount of informational uncertainty over a company's performance increases (e.g., Hirshleifer, 2001; Kumar, 2009). Companies that are hard to evaluate often have higher predictable returns because investors tend to be more confident and, therefore, trade more aggressively (Daniel et al., 1998, 2001). An ability to indicate that increased uncertainty is linked to considerably higher or lower stock returns after positive or negative news is crucial (Zhang, 2006). The results of this study also demonstrate a positive correlation between uncertainty and the reaction to newly delivered information. It was suggested that CMA *Suspected* announcements are first time news that causes concern for investors due to the principle of information uncertainty. Markets are not caught off guard by news of sanctions or *Fined* violation announcements since these only apply to companies who have already disclosed that they were under investigation. Thus, CMA suspected violation announcements have a greater effect on the market.

In the second chapter, I examine the response of stock prices and volume traded to financial news sentiments. I chose to use data from all companies listed on Boursa Kuwait (excluding auction market securities, and non-Kuwaiti companies that are listed on multiple stock exchanges) over the six-year period from 2014 to 2019 as a base for my research within this chapter. Firm trading information, company fundamentals, and news article sentiments are merged to construct my study. The open/close, high/low, and volume traded data of Boursa Kuwait stock index and the stock of 83 firms at the daily level refer to trading information. Total assets, total debt, and returns on total assets relate to company fundamentals. Both sets of data are compiled from the Thomson Reuters EIKON Datastream. News article sentiments, word count, and other measures are used to analyse the text.

According to my initial findings, news has a significant, negative effect on stock returns. My findings suggest that the stock return is lower on days when news articles are published, compared to days when no news articles are released. The stability of the capital market is a key component for determining the significance of financial news, which may help to explain the findings (Kauter et al., 2015). As a potentially influential information hub, it collects and disseminates public knowledge and opinions relating to firms. Furthermore, "investor mood," which refers to views on future cash flow and investment risk justified by emotional reasoning, may be influenced by financial news, particularly if the news' substance or presentation style includes novel elements such as "emotion" or "suspense" (Schuster, 2003). Therefore, financial news about a business may have a substantial effect on the stock return by reducing information asymmetry and facilitating a more precise valuation of the company by investors (Carretta et al., 2011).

In the same way that the emotional tone of financial news creates and sustains speculative sentiment bubbles and fads among market players (Merton, 1987), it also causes significant swings in stock returns. Existing research on the relationship between the media and the stock market has found evidence of tone of news article’s impact on stock returns (see e.g., Tetlock, 2007; Fang and Peress, 2009; Tetlock, 2011). Consistently, I find that the tone of news articles has a significant effect on the performance of the stock market and the volume of trades.

Polarity, for instance, influences stock returns significantly and positively, but does not have a significant effect on *volatility* and *volume*. This suggests that an increase in stock price performance occurs when positive news is reported. Previous research (for example, Sadique et al. 2008; Loughran and Mcdonald, 2011) posits that the optimistic or pessimistic tone of qualitative information may provide insights into the operational success of a business. Investor moods and their opinions of a firm may change as a consequence, which could have a positive or negative impact on the stock's performance. As a result, investors may have a more optimistic outlook on a business's prospects, leading to a higher stock return on days when the company announces strong firm-specific financial news. Other studies verify this conclusion by showing that an upbeat media narrative has a beneficial influence on stock returns (e.g., Tetlock et al., 2008; Narayan and Bannigidadmath, 2015; Heston and Sinha, 2017).

Difficulty, on the other hand, has positive effects on stock returns and trading volumes. This suggests that stock returns and volume may be negatively affected by news articles that utilize technical and sophisticated phrases which require readers to have a certain degree of expertise in order for them to fully comprehend them. One possible reason for this result is that investors' information processing and analysis abilities are hindered due to the low readability of certain businesses' disclosures (Boubaker et al., 2019). Therefore, stock return volatility is affected because investors are reticent to invest in companies with less legible disclosures (Lawrence, 2013). Furthermore, it is suggested that companies with more complicated annual reports have more adversely skewed returns and a greater likelihood of a stock market meltdown. This is because companies are more likely to omit negative information while writing such reports (Kim et al., 2019). Given that firm-specific financial news with a low level of readability may increase the level of uncertainty for investors in relation to a firm’s future performance, firms that are the subject of such news information could suffer from a high level of variation in their stock returns.

Subjectivity, more so, has a positive influence on volume, but a negative effect on stock returns. In other words, stock returns decline but trading volume rises when news stories include subjective thoughts and views, whereas stock returns rise but trading volume falls when news articles include objective facts. Facts are more trustworthy and honest than personal beliefs, and studies demonstrate that market participants prefer to rely on facts, rather than speculation. Trading volume is high because traders rely heavily on inside information, as shown in the research by Darrat et al. (2007). To a similar extent, Blume et al. (1994) noted that investors' opinions inspire market players to take action, which in turn raises the trading volume. Our results are further supported by the research of Yu et al. (2012), who discovered that traditional and social media news had a significant impact on stock performance. Even though social media news has a larger impact than traditional news, they discovered that trading volume is higher when a firm is the subject of social media news, than traditional news. These results suggest that subjective news is more influential than traditional news.

