Henley Business School

The University Of Reading

ICMA Centre

Asset Pricing across Asset Classes:
The Impacts of Fines and Flows

Thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

By

Rupini Deepa Rajagopalan

June 2017

Declaration of Original Authorship

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

____

Rupini Deepa Rajagopalan

Reading, June 2017

Abstract

This thesis consists of four empirical studies that examine two types of information, using a unique set of fines and fund flow data, on a multi–asset setting. The first study finds underperformance of between 29 and 57 basis points per month measured as Carhart model alphas on long-term stock returns of firms after announcements of monetary fines. Additionally, environmental fines are perceived by investors to be more of a concern while social, governance and also long-term aspects matter somewhat less. In the second study, I extend the research on fines by examining the inter-link between equities and bonds using short selling ratios and bond returns. Analysis using a fixed-income model shows that high short selling in the context of fines induces negative underperformances in bond returns. In addition, the underperformances are more profound for portfolios with longer remaining years to maturity and in crisis periods. The third study examines short-term reaction of Credit Default Swaps (CDS) spread changes and stock returns to fines. I find the CDS market is able to anticipate illegality news. Both markets react very differently to fines in different legal stages, industries and also by type of fine. Environmental issues are also a key concern in both CDS and stock markets and they also react more to higher fines per market cap. These empirical studies show that information about fines are valuable for investors as on average companies with illegalities underperform relevant benchmarks in the short and long-term. The fourth study involves fund flows on a global scale in Exchange Traded Funds (ETFs). I use panel data models and find that the explanatory power of ETF fund flows are similar to macro-economic variables in explaining indices returns. I also find investors could use ETF fund flows as information to understand market movements especially globally.

Acknowledgements

First of all, I would like to thank my supervisor and mentor, Dr. Andreas Hoepner, who has provided me with the outmost support and has believed in me from the start of my Masters until now. He has allowed me to be a part of his growing network in the Responsible Investment (RI) community and provided me with the opportunity to meet and work with many important and influential people in this area. My valuable discussions with him on not only my PhD dissertation but also on day-to-day life issues gave me the courage and determination to complete this journey. I am very glad that I not only gained a mentor but also a good friend.

I would like to thank my closest friends Tiffany, Gaini, Eunice, Dr. Muholan and Jai who cheered me up and provided me with so much of moral support. Besides that, I would also like to thank all my fellow PhD students at the ICMA Centre (ICMAC) and academic staff including Professor Adrian Bell, Professor Chris Brooks, Dr. Alfonso Dufour, Dr. Simone Varotto, Dr. Ioannis Oikonomou and Dr. Miriam Marra who provided me with additional guidance on my PhD along the way. I would also like to extend my gratitude to the administrative staff, especially Leanne Ley, who helped me in organizing many of the RI events at ICMAC. I also have to thank all the participants at the ERIIC conference in Hamburg and UNPRI conference in New York for their comments on the papers in this thesis. I also thank all of the PhD students under Dr. Andreas Hoepner's guidance for their feedback and thoughts on my research.

This PhD would not have been possible without my family. My father, Dr. K Rajagopalan and most importantly my beloved mother, Professor Dr. Jayati Roy who I admire for her strength and who I look up to as a strong women figure in my life. She always told me to think positive and to take life as a challenge. I would also want to thank my sister, Hema Raj Trukenbrod who since the day I was born always told me "To reach for the stars". With our 14-year age gap, she has always loved and protected me more than a sister and has given me all the support I needed. The encouragement and love from my brother in law Geoff and my two nieces, Naia and Sloane have also made my PhD journey a better one. This thesis is also in remembrance to my deceased grandmother, Renuka Roy, whose love and kindness will always be remembered.

However, the person who gave me the most strength is my husband and my best friend, Ralf Sobottka. He has always been by my side making sure I could finish this PhD journey. He has always been encouraging and has reminded me that the finish line is near and that I am capable of much more. He has supported me not only morally but has also made sure I am comfortable living in Germany to finish writing up my thesis. All our discussions on my PhD topic have encouraged me to think deeper. His love and support knows no boundaries. Without him, this PhD would not have been possible.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AP	Authorized Participant
APT	Arbitrage Pricing Theory
AR	Abnormal Returns
CAPM	Capital Asset Pricing Model
CARs	Cumulative Abnormal Returns
CASCs	Cumulative Abnormal Spread Changes
CDS	Credit Default Swaps
CSP	Corporate Social Performance
CV	Confirmed Violations
CVPM	Confirmed Violations but Pending other Matters
Datastream	Thomson Reuters Datastream
EFFAS	European Federation of Financial Analysts Societies
EMH	Efficient Market Hypothesis
EPA	Environmental Protection Agency
ESG	Environmental, Social or Governance
ETF	Exchange Traded Funds
ETP	Exchange Traded Product
EW	Equal Weighted
FY	Financial Year
HML	High Minus Low
IA	Initial Allegations
ICB	Industry Classification Benchmark
ISIN	International Securities Identification Number
KPI	Key Performance Indicators
LT	Long-Term
MC	Market Capitalization
MOM	Momentum
P.M	Per Month
RI	Responsible Investment or Return Index
RoW	Rest of the World
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
SIR	Short Interest Ratios
SMB	Small Minus Big
TRACE	Trade Reporting and Compliance Engine
UNPRI	United Nations supported Principles for Responsible Investment
USA	United States of America
VW	Volkswagen or Value Weighted

1. Introduction

1.1 Motivation for the Thesis

The primary focus of this thesis is to understand new information types that can help investors in their decision making process in a multi-asset setting. There are three major categories of information such as i) market-level information which usually affect the whole market such as macro-economic news, ii) industry-level information which only affect certain companies within a sector and iii) specific firm-level information which only affect that specific company (Piotroski and Roulstone 2004). Theoretically, the link between information and price changes is what denotes market efficiency. Information is very vital to investors as it affects their behaviors which are in turn reflected in returns on assets. Thus, the reaction by investors due to the release of information can provide insights into market efficiency and price discovery (Nofsinger 2001).

There are various existing theories that intend on identifying how investors react to information or news. The most traditional theory is based on the expected utility theory where *"the decision maker or investor chooses between risky or uncertain prospects by comparing their expected utility values"*(Von Neumann and Morgenstern 1944; Mongin 1997). In short, this means that during a period of uncertainty a rational investor would weigh all the possibilities of his own risk perception and probability of a possible outcome. On the other hand, there are other contrasting theories that indicate that investors do not act according to their own beliefs but rather herd, which is simply mimicking the investment decisions of other managers. Scharfstein and Stein (1990) state that investors perceive herding as a rational behavior as they are concerned about their reputation in the market. There are also other theories that are not associated with utility theory but rather predict that investors seek to reduce their internal conflict or cognitive dissonance (Nofsinger 2001). For instance, Bondt and Thaler (1985) examine the overreaction hypothesis and found that investors overreact to unexpected and dramatic news events. However, the most influential critique to the expected utility theory is the prospect theory which assumes instead that investors would make decisions more based on the probability of gain rather than loss (Kahneman and Tversky 1979).

The theories discussed above stem more on motivating short-term reactions from information. There are also theories that explain information that are not immediately captured by the market and impact firm value more on the long-term. Basically, these theories argue that stock prices adjust slowly to information and thus returns over long horizons are necessary to be examined to understand market inefficiency (Fama 1998). One theory is called long-run drift, which explains large and persistent drifts after events where the market may react to the true value of the firm only over time. There is delayed stock price reaction to events with abnormal performance persisting for years after events such as spinoffs, dividend initiations, initial public offerings, short interest announcements and mergers (Barber and Lyon 1997; Kothari and Warner 1997). For instance, Edmans (2011) captures a long-run drift in his analysis of the relationship between employee satisfaction and long-run stock returns from 1984 to 2009 and finds outperformance of 3.5% a year of the "100 Best Companies to Work for in America". The drift though declines over time and becomes insignificant in the fifth year.

The theories developed above provide various different explanations on understanding the way investors behave to information received. Investors receive information from various different sources which are usually public gained from announcements by the listed companies, the media including social media, annual reports, analyst reports from financial institutions and reports from regulators or governments. It is based on information received that investors use to make decisions. Thus, the primary purpose of this thesis is to examine the importance of information and the post-event investors' reactions. The two types of information that I examine are fines and fund flows.

Naturally the question is then why are fines considered as a new type of information. This begins with corporate scandals. Corporate scandals have always been a major attention grabber in the news and are mostly related to Environmental, Social or Governance (ESG) violations. Not only are these scandals widely reported in the media but they have also resulted in various impacts on companies from fines, product recalls, resignations of senior management and damage to company reputation. These corporate scandals are closely related to the illegal behaviors and actions of members of companies that result in decisions that are not legally permissible. Baucus and Baucus (1997) define illegal corporate behaviors *"as unlawful activities of members or agents of a firm, engaged in primarily for the firm's benefit"* (p129).The illegal actions of the members of the firms are deemed to "benefit" the firm but instead they actually cause more harm to the company.

For example, one of the largest environmental disasters was the Gulf of Mexico Oil Spill by BP Plc in 2010. This massive oil disaster is considered the largest accidental marine oil spill which also cost the lives of eleven people. The impact was also seen by an immediate drop in BP's share price by nearly 55% after the event and has still not recovered to the pre-scandal price, as seen in Figure 1[1]. In 2013, BP initially spent $14.3 billion in response to the disaster and also $8.6 billion for environmental costs[2]. In addition in 2015, BP agreed to pay a record environmental fine of $18.7 billion to settle legal actions brought by the US and several states over the fatal 2010 Gulf of Mexico oil spill. Another example in 2015, CEO of Volkswagen (VW), Martin Winterkorn, resigned due to the emissions scandal that erupted and plagued the company with questions of "bad governance" standards. VW was accused of intentionally manipulating its emissions results by having a "defeat device" installed in its diesel engines. This device could detect when cars were being checked for carbon dioxide emissions and produced better results than actual emissions on the road. The announcement made by the Environmental Protection Agency (EPA) that VW had violated the Clean Air Act by falsifying official emissions tests in diesel cars in the US from 2009 to 2015 had a major negative impact on VW stock price. It crashed nearly 45% (from €167 to only €92) at the beginning of September right after Volkswagen publicly admitted to have used programmed software in Diesel cars. The share price has not recovered to pre-crisis prices, just as in the case of BP. The EPA announcement also triggered product recalls in the US. In 2016, VW agreed to a $15 billion settlement for their violation but as of today the company still has to deal with countless legal actions. However, the scandal did not come as a surprise as it might have seemed. There had always been warning signs about the governance standards at VW even long before

---

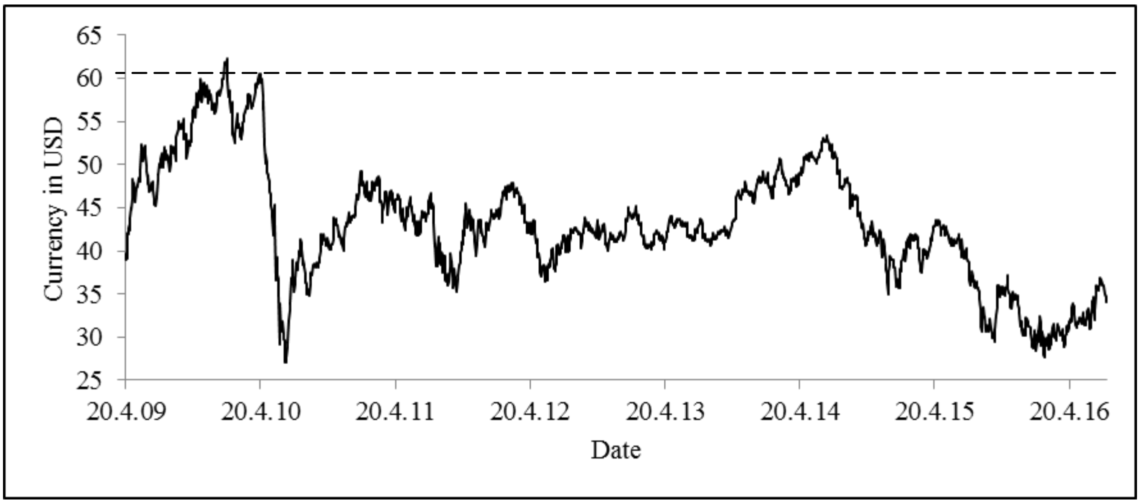
[1] It is important to note this limitation that even though BP's share price had plummeted immediately post the Gulf of Mexico Oil Spill, a potential explanation of the long-term drift drop of share price could also be due to the drop of the price of oil per barrel which was $94 in March 2010 and never recovered to that high price again (i.e.$42 in April 2016).

[2] "BP able to see beyond Deepwater at last" available at http://www.telegraph.co.uk/business/2016/07/30/bp-able-to-see-beyond-deepwater-at-last/ (accessed 20th April 2017)

the scandal due to VW's lax boardroom controls and corporate culture[3]. In 2005, VW had also been involved in another corruption scandal involving bribery[4]. VW is not the only case involving corporate governance scandals. It is evident that fines given to companies because of their illegal behaviors not only induce negative reactions in the markets but also have severe repercussions such as resignation of the CEO for VW.

Figure 1 BP Share Price Performance since the Gulf of Mexico Oil Spill (USD)

The figure below depicts the share price movement of BP pre and post the Gulf of Mexico Oil Spill which happened on 20th April 2010. As observed, BP's share price has still not recovered since the incident. BP's price before the incident was hovering slightly above $60 before 20th April 2010 but has still yet to recover (the dotted lines).



Source: Bloomberg

The first aim of this thesis is to measure the impact of fines as information on stock returns but most importantly, understanding the impact on long-term stock returns. From the BP and VW scandal, it is evident that fines are an important indicator as immediately after the announcements of the fines, investors react strongly with a

[3] "Volkswagen's 'uniquely awful' governance at fault in emissions scandal" available at http://www.cnbc.com/2015/10/04/volkswagens-uniquely-awful-governance-at-fault-in-emissions-scandal.html (accessed 4th April 2017)

[4] "Volkswagen: a history of scandals" 23rd September 2015, Financial Times" available at https://www.ft.com/content/22ca0e9a-6159-11e5-9846-de406ccb37f2 (accessed 4th April 2017)

drop of share prices of these companies. Most literature only measures the short-term impact of illegalities. However, institutional investors are more concerned about the longer term impact of holding companies in their portfolios and they are focused on identifying investments that are orientated towards a long-term performance. The above examples of BP and Volkswagen show that their share prices have not recovered to pre-crisis levels ever since and thus left shareholders with significant losses. The United Nations supported Principles for Responsible Investment (UNPRI) is the world's leading proponent for Responsible Investment (RI). Investors have shown clear support to the UNPRI as since its inception, the UNPRI has grown from 100 signatories in 2006 to 1500 signatories in 2016 with USD 62 trillion assets under management. The UNPRI advocate that RI *"is an approach to investing that aims to incorporate ESG factors into investment decisions, to better manage risk and generate sustainable, long-term returns"*[5]. Investors are not only reacting to ESG issues, they also use ESG factors as an important information to determine risk and return especially long-term. Furthermore, the UNPRI has six principles to promote RI and part of the signatories' commitment is: *"As institutional investors, I have a duty to act in the best long-term interests of our beneficiaries. In this fiduciary role, I believe that ESG issues can affect the performance of investment portfolios (to varying degrees across companies, sectors, regions, asset classes and through time*)[6]". Not only are institutional investors an important class of shareholders, but those institutional investors with longer investment horizons exhibit better sustainability footprints (Gibson and Krueger 2017). Therefore, I find there is a need for understanding whether there is a longer term impact of ESG violations and also Long-Term (LT) violations which relate to innovation (such as

[5] "What is Responsible Investment?" available at https://www.unpri.org/about/what-is-responsible-investment (accessed 19th April 2017)
[6] " The Six Principles" available at https://www.unpri.org/about/the-six-principles (accessed 21st April 2017)

patent disputes) anti-competitive behavior and monopoly practices disputes in the stock market and in different sectors. I find that this additional issue is important to be examined separately as it relates to investor's perceptions whether fines that impact the long-term viability of the company would be more of a concern compared to ESG issues.

The second aim of this thesis is to understand the inter-market link between asset classes especially between equity and fixed income after illegality announcements of companies. Considering that fines imposed on companies are based on illegal behaviors of companies, this then could relate investors having negative sentiments of companies. Short interest ratio therefore is a good indicator of the perceived "feelings" of investors, as they would short sell a company if investors are expecting that the company's stock price would decline. Previous studies only either measure the link between equity sentiment using short interest ratios on equity returns, credit rating downgrades or changes in bond spreads. I intend to investigate the impact of fines using short interest ratios on the impact on fixed income returns.

The third aim of this thesis is to measure whether there is also a short-term reaction of fines on Credit Default Swaps (CDS) spreads. CDS is an insurance contract which basically protects a buyer against a credit event on bonds such as default. As previously discussed, various research has measured the short-term impact of illegalities on stock returns. However, when VW was fined for the emissions scandal, not only did the stock return drop but their CDS spreads also widened. Thus, clearly the impact of fines can be seen not only on stock returns but also in CDS spreads. Fines would impact cash flows which could in turn increase the default risk of companies.

Most research that measure the impact of CDS spreads are based either on the reactions of earnings or ratings announcements. I find only one research by Kölbel and Busch (2013) that measures negative news on CDS spreads. However, their study is based only on overall illegalities, where as I examine the immediate impact of ESG plus LT fines.

My previous three aims are related to the impact of fines on different asset classes; stocks, fixed income and credit default swaps. Considering my main aim is to find information types that that would help investors in understanding performances better, my fourth aim of this thesis is to measure fund flows into ETFs. ETFs are securities that track an underlying index either comprised of stocks, bonds or commodities. The global ETF market has been increasing tremendously, however, I find only two papers that measure the relationship between fund flows and ETFs (Kalaycıoğlu 2004; Staer 2014), yet both those papers are based only on US data. Hence, there is still a gap in literature in understanding the impact of ETF fund flows on a global scale. Using worldwide fund flow data, I examine whether previous years ETF fund flows are able to predict next year's market returns on indices thus providing investors with a better understanding of market movements. Additionally, considering that ETFs mimic the market, I also examine if ETF fund flows are able to provide better explanations of models (i.e. higher adjusted R-squared values) compared to macro-economic variables that are commonly used by investors and researchers.

1.2 Intended Original Contributions of the Thesis

The first intended contribution of this thesis relates specifically to fines and their impact on long-term stock returns. Most importantly, the findings in this chapter extend current literature that mostly examines short-term reactions in the area of ESG and RI. Secondly, I do not rely on databases or use media to collect data on the announcement of fines. Instead, I have a unique hand-collected dataset comprising all fines given to companies in the MSCI Large Cap USA universe from 1994 to 2012, taken from the companies' 10-k filings to the US Security and Exchange Commission (SEC). I argue that this source produces a much more comprehensive dataset rather than just using media reports which usually only take the so-called "hyped" scandals. The results indicate that there are underperformances in the long-term on stocks and hence, the impact of illegalities is not just a short-term concern. Thirdly, not only do I investigate environmental, social and governance issues, I further extend the violations to even "long-term" issues which could relate to innovation (i.e. patents), anti-competitive behavior and monopoly practices.

The fourth contribution this thesis provides is its multi-asset class perspective on illegalities. I examine the impacts of fines not just on equities but also on fixed income and credit defaults swaps. This will be useful for investors as knowing the magnitude of the impact of fines on different asset classes will allow them to have a more holistic view of consequences of the illegal behaviors of companies. Traditional inter-market theory indicates that stocks and bonds move in the same direction at times (Murphy 2011). Therefore my fifth contribution in this thesis is that I investigate the inter-market link and whether short selling in the context of fines moderates a response on fixed income returns. This provides a better understanding of how connected these asset classes are especially after fines and whether traditional inter-market theory applies.

While I investigate the long-term impacts of fines in the first part of this thesis, I also examine and compare the short-term impact of fines on both equity returns and CDS spreads. This is in order to ensure that my dataset also produces similar short-term results as per literature that argues fines have a detrimental impact on the short-term. Thus, the sixth contribution of this thesis is to understand the impacts of short-term reactions on CDS spreads and equity returns especially on ESG and LT issues. My final contribution in this thesis is examining the relationship between ETF fund flows and index returns on a global level as well on different asset classes. The dataset I use is to my knowledge the first to examine global ETF fund flows of 51 countries in Europe, America, Asia, Israel and BRIC (Brazil, Russia, India and China) and Latin America.

Finally, in thesis I use different methodologies in each of the empirical analysis. Firstly, I use a time-series method to measure long-term performances using CAPM, Fama-French and Carhart models. Secondly, for the fixed income analysis, I use a multi-index model which captures different exposures to bond factors. Thirdly, I also use an event study methodology using market models for my short-term analysis and fourthly, I use panel data regressions for my final analysis on ETF fund flows. All the analyses have various robustness tests in place.

1.3 Outline of the Thesis

This thesis is structured in six chapters. The first chapter is the introductive chapter which provides an explanation of the motivation of my study and describes the original contributions of my four empirical analyses in my subsequent chapters. Table 1.1 at the end of this chapter provides a systematic overview of the four empirical chapters including its main focus, original contributions and research implications. Table 8.1 in the appendix has a detailed overview of all the datasets, sources, sample size and frequency used in this thesis.

The second chapter describes the first empirical analysis of fines on stock returns. In particular, it looks at the effects of fines on long-term stock returns. Previous studies have only looked at measuring the short-term impact of illegalities and less attention has been paid to understanding the longer-term impact of fines on stock returns. In this chapter, I begin with an introduction and motivation of my study and also on previous empirical literature on illegalities. I proceed with the explanation of my hypotheses which I develop based on my understanding from the previous literature and from theory. As this is the first empirical chapter of this thesis, I describe the unique hand-collected dataset of monetary fines I had obtained from the Securities and Exchange Commission (SEC) 10-K filings from the period 1994 to 2012 for United States of America (USA) based firms which is the basis of the fines data for the next two empirical chapters. Next, I describe the methodology I use in this chapter which is based on the Capital Asset Pricing Model (CAPM), three-factor (Fama-French) and four-factor (Carhart) models. In this chapter, I use equal weighted portfolios using both per fine and per company method and explain the rationale behind the use. For robustness, I also create value weighted portfolios. I also describe the European Federation of Financial Analysts Societies (EFFAS) classifications which I use to separate each individual E,S,G and LT factor. Furthermore, pursuant to my hand collected data, I was able to identify various stages of the legal process of the violations which I also empirically examine. In this chapter I also examine seven different industry sectors based on Standard Industrial Codes (SIC) to further examine whether there is an industry effect. In addition, I perform analyses on the different levels of fines per market size (based on market capitalization) and I also explain the rationale behind this analysis. Finally, I present my interpretations of the results and conclusions.

The third chapter examines empirically the inter-link between two asset classes, equity and fixed income. Specifically, I look at the effect of short selling after announcements of illegal violations on bond returns from the period 2000 to 2012[7]. Similar to the previous chapter, I begin with an introduction and motivation towards the reasoning of examining the link of fines between equity and fixed income. I argue that even though the US bond market is larger than the equity market, there is still lack of research in this area especially on illegality. I further examine other literature on short selling and equity performances, existing literature on the inter-link between equity and bonds and similar research that is closely related to this chapter, though naturally explaining how this study differs from those researches as I examine illegalities. I then proceed to explain my hypotheses, the bond returns and the constructed portfolios based on different levels of short interest ratios. In this chapter, I explain the use of the fixed income empirical model following Blake, E.J. Elton et al. (1993) and extended by Hoepner and Nilsson (2015). In order to examine the inter-link after fines between equity and fixed income, I proceed with interpreting the analyses not only using the whole portfolio sample but also different criteria's on the bonds such as timing (pre and post crisis periods) and duration (remaining years to maturity). This chapter also has numerous robustness and additional tests which I explain in depth.

[7] The reason the period is from 2000 to 2012 is due to the availability of the short interest ratios

The fourth chapter involves the empirical analysis of fines on credit defaults swaps. Particularly in this chapter I examine whether there is a short-term impact of fines on CDS spreads from the period 2009 to 2012[8]. In the previous chapters I examine the long-term impact of fines, however in this chapter I look at the short-term impact as I compare both CDS spreads and equity returns. The fines dataset here is similar to the ones used in the preceding two chapters and I also proceed to explain the CDS spread data. The study in this chapter is based on the event study methodology using two different models. I explain the use of the common market adjusted-model and also an index-adjusted based model which takes into account a rating based adjusted criteria and is used in numerous studies that measure short-term CDS spread impacts. The results of the empirical findings are interpreted based on CDS maturity levels, stages of different legal processes, by the value of the fines per market capitalization, by industries and by the different E,S,G and LT violations. Conclusions are then drawn between short-term equity returns and CDS spreads after fines and the implications to institutional investors.

The fifth chapter involves the empirical analysis of ETF fund flows as information in the market to understand future market movements. This chapter is different than the previous empirical chapters as it does not involve fines or illegalities nonetheless it follows the same concept of analyzing the relevance of information for institutional investors. I begin with an introduction and detailed description of the process of ETFs between various parties and the motivation behind the study. The literature review section in this chapter relates to studies in ETFs and performances and more specifically on asset allocation and variability research. In this chapter, the data I

[8] The reason the period is from 2009 to 2012 is due to the availability of the CDS spread data

use is different from the previous chapters and is retrieved from Deutsche Bank and which I explain in detail. The methodology in this paper is also different as I apply panel data econometrics and explain the reasoning behind my choices of variables. The results of the analyses are then interpreted and connected with the research question that has been posed.

The sixth and final chapter is the conclusion chapter which brings together a more holistic roundup of all the conclusions from the previous four empirical chapters. This chapter intends to provide an overview and summary of the contributions of this thesis and potential further areas for research.

[This section has been intentionally left blank]

Table 1.1 Overview of the Thesis on the Main Empirical Chapters

Table 1.1 provides an overview of the four main empirical chapters in this thesis, including the title, the major themes, the asset class, main methodologies that are used in each chapter, the geographical coverage of the studies as well as the main dataset. The table also lists the original contributions and implications of each of the four empirical chapters.

	Chapter 2	**Chapter 3**	**Chapter 4**	**Chapter 5**
Title:	Corporate Legal Responsibility and Stock Returns	Inter-market Link of Illegality: Measuring the Effect of Short Selling in the context of Fines on Fixed Income	A Comparative Event Study: The Impact of Fines on Credit Default Swaps and Stocks	ETF Fund Flows and Index Returns: A Global Multi Asset Class Analysis
Major Theme:	Impact of Environmental, Social, Governance and Long-Term Monetary Fines on Long-Term Equity Returns	Examining Different Levels of Short Selling in the Context of Monetary Fines and its Response on Bond Returns	Impact of Environmental, Social, Governance and Long-Term Monetary Fines on Short-Term CDS Spreads and Equity Returns	Examining the explanatory power of global ETF fund flows in explaining global equity, bond and future indices returns and the relationship on future market movements
Asset Class:	Equity	Equity and Bonds	Credit Default Swaps and Equity	Exchange Traded Funds and Equity, Bonds and Future Indices
Main Methodology (Models):	CAPM, Fama-French and Carhart Models	Multi-Index Bond Models	Event Study Models	Panel Data Models
Geographical Coverage:	US	US	US	Global
Main Dataset:	Monetary Fines in US MSCI US Large Cap Companies	Monetary Fines in MSCI US Large Cap Companies	Monetary Fines in MSCI US Large Cap Companies	Global ETF Funds Flows
Original Contributions:	First to examine the impact of environmental, social, governance and long-term issues on long-term stock returns and in different industries Incorporating all announcements of illegality and by different legal stages of violations that involve monetary penalization and with a data period from 1994 to 2012	First to examine whether short selling in the context of fines moderates a response on bond returns Linking of asset classes using short interest ratios and bond returns	First to examine the impact of environmental, social, governance and long-term issues on CDS spreads Examining whether the credit market anticipates illegality news	First study on global ETF fund flows from 51 countries into US, Europe, Asia Pacific and the Rest of the World Examining the relation between ETF fund flows and index returns on a global level as well on different asset classes

Table 1.1 continued

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Research Implications for:				
Institutional Investors:	Investors should divest from companies that are involved in illegalities that result in high financial penalties or advocate for a stronger change in corporate culture and behaviour that tolerates illegalities	Stock market sentiment (using short interest ratios) especially in the context of fines affects corporate bond returns i.e. high investor sentiment in equities has a direct effect on corporate bond prices	Investors should look at fines as information that can affect CDS spread changes and as indication of the credit risk and the potential health of a company	Investors should use information on ETF fund flows for decision making especially on equity and future indices, as it shows the different impact ETF fund flows have on global indices.
Companies:	Firms should have strong principles of corporate legal responsibility as illegal behaviours is detrimental for corporation's performances especially in the long run	Firm's illegal actions during crisis period are more detrimental than non-crisis periods indicating that investors are less lenient during crisis periods	Firms should be aware that their illegal behaviours impacts their company value by drop in share prices and also effects their credit worthiness which in turn can affect their future credit borrowing activities	Firms should keep track of ETF flows to better understand investor and global market movements
Academia:	Better understanding that the impact of illegal behaviours of companies not only have a short-term but also a long-term effect on stock returns	This study finds that short selling ratio is a viable indicator to measure the link between sentiment and bond returns	This study finds that that the credit market anticipates illegality news. Researchers should examine individual types of illegality and not cluster all types of violations in one category	This study adds to literature on asset allocation and prices especially on variability and ETF literature on the relationship of global ETF fund flows with market movements
Policymakers/Regulators:	Regulators should ensure that adequate controls and procedures are in place to deter corporate illegalities	Short interest selling is detrimental to companies especially after a fine	As this study finds that the CDS market anticipates illegalities, regulators could use this information to detect illegal behaviours of companies	Regulators should learn how and if flows shift markets

2. Corporate Legal Responsibility and Stock Returns

2.1 Introduction

In 2016, Volkswagen agreed to pay $15 billion in fines in the US to settle their emissions-cheating scandal which is the largest paid fine by an auto-maker for negligence. Volkswagen's share price tumbled nearly 45% since the Environmental Protection Agency (EPA) announced that the automaker manipulated emissions software. In 2012, BP paid a $4.5 billion penalty over the Deepwater Horizon disaster which at that time was the single total largest criminal resolution in the history of the United States. BP's share price dropped to a 13 year low after the incident and they have yet to recover from that pre-crisis period. BP paid an additional environmental fine in 2015 of $18.7 billion to settle legal actions based on that Gulf of Mexico oil spill. Eaglesham and Fuller (2015) find that the Securities Exchange Commission (SEC) for the fiscal year ended September 2014 levied more sanctions (including fines and repayment of illicit profits) overall on firms and individuals amounting to $4.2 billion which was a 22% increase from the previous year. The Federal Bureau of Investigation (FBI) in FY2011 secured $2.4 billion in restitution orders and $16.1 million in fines from corporate criminals in that year and the amount of fines increased drastically by 198% from FY2009 to FY2011[9]. The FBI corporate fraud data also indicate that the amount of fines had also increased from $2.8 million to $19.9 million from FY2002 to FY2008. It can be deduced that monetary penalties have risen substantially and in tandem with an increase in corporate crime. Monetary fines are growing and the

[9] This sample time frame of FBI data from FY2002 to FY2011 was chosen as it covers a part of my data sample from 1994 to 2012. There is no data available prior to FY2002. "Financial Crimes Report 2010-2011" available at http://www.fbi.gov/stats-services/publications/financial-crimes-report-2010-2011 (accessed 10 September 2016)

implications of these fines no longer hold just as a "cost" of business. There are strong impacts of these fines which are not only felt by the firm but also stakeholders. English (2014) state in the Thomson Reuters report on the rising costs of non-compliance that *"Financial implications are much wider than the actual fine levied… regulatory action can have a negative impact on the share price of a firm and damage its relationship with investors".*

I find numerous amount of literature that have measured the short-term impact of firm illegalities on stock returns (Arnold & Engelen, 2007; Bosch & Eckard, 1991; Davidson, et al., 1994; Karpoff, et al., 1999; Song & Han, 2015; Wallace & Worrell, 1988)[10]. One of the earlier studies by Wallace & Worrell (1988) used an event study methodology to examine announcements of firm illegalities and find that the market does react negatively in the short-term to socially irresponsible acts. There have been a number of studies that have measured the impact of different types of crimes on stock returns (Davidson, Worrell et al. 1994; Cohen 1996; Arnold and Engelen 2007; Song and Han 2015), on different types of industries (Baucus and Near 1991; Zeidan 2013; Song and Han 2015) and by environmental and social violations (Karpoff, John R. Lott et al. 2005; Capelle-Blancard and Laguna 2010).

However, I find only two studies that have measured the long-term impact of illegalities (Baucus and Near 1991; Baucus and Baucus 1997). I differ from them in several ways. Firstly, both studies use a sample of illegal behavior data of convicted firms to meet the criteria of only "clear illegal" behavior. Their violation data is based only on the assumption that managers knew or should have known the illegality of their actions. My study instead incorporates all announcements of illegality and by different legal stages of violations that involve monetary penalization. Secondly, even though

[10] I also measure the short-term impact of illegalities on stock returns in Chapter 4 of this thesis

Baucus & Baucus (1997) measure the longer-term performance using accounting and market returns, their study is based on a rather simple analysis of covariance procedures whereas I intend on measuring the impacts of illegalities using a more advanced, Carhart model based portfolio method to measure performance. Thirdly, their data sample is from 1963 to 1981 and my data period is from 1994 to 2012 and thus intends to examine whether investors in the more recent period react to illegal behaviors of firms with monetary fines.

In this chapter, I examine 5673 US based firms from 1994 to 2012 using hand-collected data of monetary fines from SEC filings. My review of the literature shows that on the short-term, illegal behavior is penalized by the market. Hence my first part of the study is to examine whether this also holds in the long-run. Indeed, my empirical findings indicate that when holding firms with monetary for one year there are negative underperformances of between 29 and 57 basis points per month (p.m) measured as Carhart model alphas. These results support the overall finding that fines are also detrimental to stock returns in the long run. Secondly, Karpoff, Lee, & Martin (2007) state that in determining fines to be imposed on criminal frauds, the US Sentencing Commission guidelines mandate that the fines increase with the size and scope of the violation. Thus, I also examined whether investors look at the size of the fine in respective to the size of the firm. My results confirm that firms with higher fines per firm size (based on market capitalization) have a larger underperformance compared to firms with lower fines.

Thirdly, studies such as (Karpoff and John R. Lott 1993; Karpoff, John R. Lott et al. 2005; Karpoff, Lee et al. 2005) have all measured the different stages of announcements of violations. Similarly, I also investigate the different impacts of the legal stages of violations on stock returns[11]. I find that initial announcements of the violations have larger negative returns compared to the other stages, indicating that investors are much more concerned when first announcements of the fines are out. In this stage investors are uncertain about the possible final penalty and thus feel more alarmed after the initial announcement of a possible fine. Fourthly, Zeidan (2013) states that shareholders in different industries would react differently when faced with similar problems. Therefore, it is important to examine whether these results would also hold in the long-term on different industries. Considering that environmental issues such as the depletion of natural mineral resources is a concern and scandals such as BP which caused massive fines, I find that investors react stronger to violations in the manufacturing, mining and transportation and public utilities[12] industries compared to other industries. Finally, I also measure the different types of violations based on environment, social, governance and long-term fines. Following my results, I was able to find that investors perceive environmental issues on all different stages of violations to be a cause of concern, while social, governance and surprisingly also long-term aspects matter somewhat less.

This study extends the growing literature in the area of corporate illegalities. While there is substantial research on the impact of illegalities on short-term stock returns, this paper is to my knowledge the first to examine the impact of long-term stock returns especially on different ESG plus LT issues. The results in this paper will be beneficial especially to institutional holders and regulators who are interested in understanding the longer-term consequences of illegal behaviours. Furthermore, the findings that environmental issue is a key concern to investors, support the views of

---

[11] Refer to figure 2 in for the full description of the different stages of violations
[12] Transportation and public utilities includes subcategories i.e. pipelines and electric & gas services

numerous institutional holders of the material risk climate change has to society and to the economy.[13] Thus, policymakers should raise awareness and push forward to support climate change resolutions and ensure that corporations have better ethical cultures that would benefit shareholders in the long-run.

The remainder of this chapter is ordered as follows. I begin with a literature review in section 2 on corporate legal responsibility, empirical studies that measure illegalities and firm value and the hypothesis development. Section 3 explains the method for the hand-collected data and the reasoning for the empirical methodology. Following that I discuss the results in section 4 and additional tests in section 5. Finally, I conclude with the findings from the research.

2.2 Literature Review and Hypothesis Development

2.2.1 Corporate Legal Responsibility

The definition of corporate crime can be very diverse. Becker (1968) indicates that the word "crime" should cover all violations, not just felonies like murder but also white collar crimes and punishment inflicted on offenders vary from imprisonment to fines. Baucus & Baucus (1997) define illegal corporate behaviour as *"unlawful activities of members or agents of a firm, engaged in primarily for the firm's benefit which includes intentional and unintentional illegal acts"(p129).* Song and Han (2015) adopted a comprehensive definition to corporate crime indicating that *"corporate crimes are illegal activities perpetrated by both corporate executives as individuals and corporations as organizations. Individual crimes may include white-collar crimes (e.g., fraud, embezzlement) and street crimes (e.g., assault, theft), while organizational*

[13] "CalPERS - The Importance of Corporate Engagement on Climate Change" available at https://www.calpers.ca.gov/docs/corporate-engagement-climate-change.pdf (accessed 5th June 2017)

crimes could incorporate operational crimes (e.g., price fixing, labor law violation) and financial crimes (e.g., accounting fraud)" (p2). From a firm's perspective, firm valuation theory explains whether investors are likely to react if a firm commits a crime (Wallace and Worrell 1988). The value of a firm may increase if investors believe that the crime committed for example bribery may actually increase firm value (Zeume 2014). Instead, the value of the firm might decrease if investors believe that the crime committed may be detrimental to the firm because of potential fines or penalties (Wallace and Worrell 1988).

Once a crime is committed, how are firms punished for their actions? For a firm, a court can implement retribution via monetary penalty which Ulen (1996) argues should be "calculated according to the amount of harm that the fraud imposes directly on identifiable victims (the civil loss) and indirectly on other consumers and business organizations (the social loss)". There are other theories that intend to explain the penalties that firms receive for their misconduct. Becker's (1968) seminal paper introduced the optimal penalty theory where the penalty should equal the social harm divided by the probability of detention. Cohen (1996) empirically examines the extent to which past sentencing practice for corporations convicted of federal crimes (prior to adoption of the new sentencing guidelines in 1991) has been consistent with optimal penalty theory. "*In November 1991, the U.S. Congress enacted the U.S. Federal Sentencing Guidelines legislation which had a dramatic impact on corporate America and the guidelines consisted essentially of a manual for judges to consider when determining the appropriate sentence for corporations convicted of a federal crime"pg1046* (Izraeli and Schwartz 1998). Their findings suggest that the sentencing practice is consistent with an optimal penalty framework. Cohen (1996) also found no deep pocket effects (larger firms receive larger monetary sanctions), which is in contrast to Karpoff, Lee & Martin (2007) who find there are effects of deep pockets as their data indicated that both private and regulatory monetary penalties are related to defendant's ability to pay. This shows that there is still ambiguity in the sentencing practices. Lott (1996) argues that criminal penalties should be limited to the rare situations in which there are third-party externalities. His views are opposing to Ulen (1996) who states that criminal penalties are required to ensure that offending firms internalize the losses imposed on buyers.

I find the definition of crime is vast and the sentencing practices ambiguous. Nevertheless when corporate crime is committed, it has consequences on shareholders. Though it is the firms managers that cause the violations, shareholders are left to bear the full economic burden of the fines (Kennedy 1985). Zyglidopoulos (2016) states that second-order corruption which is the abuse of power by individuals or groups to change existing (or create) rules or norms so that they can benefit unfairly is more harmful in long run and is harder to prevent, detect and stop[14]. Thus, it is crucial that the sense of corporate legal responsibility is instilled in managers to ensure violations are not re-occurring phenomena especially in the long run. The debate about corporation's responsibility, especially legally, has led to various discussions on the cultural behaviors of the risk perceptions of firms (Tully 2005). Corporations are taking risks without understanding the full extent of the consequences of their actions. Therefore, perhaps a stronger sense of the implications especially on the impact of performance on firms would deter corporations from having violations and invoking a stronger adherence to the law.

[14] The first-order corruption is the abuse of power by either individuals or groups for private gain, given a system of existing rules or norms.

2.2.2 Illegalities and Firm Value

It is evident that shareholders bear the consequences of illegal behaviors of firms and many scholars assert there are significant negative impacts of these behaviors on shareholder returns. Various literatures have used the event study methodology to measure impacts of fines on stock prices. Wallace & Worrell (1988) used that method to measure the impacts on shareholder returns of announcements of corporate illegalities as proxies for social irresponsibility. They claim that this method would be able to determine the accurate way to measure effects on very short-terms. With a sample of 131 events and 96 firms, using a market model, they find that markets do react negatively to announcements of alleged corporate crime. Bosch & Eckard (1991) investigated market reactions to only US federal indictments to price fixing. They find a total value loss of $2.18billion in equity value for the 127 observed sample firms around the announcements of their indictments.

Davidson, Worrell, & Lee (1994) extended Wallace & Worrell (1988) study by using a larger sample size of 535 announcements. In contrast, they find there is an overall insignificant market reaction to the announcements but when the samples were further broken down to specific crimes, they find that markets react significantly to bribery, tax evasion and violations of government contracts. Karpoff et al., (1999) investigated defense procurement fraud, indictments and suspensions and find significantly negative abnormal returns. Langus and Motta (2006) measured the impact of antitrust investigations in Europe on firms stock market value. They find that the European Commission’s surprise inspection of the firm’s premises has a strong and statistically significant effect on the firm’s share price, with its cumulative average abnormal return being approximately -2.2%. Arnold & Engelen (2007) measured the impact of announcements of different types of illegal corporate activities on stock prices of Belgian and Dutch firms. They find that there were no reactions to news related to corruption, and a very small reaction on day [0] and a larger, delayed reaction on day [+1]. Investors seem to anticipate news on accounting fraud as an abnormal return of -10.40% is found on day [-2]. Choi & Pritchard (2012) find that the stock market reacts more negatively to class actions relative to SEC investigations. Zeidan (2013) find that the market did not react significantly to the severity of violations. He argues even though his study is based only on financial institutions, the findings were consistent with reactions of shareholders in other industries. He also controlled for size as he indicates that larger firms have extensive resources that allow them to more easily absorb the penalties set forth. Kouwenberg and Phunnarungsi (2013) examined market reactions when firms with good and poor governance commit violations of the listing rules in Thailand. They find a strong market reaction, −8.1% on average, when firms with low past violations and low governance scores commit violations. Also using an event study methodology, Song & Han (2015) analyzed different types of corporate crime[15] in Korea from 2001 to 2010 and find negative reactions to stock prices around the announcements of corporate crimes.

The string of literature above confirms that investors react to violations negatively especially on the short-term. I find only two studies by Baucus & Near (1991) and Baucus and Baucus (1997) that investigate the long-term performance effects of corporate illegality. Baucus & Near (1991) used an event history analysis for a 19 year period to measure illegal activities of firms using financial performance measures such as return on investment. They find that large firms are more prone to

[15] The crimes that they measure are; crime type (white-collar vs. street crime, operational vs. financial), industry type (financial vs. industrial), business group affiliation (chaebol-affiliated vs. non-chaebol-affiliated), and corporate governance (strong vs. weak board structure index)

behave illegally and firms with poor performance were not prone to commit wrongdoing. Baucus and Baucus (1997) investigated the long-term performance effects of corporate illegality over the period of one through five years after a conviction. Their results indicate that firms' experience lower accounting returns over five years and slower sales growth in the third through fifth year after a conviction.

There are also various literatures that have looked into measuring different types of specific environmental and social issues on performances of firms. On environmental issues, Konar and Cohen (2001) find that legally emitted toxic chemicals have a significant effect on the intangible asset value of publicly traded firms. Thomas (2001) examined the correlation between the excess stock market returns and the adoption of an environmental protocol by firms. His results indicate that both the adoption of an environmental policy and prosecution for breach of environment standards have significant explanatory power in an analysis of excess returns. Jacobs et al., (2010) analyzed the shareholder value effects of environmental performance by measuring the stock market reaction associated with announcements of environmental performance. They find overall, that the market is selective in reacting to announcements of environmental performance with certain types of announcements even valued negatively. Karpoff, John R. Lott, et al., (2005) find firms that violate environmental laws suffer statistically significant losses in the market value of firm equity. Capelle-Blancard and Laguna (2010) examined stock market reactions to industrial disasters which caused toxic release and death or serious injuries. They find petrochemical firms drop on average 1.3% in their market value over the two days immediately following the disaster. On environmental and social issues, Ziegler, Schröder, & Rennings (2007) examined the effect of sustainability performance of European corporations on their stock performance. The main result is that the average environmental performance of the industry has a significantly positive influence on the stock performance. In contrast, the average social performance of the industry has a significantly negative influence. I proceed in the next section with the explanation of my hypotheses.

2.2.3 Hypotheses Development

This chapter makes several contributions to literature. Firstly, most of the reviewed studies have focused on event methodologies and measuring short-term effects (Wallace and Worrell 1988; Bosch and Eckard 1991; Davidson, Worrell et al. 1994; Karpoff, D. Scott Lee et al. 1999; Arnold and Engelen 2007; Song and Han 2015). What about longer term impacts of violations on the performances of stock returns? There is very little evidence empirically measuring long-term impacts other than Baucus & Near (1991) and Baucus and Baucus (1997). Stock prices are a good indicator and appropriate measure compared to accounting measures as there is an immediate market reaction to events such as illegalities. Accounting based returns would only show a reaction until the next accounting period when the report is prepared. Short-term consequences of corporate illegal activity has already been researched by academics and the results indicate following efficient market hypothesis that the new information of the illegality induces the stock prices to decline immediately (Arnold and Engelen 2007). Thus, I intend to investigate whether investors penalize firms also in the long run. The question then is why is there a long-term effect of illegality on stock returns? Baucus and Baucus (1997) state that longer-term performance measures better capture conviction performance relationships since firms suffer prolonged damage from illegality. Furthermore, illegality would indirectly hurt a firm’s image and brand with its stakeholders. Institutional investors are usually very active owners and engage with firms proactively (Gillan and Starks 2000), thus illegal activities might even cost the firm prolonged damage due to the long-term investment horizons of these investors. (Marcus and Goodman 1991) examined market reactions to signals such as accidents, scandals and product safety incidents and find that there might be reputational damages from these incidents which it might take many years before the true impact of managerial actions can be recognized. Though most of the short-term studies indicate immediate underperformances, the stock price of a firm might actually increase in the short-term after a fine. For example, JP Morgan's share price increased after a settlement announcement as investors were relieved of the legal woes[16]. Thus, this further affirms the need to examine longer-term impacts of corporate illegal activities.

Ziegler et al., (2007) also used a longer observation period in their econometric analysis as they indicate that the short-term over-reactions of stock markets can become weaker or even disappear over time. In addition,. Similar to most of the reviewed literature that find short-term negative impacts on stock returns, I expect similar results in the long-term. (Gibson and Krueger 2017) provide evidence that longer term oriented institutional investors have a higher sustainability footprint in particulate those with longer-term horizons e.g. one year. Thus, following their reasoning that it is longer-term investors with one year investment horizons that provide a significant difference, I examine long-term consequences of the illegal behaviors of firms after violations over the period of one year instead of two or three or any other years. Hence, the first hypothesis is defined as the following:

[16] "JPMorgan's Soaring Stock Price To Completely Erase $13 billion Fine" available at http://www.huffingtonpost.com/2013/11/26/jpmorgan-stock-fine_n_4343987.html (accessed at 10 June 2014)

Hypothesis 1: *Stocks of firms that are being held for one year upon announcement of violations have negative stock returns*

The second contribution this chapter makes is measuring whether the magnitude of fines in the firm has an impact on stock returns. Karpoff, John R. Lott, et al.,(2005) were one of the earlier authors to measure the size of the legal penalties imposed on environmental violations and find that firms' losses in share values are related to the size of the fine or damage award eventually imposed by regulators or the courts. As part of their independent variable, they use the dollar amount of the fine divided by the market value of the firm equity to examine the cross-sectional relations between share value losses and legal penalties. On the other hand, Karpoff, Lee, & Martin (2005) examined the legal penalties due to financial misrepresentation and find that large legal penalties can be substantial but market penalties are even larger. Both studies examine the size of the fines and its impact on returns, hence here I intend on measuring whether investors also look at the size of the fine in respective to the size of the firm. Using a rational expectations assumption, I expect that fines that are high per market size have larger underperformances. Hence, the second hypothesis is defined as following:

Hypothesis 2: *Firms with higher fines per market size have a larger negative stock return in the long-term compared to firms with lower fines per market size*

The third contribution of this chapter is to understand which legal stage of the process would bring a stronger reaction from investors. Though fines are detrimental to stock returns, at times the confirmation of fines maybe viewed positively, if the market expected worse and/or the market is relieved to have simply been removed from the uncertainty. For example, after the settlement was announced for JP Morgan's $13 billion fine of selling bad mortgage bonds ahead of the financial crisis, JP Morgan's share price jumped more than 3 percent as investors were relieved to put the legal woes to end[17]. I deduce that the initial stage of violation or announcement would be more of a concern (if there were no prior announcements or rumours) compared to the other legal stages. This similar is to Karpoff, John R. Lott, et al., (2005) who find that the stock price reactions to initial announcements on environmental fines captures most of the firm's total loss in market value. Karpoff & John R. Lott (1993) examined different types of press dates (i.e. allegation date, charges filed date and settlement date) surrounding corporate fraud and Karpoff, Lee, et al., (2005) also examined various stages of the enforcement process surrounding federal securities investigation. Here, I examine the impact on different level of the fines per market size and I hypothesize that the initial allegation stage would have larger negative returns compared to the other legal stages. Thus my third hypothesis is defined as the following:

Hypothesis 3: *Violations at the initial allegation legal stage have larger negative stock returns compared to other legal stages*

The fourth contribution this chapter makes is to examine the long-term impacts of returns within individual industries. Every industry is unique with its own characteristics. Even shareholder perception for each individual industry would differ. Zeidan (2013) specifically measured public traded banks using a short-term study methodology, noticed that there is a significant negative market reaction on violations by banks which were subject to enforcement actions by US regulators. Song and Han (2015) find that corporate crime by a financial firm has a stronger negative impact on stock market valuation than by an industrial firm in South Korea using a short-term

[17] "JPMorgan's Soaring Stock Price To Completely Erase $13 Billion Fine" available at http://www.huffingtonpost.com/2013/11/26/jpmorgan-stock-fine_n_4343987.html accessed 8th May 2017

study. Taking into account that both those studies are based only on short-term effects, I expect investors to react more on the long-term to industries that have a more profound long-term impact to the environment. The reasoning behind is based on Karpoff and John R. Lott (1993) who state that *"the firm's customers, employees, and suppliers can be motivated by environmental concern to change their reservation prices in doing business with the firm. Environmentally costly activities that attract unfavourable attention could then lower demand for the firm's products or increase the firm's costs".* In addition, considering that the depletion of natural mineral resources is a constant debate and concern (Jenkins and Yakovleva 2006), plus environmental massive disasters and scandals such as BP and Volkswagen, I expect industries that are related to extractions and usage of valuable minerals and natural resources (i.e. mining, manufacturing) would have more investor reactions in each stage of the legal process. The fourth hypothesis is therefore defined as the following:

Hypothesis 4: *Investors react more to violations in the extractions and usage of valuable minerals and natural resources industries compared to other industries based on each stage of the legal process*

The fifth contribution of this study is to understand which individual ESG plus LT factor is more of a concern to investors. There are various other studies that measure individual criteria's such as environmental and social (Ziegler, Schröder et al. 2007), environmental (Konar and Cohen 2001; Thomas 2001; Patten 2002; Karpoff, John R. Lott et al. 2005; Shimshack and Ward 2005; Jacobs, Singhal et al. 2010; Leon, Devereux et al. 2010) and governance (Baucus and Baucus 1997; Schnatterly 2003; Karpoff, Lee et al. 2007; Kouwenberg and Phunnarungsi 2013).Coleman (2011) used proxies[18] as signals of ESG, however none to my knowledge have used the European Federation of Financial Analysts Societies (EFFAS) standards on all four ESG plus LT criteria's to measure violations. I consider the LT issues key to be added to ESG because companies usually pursue corporate sustainability with both an agenda to reduce ESG risk but also to increase their long-term viability i.e. increase their profits. Hence, examining the LT separately from ESG issues would be crucial in understanding whether investors consider LT issues that affect companies as a concern. For example, the LT could relate to innovation (i.e. patents) that would affect the long-term revenue generation of the company. However, bearing in mind that in my previous hypothesis, I would perceive violations in the extractions and usage of valuable minerals and natural resources industries (i.e. environmental related) to be more of a concern compared to other industries, my fifth hypotheses are defined as the following:

Hypothesis 5a: *Investors perceive environmental violations at every stage of the legal process to be more of a concern*

Hypothesis 5b: *Investors in each industry react only to certain individual E, S, G and LT violations*

In order to measure whether my hypotheses above are valid, I examine the impacts of these violations using empirical data in the following sections.

[18] This study used fines of environmental breaches, unsafe workplaces, fraudulent accounting standards, and product recalls. Those measures are assumed to proxy for signals to stakeholders of ESG risks.

2.3 Data and Methodology

2.3.1 Data Sample

This study consists of a sample of publicly traded US firms that have violated regulations that involve only monetary penalization. The lists of US firms were taken from the MSCI World Large Cap Constituents over a 19-year period from 1994 to 2012. Baucus and Near (1991) find that large firms that operate in dynamic, munificent environments were the most likely firms to behave illegally. The overall sample consists of 597 unique firms with 2370 number of violations throughout the 19 years[19].