Finally, I investigate the impact of football match results on stock market indices in my final chapter. To conduct the analysis, I used a dataset comprising the stock market index data for 15 nations, spanning May 2000 to April 2020 and sourced from Datastream. In addition, I make use of a second dataset that I extracted using Python from Worldfootball.net and which includes information on 1,258 matches played by the national teams of the 15 nations. This website provides every detail of a football game, including when it was played, where it was played, and in which competition. My final step was to combine the two sets of data by matching stock market information with the match scores.

According to my findings, the market index returns of a nation are higher (lower) on the day after a national football victory (defeat). Results for the estimated coefficient *Win* with the interaction term *Rival* are also positive and statistically significant, whereas those for the *Rivals* coefficient are negative and significant. Conversely, the calculated coefficients for *Loss* and the interaction term *Rival* are both greater and statistically significant in a negative direction when compared to the Mean adjusted return. This indicates that competitive games have a greater influence on the stock market than ordinary games, both in terms of total losses and in the reactions of stock returns. The day after a football victory over an opponent is a positive day for the markets of rivals, whereas the day after a defeat shows the opposite to be true.

Performance in international football is particularly interesting when used as a mood indicator (Edmans et al., 2007). Football is of "national interest" in many of the nation's we analyse, as shown by the TV viewing rates, media attention, and retail sales. Extensive psychological research reveals that sports in general have a considerable influence on mood (which we explore in the third chapter). It is difficult to think of any other common, regularly occurring event that would affect such a vast percentage of a country's population in such a dramatic way. All of these elements provide a strong justification for tracking changes in investor sentiment using match outcomes.

It may be that the market's reaction to news of these listed firms' future cash flows or the quality of its football players is a reasonable reaction to the game outcomes. For instance, a club's bottom line may be significantly impacted by match results, both positively (negatively) in terms of increased (decreased) sales of linked items and marketing, and the allocation of broadcast rights. A club's profitability may improve if revenue growth is strong, leading to larger dividends. Therefore, a high dividend yield will boost the value of a company's shares. A significant amount of research has been conducted on the correlation between the outcomes of sporting events and the emotions of investors (see for example, Renneboog and Vanbrabant (2000) and Palomino et al (2005, 2009)). Studies also demonstrate that a club's share price rises after a victory and falls after a loss, with the latter having a more pronounced negative influence.

According to Boyle and Walter (2003), fan confidence and their judgments of potential future investments may be affected by the results of their favourite sports. When their team is playing, they feel boosted in both their sense of confidence and their belief that they can succeed financially. However, when their team loses, diametrically opposed feelings emerge. Particularly in football, a club's performance may have a significant effect on ticket sales, sponsorship money, licensing revenue, the team's status, and the value of the organization among investors (Brown and Hartzell, 2001 & Hickman et al., 2008).

This final chapter of my dissertation adds to the literature on how investors' emotions and behaviours affect their financial choices. Validating the findings of Engle and Ng (1993), this chapter suggests that the stock market reacts to the outcomes of international football matches. Further, it bolsters the growing trend of qualitative research in finance, and the more recent trend of incorporating behaviourism into financial research observed during the last 30 years. The subjective nature of mood, emotion, and other non-quantifiable variables must still be factored into models empirically if such models are to be accurate or predictive, given that humans are inherently irrational and rarely achieve a theoretically optimal level of intelligence and information regarding the decisions they make.

Also, my findings on the relationship between football match outcomes and stock market performance have important policy implications for various stakeholders. For governments and regulators, the findings could highlight the need for greater oversight and regulation of sports events, particularly in light of any potential negative economic impacts. For stock market investors, the results could inform investment strategies and help them make more informed decisions about the relationship between sporting events and stock market performance. For sports organizations, the findings could inform how attractive and affective their tournaments/matches are, thus, enhance sponsorship and marketing decisions and potentially drive changes in how they approach partnerships. Overall, the policy implications of such research could lead to a better understanding of the complex relationship between sporting events and the economy and inform decisions that have the potential to impact the financial markets.

Finally, it is important to recognise that this research is subject to some data limitations that can impact the generalizability of the findings. For instance, the data used in this chapter does not cover all countries and market indices, which can lead to limited results. Additionally, the research may not take into account all relevant factors that could influence the market index performance, such as changes in macroeconomic conditions or political events. To address these limitations, future research could consider using larger and more diverse datasets that span multiple countries and longer time periods, as well as incorporating additional control variables that account for a wider range of potential confounding factors. Furthermore, the use of advanced statistical methods, such as machine learning algorithms, could help overcome some of the limitations of traditional event study technique and provide a more robust analysis of the relationship between football match outcomes and stock market performance.

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