Most of the reviewed literature use media sources for the date of events such as Wall Street Journal, Dow Jones news retrieval service and other news databases such as Lexis/Nexis and Factiva. However, using such databases can create several problems. Firstly, they may not capture all the relevant or large events. Secondly, different databases might provide different event dates and finally they might only collect certain types of announcements that might skew the actual research question (Karpoff, Koester et al. 2014). Coleman (2011) had used various governmental databases but also indicate that there is no certainty of comprehensive data.

Hence, the source of information for the violations was identified and hand-collected via filings of 10-K reports in the SEC database. It is mandatory that all public firms publish this which are available at the SEC. Schnatterly (2003) indicates that there is a significant amount of repetition between annual reports and 10Ks and further states that the 10Ks are usually viewed by regulators and analysts. Hence, this legitimizes my purpose using the 10Ks as my source of data. From the 10Ks, I am able to retrieve the

[19] Table 8.2 and 8.4 in the appendix reports the distribution of sample size and the number of violations over the years respectively

reported date of the announcements of the fines of the firms. The violations were noted under Item 103 of legal proceedings or unless directed under commitment and contingencies in the fillings. In order to create the database, only firms that had any announcements of corporate violations or violations (i.e. bribery, breach of fiduciary duties, anti-trust, tax evasions, fraud, labour issues) with monetary penalties were used. However, Item 103 of Regulation S-K requires disclosure of administrative or judicial proceedings arising under any federal, state or local provisions dealing with protection of the environment, if the monetary sanctions might exceed $100,000.

2.3.2 EFFAS' Criteria

I used in this study the European Federation of Financial Analysts Societies (EFFAS) Key Performance Indicators (KPIs) 3.0 as they are the only classification that includes long-term as well. These KPIs were created as a guideline for the integration of ESG into financial analysis and corporate valuation and was specifically designed for stock listed firms.. However, in addition to ESG, these KPIs have an additional factor "Long-Term Viability" or "Viability", herein "Long-Term" which are described in section 1.3 "Purpose of the ESG Reports" *(p7).* It specifically states that "*corporate sustainability focuses on both minimising risks arising from environmental, social and corporate governance aspects and proactively seeking to gain advantages from "translating" ESG issues into a company's product and service portfolio. As such, companies pursuing corporate sustainability reconcile long-term viability with management of ESG issues"*. Thus it is this additional long-term viability (V) factor which is provided in each individual KPI section. As discussed in the hypotheses section, this could relate to innovation (i.e. patents) or even to anti-competitive behavior, anti-trust and monopoly practices. These KPIs are defined by 114 subsectors following the Dow Jones Industry Classification Benchmark (ICB). In this study I matched my list of firms to the ICB codes and then for each individual violation, matched it to the KPIs[20].

2.3.3 Data Preparation

The returns were taken from Thomson Reuters Datastream (Datastream) under the Return Index (RI) category where it is assumed that dividends are reinvested[21.] The index is under the local currency of USD. Firstly, ISIN's for the firms were searched in Datastream. The final sample consisted of 597 unique firms. Secondly, all firms were checked if either it was delisted or merged. To ensure there were no attrition biases, the returns were used until the point of time before the firms were to turn 'dead'. Finally, the returns were then converted into continuously compounded returns using the following:

$$r_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \qquad (2.1)$$

The above indicates that the natural logarithm (ln) is taken by dividing the firms' price in that period by the price of the previous period. In order to calculate the excess returns, I calculated the risk free rate (r_f) using the three months US Treasury bill rate was retrieved from Datastream. It was then converted into monthly data using the following:

$$r_{f,t,1m} = ln\left(1 + SR_{f,t,13w}\ \frac{91}{365.25}\right)^{\frac{30.4375}{91}} \qquad (2.2)$$

[20] Refer to figure 6 in the appendix for a detailed explanation on the KPIs.

[21] A return index (RI) is available for individual equities and unit trusts. This shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.

2.3.4 Portfolio Creation

Considering that this paper intends on examining the long-term impact of fines, a portfolio method is used in this paper. Firstly, Baucus & Baucus (1997) measure the longer-term performance using accounting and market returns, their study is based on a rather simple analysis of covariance procedures whereas I intend on measuring the impacts of illegalities using a more advanced, Carhart model based portfolio method to measure performance. Secondly, by using a portfolio method, this would help to evaluate the risk-adjusted performance of companies that have illegal corporate behavior. Thirdly, creating portfolios would be able to shed light on whether having companies with illegal behavior in investor's portfolios in the long-term is indeed detrimental. This is consistent with this papers intent on advocating good corporate legal responsibility. From the database, four different portfolios were created. These were depending on the stage of violation of each firm; i) initial allegation ii) confirmed violation but pending various other matters iii) confirmed violation and iv) includes an overall portfolio consisting of the three different stages. Figure 2 depicts different legal stages of a violation. The categorization of the fines according to the different stages of violations is objective and is retrieved from the 10K fillings. Furthermore, as I examine the different legal stages separately, when a violation is moved from one stage to another (i.e. from the initial allegations to the confirmed but pending other matters) it still remains in the portfolio. This is to ensure that I am able to examine the different reactions to the various legal stages after a fine. The numbers of firms in each portfolio also changes every month according to the number of fines that have been awarded to the firm. The portfolios (p) were then equally weighted using the following formula:

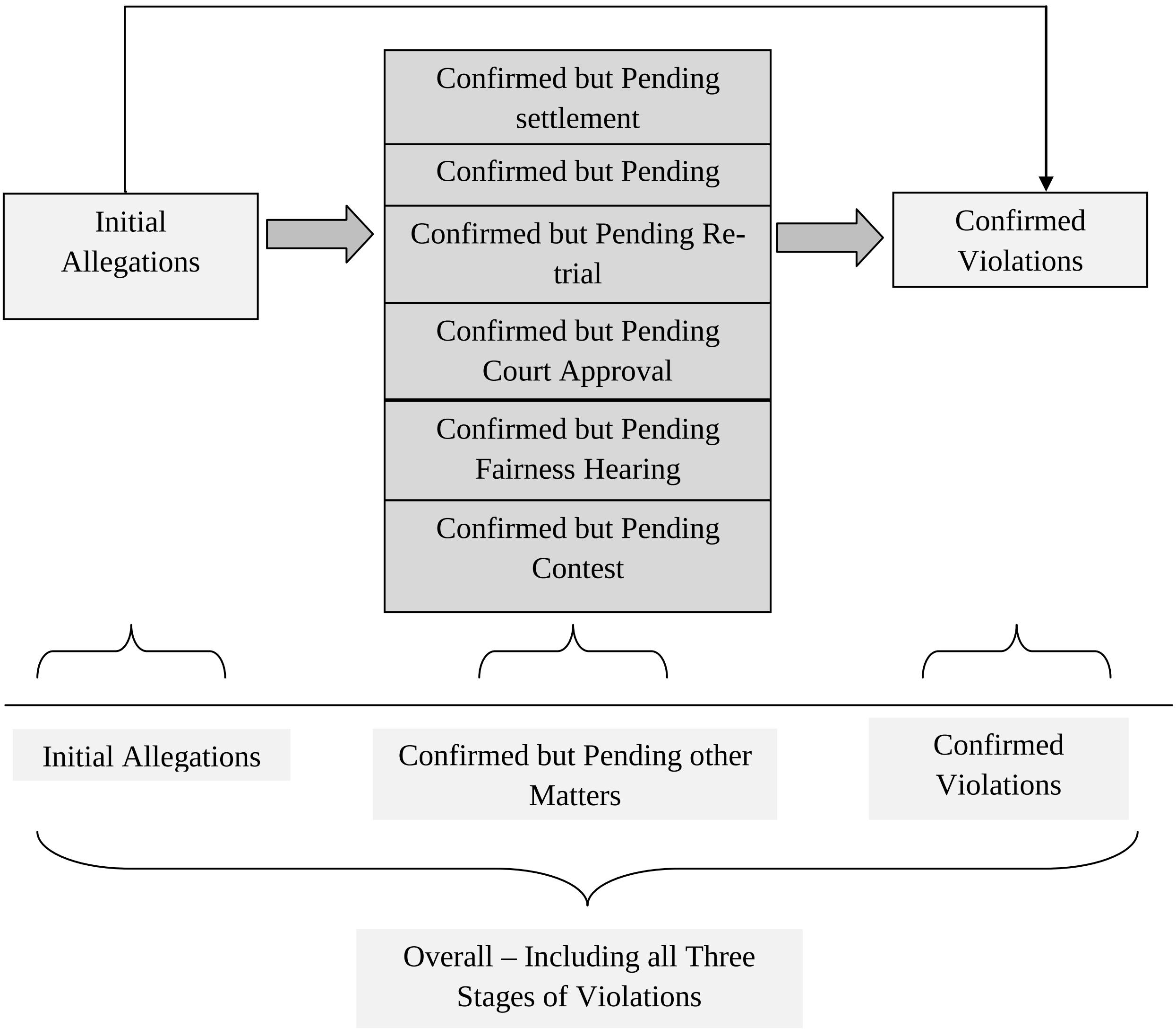
$$r_{p,t} = ln\left[\frac{1}{N}\left(\frac{P_{i1,t}}{P_{i1,t-1}} + \frac{P_{i2,t}}{P_{i2,t-1}} + \cdots + \frac{P_{iN,t}}{P_{iN,t-1}}\right)\right] \qquad (2.3)$$

where $r_{p,t}$ is the equally weighted portfolio, $P_{i,t}$is the stock price of the company at the end of month t and $P_{i,t-1}$ is the company stock price for the month prior and N is the total number of companies in the portfolio. The equal weighted (EW) portfolios were also created using two different ways. The first method is EW fine level, where all violations events or all fines are equally weighted. For example, if in the portfolio one company has five fines in a specific period of time, I would sum up all the returns and divide by the number of events/fines in that time period. The second method EW company level, I equal weighted the portfolios by individual company. For example, if in the portfolio one company has five fines in a specific period of time, I would only use the one return data in that specific period of time to ensure that there are no overlaps in returns.

[This section has been intentionally left blank]

Figure 2 Different Legal Stages of Violations

The figure below depicts the process of violation in this study from the first stage of the initial date of allegation. The second stage involves firms which are confirmed to have violations or violations but are pending numerous actions such as settlement, appeal, re-trial, court approval, fairness hearing or contest. The final stage is the actual confirmed violation without any further actions.



For the separation by fines per market size, yearly Market Capitalization (MC) data were retrieved from Datastream. For the MC portfolios, I used the end of year MC data. The amount of fines in dollar value was all summed up per year for accuracy and cohesiveness to the end of year MC figures. The next step was then to rank the fines according to percentile ranges. From the percentile ranges, I created two different portfolios which consisted of only fines between 0 to 20th percentile and 80th to 100th percentile. The low (high) percentile portfolio included all fines per market size below the 20th (above the 80th) percentile in that respective year. This portfolio is made up of all the firms from 1994 to 2012 which fell below the 20th percentile (above the 80th percentile).

2.3.5 Empirical Model and Benchmark Creation

For measuring the long-term impact, holding periods of twelve month portfolios were created. Time- series regressions were run using the single and multifactor models following the Capital Asset Pricing Model (CAPM), the three factor Fama-French model and the four factor Carhart model.

The CAPM is a widely used and known model that was developed by William Sharpe (1964) and John Lintner (1965). The intuition of this model is that the excess return can be explained by the expected risk premium, which is the beta multiplied by the market return minus risk free rate. Hence, the Jensen (1968) alpha or intercept would be zero. Any outperformance of the portfolio will be shown with a positive alpha and subsequently underperformance with a negative alpha.

The CAPM model is said to be flawed as it does not take into account other risk factors. Hence, the three factor model was proposed by Fama and French (1993) and

Fama and French (1996), where small minus big (SMB) is the difference between the returns on diversified portfolios of small and big stocks and high minus low (HML) is the difference between the returns of high and low stocks. Fama & French (2004) states that the three factor model *"captures much of the variation in average return for portfolios formed on size, book-to-market equity and other price ratios that cause problems for the CAPM".*

However, there are stocks that tend to outperform the market on a continuous basis for some point and others that tend to do poorly continuously as well. Jegadeesh and Titman (1993) find this as a momentum effect that lasts between three to twelve months. Carhart (1997) suggested to extend the three factor model with momentum (MOM) as a fourth factor. This factor is the difference between the returns of diversified portfolios of short-term winners and losers. Carhart (1997) did indicate that momentum is a very important factor that can explain stock returns. He argues that the reason momentum strategy works is not because that there is a conscious decision to hold these kind of stocks (winners) but rather by chance (Sapp and Tiwari 2004).

In this analysis, instead of using traditional market benchmarks, I constructed a specific market benchmark to match the set of firms in the created portfolios. This set of benchmark consists of all the US firms in my entire initial sample from 1994 to 2012. The MSCI USA Large Cap Index was not used as benchmark as this index was only launched in June 2007 and data prior to the launch date is only based on back-tested data (i.e. e. calculations of how the index might have performed over that time period had the index existed[22]). Tailored benchmarks are a very common practice used in studies, for example data from Style Research is used to create specific, size, value and

[22] MSCI USA Large Cap Index available at https://www.msci.com/documents/10199/40770696-16c0-4b70-89f6-9a8496722fa7 (accessed at 1 August 2017)

momentum factors for different regions (Renneboog, Ter Horst et al. 2008; Hoepner, Rammal et al. 2011). As the data sample in this study is only based on one specific country, US, the size, value and momentum factors were retrieved from the Kenneth-French data library.

Considering that the sample of US firms in the portfolios consists of only large market cap firms, using a conventional benchmark might differ as the asset sizes might vary. Hence, the market benchmark was equally weighted using only all unique firms from 1994 to 2012 which were in the sample. I start my empirical analysis using the simple CAPM as per in formula (2.4):

$$r_{p,t} = \alpha_p + \beta_{m,p}\, r_{m,t} + \varepsilon_{p,t}, \tag{2.4}$$

Where $r_{p,t}$ and $r_{m,t}$ represent the excess return of the portfolio (p) and the created equity market benchmark minus the risk free rate(r_f), respectively. $\beta_{m,p}$ is the portfolio's systematic exposure to the created equity market benchmark. The Jensen alpha is represented by α_p and $\varepsilon_{p,t}$ is the error term which captures the random components of a portfolio's excess return for each observation(t) (Sharpe 1964; Lintner 1965). I also run my analysis using Fama-French in formula (2.5) and Carhart in formula (2.6) models, where the SMB, HML and MOM have been described previously:

$$r_{p,t} = \alpha_p + \beta_{m,p}\, r_{m,t} + \gamma_p\, SMB_t + \delta_p HML_t + \varepsilon_{p,t}, \tag{2.5}$$

$$r_{p,t} = \alpha_p + \beta_{m,p} r_{m,t} + \gamma_p SMB_t + \delta_p HML_t + \theta_p MOM_t + \varepsilon_{p,t}, \tag{2.6}$$

I also created a second type of market benchmark with the similar methodology but for each of the seven individual industries. In order to do so, instead of using all firms, only firms within those industries are used to create the specific industry benchmark following the SIC codes as per in table 8..3 in the appendix:

This specific industry equity benchmark (*ind*) was used for the regressions of the industry separation portfolio:

$$r_{p,t} = \alpha_p + \beta_{ind,p}\, r_{ind,t} + \varepsilon_{p,t}, \tag{2.7}$$

$$r_{p,t} = \alpha_p + \beta_{ind,p}\, r_{ind,t} + \gamma_p\, SMB_t + \delta_p HML_t + \varepsilon_{p,t}, \tag{2.8}$$

$$r_{p,t} = \alpha_p + \beta_{ind,p} r_{ind,t} + \gamma_p SMB_t + \delta_p HML_t + \theta_p MOM_t + \varepsilon_{p,t,} \tag{2.9}$$

2.4 Empirical Results and Analysis

The following section is to discuss the results from the i) overall (all industries) portfolio, ii) portfolios separated by the seven industries, as per the two digit SIC code, iii) the results of the portfolios for fines per market size and vi) the results from each ESGV portfolio and per industry. Each portfolio has four different subset of portfolios; i) Initial Allegations (IA) ii) Confirmed Violations but Pending other Matters (CVPM), iii) Confirmed Violations (CV) and iv) Overall including all three stages of violations (Overall). Figure 2 previously provides a descriptive view of the different stages. In order to control for heteroscedasticity and autocorrelation, the Newey and West (1986) estimations have been used. Following the empirical model, the alphas are obtained using the CAPM, and Fama-French and Carhart models.

2.4.1 Impact of Overall (All industries) Results

The results of the alphas in Table 2.1 indicate that three out of the four portfolios (IA, CV and Overall) underperform. Examining the initial allegations portfolios, I find underperformances of 55 and 57 basis points p.m respectively for the

EW per fine and company level with a statistical significance level of 1% at the Carhart level. The confirmed violations portfolio also exhibits underperformance of 38 and 41 basis points p.m respectively for the EW per fine and company level with a stastical significance level of 1% at the Carhart levels. For the overall portfolios, I find also underperformances of 29 and 34 basis points p.m with a 5% statistical significance level at the Carhart level. Though this overall portfolio has a lower level of undeperformance compared to the IA and CV portfolio, this still indicates that investors are concerned about violations even on an overall basis. All three portfolios also indicate results that are relatively similar for even the CAPM and Fama-French models. i. The adjusted r-squared values increase for all results and are rather high between 0.73 and 0.90 indicating a good fit of the model. The results confirm my hypothesis that on an overall basis, investors are concerned in the long run and do react negatively to violations and specifically monetary fines.

2.4.2 Impact of Fines per Firm Size Results

In this section, I compare the results between the lowest portfolio, 20th percentile and lower (table 2.2) and the highest portfolio, 80th percentile and higher (table 2.3) for the fines per firm size. I find that in fact firms with higher fines per firm size do have larger underperformances compared to firms with lower fines per firm size. This is evident in the example of the IA portfolio, whereby the underperformance for the lower and highest percentile in the EW fine level is 51 and 84 basis points p.m respectively. Even comparing the overall portfolios, the underperformance for the lower and highest percentile in the EW fine level is 40 and 51 basis points p.m respectively. This confirms my second hypothesis that firms with higher fines per firm size would have a larger negative stock returns in the long-term.

2.4.3 Impact of Individual Legal Stages

As observed in table 2.1 in the Carhart model, IA underperforms in both EW fine and company level at 55 and 57 basis points per month respectively, the confirmed stage underperforms at only 38 and basis points per month respectively 41 and overall underperforms at 29 and 34 basis points per month. These results are similar to the fines per firm size results in table 2.2 and 2.3, where IA has a larger underperformance compared to other legal stages. This shows that investors react more negatively to fines that are large at the IA stage. This result supports my hypothesis that the initial announcement of the violations has a larger negative impact on returns compared to other legal stages indicating that investors react more to the first announcements of the fines. These results are also comparable to Karpoff and John R. Lott (1993) as it confirms the notion that the first announcements of the fines have a larger "shock" impact compared to settlement announcements even on an all industry level and based on the size of the fines per market size.

[This section has been intentionally left blank]

Table 2.1 Overall portfolio (All Industries) results of CAPM,Fama-French and Carhart

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. N represents the number of observations in each panel A and B.

	All Industries											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	**Adj** R^2	**N**	**Alpha**			R^2	**Adj** R^2	**N**
Initial allegations	**-0.0043**	**	**(-2.4766)**	0.7534	0.7524	241	**-0.0052**	***	**(-3.4402)**	0.7981	0.7972	241
Confirmed violations but still pending other matters	-0.0016		(-0.9894)	0.7335	0.7324	240	-0.0023		(-1.4945)	0.7804	0.7795	240
Confirmed violations	**-0.0034**	***	**(-2.6362)**	0.8454	0.8448	245	**-0.0036**	***	**(-2.8616)**	0.8485	0.8478	245
Overall - Including all three stages of violations	**-0.0024**	**	**(-1.9929)**	0.8609	0.8604	246	**-0.0031**	***	**(-2.7239)**	0.8773	0.8768	246
Fama-French Results												
Initial allegations	**-0.0041**	**	**(-2.4433)**	0.7838	0.7811	241	**-0.0050**	***	**(-3.5707)**	0.8328	0.8307	241
Confirmed violations but still pending other matters	-0.0015		(-0.9282)	0.7459	0.7427	240	-0.0022		(-1.4605)	0.7928	0.7902	240
Confirmed violations	**-0.0032**	**	**(-2.5802)**	0.8568	0.8550	245	**-0.0035**	***	**(-2.8353)**	0.8633	0.8616	245
Overall - Including all three stages of violations	**-0.0022**	**	**(-1.9474)**	0.8815	0.8800	246	**-0.0029**	***	**(-2.7712)**	0.8991	0.8979	246
Carhart Results												
Initial allegations	**-0.0055**	***	**(-3.4697)**	0.7956	0.7922	241	**-0.0057**	***	**(-4.0484)**	0.8359	0.8331	241
Confirmed violations but still pending other matters	-0.0012		(-0.6353)	0.7465	0.7422	240	-0.0020		(-1.1448)	0.7931	0.7895	240
Confirmed violations	**-0.0038**	***	**(-2.7671)**	0.8588	0.8564	245	**-0.0041**	***	**(-3.0838)**	0.8658	0.8635	245
Overall - Including all three stages of violations	**-0.0029**	**	**(-2.4585)**	0.8848	0.8829	246	**-0.0034**	***	**(-3.0468)**	0.9008	0.8991	256

Table 2.2 Portfolio results of CAPM,Fama-French and Carhart regressions with created benchmarks for the fines per market cap (0 to 20th percentile)

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	0 to 20th Percentile Level											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	Adj R^2	**N**	**Alpha**			R^2	Adj R^2	**N**
Initial allegations	**-0.0045**	*	**(-1.7087)**	0.5427	0.5408	234	**-0.0047**	*	**(-1.9059)**	0.5355	0.5335	234
Confirmed violations but still pending other matters	-0.0016		(-0.5561)	0.4265	0.4241	240	-0.0026		(-1.0161)	0.5506	0.5487	240
Confirmed violations	-0.0011		(-0.4036)	0.5727	0.5709	238	-0.0010		(-0.3532)	0.5908	0.5891	238
Overall - Including all three stages of violations	-0.0028		(-1.3275)	0.6261	0.6246	240	-0.0029		(-1.5064)	0.6720	0.6707	240
Fama-French Results												
Initial allegations	**-0.0042**	*	**(-1.6714)**	0.5783	0.5729	234	**-0.0044**	*	**(-1.8754)**	0.5712	0.5658	234
Confirmed violations but still pending other matters	-0.0016		(-0.5495)	0.4321	0.4249	240	-0.0027		(-1.0305)	0.5554	0.5497	240
Confirmed violations	-0.0011		(-0.4100)	0.5845	0.5791	238	-0.0010		(-0.3595)	0.5992	0.5940	238
Overall - Including all three stages of violations	-0.0027		(-1.2891)	0.6314	0.6267	240	-0.0028		(-1.4574)	0.6773	0.6732	240
Carhart Results												
Initial allegations	**-0.0051**	**	**(-2.0074)**	0.5825	0.5754	234	**-0.0052**	**	**(-2.1784)**	0.5745	0.5672	234
Confirmed violations but still pending other matters	-0.0019		(-0.6532)	0.4324	0.4228	240	-0.0027		(-1.0258)	0.5554	0.5478	240
Confirmed violations	-0.0031		(-1.1157)	0.6017	0.5948	238	-0.0026		(-0.9337)	0.6110	0.6043	238
Overall - Including all three stages of violations	**-0.0040**	*	**(-1.8152)**	0.6424	0.6363	240	**-0.0036**	*	**(-1.7984)**	0.6817	0.6763	240

Table 2.3 Portfolio results of CAPM,Fama-French and Carhart regressions with created benchmarks for the fines per market cap (80th to 100th percentile)

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	80th to 100th Percentile Level											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	Adj R^2	**N**	**Alpha**			R^2	Adj R^2	**N**
Initial allegations	**-0.0074**	**	**(-2.2470)**	0.4979	0.4958	239	**-0.0092**	***	**(-3.2961)**	0.5568	0.5549	239
Confirmed violations but still pending other matters	-0.0047		(-0.9384)	0.5137	0.5116	233	-0.0049		(-1.001)	0.5241	0.5220	233
Confirmed violations	**-0.0062**	**	**(-2.4686)**	0.5412	0.5393	240	**-0.0065**	**	**(-2.462)**	0.5443	0.5424	240
Overall - Including all three stages of violations	**-0.0051**	**	**(-2.3893)**	0.7116	0.7104	240	**-0.0066**	***	**(-3.443)**	0.7339	0.7327	240
Fama-French Results												
Initial allegations	**-0.0071**	**	**(-2.2145)**	0.5425	0.5366	239	**-0.0089**	***	**(-3.2423)**	0.6003	0.5952	239
Confirmed violations but still pending other matters	-0.0042		(-0.8842)	0.5588	0.5530	233	-0.0045		(-0.9454)	0.5714	0.5658	233
Confirmed violations	**-0.0060**	**	**(-2.4462)**	0.5468	0.5410	240	**-0.0063**	**	**(-2.4691)**	0.5523	0.5467	240
Overall - Including all three stages of violations	**-0.0049**	**	**(-2.4184)**	0.7371	0.7337	240	**-0.0063**	***	**(-3.5431)**	0.7695	0.7666	240
Carhart Results												
Initial allegations	**-0.0084**	***	**(-2.7015)**	0.5474	0.5396	239	**-0.0090**	***	**(-3.3377)**	0.6004	0.5936	239
Confirmed violations but still pending other matters	-0.0047		(-0.8859)	0.5592	0.5515	233	-0.0048		(-0.909)	0.5717	0.5642	233
Confirmed violations	**-0.0059**	**	**(-2.0008)**	0.5469	0.5391	240	**-0.0066**	**	**(-2.1552)**	0.5527	0.5451	240
Overall - Including all three stages of violations	**-0.0051**	**	**(-2.5617)**	0.7374	0.7329	240	**-0.0061**	***	**(-2.9563)**	0.7696	0.7657	240

2.4.4 Impact of Individual Industry Results

The results of the individual industry portfolios (tables 2.4 to 2.8) are very interesting. I find that not all the portfolios display risk-adjusted returns that are statistically significant. This is evident for the Retail Trade and Wholesale Trade industries which I find statistically no significant results[23]. I constructed unique industry market benchmarks in these portfolios to ensure that appropriate industry level benchmarks are regressed. Comparing the remaining five industries, I find for the IA portfolios the Manufacturing industry underperforms in both EW fine and company level (Carhart model) at 41 and 38 basis points per month respectively.

For the CVPM portfolio only two industries, namely transportation and public utilities and the Services underperform. In both EW fine and company level, the Transportation industry indicates underperformances of 73 and 72 basis points p.m respectively in the Carhart model. In contrary, the services industry underperforms by 120 and 131 basis points p.m for the EW fine and company level portfolios respectively in the Fama-French models. I find that the significances disappear in the Carhart model.

For the CV portfolios, only two industries underperform which are Transportation and Public Utilities and Mining. At the EW fine and company level, the transportation industry underperformed by 73 and 72 basis points p.m respectively and mining industry underperformed by 63 basis points p.m only at the EW fine level in the Carhart models.

In the overall portfolios I find four industries underperform. The finance, insurance & real estate industry herein Finance, has underperformances of 48 and 52

[23] Results for the Retail and Whole Trade portfolios are available upon request

basis points p.m at the EW fine and company level respectively but only in the Fama-French model. The transportation and public utilities industry underperforms by 36 basis points p.m at the EW company level in the Carhart model. The Services industry underperforms by 63 and 70 basis points p.m at the EW fine and company level respectively also only in the Fama-French model. The mining industry underperforms in the Carhart model by 42 and 41 basis points in the EW fine and company level respectively.

My initial hypothesis is that investors would react more to violations in the extractions and usage of valuable minerals and natural resources industries compared to other industries. In examining only the Carhart results, I find that manufacturing, mining, transportation and public utilities have at least two stages of the legal process with statistical significance compared to the other industries, thus supporting my hypothesis[24]. Though I find that the majority of the portfolios underperform, the manufacturing industry for CVPM portfolio outperforms with 39 basis points p.m at the EW fine level in Carhart model. One explanation could be that investors in manufacturing industries perceive the violation at the IA to be of more of a concern, hence the negative return. However, once the violation is subject to legal procedures, investors are much more confident of a better outcome of the fine.

[24] Transportation and public utilities includes subcategories i.e. pipelines and electric and gas services

Table 2.4 Finance, Insurance and Real Estate portfolio results of CAPM, Fama-French and Carhart regressions

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistic. N represents the number of observations in each panel A and B.

	Finance, Insurance and Real Estate										
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	**Adj** R^2	**N**	**Alpha**			R^2	**Adj** R^2	**N**
Initial allegations	-0.0058		(-1.3868)	0.4182	0.4157	238	-0.0069		(-1.4445)	0.4058	0.4033	238
Confirmed violations but still pending other matters	-0.0039		(-1.0181)	0.5028	0.5006	233	-0.0038		(-0.9935)	0.5021	0.4999	233
Confirmed violations	-0.0054		(-1.4569)	0.4712	0.4690	241	-0.0047		(-1.5278)	0.4854	0.4832	241
Overall - Including all three stages of violations	-0.0043		(-1.6131)	0.5954	0.5937	241	-0.0047		(-1.7888)	0.6015	0.5998	241
Fama-French Results												
Initial allegations	-0.0064		(-1.545)	0.4260	0.4186	238	-0.0075		(-1.5498)	0.4121	0.4045	238
Confirmed violations but still pending other matters	-0.0043		(-1.1471)	0.5117	0.5053	233	-0.0043		(-1.1288)	0.5118	0.5054	233
Confirmed violations	-0.0058		(-1.5785)	0.4878	0.4813	241	-0.0062		(-1.6451)	0.5041	0.4979	241
Overall - Including all three stages of violations	**-0.0048**	*	**(-1.8851)**	0.6118	0.6069	241	**-0.0052**	**	**(-2.0265)**	0.6197	0.6149	241
Carhart Results												
Initial allegations	-0.0045		(-1.1485)	0.4345	0.4248	238	-0.0057		(-1.239)	0.4202	0.4102	238
Confirmed violations but still pending other matters	-0.0036		(-0.9027)	0.5139	0.5054	233	-0.0035		(-0.8857)	0.5140	0.5055	233
Confirmed violations	-0.0054		(-1.2991)	0.4883	0.4796	241	-0.0060		(-1.4124)	0.5042	0.4958	241
Overall - Including all three stages of violations	-0.0038		(-1.4573)	0.6159	0.6094	241	-0.0043		(-1.647)	0.6229	0.6165	241

Table 2.5 Manufacturing portfolio results of CAPM,Fama-French and Carhart regressions

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Manufacturing											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
One Year Holding Period - CAPM Results	**Alpha**			**R^2**	**Adj R^2**	**N**	**Alpha**			**R^2**	**Adj R^2**	**N**
Initial allegations	**-0.0037**	**	**(-2.0362)**	0.7312	0.7301	240	**-0.0039**	**	**(-2.3644)**	0.7574	0.7564	240
Confirmed violations but still pending other matters	**0.0045**	**	**(2.2349)**	0.5126	0.5105	237	**0.0031**	*	**(1.7417)**	0.5907	0.5890	237
Confirmed violations	-0.0003		(-0.2411)	0.7113	0.7102	245	-0.0002		(-0.1672)	0.7371	0.7360	245
Overall - Including all three stages of violations	-0.0002		(-0.2123)	0.7795	0.7786	245	-0.0007		(-0.6679)	0.8128	0.8120	245
One Year Holding Period - Fama-French Results												
Initial allegations	**-0.0034**	**	**(-2.2325)**	0.7964	0.7938	240	**-0.0037**	***	**(-2.6549)**	0.8283	0.8262	240
Confirmed violations but still pending other matters	**0.0045**	**	**(2.2955)**	0.5191	0.5129	237	**0.0031**	*	**(1.7992)**	0.5989	0.5937	237
Confirmed violations	-0.0002		(-0.1115)	0.7383	0.7351	245	-0.0001		(-0.042)	0.7633	0.7603	245
Overall - Including all three stages of violations	0.0000		(-0.0399)	0.8242	0.8220	245	-0.0005		(-0.5404)	0.8569	0.8551	245
One Year Holding Period - Carhart Results												
Initial allegations	**-0.0041**	***	**(-2.6595)**	0.7984	0.7949	240	**-0.0038**	***	**(-2.6968)**	0.8284	0.8254	240
Confirmed violations but still pending other matters	**0.0039**	**	**(1.9885)**	0.5214	0.5132	237	0.0022		(1.2959)	0.6031	0.5962	237
Confirmed violations	-0.0006		(-0.3727)	0.7394	0.7351	245	-0.0002		(-0.168)	0.7635	0.7596	245
Overall - Including all three stages of violations	-0.0005		(-0.446)	0.8255	0.8226	245	-0.0008		(-0.7779)	0.8573	0.8550	245

Table 2.6 Transportation and Public Utilities portfolio results of CAPM,Fama-French and Carhart regressions

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Transportation and Public Utilities											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	**Adj** R^2	**N**	**Alpha**			R^2	**Adj** R^2	**N**
Initial allegations	0.0004		(0.1163)	0.4229	0.4204	238	-0.0006		(-0.2268)	0.4886	0.4864	238
Confirmed violations but still pending other matters	**-0.0074**	**	**(-2.1382)**	0.5365	0.5345	233	**-0.0074**	**	**(-2.1366)**	0.5358	0.5338	233
Confirmed violations	-0.0028		(-1.1863)	0.4679	0.4657	243	-0.0031		(-1.3054)	0.5066	0.5046	243
Overall - Including all three stages of violations	-0.0007		(-0.3092)	0.6087	0.6071	243	-0.0021		(-1.1935)	0.6785	0.6771	243
Fama-French Results												
Initial allegations	0.0008		(0.2887)	0.4637	0.4569	238	-0.0001		(-0.05)	0.5282	0.5222	238
Confirmed violations but still pending other matters	**-0.0073**	**	**(-2.0889)**	0.5505	0.5446	233	**-0.0073**	**	**(-2.0832)**	0.5515	0.5457	233
Confirmed violations	-0.0025		(-1.0641)	0.4764	0.4698	243	-0.0029		(-1.1942)	0.5136	0.5075	243
Overall - Including all three stages of violations	-0.0003		(-0.1579)	0.6364	0.6318	243	-0.0018		(-1.0112)	0.7066	0.7029	243
Carhart Results												
Initial allegations	-0.0024		(-0.8654)	0.5352	0.5272	238	-0.0029		(-1.1849)	0.5848	0.5777	238
Confirmed violations but still pending other matters	**-0.0073**	**	**(-2.0302)**	0.5505	0.5426	233	**-0.0072**	**	**(-2.0055)**	0.5516	0.5438	233
Confirmed violations	**-0.0042**	*	**(-1.7875)**	0.5007	0.4923	243	**-0.0044**	*	**(-1.8554)**	0.5338	0.5260	243
Overall - Including all three stages of violations	-0.0026		(-1.2677)	0.6892	0.6840	243	**-0.0036**	**	**(-2.0255)**	0.7410	0.7367	243

Table 2.7 Services portfolio results of CAPM,Fama-French and Carhart regressions

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Services											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			***R^2***	**Adj *R^2***	**N**	**Alpha**			***R^2***	**Adj *R^2***	**N**
Initial allegations	-0.0068		(-1.5454)	0.4854	0.4832	232	-0.0063		(-1.4589)	0.4930	0.4908	232
Confirmed violations but still pending other matters	**-0.0117**	**	**(-2.3523)**	0.3718	0.3690	226	**-0.0127**	**	**(-2.4031)**	0.3808	0.3781	226
Confirmed violations	-0.0023		(-0.4675)	0.4102	0.4074	212	-0.0031		(-0.62)	0.3942	0.3913	212
Overall - Including all three stages of violations	-0.0060		(-1.616)	0.5255	0.5235	232	**-0.0067**	*	**(-1.6748)**	0.5225	0.5204	232
Fama-French Results												
Initial allegations	-0.0068		(-1.5555)	0.4898	0.4831	232	-0.0063		(-1.4669)	0.4982	0.4916	232
Confirmed violations but still pending other matters	**-0.0120**	**	**(-2.4078)**	0.3996	0.3915	226	**-0.0131**	**	**(-2.4768)**	0.4100	0.4021	226
Confirmed violations	-0.0030		(-0.6829)	0.4546	0.4467	212	-0.0039		(-0.8504)	0.4457	0.4377	212
Overall - Including all three stages of violations	**-0.0063**	*	**(-1.845)**	0.5588	0.5532	232	**-0.0070**	*	**(-1.9)**	0.5583	0.5526	232
Carhart Results												
Initial allegations	-0.0074		(-1.5395)	0.4903	0.4813	232	-0.0068		(-1.444)	0.4985	0.4897	232
Confirmed violations but still pending other matters	-0.0059		(-1.198)	0.4360	0.4258	226	-0.0073		(-1.3033)	0.4409	0.4308	226
Confirmed violations	-0.0042		(-0.8536)	0.4568	0.4463	212	-0.0060		(-1.187)	0.4530	0.4424	212
Overall - Including all three stages of violations	-0.0052		(-1.3386)	0.5609	0.5533	232	-0.0064		(-1.4946)	0.5589	0.5513	232

Table 2.8 Mining portfolio results of CAPM,Fama-French and Carhart regressions

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Mining											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	**Adj** R^2	**N**	**Alpha**			R^2	**Adj** R^2	**N**
Initial allegations	-0.0027		(-1.0504)	0.6521	0.6506	238	-0.0022		(-0.8869)	0.6534	0.6519	238
Confirmed violations but still pending other matters	-0.0044		(-1.0097)	0.3338	0.3307	216	-0.0008		(-0.2510)	0.7128	0.7114	216
Confirmed violations	**-0.0078**	**	**(-2.3216)**	0.5848	0.5830	235	**-0.0056**	*	**(-1.7656)**	0.5461	0.5441	235
Overall - Including all three stages of violations	**-0.0050**	**	**(-1.9804)**	0.7000	0.6987	238	**-0.0048**	**	**(-1.9702)**	0.7207	0.7195	238
Fama-French Results												
Initial allegations	-0.0028		(-1.0913)	0.6624	0.6581	238	-0.0022		(-0.9058)	0.6643	0.6600	238
Confirmed violations but still pending other matters	-0.0040		(-0.9647)	0.3440	0.3347	216	-0.0005		(-0.1810)	0.7200	0.7160	216
Confirmed violations	**-0.0079**	**	**(-2.4432)**	0.6081	0.6030	235	**-0.0060**	**	**(-2.0219)**	0.5872	0.5818	235
Overall - Including all three stages of violations	**-0.0051**	**	**(-2.1564)**	0.7383	0.7350	238	**-0.0049**	**	**(-2.1347)**	0.7567	0.7536	238
Carhart Results												
Initial allegations	-0.0029		(-1.1057)	0.6625	0.6567	238	-0.0024		(-0.9214)	0.6644	0.6586	238
Confirmed violations but still pending other matters	-0.0035		(-0.7591)	0.3452	0.3328	216	0.0005		(0.1400)	0.7234	0.7181	216
Confirmed violations	**-0.0063**	*	**(-1.9291)**	0.6184	0.6118	235	-0.0048		(-1.5432)	0.5932	0.5861	235
Overall - Including all three stages of violations	**-0.0042**	*	**(-1.6812)**	0.7430	0.7386	238	**-0.0041**	*	**(-1.7091)**	0.7601	0.7560	238

2.4.5 Impact of ESG plus LT Results

In this section, I discuss the results from the four different ESG plus LT portfolios (tables 2.9 to 2.12). For the environment portfolios results, I find strong statistical significance at a 1% level on all four different types of allegation portfolios in the Carhart model. The alphas indicate underperformances of between 38 and 127 basis points per month on a consistent basis for both EW fine and company level and the adjusted r-squared values are relatively high between 0.43 and 0.78.

The social portfolio on the other hand does not indicate any statistical significance on the EW fine level but only on the company level. Only two portfolios, the IA and CV portfolios underperform by 72 and 51 basis points per month respectively in the Carhart model. Only at the EW company level for the governance portfolios, the IA and Overall portfolios underperform by 53 and 37 basis points per month in the Carhart model. The LT portfolios for the EW fine level showed underperformance of 27 basis points p.m only at the Overall portfolio. However on the EW company level, both the IA and Overall portfolios underperformed by 44 and 33 basis points per month.

When comparing the four ESG plus LT portfolios, my hypothesis is confirmed that investors in overall are concerned more on the illegal behaviours of firms relating to environmental issues as I find statistical significance at all four levels of violations and with a larger underperformance of 127 basis points per month. This concurs with other literature that indicates environmental performances of firms can impact their firm value (Konar and Cohen 2001; Jacobs, Singhal et al. 2010). My results further extends Capelle-Blancard and Laguna (2010) who examined market reactions to only industrial disasters of 64 chemical plants and refineries worldwide. They find that not only is there a 1.3% drop in market value of the firms in their sample but also this loss is significantly related to the seriousness of the accident as measured by the number of casualties and by chemical pollution: each casualty corresponds to a loss of $164 million and a toxic release to a loss of $1 billion. I am to my knowledge the first to show that environmental fines have larger underperformances compared to social, governance and long-term fines. A further possible explanation of investor's strong reaction to environmental fines could be the increase of fines in FY11 and FY12 and tighter inspections and evaluations[25]. The fiscal year 2015 Environmental Protection Agency (EPA) enforcement and compliance annual results showed that Administrative and Civil Judicial Penalties assessed in FY11 was $162 million and increased to $215 million in FY12. Federal Inspections and Evaluations also increased in FY12.

[This section has been intentionally left blank]

[25] Available at https://www.epa.gov/sites/production/files/2015-12/documents/fy-2015-enforcement-annual-results-charts_0.pdf#page=1 (accessed 10 February 2016)

Table 2.9 Environment portfolio results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Environment											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			**R^2**	**Adj R^2**	**N**	**Alpha**			**R^2**	**Adj R^2**	**N**
Initial allegations	-0.0024		(-1.3017)	0.6641	0.6627	241	-0.0026		(-1.4351)	0.6654	0.6640	241
Confirmed violations but still pending other matters	**-0.0128**	*******	**(-2.8927)**	0.4407	0.4383	236	**-0.0119**	*******	**(-2.975)**	0.5269	0.5249	236
Confirmed violations	-0.0032		(-1.646)	0.6402	0.6387	245	**-0.0038**	******	**(-2.1394)**	0.6895	0.6882	245
Overall - Including all three stages of violations	**-0.0034**	*****	**(-1.9516)**	0.7151	0.7139	245	**-0.0036**	******	**(-2.3151)**	0.7506	0.7496	245
Fama-French Results												
Initial allegations	-0.0021		(-1.1932)	0.7064	0.7027	241	-0.0022		(-1.3180)	0.7137	0.7101	241
Confirmed violations but still pending other matters	-0.0126	***	(-2.8182)	0.4440	0.4369	236	-0.0118	***	(-2.9231)	0.5300	0.5240	236
Confirmed violations	-0.0030		(-1.5632)	0.6531	0.6488	245	-0.0036	**	(-2.0403)	0.7001	0.6964	245
Overall - Including all three stages of violations	-0.0031	*	(-1.8894)	0.7403	0.7371	245	-0.0033	**	(-2.2568)	0.7764	0.7736	245
Carhart Results												
Initial allegations	**-0.0038**	******	**(-2.2462)**	0.7241	0.7194	241	**-0.0038**	******	**(-2.2671)**	0.7285	0.7239	241
Confirmed violations but still pending other matters	**-0.0127**	*******	**(-2.669)**	0.4441	0.4344	236	**-0.0123**	*******	**(-2.9479)**	0.5306	0.5226	236
Confirmed violations	**-0.0043**	******	**(-2.1442)**	0.6631	0.6575	245	**-0.0045**	******	**(-2.3014)**	0.7049	0.7000	245
Overall - Including all three stages of violations	**-0.0047**	*******	**(-2.8633)**	0.7565	0.7525	245	**-0.0046**	*******	**(-3.0239)**	0.7868	0.7832	245

Table 2.10 Social portfolio results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Social										
	Panel A: Equal Weighted (Fine Level)					**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**		***R^2***	**Adj *R^2***	N	**Alpha**			***R^2***	**Adj *R^2***	N
Initial allegations	-0.0030	(-0.8618)	0.2837	0.2806	234	-0.0054		(-1.5628)	0.3515	0.3487	234
Confirmed violations but still pending other matters	0.0028	(0.7898)	0.2715	0.2682	225	0.0027		(0.8252)	0.3450	0.3421	225
Confirmed violations	-0.0034	(-1.2763)	0.4048	0.4023	240	-0.0039		(-1.4124)	0.4518	0.4495	240
Overall - Including all three stages of violations	0.0001	(0.0495)	0.4984	0.4963	240	-0.0009		(-0.501)	0.5762	0.5745	240
Fama-French Results											
Initial allegations	-0.0029	(-0.8256)	0.2950	0.2858	234	-0.0052		(-1.5232)	0.3694	0.3611	234
Confirmed violations but still pending other matters	0.0031	(0.892)	0.2915	0.2819	225	0.0030		(0.928)	0.3611	0.3524	225
Confirmed violations	-0.0030	(-1.1764)	0.4451	0.4380	240	-0.0035		(-1.375)	0.4981	0.4918	240
Overall - Including all three stages of violations	0.0005	(0.2264)	0.5451	0.5394	240	-0.0006		(-0.3351)	0.6299	0.6252	240
Carhart Results											
Initial allegations	-0.0052	(-1.4624)	0.315718	0.3038	234	**-0.0072**	**	**(-2.051)**	0.3848	0.3741	234
Confirmed violations but still pending other matters	0.0041	(1.1553)	0.295219	0.2824	225	0.0041		(1.2519)	0.3657	0.3541	225
Confirmed violations	-0.0042	(-1.5176)	0.450437	0.4411	240	**-0.0051**	*	**(-1.8633)**	0.5085	0.5001	240
Overall - Including all three stages of violations	0.0003	(0.1224)	0.545388	0.5377	240	-0.0009		(-0.4906)	0.6305	0.6242	240

.

Table 2.11 Governance portfolio results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Governance											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
One Year Holding Period - CAPM Results	**Alpha**			R^2	Adj R^2	**N**	**Alpha**			R^2	Adj R^2	**N**
Initial allegations	-0.0049		(-1.6212)	0.5228	0.5208	237	**-0.0057**	**	**(-1.9793)**	0.5341	0.5321	237
Confirmed violations but still pending other matters	-0.0029		(-0.7453)	0.3922	0.3895	233	0.0070		(1.2861)	0.3955	0.3936	233
Confirmed violations	**-0.0040**	*	**(-1.7309)**	0.6512	0.6498	240	-0.0038		(-1.6344)	0.6560	0.6545	240
Overall - Including all three stages of violations	**-0.0039**	**	**(-2.0343)**	0.7350	0.7338	240	**-0.0039**	**	**(-2.1862)**	0.7601	0.7591	240
One Year Holding Period - Fama-French Results												
Initial allegations	-0.0045		(-1.5416)	0.5345	0.5284	237	**-0.0053**	*	**(-1.8917)**	0.5482	0.5423	237
Confirmed violations but still pending other matters	-0.0030		(-0.7332)	0.3934	0.3855	233	0.0068		(1.2414)	0.3977	0.3948	233
Confirmed violations	**-0.0040**	*	**(-1.7311)**	0.6601	0.6558	240	-0.0038		(-1.6353)	0.6649	0.6606	240
Overall - Including all three stages of violations	**-0.0039**	**	**(-2.0486)**	0.7401	0.7368	240	**-0.0038**	**	**(-2.1911)**	0.7656	0.7627	240
One Year Holding Period - Carhart Results												
Initial allegations	-0.0046		(-1.5268)	0.5345	0.5264	237	**-0.0053**	*	**(-1.8429)**	0.5482	0.5403	237
Confirmed violations but still pending other matters	-0.0012		(-0.3132)	0.4006	0.3901	233	0.0092		(1.5832)	0.4011	0.3966	233
Confirmed violations	-0.0034		(-1.3356)	0.6615	0.6558	240	-0.0038		(-1.5357)	0.6649	0.6592	240
Overall - Including all three stages of violations	-0.0034		(-1.5728)	0.7409	0.7365	240	**-0.0037**	*	**(-1.8756)**	0.7657	0.7617	240

Table 2.12 Long-Term portfolio results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Long-Term											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			**R^2**	**Adj R^2**	**N**	**Alpha**			**R^2**	**Adj R^2**	**N**
Initial allegations	-0.0028		(-1.1238)	0.5936	0.5918	236	**-0.0054**	**	**(-2.4039)**	0.6542	0.6527	236
Confirmed violations but still pending other matters	-0.0015		(-0.7002)	0.6664	0.6650	238	-0.0008		(-0.3435)	0.6536	0.6521	238
Confirmed violations	-0.0016		(-0.8447)	0.6972	0.6960	237	-0.0008		(-0.4438)	0.6810	0.6797	237
Overall - Including all three stages of violations	-0.0022		(-1.3961)	0.8094	0.8086	238	**-0.0032**	**	**(-2.2038)**	0.8375	0.8368	238
Fama-French Results												
Initial allegations	-0.0025		(-1.0402)	0.6218	0.6169	236	**-0.0052**	**	**(-2.3956)**	0.6894	0.6854	236
Confirmed violations but still pending other matters	-0.0014		(-0.6572)	0.6824	0.6784	238	-0.0008		(-0.3082)	0.6664	0.6622	238
Confirmed violations	-0.0014		(-0.7963)	0.7046	0.7008	237	-0.0006		(-0.3467)	0.6984	0.6945	237
Overall - Including all three stages of violations	-0.0020		(-1.302)	0.8203	0.8180	238	**-0.0030**	**	**(-2.1125)**	0.8571	0.8552	238
Carhart Results												
Initial allegations	-0.0029		(-1.2777)	0.6223	0.6158	236	**-0.0044**	**	**(-1.9751)**	0.6921	0.6868	236
Confirmed violations but still pending other matters	-0.0017		(-0.7154)	0.6830	0.6775	238	-0.0010		(-0.3495)	0.6666	0.6609	238
Confirmed violations	-0.0022		(-1.0872)	0.7077	0.7027	237	-0.0020		(-0.9737)	0.7086	0.7035	237
Overall - Including all three stages of violations	**-0.0027**	*	**(-1.6694)**	0.8226	0.8196	238	**-0.0033**	**	**(-2.1233)**	0.8576	0.8551	238

2.4.6 Impact of ESG plus LT per Industry Results

The results on the single and multifactor regressions on the industry level are based only on the Overall - all three stages of the violations (tables 2.13 to 2.15). Supporting my hypothesis, I find investors in each industry react only to certain individual E, S, G and LT violations.

For the environmental portfolios, observing the Carhart model, I find that only two industries show underperformance. Both manufacturing and transportation and public utilities underperformed by 47 and 61 basis points p.m at the EW fine level respectively. This supports my earlier findings that investors in the extractions and usage of valuable minerals and natural resources industries react to environmental fines.

For the social portfolio, based on the Carhart model, the manufacturing industry outperforms and services underperform on the EW fine level portfolios by 42 and 121 basis points p.m respectively. I find these results similar with the findings in table 2.4 where the manufacturing CVPM portfolio outperforms. Interestingly, on the EW company level I find that manufacturing industry does not have any significance but instead Services and transportation underperforms by 117 and 12 basis points p.m respectively. These results show that investors in the manufacturing industry do not perceive social fines to be of a concern.

For the governance portfolio, after controlling for momentum, the EW fine level shows that only mining and services underperform by 63 and 87 basis points p.m respectively. However, in EW company level in addition to mining and services, I find now finance has statistical significance and underperforms by 61 basis points p.m. Thus, when looking deeply at the type of fine it does show that investors in the finance industry do react negatively to illegal behaviours of finance firms. Finally, for the LT portfolio, surprisingly I also find no statistical significant results on an industry level[26].

[This section has been intentionally left blank]

[26] Results for the LT portfolios are available upon request

Table 2.13 Environment portfolio results (individual industries) of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Environment											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	Adj R^2	**N**	**Alpha**			R^2	Adj R^2	**N**
Finance	-0.0039		(-1.0343)	0.2372	0.2330	183	-0.0037		(-0.9907)	0.2368	0.2326	183
Manufacturing	-0.0032		(-1.5975)	0.7080	0.7068	245	**-0.0033**	*	**(-1.9653)**	0.7562	0.7552	245
Mining	-0.0016		(-0.5323)	0.6694	0.6680	239	-0.0019		(-0.7307)	0.7173	0.7161	239
Services	-0.0070		(-1.546)	0.7350	0.7301	56	-0.0069		(-1.4399)	0.5998	0.5924	56
Transportation and Public Utilities	-0.0041		(-1.557)	0.4725	0.4703	244	-0.0048		(-1.6302)	0.3133	0.3105	244
Retail and Wholesale Trade	0.0026		(0.7708)	0.4599	0.4576	242	0.0026		(0.7708)	0.4599	0.4576	242
Fama-French Results												
Finance	-0.0041		(-1.0961)	0.2593	0.2468	183	-0.0039		(-1.0495)	0.2598	0.2474	183
Manufacturing	-0.0029		(-1.6045)	0.7573	0.7543	245	**-0.0031**	*	**(-1.9382)**	0.8127	0.8104	245
Mining	-0.0016		(-0.5684)	0.6829	0.6788	239	-0.0019		(-0.7328)	0.7307	0.7272	239
Services	-0.0064		(-1.529)	0.7699	0.7566	56	-0.0068		(-1.5014)	0.6289	0.6075	56
Transportation and Public Utilities	-0.0036		(-1.4382)	0.4918	0.4855	244	-0.0044		(-1.6054)	0.3581	0.3501	244
Retail and Wholesale Trade	0.0027		(0.7901)	0.4667	0.4599	242	0.0027		(0.7901)	0.4667	0.4599	242
Carhart Results												
Finance	-0.0015		(-0.4152)	0.2797	0.2635	183	-0.0013		(-0.3723)	0.2802	0.2641	183
Manufacturing	**-0.0047**	***	**(-2.8133)**	0.7719	0.7682	245	**-0.0042**	***	**(-2.6077)**	0.8188	0.8158	245
Mining	-0.0012		(-0.4198)	0.6836	0.6782	239	-0.0017		(-0.643)	0.7309	0.7262	239
Services	-0.0060		(-1.4531)	0.7717	0.7538	56	-0.0069		(-1.4755)	0.6294	0.6003	56
Transportation and Public Utilities	**-0.0061**	**	**(-2.3761)**	0.5450	0.5373	244	**-0.0076**	***	**(-2.6523)**	0.4312	0.4217	244
Retail and Wholesale Trade	0.0032		(0.8545)	0.4674	0.4584	242	0.0032		(0.8545)	0.4674	0.4584	242

Table 2.14 Social portfolio results (individual industries) of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Social											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			**R^2**	**Adj R^2**	**N**	**Alpha**			**R^2**	**Adj R^2**	**N**
NFinance	-0.0038		(-0.8629)	0.4293	0.4266	212	-0.0039		(-0.8895)	0.4288	0.4261	212
Manufacturing	**0.0046**	**	**(2.175)**	0.3833	0.3808	241	0.0030		(1.5942)	0.4831	0.4809	241
Mining	-0.0029		(-0.8195)	0.6737	0.6722	217	-0.0026		(-0.7406)	0.6781	0.6766	217
Services	**-0.0082**	*	**(-1.8591)**	0.3538	0.3506	210	**-0.0083**	*	**(-1.8856)**	0.3530	0.3498	210
Transportation and Public Utilities	**-0.0111**	*	**(-1.7504)**	0.2397	0.2361	227	**-0.0105**	*	**(-1.657)**	0.2367	0.2330	227
Retail and Wholesale Trade	-0.0007		(-0.2632)	0.4252	0.4226	231	-0.0005		(-0.1639)	0.4214	0.4189	231
Fama-French Results												
Finance	0.0032		(0.8124)	0.4997	0.4973	212	0.0032		(0.8124)	0.4997	0.4973	**212**
Manufacturing	-0.0034		(-0.7468)	0.4347	0.4266	241	-0.0035		(-0.7722)	0.4349	0.4267	241
Mining	**0.0048**	**	**(2.2457)**	0.4304	0.4231	217	**0.0032**	*	**(1.698)**	0.5234	0.5174	217
Services	-0.0025		(-0.7513)	0.6837	0.6792	210	-0.0022		(-0.6712)	0.6867	0.6822	210
Transportation and Public Utilities	**-0.0078**	*	**(-1.8271)**	0.3691	0.3596	227	**-0.0079**	*	**(-1.8547)**	0.3687	0.3592	227
Retail and Wholesale Trade	**-0.0115**	*	**(-1.9479)**	0.3036	0.2934	231	**-0.0110**	*	**(-1.8627)**	0.3014	0.2912	231
Carhart Results												
Finance	-0.0002		(-0.0899)	0.5072	0.5005	212	0.0000		(0.0159)	0.5049	0.4983	212
Manufacturing	0.0033		(0.8449)	0.5082	0.5008	241	0.0033		(0.8449)	0.5082	0.5009	241
Mining	-0.0025		(-0.5315)	0.4365	0.4256	217	-0.0026		(-0.5579)	0.4366	0.4257	217
Services	**0.0042**	*	**(1.9111)**	0.4322	0.4226	210	0.0026		(1.3419)	0.5254	0.5174	210
Transportation and Public Utilities	-0.0019		(-0.5101)	0.6846	0.6787	227	-0.0015		(-0.4101)	0.6880	0.6821	227
Retail and Wholesale Trade	-0.0057		(-1.2826)	0.3820	0.3696	231	-0.0058		(-1.308)	0.3817	0.3692	231

Table 2.15 Governance portfolio results (individual industries) of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the equal-weighted at the fine level (Panel A) followed by the equal-weighted at company level (Panel B). Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Governance											
	Panel A: Equal Weighted (Fine Level)						**Panel B: Equal Weighted (Company Level)**					
CAPM Results	**Alpha**			**R^2**	**Adj R^2**	**N**	**Alpha**			**R^2**	**Adj R^2**	**N**
Finance	**-0.0058**	*****	**(-1.6966)**	0.5105	0.5085	238	**-0.0077**	******	**(-2.2424)**	0.5316	0.5296	238
Manufacturing	**-0.0040**	*****	**(-1.687)**	0.5124	0.5103	234	-0.0038		(-1.6107)	0.5057	0.5036	234
Mining	**-0.0055**	******	**(-2.3767)**	0.7550	0.7539	224	**-0.0055**	******	**(-2.3767)**	0.7550	0.7539	224
Services	**-0.0109**	******	**(-2.4472)**	0.4536	0.4513	234	**-0.0099**	******	**(-2.3078)**	0.4990	0.4968	234
Transportation and Public Utilities	0.0010		(0.5277)	0.5277	0.5255	222	0.0011		(0.3585)	0.5337	0.5316	222
Retail and Wholesale Trade	0.0037		(1.0203)	0.5416	0.5385	253	0.0037		(1.0203)	0.5416	0.5385	253
Fama-French Results												
Finance	**-0.0069**	******	**(-2.165)**	0.5324	0.5264	238	**-0.0086**	*******	**(-2.6062)**	0.5474	0.5416	238
Manufacturing	**-0.0038**	*****	**(-1.7542)**	0.5604	0.5547	234	**-0.0037**	*****	**(-1.6794)**	0.5525	0.5467	234
Mining	**-0.0059**	*******	**(-2.6486)**	0.7673	0.7641	224	**-0.0059**	*******	**(-2.6486)**	0.7673	0.7641	224
Services	**-0.0109**	******	**(-2.4255)**	0.4567	0.4496	234	**-0.0099**	******	**(-2.294)**	0.5029	0.4964	234
Transportation and Public Utilities	0.0013		(0.4593)	0.5512	0.5451	222	0.0014		(0.4663)	0.5565	0.5504	222
Retail and Wholesale Trade	0.0040		(1.1032)	0.5434	0.5339	253	0.0040		(1.1032)	0.5434	0.5339	253
Carhart Results												
Finance	-0.0042		(-1.2198)	0.5503	0.5426	238	**-0.0061**	*****	**(-1.6584)**	0.5622	0.5547	238
Manufacturing	-0.0033		(-1.5843)	0.5617	0.5540	234	-0.0032		(-1.5566)	0.5534	0.5456	234
Mining	**-0.0063**	*******	**(-2.7226)**	0.7678	0.7635	224	**-0.0063**	*******	**(-2.7226)**	0.7678	0.7635	224
Services	**-0.0087**	*****	**(-1.7341)**	0.4621	0.4527	234	-0.0079		(-1.6207)	0.5079	0.4993	234
Transportation and Public Utilities	-0.0002		(-0.0681)	0.5648	0.5567	222	**-0.0001**	*****	**(-0.0436)**	0.5693	0.5614	222
Retail and Wholesale Trade	0.0041		(1.0552)	0.5435	0.5307	253	0.0041		(1.0552)	0.5435	0.5307	253

2.5 Additional Analyses

2.5.1 Value Weighted Results

In this section I compare the results of the equal weighted portfolios with the portfolios which are value weighted. Hoepner and Zeume (2013) and Adamsson and Hoepner (2015) have critiqued the use of only equal weighted (EW) portfolios as most studies regress equal weighted portfolios on value weighted (VW) benchmarks (Fabozzi, Ma et al. 2008; Hong and Kacperczyk 2009). However, in my previous analysis, my EW portfolios are regressed on EW benchmarks which therefore does not create any discrepancies or biases, thus in this section I conduct additional VW analysis which is regressed on VW benchmarks similar to Hoepner and Schopohl (2016), to measure whether VW portfolios would have similar results to my EW portfolios. The VW portfolios were created using the below:

$$r_{p,t} = ln\left[\left(\frac{P_{i1,t}}{P_{i1,t-1}} * \frac{MC_{i1,t-1}}{\sum_{i=1}^{N} MC_{i1,t-1}}\right) + \cdots + \left(\frac{P_{i,t}}{P_{i,t-1}} * \frac{MC_{iN,t-1}}{\sum_{i=1}^{N} MC_{iN,t-1}}\right)\right] \tag{2.10}$$

where $P_{i1,t}$ is firms' price in that period over the price of the previous period $P_{i1,t-1}$ and the weight of the company using the MC of the firm *i* at period *t* over the total sum of the MC of firms in the portfolio at period *t* .My VW portfolios were also regressed on created value weighted market benchmarks even on different industry levels. It can be observed that my overall portfolio in table 2.16 (Panel A) has similar underperformance results in a four factor regression setting. The alphas, the r-squared value and the level of statistical significance are reduced. Nevertheless, the fit of the model is still relatively high with adjusted r-squared values of between 0.54 and 0.86.

The separate VW industry portfolios results are shown in table 2.16 (Panel B) to table 2.18 (Panel A). For IA, in addition to manufacturing in the EW model I now find finance underperforms by 77 basis points p.m in the Carhart model and mining underperforms by 37 basis points p.m in the Fama-French model. For EW CVPM, I initially had underperformances in both transportation and public utilities and services, and outperformance in manufacturing. Now the VW portfolios show no statistical significance at all. The EW and VW CV portfolio both show underperformance in Transportation and Mining. In the VW overall portfolios, I also find the same industries, Finance, Mining and Transportation exhibiting underperformances. I still observe no risk-adjusted returns that are statistically significant for the Retail and Wholesale Trade industry portfolios.

When analysing the ESG plus LT portfolios, I find that the environmental VW Carhart model results in table 2.18 (Panel B) is similar to the EW portfolios even on statistical significance levels. The VW CVPM underperformance is larger at 142 basis points p.m compared to 127 basis points p.m in the EW model. Interestingly, I find now outperformance of 250 basis points p.m in the social CVPM VW model in table 2.18 (Panel A). The governance VW portfolio in table 2.19 (Panel B) still underperforms in the overall portfolio. However, the LT portfolio for the VW model does not indicate any statistical significance[27]. The results above affirm that the environmental portfolio on both EW and VW model is strongly robust. In relation to the VW fines per market cap in table 2.20, I find similar results to the EW model where the portfolio with higher fines indicates larger underperformance compared to lower fines.

[27] Results for the LT portfolios are available upon request

Examining the VW ESG plus LT per industry results (table 2.21 to 2.22) for environment portfolios, I find similar results that manufacturing and transportations and public utilities underperform. However, in the social portfolio I find no statistical significance in the Carhart model. For the governance portfolio, I find manufacturing, mining and services underperform. I still observe no risk-adjusted returns that are statistically significant for the LT portfolios[28]. Hereby, the VW portfolios also indicate that investors in each industry react only to certain individual E, S, G and LT violations.

[This section has been intentionally left blank]

[28] Results for the LT portfolios are available upon request.

Table 2.16 Value Weighted (Company level) results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the value-weighted results at company level. Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Overall - All Industries						Finance					
	Panel A: Value Weighted (Company Level)						**Panel B: Value Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	**Adj** R^2	**N**	**Alpha**			R^2	**Adj** R^2	**N**
Initial allegations	-0.0022		(-1.3974)	0.6573	0.6559	241	**-0.0079**	**	**(-2.5930)**	0.6508	0.6494	238
Confirmed violations but still pending other matters	0.0005		(0.2238)	0.5454	0.5435	240	-0.0027		(-0.6925)	0.4962	0.4940	233
Confirmed violations	-0.0016		(-1.3107)	0.7962	0.7953	245	-0.0038		(-1.1795)	0.5929	0.5912	241
Overall - Including all three stages of violations	-0.0012		(-1.0572)	0.8163	0.8156	246	-0.0036		(-1.4399)	0.7027	0.7014	241
Fama-French Results												
Initial allegations	-0.0021		(-1.4830)	0.7369	0.7335	241	**-0.0087**	***	**(-3.0088)**	0.6633	0.6589	238
Confirmed violations but still pending other matters	0.0003		(0.1349)	0.5716	0.5661	240	-0.0033		(-0.8755)	0.5103	0.5038	233
Confirmed violations	-0.0017		(-1.6239)	0.8245	0.8223	245	-0.0046		(-1.522)	0.6268	0.6221	241
Overall - Including all three stages of violations	-0.0012		(-1.3253)	0.8493	0.8474	246	**-0.0044**	**	**(-1.9999)**	0.7306	0.7272	241
Carhart Results												
Initial allegations	**-0.0026**	*	**(-1.6533)**	0.7379	0.7335	241	**-0.0077**	***	**(-2.6333)**	0.6655	0.6597	238
Confirmed violations but still pending other matters	-0.0007		(-0.3463)	0.5761	0.5689	240	-0.0025		(-0.5911)	0.5126	0.5041	233
Confirmed violations	**-0.0028**	**	**(-2.3304)**	0.8322	0.8294	245	-0.0036		(-1.0824)	0.6297	0.6234	241
Overall - Including all three stages of violations	**-0.0022**	**	**(-2.3206)**	0.8558	0.8534	246	-0.0035		(-1.4746)	0.7331	0.7286	241

Table 2.17 Value Weighted (Company level) results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the value-weighted results at company level. Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Manufacturing						Transportation and Public Utilities					
	Panel A: Value Weighted (Company Level)						**Panel B: Value Weighted (Company Level)**					
CAPM Results	**Alpha**			***R^2***	**Adj *R^2***	**N**	**Alpha**			***R^2***	**Adj *R^2***	**N**
Initial allegations	-0.0019		(-0.8940)	0.5939	0.5922	240	0.0011		(0.2884)	0.2054	0.2020	238
Confirmed violations but still pending other matters	0.0035		(1.3048)	0.3387	0.3358	237	-0.0052		(-1.1703)	0.2706	0.2674	233
Confirmed violations	-0.0004		(-0.3143)	0.6689	0.6676	245	-0.0045		(-1.5800)	0.4034	0.4009	243
Overall - Including all three stages of violations	-0.0001		(-0.0448)	0.7170	0.7159	245	-0.0023		(-1.0734)	0.4880	0.4859	243
Fama-French Results												
Initial allegations	-0.0022		(-1.2341)	0.6798	0.6757	240	0.0011		(0.3279)	0.2821	0.2727	238
Confirmed violations but still pending other matters	0.0033		(1.2380)	0.3638	0.3556	237	-0.0061		(-1.4071)	0.3452	0.3366	233
Confirmed violations	-0.0004		(-0.3645)	0.7006	0.6968	245	-0.0046		(-1.5716)	0.4109	0.4035	243
Overall - Including all three stages of violations	-0.0001		(-0.1218)	0.7724	0.7696	245	-0.0024		(-1.171)	0.5233	0.5173	243
Carhart Results												
Initial allegations	**-0.0033**	*****	**(-1.8242)**	0.6849	0.6795	240	-0.0015		(-0.4787)	0.3129	0.3009	238
Confirmed violations but still pending other matters	0.0015		(0.6359)	0.3766	0.3658	237	-0.0057		(-1.3483)	0.3457	0.3342	233
Confirmed violations	-0.0019		(-1.4607)	0.7140	0.7093	245	**-0.0062**	******	**(-2.1901)**	0.4263	0.4166	243
Overall - Including all three stages of violations	-0.0015		(-1.4897)	0.7851	0.7815	245	**-0.0042**	******	**(-2.0258)**	0.5513	0.5438	243

Table 2.18 Value Weighted (Company level) results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the value-weighted results at company level. Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Mining						Environment					
	Panel A: Value Weighted (Company Level)						**Panel B: Value Weighted (Company Level)**					
CAPM Results	**Alpha**			**R^2**	**Adj R^2**	**N**	**Alpha**			**R^2**	**Adj R^2**	**N**
Initial allegations	-0.0034		(-1.4479)	0.7225	0.7214	238	-0.0021		(-1.0088)	0.5392	0.5373	241
Confirmed violations but still pending other matters	-0.0017		(-0.5546)	0.7111	0.7098	216	**-0.0126**	***	**(-2.5954)**	0.3693	0.3667	236
Confirmed violations	**-0.0055**	*	**(-1.7065)**	0.5553	0.5534	235	-0.0026		(-1.4066)	0.5675	0.5658	245
Overall - Including all three stages of violations	-0.0033		(-1.4229)	0.7224	0.7212	238	**-0.0027**	*	**(-1.7232)**	0.6434	0.6420	245
Fama-French Results												
Initial allegations	**-0.0037**	*	**(-1.8473)**	0.7707	0.7678	238	-0.0020		(-1.0711)	0.6000	0.5949	241
Confirmed violations but still pending other matters	-0.0017		(-0.5706)	0.7179	0.7139	216	**-0.0128**	***	**(-2.6359)**	0.3756	0.3677	236
Confirmed violations	**-0.0059**	*	**(-1.9455)**	0.5976	0.5924	235	-0.0024		(-1.3058)	0.5740	0.5687	245
Overall - Including all three stages of violations	**-0.0036**	*	**(-1.8122)**	0.7705	0.7676	238	**-0.0026**	*	**(-1.7018)**	0.6671	0.6630	245
Carhart Results												
Initial allegations	-0.0032		(-1.4845)	0.7721	0.7681	238	**-0.0038**	**	**(-1.9905)**	0.6200	0.6136	241
Confirmed violations but still pending other matters	-0.0010		(-0.3019)	0.7195	0.7141	216	**-0.0142**	***	**(-2.926)**	0.3796	0.3690	236
Confirmed violations	-0.0048		(-1.4802)	0.6027	0.5958	235	**-0.0049**	***	**(-2.7783)**	0.6105	0.6041	245
Overall - Including all three stages of violations	-0.0031		(-1.4524)	0.7719	0.7680	238	**-0.0042**	***	**(-2.7206)**	0.6923	0.6873	245

Table 2.19 Value Weighted (Company level) results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the value-weighted results at company level. Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

	Social						Governance					
	Panel A: Value Weighted (Company Level)						**Panel B: Value Weighted (Company Level)**					
CAPM Results	**Alpha**			***R^2***	**Adj *R^2***	**N**	**Alpha**			***R^2***	**Adj *R^2***	**N**
Initial allegations	**0.0130**	*	**(1.8292)**	0.5392	0.5373	234	-0.0043		(-1.2801)	0.4334	0.4310	237
Confirmed violations but still pending other matters	**0.0255**	**	**(2.3831)**	0.3693	0.3667	225	0.0060		(1.0763)	0.3182	0.3139	233
Confirmed violations	-0.0022		(-0.8345)	0.5675	0.5658	240	-0.0028		(-0.9852)	0.5036	0.5015	240
Overall - Including all three stages of violations	0.0006		(0.2711)	0.6434	0.6420	240	-0.0032		(-1.3586)	0.6460	0.6445	240
Fama-French Results												
Initial allegations	**0.0135**	*	**(1.8908)**	0.6000	0.5949	234	-0.0050		(-1.6025)	0.4894	0.4828	237
Confirmed violations but still pending other matters	**0.0255**	**	**(2.4824)**	0.3756	0.3677	225	0.0062		(1.1099)	0.3469	0.3441	233
Confirmed violations	-0.0023		(-0.9004)	0.5740	0.5687	240	-0.0036		(-1.3437)	0.5647	0.5592	240
Overall - Including all three stages of violations	0.0006		(0.2848)	0.6671	0.6630	240	**-0.0039**	*	**(-1.8564)**	0.7113	0.7076	240
Carhart Results												
Initial allegations	0.0099		(1.5586)	0.6200	0.6136	234	-0.0049		(-1.6007)	0.4894	0.4806	237
Confirmed violations but still pending other matters	**0.0250**	**	**(2.5515)**	0.3796	0.3690	225	0.0093		(1.5794)	0.3486	0.3467	233
Confirmed violations	-0.0041		(-1.5471)	0.6105	0.6041	240	-0.0040		(-1.3751)	0.5652	0.5578	240
Overall - Including all three stages of violations	-0.0006		(-0.3229)	0.6923	0.6873	240	**-0.0040**	*	**(-1.6856)**	0.7113	0.7064	240

Table 2.20 Value Weighted (Company level) results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the four different portfolios based on the stages of the violations, column two indicates the value-weighted results at company level. Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The values in the parentheses represent the values of the t-statistics. N represents the number of observations in each panel A and B.

Fines per Market Cap	0 to 20th Percentile Level						80th to 100th Percentile Level					
	Panel A: Value Weighted (Company Level)						**Panel B: Value Weighted (Company Level)**					
CAPM Results	**Alpha**			R^2	**Adj** R^2	**N**	**Alpha**			R^2	**Adj** R^2	**N**
Initial allegations	-0.0029		(-1.0443)	0.4462	0.4439	234	**-0.0101**	*******	**(-2.8717)**	0.3524	0.3496	239
Confirmed violations but still pending other matters	-0.0012		(-0.4306)	0.4244	0.4220	240	0.0025		(0.4608)	0.3528	0.3500	233
Confirmed violations	-0.0012		(-0.549)	0.5356	0.5336	238	**-0.0048**	*****	**(-1.7266)**	0.5051	0.5031	240
Overall - Including all three stages of violations	-0.0001		(-0.0593)	0.5389	0.5370	240	**-0.0048**	*****	**(-1.8329)**	0.5545	0.5526	240
Fama-French Results												
Initial allegations	-0.0026		(-1.0025)	0.4894	0.4829	234	**-0.0110**	*******	**(-3.4486)**	0.4419	0.4346	239
Confirmed violations but still pending other matters	-0.0014		(-0.4745)	0.4279	0.4206	240	0.0018		(0.3705)	0.4230	0.4154	233
Confirmed violations	-0.0010		(-0.4596)	0.5407	0.5348	238	**-0.0053**	******	**(-2.0181)**	0.5361	0.5302	240
Overall - Including all three stages of violations	0.0000		(-0.0142)	0.5548	0.5492	240	**-0.0056**	*******	**(-2.629)**	0.6695	0.6653	240
Carhart Results												
Initial allegations	-0.0039		(-1.4589)	0.4958	0.4872	234	**-0.0102**	*******	**(-3.1502)**	0.4434	0.4336	239
Confirmed violations but still pending other matters	-0.0025		(-0.9384)	0.4320	0.4223	240	0.0011		(0.2082)	0.4239	0.4138	233
Confirmed violations	**-0.0046**	******	**(-2.0657)**	0.5848	0.5777	238	**-0.0065**	******	**(-2.3609)**	0.5409	0.5331	240
Overall - Including all three stages of violations	-0.0020		(-1.0694)	0.5747	0.5675	240	**-0.0059**	******	**(-2.5573)**	0.6698	0.6642	240

Table 2.21 Value Weighted (Company level) results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the portfolios from seven different industries, column two indicates the value-weighted results at company level. Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The value in the parentheses represents the values of the t-statistics. N represents the number of observations in each panel A and B.

	Environment						Social					
	Panel A: Value Weighted (Company Level)						**Panel B: Value Weighted (Company Level)**					
One Year Holding Period - CAPM Results	**Alpha**			R^2	**Adj** R^2	**N**	**Alpha**			R^2	**Adj** R^2	**N**
Finance	-0.0044		(-1.0458)	0.4432	0.4401	183	-0.0014		(-0.3408)	0.3027	0.2994	212
Manufacturing	**-0.0032**	*	**(-1.7146)**	0.6413	0.6399	245	0.0026		(1.0324)	0.3892	0.3866	241
Mining	-0.0019		(-0.7466)	0.6908	0.6895	239	-0.0017		(-0.5105)	0.6157	0.6138	217
Services	-0.0032		(-0.7487)	0.2758	0.2729	56	-0.0049		(-0.7269)	0.0745	0.0701	210
Transportation and Public Utilities	-0.0036		(-1.213)	0.2758	0.2729	244	0.0026		(0.8993)	0.1158	0.1119	227
Retail and Wholesale Trade	-0.0013		(-0.3904)	0.4001	0.3976	242	**-0.0083**	*	**(-1.6891)**	0.6039	0.5980	231
One Year Holding Period - Fama-French Results												
Finance	-0.0050		(-1.1539)	0.4543	0.4452	183	-0.0012		(-0.3052)	0.3187	0.3089	212
Manufacturing	**-0.0034**	**	**(-2.0443)**	0.6903	0.6864	245	0.0022		(0.9612)	0.4731	0.4664	241
Mining	-0.0022		(-0.9162)	0.7155	0.7119	239	-0.0013		(-0.4342)	0.6287	0.6231	217
Services	-0.0028		(-0.6749)	0.6901	0.6722	56	-0.0072		(-1.1166)	0.1637	0.1515	210
Transportation and Public Utilities	-0.0034		(-1.1897)	0.2993	0.2905	244	0.0026		(1.0454)	0.2717	0.2619	227
Retail and Wholesale Trade	-0.0013		(-0.3817)	0.4009	0.39335	242	**-0.0082**	*	**(-1.6861)**	0.1556	0.1430	231
One Year Holding Period - Carhart Results												
Finance	-0.0033		(-0.7394)	0.4617	0.4496	183	0.0003		(0.0594)	0.3254	0.3124	212
Manufacturing	**-0.0056**	***	**(-3.3379)**	0.7118	0.7070	245	0.0003		(0.141)	0.4898	0.4811	241
Mining	-0.0022		(-0.8969)	0.7155	0.7107	239	-0.0006		(-0.1896)	0.6299	0.6224	217
Services	-0.0033		(-0.769)	0.6946	0.6707	56	-0.0076		(-1.2144)	0.1639	0.1475	210
Transportation and Public Utilities	**-0.0058**	**	**(-2.0524)**	0.3387	0.3276	244	0.0011		(0.4805)	0.2887	0.2759	227
Retail and Wholesale Trade	-0.0002		(-0.0639)	0.4051	0.3951	242	-0.0059		(-1.2321)	0.1701	0.1534	231

.

Table 2.22 Value Weighted (Company level) results of CAPM,Fama-French and Carhart regressions with created benchmarks

The following table displays the Jensen's alpha's results from CAPM, Fama-French and Carhart regressions with the specific overall created benchmark. Column one indicates the portfolios from seven different industries, column two indicates the value-weighted results at company level. Each portfolio reports the r-squared and adjusted r-squared values. T-statistics are computed with Newey-West (1987) corrections for serial correlation. ***,**,* indicates statistical significance at the 1%,5% and 10% levels respectively. The value in the parentheses represents the values of the t-statistics. N represents the number of observations in each panel A and B.

	Governance					
	Panel A: Value Weighted (Company Level)					
CAPM Results	**Alpha**			**R^2**	**Adj R^2**	**N**
Finance	**-0.0051**	*****	**(-0.3408)**	0.7207	0.7195	238
Manufacturing	-0.0038		(1.0324)	0.2986	0.2956	234
Mining	**-0.0058**	*******	**(-0.5105)**	0.7432	0.7420	224
Services	**-0.0127**	*******	**(-0.7269)**	0.3532	0.3505	234
Transportation and Public Utilities	0.0033		(0.8993)	0.2961	0.2929	222
Retail and Wholesale Trade	0.0069		(0.8111)	0.1029	0.09672	253
Fama-French Results						
Finance	**-0.0062**	******	**(-0.3408)**	0.7389	0.7355	238
Manufacturing	**-0.0048**	*****	**(1.0324)**	0.4530	0.4458	234
Mining	**-0.0062**	*******	**(-0.5105)**	0.7546	0.7513	224
Services	**-0.0134**	*******	**(-0.7269)**	0.3725	0.3643	234
Transportation and Public Utilities	0.0032		(0.8993)	0.3359	0.3268	222
Retail and Wholesale Trade	0.0052		(0.8300)	0.2028	0.18619	253
Carhart Results						
Finance	-0.0042		(-0.3408)	0.7479	0.7436	238
Manufacturing	**-0.0048**	*****	**(1.0324)**	0.4530	0.4434	234
Mining	**-0.0067**	*******	**(-0.5105)**	0.7555	0.7510	224
Services	**-0.0127**	******	**(-0.7269)**	0.3730	0.3621	234
Transportation and Public Utilities	0.0006		(0.8993)	0.3675	0.3558	222
Retail and Wholesale Trade	0.0033		(0.4981)	0.2185	0.19665	253

2.5.2 Effect of Value of Fines on Short Interest

To analyze whether investors have a negative sentiment when a company has a high fine, I investigate whether firms have high short interest due to fines. I find that indeed there is a significantly positive relation to the amount of fines with short interest. This confirms my notion that fines can induce higher short selling.

Short interest can be perceived as a sentiment indicator of investors. If short interest is high, it can be an indication that they expect the value of shares to decline and vice versa. Karpoff & Lou (2010) found that abnormal short interest increases steadily in the last 19 months before financial misrepresentation is publically revealed. Their study revealed that short selling had anticipated an eventual discovery and severity of financial conduct. Hence, following their study, I anticipate that fines would have an effect on the sentiment of investors, thus inducing them to short sell.

For each month *t*, the short interest ratio (SIR) is regressed on variables that would explain whether the values of fines have an effect on short selling. Short interest is measured as the total number of shares an investor has sold short divided by the average daily trading volume for a specific time period. The explanatory variables include Institutional Ownership (Int_Ownership), Share Turnover (Turnover), Cash over Assets (Cash_Assets) and Total Assets (Assets) which are all measured monthly. Accruals (Acc) and the value of fines (Fine) is measured using annual data, so it is the same in all months *t* in a given year. To calculate accruals for firm *i* in month *t*, I used the basic formula as per in Hribar & Collins (2002):

$$Acc_{bs} = (\Delta CA - \Delta CL - \Delta Cash + \Delta STDebt - Dep) \qquad (2.11)$$

where ΔCA is the change in current assets during period *t*; ΔCL is the change in current liabilities in period *t*; $\Delta Cash$ is the change in cash and cash equivalents during period *t*; $\Delta STDebt$ is the change in current maturities of long-term debt and other short-term debt included in current liabilities during period *t* and Dep is the depreciation and amortization expense during period *t*.

Following, Karpoff & Lou (2010) I used institutional ownership, total accruals data and turnover for the explanatory variable for Model 1(Eq 2.12). Investors are usually concerned with the cash balances when a company is hit with a fine. Hence, I added Cash and Cash per Assets as additional explanatory variables as per Model 2(Eq 2.13). Assets was orthogonalized (Asset_ort) due to its high correlation with Cash per Assets. Finally, I added the value of fines variable which was calculated based on the data collected for Model 3(Eq 2.14). The short interest ratio data was retrieved from Bloomberg. The regressions are based on monthly ten years data from April 2002 to December 2012.

$$SIR_{i,t} = \alpha_i + \beta 1 Int\_Ownership_{i,t} + \beta 2 Acc_{i,t} + \beta 3 Turnover_{i,t} + e \qquad (2.12)$$

$$SIR_{i,t} = \alpha_i + \beta 1 Int\_Ownership_{i,t} + \beta 2 Acc_{i,t} + \beta 3 Turnover_{i,t} + \beta 4 Cash\_Assets_{i,t} + \beta 5 Asset\_ort_{i,t} + e \qquad (2.13)$$

$$SIR_{i,t} = \alpha_i + \beta 1 Int\_Ownership_{i,t} + \beta 2 Acc_{i,t} + \beta 3 Turnover_{i,t} + \beta 4 Cash\_Assets_{i,t} + \beta 5 Asset\_ort_{i,t} + \beta 6 Fine_{i,t} + e \qquad (2.14)$$

Table 2.23 reports the empirical results from the time-series and t-statistics monthly coefficient for the three models. Table 8.5 in the appendix provides the full description of the variables and sources. The adjusted r-squared value increases from

0.37 to 0.40 in each model indicating a sufficient fit. According to the estimates, it appears that share turnover is significantly negatively related to short interest. This is quite intuitive as a drop in share turnover could indicate low confidence in the stocks and a move to short sell. The results in the first model indicate a significantly positive relation of institutional ownership with short selling. This shows when there are more institutional investors, there is higher short selling. In the second and third model, I find no statistical significance of this variable. Additionally in the second and third model, I find statistical significance in the cash per asset variable. On a first glance, the significantly positive relation of the cash per asset to short interest may not be intuitive. However, considering that these firms are large in size and their cash balances do not deteriorate per asset, this would not have a negative relation to short interest. The results in the third model with the fines variable show a positive statistical significance which indicates the when there is more fines, there is higher short selling.

[This section has been intentionally left blank]

Table 2.23 The Effect of Value of Fines on Short Selling

This table presents OLS regressions over the period of 2002 to 2012. For each month *t*, the short interest ratio (SIR) is regressed on variables that would explain whether the values of fines have an effect on short selling. Short interest is measured as the total number of shares an investor has sold short divided by the average daily trading volume for a specific time period. The explanatory variables include institutional ownership, share turnover, cash over assets and assets which are all measured monthly. Accruals and the value of fines is measured using annual data, so it is the same in all months *t* in a given year. The table below reports the results from the time-series averages of the coefficient estimates and t-statistics are computed with Newey–West (1987) corrections for serial correlation for the three models.***,** ,* indicates statistical significance at 1%,5% and 10% levels respectively. The value in the parentheses represents the value of the T-Statistics.

Model	1	2	3
Independent Variables	SIR	SIR	SIR
Constant	33.6687***	21.4880**	8.3984**
	(3.5541)	(2.0108)	(0.677)
Institutional Ownership	0.0000**	0.0000	0.0000
	(2.5883)	(0.1856)	(-0.5086)
Ln(Accruals)	0.1574	0.0236	0.1366
	(1.0199)	(0.1179)	(0.6652)
Ln(Share Turnover)	-1.8714***	-1.4350***	-1.2052***
	(-4.317)	(-3.0821)	(-2.5427)
Cash/Assets		0.1040**	0.1448**
		(2.2794)	(2.9288)
Ln(Assets)		0.0006	0.0005
		(0.9466)	(0.7092)
Ln(Fines)			0.2241***
			(2.0093)
R - squared	0.3862	0.4130	0.4318
adjusted R- squared	0.3715	0.3891	0.4038

2.6 Summary

The aim of this chapter is to use the information of fines to measure the impact on long-term performance of stock returns. Various literatures have measured the short-term impact of negative events such as fines on the performance of stock returns. However, I find that there is a gap in understanding the long-term impact of fines. The sample of firms used in this chapter is comprised of large cap firms and institutional investors usually hold stocks of large cap firms for the long run. In this chapter I used hand-collected data of monetary fines from 10-K fillings which is in contrast to most data sources used in comparable studies. Furthermore, my sample size of nineteen years reflects a larger observable period. Instead of using conventional benchmarks, I created a specific market benchmarks for the overall and each individual industry.

I began with analyzing the CAPM, Fama-French and Carhart models which control for size, value and growth factors for the overall industry. My results affirm my first hypothesis that firms that are being held for one year upon announcement of violations do show underperformances of between 29 and 57 basis points p.m. My findings are sturdy as the adjusted r squared values are rather high. Next, I measured the different levels of fines per market size. My results on an overall basis confirm my second hypothesis that firms with higher fines do indeed have a higher level of underperformance compared to firms with lower fines. My third hypothesis that initial announcements of the violations have a larger negative returns compared to other legal stages is also supported. My results are in line with my fourth hypothesis, which suggests that investors react more to violations in manufacturing, mining and transportation and public utilities, which are firms that have a strong connection with natural resources. Using the EFFAS ESG plus LT classifications, I was able to confirm my fifth hypothesis that investors perceive environmental issues on all different stages of violations to be a cause of concern and with larger underperformance. In addition, I find that investor's considerations of ESG plus LT issues in different industries vary and hence confirms my final hypothesis that each individual E,S,G, and LT issues are relevant in only certain industries. This confirms my fourth hypothesis that investors are concerned more on industry specific types of ESG plus LT issue. In totality my portfolios indicate underperformances after fines are imposed, however this does not hold for the manufacturing industry where I find outperformance in social and confirmed but pending other matters fines. This warrants interesting further research to investigate and understand the behaviors of investors in the manufacturing industry.

This chapter shows that investors perceive the value of the firm will decrease not only in the short but also in the long run after a fine. In summary, this chapter further sheds light on the impact of corporate violations on the performance of firms. Literature has already confirmed that in the short-term, illegality does indeed have negative consequences on firms. Here I provide evidence that this also holds for the long run. These results will be especially important to institutional investors who hold portfolios of firms on a long-term basis. Based on these results, investors should divest from companies that are involved in illegalities that result in high financial penalties or advocate for a stronger change in corporate culture and behaviour that tolerates illegalities. On the other hand, firms should have strong principles of corporate legal responsibility as behaviors of violations would be detrimental for corporation's performances especially in the long run. Instilling this sense of corporate legal responsibility could stem out from firms having sufficient steps and measures in place such as the creation of adequate controls, the protection of whistleblowers, the simplification and visibility of its structures and procedures, and the creation of an ethics-based culture (Zyglidopoulos and Fleming 2016).

Although I have tried to obtain the most accurate and reliable data to measure violations, there are some limitations to be noted. My results are only prevalent for large US firms and further research might be directed towards measuring smaller US firms. In addition, due to database limitations and my long sample period of nineteen years, I was unable to collect data regarding rumors prior to the fines and hence it would be an avenue for further research.

[This section has been intentionally left blank]

3. Inter-market Link of Illegality: Measuring the Effect of Short Selling in the context of Fines on Fixed Income

3.1 Introduction

In the previous chapter, I examined the impact of fines on stock returns and presented various research on the impact of illegal activities of companies which has been more on the performances of stock returns (Karpoff, John R. Lott et al. 2005; Karpoff, Lee et al. 2007; Karpoff, Scott Lee et al. 2008; Zeidan 2013). However, as of 2016, the size of the US bond market (total outstanding debt) is $40 trillion and is larger than the US equity market (market capitalization) which stands at $23.8 trillion.[29]. Nevertheless, there has been very little research on the impacts on fixed income returns after illegal behaviors of companies.

Investor sentiment has been researched strongly to find out whether their behaviours influence security prices. Brown & Cliff (2004) found that there is a strong relation that exists between institutional sentiment and large stocks. Results by Baker & Wurgler (2006) also indicated that investor sentiment does indeed explain stock returns. They find that during the beginning period of low (high) sentiment, the subsequent returns of stocks are high (low). However, their results are true only for younger stocks, small stocks, unprofitable stocks, non-dividend paying stocks, high volatility stocks, extreme growth stocks, and distressed stocks. On the bond front, Nayak (2010) found that investor sentiment is a significant factor in determining corporate bond yield spreads. Their findings indicate that it is high yield bonds that are

[29] " US Bond Market and Issuance" available at http://www.sifma.org/research/statistics.aspx (accessed 5 December 2016) and " China's stock market have soared by 1,479% since 2003" available at http://www.businessinsider.com/world-stock-market-capitalizations-2016-11?IR=T (accessed 17 June 2017)

more susceptible to mispricing due to sentiment than low yield bonds. One can conclude that investor sentiment shows clear signs of impact on financial markets.

Yet, there is very little empirical research that measures the effects of different levels of equity sentiment and whether or not that has a direct impact on bond returns. Even though equities and bonds have some similar fundamental characteristics, they are still different in nature. The seminal paper by Fama & French (1993) indicates that both bonds and stocks have common risk factors and Merton (1974) state they have joint claims on a firms assets. However, bonds are illiquid, have cash flows that are pre-determined by maturities and interest rates, and are primarily traded by institutions (Nayak 2010). Nevertheless, Murphy (2011) indicate that there is a strong positive relationship between bonds and stocks. In essence the price reaction of both these asset classes should confirm each other and move in the same direction. Hence, there should be a link between sentiment driven by equity holders and the impacts it has on bond holders.

In this study, I investigate whether short selling in the context of fines has an impact on bond returns. This is also supported by my results (section 2.5.2) in the previous chapter, where I find a significantly positive relation to the amount of fines with short interest. I use short selling as an indicator of sentiment as it is done by investors who believe that the prices of stocks would eventually decline, though controversial in nature (as some indicate that short sellers profit by spreading rumours[30]). Karpoff & Lou (2010) find that short sellers are able to anticipate the

---

[30] For example, in April 2008, SEC charged a Wall Street trader with securities fraud and market manipulation for intentionally spreading false rumours about The Blackstone Group's acquisition of

eventual discovery and severity of financial misconduct. This indicates that short selling can be a good predictor of misconduct.

I find four papers which are closely related to this study (Dyck, Morse et al. 2010; Karpoff and Lou 2010; Henry, Kisgen et al. 2015; Huang, Rossi et al. 2015). However, my study differs significantly from theirs. Firstly, both Dyck, Morse, & Zingales (2010) and Karpoff and Lou (2010) use short selling in their research to identify misconduct. On the other hand, Henry, Kisgen et al. 2015 uses short sellers and examines whether they can identify firms that have significant changes in default likelihoods and credit rating downgrades. My study is different as I use short selling to examine the impact on bond returns. Finally, the next closest paper to my research is by Huang, Rossi et al. (2015). They instead use the Baker-Wurgler sentiment index[31] to examine the link between sentiment and corporate bond spreads. My paper differs from theirs in the sentiment variable as I use short selling as an investor sentiment especially since both Dyck, Morse, & Zingales (2010) and Karpoff and Lou (2010) find that short selling is a good predictor of corporate misconduct. Secondly, they only examine the link between stock market sentiment on corporate bond yields. Instead, I examine further whether short selling in the context of fines impacts corporate bond returns. Thirdly, as their paper is interested in the sentiment effect on corporate bond yields, they run their analysis using control variables such as bond specific characteristics, firm-specific variables and macro-economic variables. My study is different, as I use a

Alliance Data Systems (ADS) while selling ADS short (available at https://www.sec.gov/news/press/2008/2008-64.htm accessed 29 July 2016)

[31] This index is constructed using two versions of equity market-based sentiment series. “The first version of the sentiment measure is constructed by taking the first principal component of six measures of investor sentiment. The six measures include the closed-end fund discount, the number and the first-day returns of initial public offerings (IPOs), turnover of stocks traded on New York Stock Exchange (NYSE), the equity share in total new issues and the dividend premium. The principal component analysis aims at filtering out idiosyncratic noise in the six measures and capturing their common component. The second BW measure is the one where each of the six measures has first been orthogonalized with respect to a set of macroeconomic conditions”pg6 Huang, Rossi et al. (2015)

more advanced multi index model which was an extension of the initial 4 factor model used by Blake, E.J. Elton, & Gruber (1993).

To examine whether short selling in the context of fines can in fact have an effect on bond returns, I use Short Interest Ratios (SIR) from only US companies in the MSCI Large Cap universe and announcements of fines and settlements that have been published in 10-K fillings of firms in Securities Exchange Commission (SEC) reports and are therefore considered legitimate. In my sample of 691 firms and 4661 only US dollar and non-callable bonds from 2000 to 2012, I find an average of 20 basis points p.m drop of bond returns after a fine. This pattern is evident in high SIR portfolios of between 60th to 80th percentiles on equal and value weighted portfolios which confirm my assumption that it is higher SIR portfolios that underperform. In line with expectations I find none of the lower SIR portfolios have any statistical significance in the equal weighted portfolios. Nevertheless, I find in the value weighted portfolios that there are underperformances in the lower SIR portfolio of between 20th to 40th percentiles. However, this underperformance is on average 7 basis points p.m lesser than the high SIR portfolio between 60th to 80th percentiles. This confirms the view that high short selling can affect bond returns more and there is a positive relationship between equity sentiment and bond returns after illegal activities. This chapter is the first to document that bad sentiment caused by illegal behaviours of companies also has a negative effect on bond returns.

I also investigate whether short selling during crisis periods has a stronger effect than during non-crisis periods. Separating the data into periods of recessions, I find that short selling in the context of fines does indeed have larger underperformance in bond returns compared to non-crisis periods. I find that three out of the six different SIR portfolios indicate underperformances in the crisis period compared to only one portfolio in the non crisis period. This indicates that investors perceive crisis periods to be more detrimental compared to non-crisis periods. Furthermore, it is only in the crisis periods that the higher SIR percentiles (both the 40^{th} to 60^{th} and the 60^{th} to 80^{th}) have underperformances. . This result is quite intuitive as investors would penalize companies more during crisis periods as fines and settlements would be a higher cost incurred for the company and would affect potentially already distressed cash flows.

Bonds are considered long-term investments and the maturity levels of bonds affect returns. Hence, I measure different investment horizons and their effect on returns of bonds after announcements of violations. My results show that the negative underperformance is more profound on bonds with longer remaining years to maturity compared to those with shorter remaining years to maturity. This coincides closely with the long-term outlook of responsible investment investors and very instinctively states that negative events would carry a worst effect on bonds that have longer remaining years to last redemption.

To the best of my knowledge, this study is the first to show that high short selling in the context of fines induces negative returns on bonds. This paper is also the first to show that bond investors perceive fines during crisis periods to be more detrimental. Finally, this study adds to the literature on the inter link effects between asset classes especially on equity and bonds. Furthermore, this study complements the paper by Huang, Rossi et al. (2015) who examine equity sentiment using the Baker-Wurgler sentiment index on corporate bond spreads. I conclude that fines can be a very valuable piece of information when assessing the value of bonds. Investors should make use of this in addition to other traditional information such as bond ratings, earnings announcements and even macro-economic news.

The remainder of the chapter proceeds as follows. Section 2 reviews the relevant literature. Section 3 presents the data and the bond methodology used. Section 4 describes the descriptive statistics of the monthly return data. Section 5 discusses the empirical results and Section 6 provides the robustness followed with additional analyses. Finally Section 7 concludes.

3.2 Literature Review

3.2.1 Short Selling and Equity Performances

Short selling has always been associated as a controversial activity. Short selling literature has revolved around valuation perception of the stock amongst investors. There have been cases of bad rumors spread to benefit investors when the price of the stock decline[32]. This would then allow the investor to sell the stock and buy it back with a profit.

Short interest research has revolved mainly on the performances of stock returns. One of the earlier studies by Seneca (1967) find evidence that stocks do experience underperformances after high short interest. The paper also states that short sales act as a predictor rather than a causal variable on a stock price. Desai, Ramesh, Thiagarajan, & Balachandran (2002) measures the level of short interest ratio and stock returns in the Nasdaq market from 1988 to 1994. They find that heavily shorted firms experience significant negative abnormal returns of between -0.76 to -1.13 percent per month. This also confirmed by (Boehmer, Jones et al. 2008; Boehmer, Huszar et al. 2010) who find that high short interest does experience subsequent negative abnormal

---

[32] For example, in April 2008, SEC charged a Wall Street trader with securities fraud and market manipulation for intentionally spreading false rumours about The Blackstone Group's acquisition of Alliance Data Systems (ADS) while selling ADS short (available at https://www.sec.gov/news/press/2008/2008-64.htm accessed 29 July 2016)

stock returns. Asquith, Pathak, & Ritter (2005) find that on an equal weighted basis, stocks with high short interest ratios and low institutional ownership underperform 176 basis points p.m more than on a value weighted basis. Diether, Lee & Warner (2009) examined daily short selling activity and find increased short selling activity predicts negative abnormal returns in a portfolio setting. Even though there have been numerous researches on the effects of short selling on equity performances, I find no literature on the effects of short selling on bond prices.

3.2.2 Different Information Effects on Asset Classes (Equity and Bond)

There are various papers related to measuring the inter-link between equity and bond. The first aspect is information about changes in bond ratings as a reaction by investors and on stock returns. The earlier work by Goh & Ederington (1993) measured the reaction of common stock returns to bond rating changes and find results of negative stock responses to downgrades. Nevertheless, they argue that this should not be expected for all downgrades as it is only downgrades that result from revaluation of a firm's or industry's financial prospects that provide those negative reactions. Dichev and Piotroski (2001) use Moody's bond rating changes to find that there are no reliable abnormal stock returns following upgrades of rating. They indicate, however, that a downgrade results in between 10 to 14 percent negative abnormal returns and these findings are most pronounced in the first months following the downgrade and on small and low credit-quality firms. Their paper highlights that the "downside" of information such as downgrades provides more of an extreme reaction. This notion perhaps stems from a behavioral stand point that negativism can carry more of an impact than optimistic news and hence provide more extreme reactions to stock returns.

The second aspect is earnings announcements in the stock market and whether there is an impact on bond markets. Datta & Dhillon (1993) were one of the earliest to measure both bond and stock market reaction to unexpected earnings announcements. Their findings suggest that earnings surprises convey information to the bond markets and changes in the firm value are split among bondholders and stockholders. Their study also confirms earlier studies that bondholders react positively (negatively) to unexpected earnings increases (decreases). However, one can argue that their sample was small and for only six years from 1984 to 1990. DeFond & Zhang (2008) extended the research on earnings surprises and bonds. They instead measured whether and how earnings surprises convey information to the bond market. Their results indicate in contrast to Datta & Dhillon (1993) that the bond market has a significant positive reaction to both positive and negative earnings surprise and is weaker than the stock market's reaction. They also studied if the information content of earning surprises is smaller for bonds with low default risk. They found that investment grade bonds have a weaker reaction to both positive and negative earnings surprises. In addition, their results indicated bond's market reaction to negative earnings surprises news is stronger for profitable firms than for loss firms. Their study has a wider sample from 1994 to 2006 and consists of a final sample of 690 issuers and 11,525 firm-quarter observations. Not just measuring whether news has a good or bad impact on bond prices, Defond & Zhang (2014) tested the timelines of bond as well as stock market reaction to good and bad earnings news. They find that bond price quotes react on a timelier basis to bad news than to good news and that that bond price quotes impound bad news on a timelier basis than the stock market. According to their rational based on conservatism, even though bondholders would receive bad news at the similar time with shareholders, bondholders prefer timelier recognition.

The third aspect is measuring the impact of bond prices based on economic news. Fleming & Remolana (1997) examined the U.S treasury securities market and found that sharpest price changes were attributed to just released macroeconomic announcement. Balduzzi, Elton, & Green (2001) studied intraday data from U.S Treasury bonds to investigate the effects of scheduled macroeconomic announcements on prices, trading volumes and bid-ask spreads. Their main findings is that based on 17 news releases, which were measured by the surprise in announcement, had a significant impact on the price of at least one of the following instruments: i) 3 month bill ii) two year note iii) 10 year note and iv) 30 year bond. Furthermore, those effects varied significantly according to maturity [33]. Green (2004) examined the influence of macroeconomic news releases on bond prices and found that there is a significant increase in the informational role of trading following economic announcements, which suggests the release of public information increases the level of information asymmetry in the government bond market.

3.2.3 Related Research

I find four prior studies that are closely related to this study. The first is the paper by Henry, Kisgen, & Wu (2015) and they investigate whether short sellers identify firms that have significant changes in default likelihoods and credit rating downgrades. Their results indicate that short sellers predict changes in default probabilities that lead to bond rating downgrades by focusing on firms with inaccurate

[33] *"While nine announcements affect the price of the T-bill, 13 announcements affect the price of the two-year note, 16 announcements affect the price of the 10-year note, and 10 announcements affect the price of the 30-year bond"* pg 524. Balduzzi, Elton, & Green Balduzzi, P., E. J. Elton, et al. (2001). "Economic News and Bond Prices: Evidence from the U.S. Treasury Market." Journal of Financial and Quantitative Analysis **36**(04): 523-543.

or biased ratings. Their paper adds to the body of knowledge on short sellers as a useful tool for assessing credit risk on a timely basis.

The next two papers measure the link between short selling and an actual misconduct. First, Karpoff & Lou (2010) examine whether short sellers are able to detect firms that misrepresent their financial statements using data from 632 SEC enforcement actions from 1988 through 2005. They find that abnormal short interest increases steadily in the 19 months before misrepresentation is publically revealed. The second, Dyck, Morse, & Zingales (2010) measure short interest to corporate fraud cases of U.S firms against security class action lawsuits from 1996 to 2004. Using both equal and value weighted methodology, they find fraud detection when short selling activity is three standard deviations over the three month prior average prior to a revelation. Their findings indicate that between 3.5% and 14.5% of their 216 events is detected by short sellers. Both paper's findings indicate that short selling can indeed be a measure for eventually discovery of misconduct.

The fourth paper measures the link between sentiment and corporate bond spreads. Huang, Rossi, & Wang (2015) provide evidence that stock market sentiment can be an important driver of corporate bond valuations. Using the Baker-Wurgler (BW) sentiment index, they find that sentiment is negatively related to corporate bond spreads, especially after the 2007-2008 financial crises.

From the papers above, it can be concluded that the level of short selling affects not only the performances of stocks but can also be a good measure to detect illegal behaviors. Most importantly, the impact of short selling is not limited to it equity returns class but also impacts bonds. Nevertheless, this study differs from the above papers in several ways. Firstly, I am using different levels of short interest as a measure of sentiment and examining its impact on bond performances. Secondly, using 12 years of hand collected data and with 1652 monetary fines, I further investigate whether there is an interlink between companies that short sell when fines are given to a company and if that can be a new useful piece of information when assessing bond performance.

3.2.4 Bonds and Socially Responsible Investment (SRI)

There has been growing research interest on SRI and bonds. One of the earlier papers to measure SRI bond funds performance was by Derwall & Koedijk (2009). They found that average SRI bond funds performed similar to conventional funds while the average SRI balanced outperformed its conventional peers by more than 1.3% per year. Their paper could be called a pioneer in the SRI field as it opened up the way for more SRI research in mutual funds. Following them there are two recent studies using their similar methodology which is an extension of the Blake, E.J. Elton, & Gruber (1993) model to measure the performances of bond mutual funds. Henke, et al., (2014) measured the performance of 103 US and Eurozone socially responsible bond funds and compared them with a matched sample of conventional funds. They found that during the period 2001-2014 socially responsible bond funds outperform by half a percent annually. Hoepner & Nilsson (2015), extended Derwall & Koedijk (2009) multi index model by adding 4 additional factors. They find that SRI bond funds that are from fund management companies that are not involved in ESG engagement perform significantly worse indicating the materiality of fund management companies' ESG expertise and ESG engagement in bond investments.

Drut (2010) analyzed sovereign bonds in 20 developed countries in a SRI framework and their results indicated that socially responsible portfolios of sovereign bonds can be built without a significant loss of mean-variance efficiency. So far the research mentioned above have shed a positive light on SRI and bonds. Menz (2010) investigated the relationship between the valuation of European corporate bonds and the standards of Corporate Social Responsibility (CSR) and found that the premium for socially responsible firms were the similar with non-socially responsible companies. Their results show that the effects of CSR have yet to be incorporated into pricing of bonds. Oikonomou, Brooks, & Pavelin (2014), using KLD stats with an extensive set of data of more than 3000 bonds issued by 742 firms operating in 17 industries, were the first to investigate the differential impact that various dimensions of Corporate Social Performance (CSP) has on pricing of corporate debt as well as the assessment of the credit quality of specific bond issues. Their work is one of the first to use an extensive cross-industrial longitudinal data set of U.S bonds from 1991 to 2008. Their results indicate that overall, good performance is rewarded and corporate social transgressions are penalized through lower and higher corporate bond yield spreads, respectively. Their paper induces the notion that doing good pays off for a company and thus increasing efforts in CSP would be beneficial for the company as well as for the bondholders. Stellner, Klein, & Zwergel (2015) instead measured whether CSR reduces a company's credit risk using 872 bonds from twelve European countries. Their results interestingly indicate that there is weak evidence to support the notion that superior CSP results in systematically reduced credit risk. However, in a deeper analysis they find strong results that it rather is a country's ESG performance that moderates the CSP–credit risk relationship.

3.2.5 Conceptual background and Hypotheses Development

Freeman (1984) defines a stakeholder as "any group or individual who can affect or is affected by the achievement of the firm's objectives". Stakeholders of the firm include stockholders, creditors, employees, customers, suppliers, public interest groups, and governmental bodies. There is a vast amount of literature that measure companies' performances based on stakeholder theories. However, only in the last decade has there been an increase in measuring the actions of companies based on ESG issues. One of the main concerns is that the competitive environment that has been put in place by society has rather forced or urged corporations or specifically managers to react only in their self-interest (Campbell 2007). In order to pursue short-term profits which would inevitably look good for the corporation, managers are instead closing an eye to acting responsibly within the purview of good corporate behaviour. Narayanan (1985) indicates that when the manager has private information regarding his or her decisions, situations exist wherein the manager has incentives to make decisions which yield short-term profits but are not in the stockholders best interest. This risk is called agency risk which was introduced in the seminal paper by Jensen & Meckling (1976). There are many such cases of managers acting irresponsibly or illegally in order to benefit themselves in the name of pursuing profits. For example the Enron corporate accounting scandal in the early 2000s which inevitably led to its bankruptcy.

Oikonomou, et al.,(2014) state that *"a firm that is found to behave irresponsibly in a given dimension of its Corporate Social Performance risks a higher probability of a class of negative events occurring such as product boycotts, employees going on strike or withholding best efforts, imposition of fines, penalties, government sanctions, punitive damages, and associated litigation costs".* Illegal behaviours of companies are detrimental to a company as it causes not only reduced loyalty but also serious governance implications. The credibility of the company can be questioned which could then tarnish its reputation and create further repercussions.

It can be deduced that illegal behaviours of managers due to their own self-interest have a negative impact on stakeholders. Hence, in this chapter I try to measure whether there is a link between those two types of stakeholders: shareholders and bondholders. Bhojraj & Sengupta (2003) account for agency risk in their paper when measuring the link of corporate governance on bond rating and yields. They find that bond ratings (yields) on new debt issues are positively (negatively) associated with the percentage of shares held by the institutions and the fraction of the board made up of non-officers. They advocate that governance mechanisms can reduce default risk by mitigating agency costs and monitoring managerial performance and by reducing information asymmetry between the firm and the lenders. Ashbaugh-Skaife, Collins, & LaFond (2006) investigated how various governance mechanisms that are intended to control agency conflicts between management and all stakeholders impact credit ratings. They indicated that the interests of bondholders and shareholders can diverge when there are differing stakes in firm performance and differing views on management's investment policies. They find that firms with stronger shareholder rights have lower credit ratings implying a higher cost of debt financing. Weber (2006) affirmed and believed that Ashbaugh-Skaife, Collins, & LaFond (2006) study does indeed provide persuasive evidence that debt holders value different aspects of a firm's system of corporate governance. The studies above investigate the effects of governance mechanisms on yields and credit ratings; instead I intend to measure the inter-link of equity shareholders reactions with the returns on bonds due to the illegal behaviours of companies.

From the above literature, it can be observed there is clearly a relationship between equity holders and bond holders. There is a gap though in measuring the inter-market reaction of shareholders with bondholders due to illegal behaviours of companies especially those fined. All markets are related, the key question here is investigating the directions of these reactions. There is a strong positive link between stocks and bonds and both markets have a tendency to trend together (Murphy 2011). Hence, the main hypothesis of my study is:

Hypothesis 1: *Firms with high short interest ratios have lower bond returns upon announcement of illegal violations of companies compared to firms with lowers short interest ratios*

The sample periods of this study is from 2000 to 2012 and in that span of 12 years there were two major crisis periods, the dot com bubble burst and the subprime mortgage crisis. Many studies test the effect of crisis periods on performances. Nofsinger & Varma (2014) found that socially responsible mutual funds outperform conventional mutual funds during periods of market crisis.. On a bond level, Henke, et al., (2014) measured whether socially responsible bond funds have better performances during crisis periods compared to conventional bunds funds. Similarly to Nofsinger & Varma (2014), their study confirmed that there is a crisis related return effect out of sample among socially screened indices for their US sample. In both studies, they find that the reduction in downside risk during crisis periods nevertheless comes at a cost during non-crisis periods, as then SRI funds under-perform. Callen & Fang (2015) find evidence that short interest is positively related to one year ahead stock price crash. They also find that this relationship is more salient with firms that have weak governance mechanism, excessive risk-taking behaviour, and high information asymmetry between managers and shareholders. Hence, as my companies in the portfolio are based on illegal behaviours and more risky, during a financial crisis, the impacts of the "bad behaviours" should be penalized more. My second hypothesis is as below:

Hypothesis 2: *Firms with announcements of illegal violations have lower e bond returns during crisis period than non-crisis periods*

SRI research has always been focused on long-term impacts as SRI investors are more concerned on long-term returns. The US Forum for Sustainable and Responsible Investment (USSIF) even states that *"(SRI) is an investment discipline that considers ESG criteria to generate long-term competitive financial returns and positive societal impact[34]"*. Furthermore, bondholders in definition are long-term holders and are more inclined to consider long-term issues such as event risks. Oikonomou, Brooks et al. (2014) examine the effect of CSP on corporate bond spreads based on different levels of maturities and find the link between CSP and yield spreads is more significantly negative for longer maturity bonds. Announcement of illegal violations can be considered as long-term event risks as implications of violations usually have longer time frames for regulatory enforcements. Hence, from the above I believe that the impacts of these illegalities should be more profound on bond returns that have longer remaining years to maturity. Hence my third hypothesis is as below:

Hypothesis 3: *Firms with announcements of illegal violations have more pronounced lower bond returns with longer remaining years to maturity than shorter remaining years to maturity*

[34] "SRI Basics" http://www.ussif.org/sribasics accessed 11 June 2017

I proceed in the next sections to explain the data collection methods which were used to test the above hypotheses and the empirical findings.

3.3 Data and Methodology

3.3.1 Data of Illegal Violations

The source of monetary fines data obtained in this study is similar to the previous chapter. This study consists of a sample of publicly traded US firms that have violations and involve only monetary penalization. The lists of US firms were taken from the MSCI World Large Cap Constituents over a 12-year period from 2000 to 2012. The twelve year period is chosen because of the availability of data. The SIR ratios from Bloomberg were only from 2000 onwards. As shown in table 8.6 in the appendix, the final sample consisted of 691 unique firms with 4661 bonds.

3.3.2 Data Preparation

Monthly bond return data was retrieved from Thompson Reuters Datastream from the period 2000 to 2012. According to DeFond & Zhang (2008), Datastream tends to have a more comprehensive coverage of bond prices in contrast to alternative databases such as the Fixed Income Securities Database (FISD) or the Lehman Brothers bond databases. In addition, the bond prices in Datastream are actual quotes by market markets. Another alternative would be to use the Trade Reporting and Compliance Engine (TRACE) which is corporate bond data provided by the Financial Industry Regulatory Authority. TRACE was introduced to increase the price transparency in the

U.S corporate debt market[35]. TRACE could have been a good substitute to collect monthly bond prices as it includes almost all over-the-counter bonds trades, unfortunately their data coverage only starts in July 2002. Defond & Zhang (2014) also compared the TRACE and Datastream databases on the number of bonds and issuers. They also conclude that Datastream has a longer history of bond data compared to TRACE, resulting in a larger sample of issues and issuers. They go on to add that TRACE has issuers that are larger, more profitable and more highly leveraged than issuers on Datastream. The bonds have lower offering yields, larger offering amounts and shorter maturity. Therefore, in this study I proceed to use Datastream data for the bond prices.

To create my portfolios, I included only bond equivalents in US dollar (USD) denominated currencies and in the US market. Following Oikonomou, et al., (2014) I excluded banks and financial institutions as the large number of bonds in that sector would dominate the sample. Furthermore, in 2008 there was a US ban on short selling of financial firms during the financial crisis and shorting activity for large-cap firms dropped by an average of 77% (Boehmer, Jones et al. 2013; Jain, Jain et al. 2013). As I am using short selling as an investor sentiment, this would only reduce the variability of explanation.

Bonds that have a callable feature provide an option for the borrowing corporation to buy back the bond at a stated price prior to maturity. Should the rates fall, this option would provide the borrower with financial flexibility to replace the bond (Boyce and Kalotay 1979). Considering that my analysis is based on measuring the impacts of bond prices after an event and to ensure that the effect is not based on

[35] https://www.finra.org/industry/trace/corporate-bond-data

other arguments such as predictions or expectations of interest rate changes, I included only bonds that have no callable features. I exclude all floating rate notes, index-linked bonds, convertible bonds, exchangeable bonds, hybrids, preferred bonds, perpetual bonds, private placements, sinking fund provisions, bonds with embedded options or warrants, and bonds with any other nonstandard characteristic (Campbell and Taksler 2003; Oikonomou, Brooks et al. 2014). Also, having a bond that has a non-callable feature signals the long-term nature and characteristics of the bond. To ensure that my portfolios are not subjected to potential survivorship bias, I include firms that are dead in my sample (Grinblatt and Titman 1989; Adamsson and Hoepner 2015).Nevertheless, I do not use any bond prices that are constant throughout a significant period of time. S.J. Brown, Goetzmann, Ibbotson, & Ross (1992) indicate that if a sample inclusion depends in part on rate of return, then survivorship bias will lead to possible biases in the moments of returns and the beta. The three month US Treasury bill for the calculation of risk free return was also downloaded from Thompson Reuters Datastream.

In this chapter I used the Barclays Capital United States Aggregate Indices as the benchmark factors. Barclays is the leading provider of bond indices. Barclays Capital Indices was a rebranding in 2008 which combines the Lehman Brothers and Barclays Capital Indices into a single platform. The quality of the bonds here must be rated investment grade (Baa3/BBB-/BBB- or above) using the middle rating of Moody's, S&P, and Fitch respectively. All these bonds are denominated in USD. This index excludes bonds with equity-type features (e.g. warrants, convertibility), private placements, floating-rate issues, strips, inflation linked bonds, Securities with both Regulation S and SEC Rule 144A without Registration Rights tranches USD25/50 par bonds (Barclays, 2008). Table 8.7 in the appendix provides details of the benchmark, sources and codes used.

3.3.3 Data Construction

Short interest ratio monthly (SIR) data was retrieved from Bloomberg from 2000 to 2012. SIR is defined as the total number of shares an investor has sold short divided by the average daily trading volume for a specific time period. Firstly, I matched the SIR data with each companies ISIN code in each respective month. Secondly, I then created a percentile ranking in terms of the level of SIR in that respective quarter (March, June, September and December). Following those percentile rankings, I was then able to separate each company into different levels of SIR. The first, second, third, fourth and fifth portfolio's consisted of the level of SIR from 0% to 20%, 20 % to 40 %, 40% to 60%, 60% to 80% and 80% to 100% respectively. I also created a sixth portfolio of companies that did not have any SIR data.

Once I was able to identify companies in their respective levels of SIR, I then matched those companies with their monthly bond return data. These portfolios are updated every quarter and held for three months after an event. For example, in December 2005, company XYZ was ranked in the first portfolio (level of SIR from 0% to 20%). Firstly, I check if that company had any illegal events in December 2005, if yes, I then used the data of the returns from all its bonds with a three months holding period (January to March 2006) I repeat this every quarter to have full year returns in my portfolio. Secondly, I then added these returns in the first portfolio. I carry on this exercise with other companies.

3.3.4 Bond Methodology

Following Hoepner & Nilsson (2015) I used their multi index model which was an extension of the initial 4 factor model used by Blake, E.J. Elton, & Gruber (1993) as per the formula (3.1) below. Their seminal work was the first to measure the performance of mutual fund bonds. Multi index models are a better measure than single index models because they are unable to explain the returns of all bond classes (Derwall and Koedijk 2009).

$$R_{pt} - R_{ft} = \alpha_i + \beta_i(MARKET_{mt} - R_{ft}) + \beta_{1i}DEFAULT_t + \beta_{2i}OPTION_t + \beta_{3i}EQUITY_t + \varepsilon_{it} \tag{3.1}$$

where Rpt is the monthly portfolio return of the bonds equal weighted in month t, R_{ft} is the monthly US T-Bill rate. This model consists of the excess return of a created bond market benchmark to take into the account the overall exposure to the entire portfolio (MARKET). I created this unique market benchmark using only the returns from all the companies in the portfolio. This market benchmark is on securities level and uses the bond return data. It also includes the excess return of a high yield bond index to take into account exposure to the high yield market and the potential default risk inherent in this exposure (DEFAULT). However, in this chapter, I follow Hoepner & Nilsson (2015), who altered the DEFAULT factor to instead of consisting of the excess return of a high yield index, to consist of the difference between a high yield index and an AAA only bond index. They believe that this would clean the factor to purely take into account high yield exposure. The model also includes a factor to capture exposure to the market for securitized debt and option characteristics of bonds, consisting of the excess return of a mortgage index (OPTION). Finally, it includes the excess return of an equity index to cover any exposure to the equity market (EQUITY).

Hoepner & Nilsson (2015) improved on the 4 factor model by introducing a 8 factor model which takes into account 3 main exchange rates; USD:EUR, USD:GBP, and USD:YEN. They indicate that exchange rates are an important factor in explaining bond returns because there may be an inherent exchange rate risk in bond funds. Even though this chapter is not on funds but on firm level bonds, I find that the influence is crucial as investors who buy bond bonds from another currency would receive payments of their coupons and principal payment in US dollar. They also added (DURATION) which is the difference between a long and short-term government bond index to capture the exposure to the difference in duration and expectation changes in interest rates over time.

$$R_{pt} - R_{ft} = \alpha_i + \beta_i(MARKET_{mt} - R_{ft}) + \beta_{1i}DEFAULT_t + \beta_{2i}OPTION_t + \beta_{3i}EQUITY_t + \beta_{4i}\mathrm{DURATION}_t + \beta_{5i}€ + \beta_{6i}£ + B_{7i}¥ + \varepsilon_{it} \quad (3.2)$$

My portfolios are equally weighted (EW) which is the most common weighting scheme. This means that each investor would hold the same value of its stock within the portfolio and would be an equal part. Bender (2012) using equal weighted MSCI flagship indexes such as MSCI EAFE and Emerging market indices, indicated that those indexes delivered significantly enhanced returns over its cap weighted counterparts. This clearly indicates that there are biases on methodology in portfolio creation that can tilt results to benefit certain type of investors. Various literature have critiqued the use of just equal weighted portfolios indicating that portfolio managers use equal weighted portfolios on value weighted benchmarks (Hoepner and Zeume 2013; Adamsson and Hoepner 2015). In order to ensure that my study is not bias on certain tilted weights, for robustness, I also value weighted (VW) the portfolios within each company. I used the Market Value code in Datastream which is defined as, the current market value of the issue, that is, the current market price multiplied by the amount currently in issue, to calculate the market weights for each individual company. The process to value weight the bonds is as per the following steps:

i) The first step is retrieving the current market value issued of each bond for each firm at time *t*

ii) The second step is calculating the weights at the specific period of time of the firm for each respective portfolio per bond in each individual company. The total weights for at period *t* should equal to 1 for each individual firm (i.e. each individual bond weight summed up per firm)

iii) The third step is then multiplying the returns of the individual bond with the individual calculated bond weights. Then summing up the calculated returns per weight for each individual firm (i.e. if firm x has 6 bonds, then all the calculated returns per weight of the 6 bonds are summed up for firm x)

iv) The fourth step is calculating the overall market weights of each individual firm. This is done by summing up all the individual bonds market value for each firm and calculating its weight in the entire portfolio at individual time *t.* (i.e. The total weight at period *t* should equal to 1 for the entire portfolio)

v) The final step is then to use the calculated returns per weight for each individual firm in the third step and multiply it with the overall weight of the portfolio in the fourth step.

There are various studies in the portfolio selection literature that measure the use of both equal-weighted and value-weighted portfolios (Plyakha, Uppal et al. 2012; Chung, Liao et al. 2015; Adamsson and Hoepner 2015). Value weighting portfolios is also a common practice with portfolio managers. The use of different weights that a manager assigns to its portfolio can affect its portfolio returns and is just as important as investment timing and stock selection decisions (Chung, Liao et al. 2015).

3.4 Descriptive Statistics

In this section, I discuss the descriptive statistics of both the equal-weighted and value-weighted portfolios which can be viewed in table 3.1. Comparing the equal-weighted portfolios against the value-weighted portfolios, I find three portfolios have higher mean returns (20^{th} to 40^{th}, 40^{th} to 60^{th} and 80^{th} to 100^{th}) but all equal-weighted portfolios have higher standard deviations. Standard deviation can be measured as the volatility of the portfolio. A (low) high volatile portfolio will have a (lower) higher standard deviation. This indicates that the equal-weighted portfolios show higher risk-return behavior. For example, the highest equal-weighted SIR portfolio has a mean return of 61 basis points whereas the value-weighted portfolio has a mean return of 59 basis points and the standard deviations are 0.0187 and 0.0169 respectively. I further observe the equal-weighted 20^{th} to 40^{th} SIR percentile portfolio has higher mean returns and standard deviations compared to the other SIR percentile portfolios.

[This section has been intentionally left blank]

Table 3.1 Descriptive Statistics

The table below is the descriptive statistics for both equal weighted and value weighted portfolios. It describes the mean return, maximum return, minimum return and standard deviation. The data is based on monthly total return**.**

Portfolio	**Mean**	**Maximum**	**Minimum**	**Std. Dev.**
Panel A: Equal Weighted				
Zero - SIR	0.0058	0.0672	-0.0803	0.0184
0 to 20th Percentile - SIR	0.0054	0.0678	-0.0803	0.0208
20th to 40th Percentile - SIR	0.0071	0.1206	-0.0847	0.0212
40th to 60th Percentile- SIR	0.0060	0.0810	-0.0879	0.0187
60th to 80th Percentile - SIR	0.0039	0.0480	-0.0896	0.0181
80th to 100th Percentile - SIR	0.0061	0.0593	-0.0639	0.0187
Panel B:Value Weighted				
Zero - SIR	0.0062	0.0705	-0.0716	0.0174
0 to 20th Percentile - SIR	0.0062	0.0543	-0.0567	0.0163
20th to 40th Percentile - SIR	0.0061	0.0742	-0.0693	0.0175
40th to 60th Percentile- SIR	0.0050	0.0540	-0.0751	0.0165
60th to 80th Percentile - SIR	0.0044	0.0500	-0.0760	0.0174
80th to 100th Percentile - SIR	0.0059	0.0584	-0.0621	0.0169

3.5 Empirical Results

3.5.1 Bond Returns on Overall Portfolios

Table 3.2 presents the results for the equal weighted single and multi-factor regressions respectively. Column 1 represents the various different levels of SIR portfolios and column 2 reports the monthly alphas obtained when running the 1, 5 and 8 factor models against the created benchmark and the additional variables. These portfolios use the Barclays US indices to represent the benchmark factors in the model. The equity factor in my regression is based on the MSCI USA index. I note that the adjusted R squared values are considerably high, ranging from 0.5 to 0.9. However,, when comparing the 1 factor, 5 factor and 8 factor model, the adjusted r squared values increase though only marginally. Hoepner & Nilsson (2015) indicate that their additional 8 factor model produces an increase in R squared values. Thus, it is noted that using their extended model with my data only produces slightly better adjusted r-squared values. Nevertheless, using the extended model is important to ensure I have captured all the necessary additional factors. All market betas are statistically significant at a 1% level and are very high. My benchmarking procedure was to closely match the firms in the sample, hence when observing the betas I find that most of the portfolios are close to 1 (except the 60th to 80th percentile SIR portfolio) indicating that the portfolios have a tendency to follow the created market benchmark. In both the 5 and 8 factor model, the two lowest SIR portfolios[36] have a beta of more than 1 indicating a higher volatility compared to the market. This is consistent with my initial observation of its standard deviation which was very high in comparison to the other portfolios. Similarly when examining the other 8 factor variables (refer to table 8.13 in the appendix), I find that the portfolio has very low exposure to either long or short term bonds as I find no significant coefficients. The portfolios also seem to have also no significant exposure to the default, option or even to the equity market. However, the 40th to 60th percentile SIR portfolio has a negative coefficient sign to USD-YEN and the 80th to 100th percentile SIR portfolio has a negative coefficient to USD-EUR.

My objective is to examine whether firms with high short interest ratios have negative bond returns upon announcement of illegal violations of companies. When analyzing the results, in each of the three different factor models, I find consistent statistically significant underperformance in the 2nd highest SIR[37] portfolio. For example, in the 8 factor model, I find a decrease in alpha of 20 basis points p.m. I note the low beta of 0.6 and this was also evident in its low standard deviation in comparison to the other portfolios. Despite the fact that only the 2nd highest and not also the highest portfolio indicates underperformance, this still shows that fines can be a sign of "bad"

[36] 0 to 20th and 20th to 40th percentile
[37] 60th to 80th percentile

sentiment from equity investors especially when there is high level of short selling. Additionally, the lower SIR portfolios do not show any statistical significance which is in line with expectations. In Table 3.3, I split the sample into two sub periods; 10/2000 to 12/2006 and 1/2007 to 4/2013. I find that only the first half of the sample period has underperformance in the 60^{th} to 80^{th} percentile of 28 basis points p.m. The underperformance though vanishes in the 5 and 8 factor model. This indicates that the results are primarily driven by the first half of the sample. Examining the other factor variables, I find in the first half of the sample, only the 40^{th} to 60^{th} percentile portfolio has a positive exposure to the option factor and for the second half of the sample only the zero SIR portfolio has a negative coefficient to the option factor. In overall, it can be deduced that the SIR portfolios do not have any significant exposure to the additional factor variables and most of the alpha results are driven by the market beta.

[This section has been intentionally left blank]

Table 3.2 Equal Weighted Results based on Barclays US Index Benchmark (Full Sample Period)

The table below displays the regression results of the monthly alphas and market variable which are adjusted based on Newey-West (1987) standard errors. The portfolios are equally weighted. The table displays the adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics

Portfolio	Alpha			Market			Adj R^2
1 Factor							
Zero - SIR	-0.0010		(-1.1765)	0.9615	***	(13.1315)	0.69
0 to 20th Percentile - SIR	-0.0014		(-1.3859)	0.9683	***	(8.8141)	0.55
20th to 40th Percentile - SIR	-0.0003		(-0.2841)	1.0821	***	(8.2815)	0.65
40th to 60th Percentile- SIR	-0.0006		(-0.7472)	0.9527	***	(12.0034)	0.65
60th to 80th Percentile - SIR	**-0.0021**	*****	**(-1.9176)**	**0.8488**	***	**(11.8152)**	0.55
80th to 100th Percentile - SIR	0.0002		(0.1873)	0.8180	***	(11.1781)	0.47
5 Factor							
Zero - SIR	-0.0005		(0.6520)	0.8222	***	(6.7654)	0.70
0 to 20th Percentile - SIR	-0.0018		(-1.4414)	1.0746	***	(4.3335)	0.56
20th to 40th Percentile - SIR	-0.0006		(-0.7566)	1.0436	***	(4.0556)	0.66
40th to 60th Percentile- SIR	-0.0008		(-0.9156)	0.9304	***	(9.0911)	0.65
60th to 80th Percentile - SIR	**-0.0022**	**	**(-2.0369)**	**0.6713**	***	**(5.084)**	0.55
80th to 100th Percentile - SIR	-0.0002		(-0.1643)	0.8342	***	(6.5363)	0.48
8 Factor							
Zero - SIR	-0.0005		(-0.6823)	0.8173	***	(6.3057)	0.71
0 to 20th Percentile - SIR	-0.0014		(-1.2293)	1.0695	***	(4.1258)	0.57
20th to 40th Percentile - SIR	-0.0008		(-1.0219)	1.0850	***	(3.5857)	0.66
40th to 60th Percentile- SIR	-0.0010		(-1.2958)	0.9459	***	(7.927)	0.66
60th to 80th Percentile - SIR	**-0.0020**	*	**(-1.9389)**	**0.6427**	***	**(4.5429)**	0.55
80th to 100th Percentile - SIR	-0.0003		(-0.2527)	0.9258	***	(7.6092)	0.49

.

Table 3.3 Equal Weighted Results based on Barclays US Index Benchmark (Split Sample Period)

The table below displays the regressions results of the monthly alphas which are based on the Barclays US Benchmark factors .The portfolios are equally weighted. Column 1 and 2 are the first half of the sample period from 2000 to 2006. Column 3 and 4 are the second half of the sample period from 2007 to 2013. The table displays adjusted R-square for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	First Half (2000 to 2006) Equal Weighted				Second Half (2007 to 2012) Equal Weighted		
Portfolio	**Alpha**			**Adj R^2**	**Alpha**		**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**		**(4)**
Zero - SIR	-0.0004		(-0.3673)	0.54	-0.0014	(-0.9928)	0.78
0 to 20th Percentile - SIR	-0.0021		(-1.2079)	0.55	-0.0013	(-0.6911)	0.57
20th to 40th Percentile - SIR	-0.0015		(-1.1088)	0.71	0.0009	(0.6423)	0.61
40th to 60th Percentile- SIR	-0.0003		(-0.2976)	0.76	-0.0008	(-0.7285)	0.61
60th to 80th Percentile - SIR	**-0.0028**	*	**(-1.7732)**	0.53	-0.0014	(-0.9456)	0.57
80th to 100th Percentile - SIR	-0.0007		(-0.3392)	0.36	0.0012	(1.0240)	0.65
5 Factor							
Zero - SIR	-0.0008		(-0.795)	0.55	-0.0002	(-0.1625)	0.83
0 to 20th Percentile - SIR	-0.0017		(-0.8899)	0.54	-0.0019	(-0.9072)	0.59
20th to 40th Percentile - SIR	-0.0011		(-1.1822)	0.72	0.0005	(0.4313)	0.62
40th to 60th Percentile- SIR	-0.0002		(-0.2441)	0.82	-0.0006	(-0.4174)	0.59
60th to 80th Percentile - SIR	-0.0024		(-1.5501)	0.57	-0.0021	(-1.0948)	0.57
80th to 100th Percentile - SIR	-0.0028		(-1.3693)	0.40	0.0010	(0.9693)	0.70
8 Factor							
Zero - SIR	-0.0010		(-0.9051)	0.54	-0.0003	(-0.2482)	0.85
0 to 20th Percentile - SIR	-0.0008		(-0.5488)	0.58	-0.0014	(-0.7096)	0.58
20th to 40th Percentile - SIR	-0.0012		(-1.2215)	0.71	0.0001	(0.082)	0.61
40th to 60th Percentile- SIR	-0.0003		(-0.3149)	0.81	-0.0013	(-1.0929)	0.60
60th to 80th Percentile - SIR	-0.0024		(-1.6273)	0.57	-0.0019	(-1.0175)	0.57
80th to 100th Percentile - SIR	-0.0032		(-1.4378)	0.41	0.0008	(0.7462)	0.70

3.5.2 Bond Returns in Crisis and Non-Crisis Periods

In this section I categorize crisis periods during economic recessions as this is a time of market turmoil and instability during a period of more than a few months. During an economic recession there is usually a drop in pricing in stock markets and negative economic growth as measured by Gross Domestic Product (GDP). The most recent financial crisis which began in 2007 had a profound impact on the debt market due to the mortgage back securities market. This resulted in numerous downgrades of bond credit ratings and inevitably the failure of various financial institutions. I follow Henke, et al., (2014) who used the National Bureau of Economic Research Lists for the US 38 recessionary periods which began from December 2001 until June 2003 and from December 2007 until June 2009. The non-recession periods are the other remaining months in the sample from 10/2000 to 04/2013.

Table 3.4 presents the monthly alpha results of both the crisis and non-crisis periods. Three out of six of the crisis period portfolios for both the 5 and 8 factor models are statistically significant with underperformances. In the 8 factor model, I find the three portfolios[38] underperform by 99, 39, and 65 basis points p.m respectively. On the non-crisis periods, I still find statistical significant underperformances. The underperformance is in the 20th to 40th percentile portfolio and in all three different factor models. For instance the 8 factor model shows a decrease of 27 basis points per month. When comparing both the different periods, my hypothesis is confirmed. I find there are lower returns in the crisis periods and when comparing it to the non-crisis periods at the respective SIR percentile levels, I find no statistical significance at all.

[38] 0 to 20th, 40th to 60th and 60th to 80th percentile

This could indicate that investors at the specific SIR percentile level feel that the illegalities are more detrimental during crisis periods. When examining the crisis and non-crisis period 8 factor variables (table8.14 and 8.15 in the appendix), I find two out of the six portfolios only in the crisis periods have a positive exposure to the duration factor. I find only one portfolio in the crisis period (20^{th} to 40^{th}) and one in the non-crisis period (60^{th} to 80^{th}) has negative and positive significant coefficients to the default factor respectively. The default factor indicates exposure to the high yield bonds. I also find relatively low exposure to the equity market. Only the 0 to 20^{th} SIR percentile in crisis and non crisis periods have a negative and positive significance coefficient respectively. Only two portfolios in the non-crisis period (zero in the crisis period) had any exposure to the option factor which indicates in both periods there is low exposure to the mortgage market. In terms of the currency exposure, I find that only the crisis period (60^{th} to 80^{th}) is exposed to the USD-EUR and USD-GBP factor and the 20^{th} to 40^{th} percentile to the USD- YEN factor. Additionally, as I find 3 out of 6 of the SIR portfolios in the 8 factor model shows negative statistical significance, this indicates that investors are clearly reacting to illegal events more during crisis periods regardless of the different levels of shorting. Both crisis and non-crisis portfolios show high adjusted r-squared values of 0.5 to 0.8.

These results support my hypothesis that firms with announcements of illegal violations have larger negative bond returns during crisis period than non-crisis periods. One can conclude that the strong negative sentiment investors have on companies are very much significant during recessions periods especially on companies that behave illegally and are monetarily penalized for their actions. This confirms the notion that investors would penalize companies for their bad behavior even more during these crisis periods. My study adds to this body of literature of crisis and non-crisis periods, by indicating that companies that are fined based on illegal activities have a more pronounced effect during crisis times than non-crisis times.

[This section has been intentionally left blank]

Table 3.4 Equal Weighted Alpha Results for Crisis and Non-Crisis Periods

The table below displays the regression results (alphas) for both equal monthly returns for the different levels of SIR percentile of firms The regressions are run using the Barclays US Benchmark factors and are equal weighted. The crisis periods cover economic recessions for the US of 38 months from 12/2001 until 06/2003 and from 12/2007 until 06/2009. The non recession periods are the other remaining months in the sample from 01/2000 to 12/2013.The table displays the T-statistics in parentheses and the adjusted R-square values for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *, ** and *** for 10%, 5% and 1% significance levels respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Recession Periods				Non - Recession Periods			
	Equal Weighted				Equal Weighted			
Portfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**			**(4)**
Zero - SIR	-0.0022		(-1.009)	0.73	-0.0004		(-0.5702)	0.64
0 to 20th Percentile - SIR	-0.0057		(-1.612)	0.45	-0.0001		(-0.1476)	0.72
20th to 40th Percentile - SIR	0.0020		(1.3166)	0.71	**-0.0019**	**	**(-2.3507)**	0.68
40th to 60th Percentile- SIR	-0.0030		(-1.6515)	0.64	0.0004		(0.5067)	0.69
60th to 80th Percentile - SIR	**-0.0072**	***	**(-2.8417)**	0.61	0.0000		(-0.0342)	0.50
80th to 100th Percentile - SIR	0.0030		(1.0891)	0.49	-0.0010		(-0.7937)	0.46
5 Factor								
Zero - SIR	0.0005		(0.1783)	0.78	-0.0006		(-0.7548)	0.63
0 to 20th Percentile - SIR	**-0.0098**	**	**(-2.2273)**	0.53	-0.0003		(-0.4372)	0.75
20th to 40th Percentile - SIR	0.0003		(0.1897)	0.79	**-0.0025**	***	**(-2.6403)**	0.69
40th to 60th Percentile- SIR	**-0.0043**	**	**(-2.1179)**	0.63	0.0002		(0.2896)	0.69
60th to 80th Percentile - SIR	**-0.0087**	***	**(-3.068)**	0.58	-0.0006		(-0.6078)	0.52
80th to 100th Percentile - SIR	0.0007		(0.2332)	0.55	-0.0011		(-0.7849)	0.48
8 Factor								
Zero - SIR	0.0003		(0.1106)	0.76	-0.0005		(-0.5903)	0.63
0 to 20th Percentile - SIR	**-0.0099**	*	**(-1.9609)**	0.50	-0.0001		(-0.2)	0.75
20th to 40th Percentile - SIR	-0.0002		(-0.0912)	0.80	**-0.0027**	**	**(-2.518)**	0.69
40th to 60th Percentile- SIR	**-0.0039**	*	**(-1.7263)**	0.61	0.0000		(0.0246)	0.69
60th to 80th Percentile - SIR	**-0.0065**	**	**(-2.2428)**	0.59	-0.0005		(-0.4774)	0.51
80th to 100th Percentile - SIR	0.0007		(0.1762)	0.51	-0.0014		(-0.9478)	0.48

3.5.3 Bond Returns according to Remaining Years to Maturity

The very common perception on bond pricing literature is that *"…for a given change in yields, the fluctuations in market price will be greater the longer the term to maturity"*(Hopewell and Kaufman 1973). Most corporate bond literatures have measured the relationship of debt maturity as the riskiness of the bond varies according to the level of remaining years to maturity. Oikonomou, et al.(2014) measured the relation between CSP and yield spreads according to different bond maturity. Following, J. Y. Campbell & Taksler (2003), I similarly group my portfolios of bonds according to their remaining years to maturity; which is short-term if they have 2 to 7 years remaining years to maturity, medium term if they have 7 to 15 years remaining years to maturity and long-term if they have more than 15 years remaining to maturity. Additionally, I also include low term maturities of less than 2 years. I use the starting event date of the announcement of the fines to calculate the remaining years to maturity. According to the results in Table 3.5, I find that both portfolios of low and short-term years remaining to maturity have statistically significant outperformance. In the 8 factor model, the low YTM has a 16 basis points outperformance in the 40^{th} to 60^{th} percentile and the short YTM has a 15 basis points outperformance in the 80^{th} to 100^{th} percentile. This indicates that short-term investors believe that fines would not have any significant negative impact if the remaining years to maturity of the bond after the fines are both on the lower end.

Confirming my hypothesis, results in Table 3.6 show statistical significant underperformances of the medium and long-term years remaining to maturity. This concurs with responsible investment literature that the mindset of SRI investors are within a long-term investment horizon. The results are more profound with the long-term remaining years to maturity of more than 15 years. I find that negative outperformance is no more just for the high SIR portfolios but also for lower SIR portfolios but the significance vanishes in the 8 factor model when controlling for currency exposure. I also continue to observe high adjusted r-squared values ranging from 0.5 to 0.9. This indicates that the effect of illegal behaviors on corporate bonds is more pronounced in long-term investment horizons. Examining the additional factor variables (table 8.15 to 8.17 in the appendix), I find that three out of six portfolios in each of the low, short and medium YTM displayed significant coefficients for the duration factor, where six were positive and three were negative, indicating that these YTM portfolios have a significant exposure to short term bonds. On contrast, only two out (with positive statistical significance) of the six long YTM portfolios have exposures to the duration factor. This indicates that the longer YTM portfolios have more of an exposure to long term bonds. For the default factor which indicates exposure to high yield bonds, I find that only either one or two of the portfolios in each of the low, short, medium and high YTM has statistical significances. This indicates not much exposure to high yield bonds. In the option variable, I find also not much exposure to the mortgage market as only one portfolio in the low and high YTM and two portfolios in the short YTM showed any statistical significance. This is also similar with the equity and currency factor which also indicates relatively low exposure to the equity market and to the currency exchanges. Similar to the results in the previous sections (3.5.1 and 3.5.2) it can be observed that the alpha results are mainly driven by the market beta and have very low exposure to the other factor variables.

Table 3.5 Equal Weighted Alpha Results for Remaining Years to Maturity (YTM)

The table below displays the regression results (alphas) of the monthly returns for the different levels of SIR percentile of firms which had illegal violations/fines. The regressions are run using the Barclays US Benchmark factors and are equal weighted. I classify bonds by maturity with low term (Panel 1 and 2) if they have less than 2 years remaining maturity and short-term (Panel 3 and 4) if they have 2 to 7 remaining years to maturity. The table displays the T-statistics in parentheses and the adjusted R-square values for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *, ** and *** for 10%, 5% and 1% significance levels respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Equal Weighted - US Benchmark							
	Low YTM				Short YTM			
Porfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**			**(4)**
Zero - SIR	0.0002		(0.2712)	0.77	0.0001		(0.1569)	0.69
0 to 20th Percentile - SIR	0.0001		(0.1978)	0.62	-0.0001		(-0.2182)	0.66
20th to 40th Percentile - SIR	**0.0018**	*	**(1.8055)**	0.38	0.0001		(0.1479)	0.67
40th to 60th Percentile- SIR	**0.0020**	***	**(2.7291)**	0.40	0.0001		(0.1531)	0.66
60th to 80th Percentile - SIR	0.0002		(0.2286)	0.54	0.0003		(0.368)	0.49
80th to 100th Percentile - SIR	-0.0001		(-0.1562)	0.76	**0.0021**	**	**(2.2146)**	0.48
5 Factor								
Zero - SIR	0.0001		(0.1303)	0.78	-0.0003		(-0.3531)	0.69
0 to 20th Percentile - SIR	-0.0002		(-0.3023)	0.67	-0.0006		(-0.8386)	0.67
20th to 40th Percentile - SIR	0.0015		(1.5986)	0.41	-0.0004		(-0.5276)	0.68
40th to 60th Percentile- SIR	**0.0017**	**	**(2.1176)**	0.47	-0.0002		(-0.2841)	0.70
60th to 80th Percentile - SIR	0.0002		(0.2603)	0.56	-0.0005		(-0.7201)	0.54
80th to 100th Percentile - SIR	0.0001		(0.1134)	0.78	**0.0015**	*	**(1.6897)**	0.51
8 Factor								
Zero - SIR	0.0000		(0.0422)	0.78	-0.0002		(-0.2418)	0.68
0 to 20th Percentile - SIR	-0.0002		(-0.2208)	0.68	-0.0005		(-0.6686)	0.67
20th to 40th Percentile - SIR	0.0015		(1.6165)	0.42	-0.0002		(-0.3425)	0.68
40th to 60th Percentile- SIR	**0.0016**	**	**(2.2346)**	0.49	-0.0004		(-0.5818)	0.71
60th to 80th Percentile - SIR	0.0001		(0.1027)	0.57	-0.0005		(-0.6745)	0.55
80th to 100th Percentile - SIR	0.0000		(-0.0062)	0.79	**0.0015**	*	**(1.7324)**	0.54

Table 3.6 Equal Weighted Alpha Results for Remaining Years to Maturity (YTM)

The table below displays the regression results (alphas) of the monthly returns for the different levels of SIR percentile of firms which had illegal violations/fines. The regressions are run using the Barclays US Benchmark factors and are equal weighted. I classify bonds by maturity with medium term (Panel 1 and 2) if they have 7 to 15 remaining years to maturity and long-term (Panel 3 and 4) if they have more than 15 remaining years to maturity. The table displays the T-statistics in parentheses and the adjusted R-square values for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *, ** and *** for 10%, 5% and 1% significance levels respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Equal Weighted - US Benchmark							
	Medium YTM				Long YTM			
Porfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**			**(4)**
Zero - SIR	-0.0013		(-1.6034)	0.77	**-0.0020**	**	**(-2.3151)**	0.85
0 to 20th Percentile - SIR	-0.0022		(-1.5378)	0.46	**-0.0028**	*	**(-1.8450)**	0.54
20th to 40th Percentile - SIR	0.0000		(-0.0295)	0.64	0.0000		(0.0016)	0.52
40th to 60th Percentile- SIR	**-0.0021**	*	(-1.9028)	0.60	**-0.0023**	**	**(-2.3995)**	0.60
60th to 80th Percentile - SIR	-0.0012		(-1.0948)	0.58	**-0.0045**	**	**(-2.5018)**	0.59
80th to 100th Percentile - SIR	0.0013		(1.4995)	0.58	-0.0015		(-0.7902)	0.46
5 Factor								
Zero - SIR	-0.0002		(-0.3481)	0.82	**-0.0016**	**	**(-2.0938)**	0.85
0 to 20th Percentile - SIR	-0.0023		(-1.3298)	0.46	-0.0018		(-1.2453)	0.57
20th to 40th Percentile - SIR	0.0004		(0.3677)	0.65	0.0012		(0.5220)	0.56
40th to 60th Percentile- SIR	-0.0016		(-1.5240)	0.64	**-0.0022**	*	**(-1.9676)**	0.60
60th to 80th Percentile - SIR	-0.0008		(-0.7730)	0.60	**-0.0034**	**	**(-2.3900)**	0.62
80th to 100th Percentile - SIR	0.0009		(1.1187)	0.60	-0.0010		(-0.4443)	0.48
8 Factor								
Zero - SIR	-0.0003		(-0.6420)	0.82	-0.0013		(-1.6523)	0.86
0 to 20th Percentile - SIR	-0.0021		(-1.3483)	0.46	-0.0016		(-1.1139)	0.57
20th to 40th Percentile - SIR	0.0000		(-0.0375)	0.66	0.0009		(0.4435)	0.56
40th to 60th Percentile- SIR	-0.0016		(-1.5016)	0.63	**-0.0026**	**	**(-2.2483)**	0.60
60th to 80th Percentile - SIR	-0.0007		(-0.7308)	0.59	**-0.0031**	**	**(-2.2349)**	0.62
80th to 100th Percentile - SIR	0.0008		(1.0119)	0.62	-0.0011		(-0.5065)	0.47

3.6 Robustness Test

3.6.1 Different Benchmark Index

For robustness, I used the Barclays Capital Global Aggregate indices in table 8.8 in the appendix as my benchmark factor. These indices are still under the family of Barclays index returns and are part of their global/multi-currency benchmark. The purpose of using a Global index is to check whether my results would still hold even with different benchmark factors[39]. I follow the same methodology and model as described in section 4. In addition, I also split the sample into two sub periods; 10/2000 to 12/2006 and 1/2007 to 4/2013. From the results in table 3.7 I find statistical significance for the full sample for the 60^{th} to 80^{th} SIR percentile but only in the 1 factor model. In the first half of the sample period, I find that not only the 60^{th} to 80^{th} percentile but also the 80^{th} to 100^{th} percentile portfolios have negative coefficients and are statistically significant. The 60^{th} to 80^{th} and 80^{th} to 100^{th} SIR percentile portfolio has an underperformance of 26 and 42 basis points per month respectively. This indicates that the results are more profound by the first half of the sample period which is similar to the results using the US benchmarks. There is no statistical significance in the second half of the sample.

[39] I also conduct re-examinations using a different equity factor (S&P500) and the results are similar and consistent. I have not included the tables in the chapter for simplicity purposes.

Table 3.7 Equal Weighted Alpha Results based on Barclays Global Index Benchmark

The table below displays the regressions results of the monthly alphas which are based on the Barclays Global Benchmark factors .The portfolios are equally weighted. Column 1 and 2 indicate the full sample period from 2000 to 2013. Column 3 and 4 is the first half of the sample period from 2000 to 2006. Column 5 and 6 is the second half of the sample period from 2007 to 2012. The table displays adjusted R-square for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Full Period (2000 to 2012)				**First Half (2000 to 2006)**				**Second Half (2007 to 2012)**			
	Equal Weighted				**Equal Weighted**				**Equal Weighted**			
Portfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**			**(4)**	**(5)**			**(6)**
Zero - SIR	-0.0010		(-1.1765)	0.69	-0.0004		(-0.3673)	0.54	-0.0014		(-0.9928)	0.78
0 to 20th Percentile - SIR	-0.0014		(-1.3859)	0.55	-0.0021		(-1.2079)	0.55	-0.0009		(-0.5433)	0.57
20th to 40th Percentile - SIR	-0.0006		(-0.7472)	0.65	-0.0009		(-0.5433)	0.57	0.0009		(0.6423)	0.61
40th to 60th Percentile- SIR	-0.0006		(-0.7472)	0.65	-0.0003		(-0.2976)	0.76	-0.0008		(-0.7285)	0.61
60th to 80th Percentile - SIR	**-0.0021**	*	**(-1.9176)**	0.55	**-0.0028**	*	**(-1.7732)**	0.53	-0.0014		(-0.9456)	0.57
80th to 100th Percentile - SIR	0.0002		(0.1873)	0.47	-0.0007		(-0.3392)	0.36	0.0012		(1.024)	0.65
5 Factor												
Zero - SIR	-0.0008		(-1.1162)	0.69	-0.0008		(-0.7119)	0.54	-0.0013		(-1.1713)	0.81
0 to 20th Percentile - SIR	-0.0015		(-1.2128)	0.56	-0.0015		(-0.7819)	0.54	-0.0010		(-0.548)	0.56
20th to 40th Percentile - SIR	-0.0005		(-0.7216)	0.65	-0.0010		(-0.548)	0.56	0.0004		(0.3763)	0.61
40th to 60th Percentile- SIR	-0.0005		(-0.7216)	0.65	0.0000		(-0.0452)	0.79	-0.0005		(-0.4404)	0.59
60th to 80th Percentile - SIR	-0.0017		(-1.6125)	0.57	-0.0029		(-1.6179)	0.55	-0.0008		(-0.5661)	0.59
80th to 100th Percentile - SIR	0.0001		(0.0426)	0.50	**-0.0035**	*	**(-1.7520)**	0.45	0.0012		(1.1431)	0.72
8 Factor												
Zero - SIR	-0.0011		(-1.4494)	0.70	-0.0013		(-1.1117)	0.56	-0.0007		(-0.661)	0.83
0 to 20th Percentile - SIR	-0.0012		(-1.111)	0.56	-0.0006		(-0.4281)	0.59	-0.0008		(-0.4752)	0.55
20th to 40th Percentile - SIR	-0.0011		(-1.3694)	0.65	-0.0008		(-0.4752)	0.55	-0.0004		(-0.4144)	0.61
40th to 60th Percentile- SIR	-0.0011		(-1.3694)	0.65	-0.0003		(-0.3707)	0.82	-0.0009		(-0.7604)	0.59
60th to 80th Percentile - SIR	-0.0010		(-1.0878)	0.58	**-0.0026**	*	**(-1.7401)**	0.55	-0.0003		(-0.1942)	0.59
80th to 100th Percentile - SIR	-0.0004		(-0.3443)	0.51	**-0.0042**	*	**(-1.9519)**	0.45	0.0012		(1.1522)	0.71

3.6.2 Value Weighted

In addition to using different benchmarks, the portfolios are also value weighted. Taking into consideration that the number of bonds per company in the sample varies from a few to hundreds, equal weighting the portfolios and giving each company similar weights might not be precise. Hence, I value weight the portfolios using market values within each bond in the company. The results in table 3.8 show both value weighted portfolios using the US and Global benchmark indices. Using the US benchmark indices portfolios, I find now negative coefficients that are statistically significant in the 20th to 40th percentile portfolios. Similarly to the equal weighted portfolios, the 60th to 80th percentile portfolios also underperform with statistical significance. These results are interesting as I now find that value weighting the portfolios induces negative underperformances for the lower SIR portfolios. This is also evident in the 8 factor model using Global benchmark indices. The underperformances though are much larger for the higher SRI portfolio compared to the lower SRI portfolio. However, in the global benchmark indices, the statistical significance for the 60 to 80th portfolio vanishes. I also value weight the results during the crisis and non-crisis periods using both US and Global Benchmarks. Reviewing tables 3.9 and 3.10, I find that there are still larger underperformances during crisis periods compared to non-crisis periods. This therefore still supports my second hypothesis. While some results are slightly weaker with this approach, my overall conclusion that short selling based on fines has a negative impact on bond returns, remains unchanged.

Table 3.8 Value Weighted Alpha Results based on Barclays US and Global Benchmark

The table below displays the regressions results of the monthly alphas which are based on the Barclays US and Global Benchmark factors .The portfolios are value weighted based on market value of each individual bond. The sample period is from 2000 to 2013. The table displays the adjusted R-square for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *, ** and *** for 10%,5% and 1% significance level respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Barclays US Benchmark Value Weighted				**Barclays Global Benchmark Value Weighted**			
Portfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**			**(4)**
Zero - SIR	-0.0007		(-0.8037)	0.56	-0.0007		(-0.803)	0.56
0 to 20th Percentile - SIR	-0.0006		(-0.9077)	0.62	-0.0006		(-0.8763)	0.62
20th to 40th Percentile - SIR	-0.0012		(-1.4934)	0.66	-0.0012		(-1.4934)	0.66
40th to 60th Percentile- SIR	-0.0013		(-1.0642)	0.56	-0.0013		(-1.0642)	0.56
60th to 80th Percentile - SIR	**-0.0019**	*	(-1.763)	0.48	**-0.0019**	*	(-1.763)	0.48
80th to 100th Percentile - SIR	-0.0008		(-0.781)	0.54	-0.0007		(-0.6449)	0.56
5 Factor								
Zero - SIR	0.0002		(0.2406)	0.62	-0.0003		(-0.4011)	0.60
0 to 20th Percentile - SIR	-0.0005		(-0.7145)	0.64	-0.0003		(-0.3631)	0.65
20th to 40th Percentile - SIR	**-0.0013**	*	(-1.6921)	0.66	-0.0011		(-1.4368)	0.65
40th to 60th Percentile- SIR	-0.0007		(-0.7104)	0.60	-0.0009		(-0.8866)	0.59
60th to 80th Percentile - SIR	**-0.0020**	**	(-2.0382)	0.50	-0.0017		(-1.6183)	0.51
80th to 100th Percentile - SIR	-0.0010		(-0.9455)	0.55	-0.0008		(-0.7201)	0.58
8 Factor								
Zero - SIR	0.0001		(0.1535)	0.63	-0.0005		(-0.7018)	0.61
0 to 20th Percentile - SIR	-0.0003		(-0.4112)	0.64	0.0000		(0.0143)	0.65
20th to 40th Percentile - SIR	**-0.0014**	*	(-1.8336)	0.65	**-0.0014**	*	(-1.8754)	0.65
40th to 60th Percentile- SIR	-0.0009		(-0.9834)	0.61	-0.0011		(-1.1451)	0.60
60th to 80th Percentile - SIR	**-0.0019**	*	(-1.9285)	0.50	-0.0011		(-1.1847)	0.53
80th to 100th Percentile - SIR	-0.0011		(-1.0236)	0.56	-0.0008		(-0.728)	0.57

Table 3.9 Value Weighted Alpha Results for Crisis and Non-Crisis Periods (US Benchmark)

The table below displays the regression results (alphas) of the monthly returns for the different levels of SIR percentile of firms which had illegal violations/fines during crisis and non-crisis periods. The regressions are run using the Barclays US Benchmark factors and are value weighted. The crisis periods cover economic recessions for the US of 38 months from 12/2001 until 06/2003 and from 12/2007 until 06/2009. The non recession periods are the other remaining months in the sample from 01/2000 to 12/2013.The table displays the T-statistics in parentheses and the adjusted R-square values for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *, ** and *** for 10%, 5% and 1% significance levels respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Value Weighted - US Benchmark							
	Recession Periods				**Non - Recession Periods**			
Portfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**			**(4)**
Zero - SIR	-0.0015		(-0.5347)	0.50	-0.0004		(-0.5031)	0.63
0 to 20th Percentile - SIR	-0.0011		(-0.4719)	0.61	-0.0004		(-0.6793)	0.63
20th to 40th Percentile - SIR	0.0001		(0.0933)	0.74	**-0.0020**	**	**(-2.4499)**	0.64
40th to 60th Percentile- SIR	**-0.0070**	**	**(-2.3606)**	0.56	0.0007		(0.7685)	0.65
60th to 80th Percentile - SIR	**-0.0070**	**	**(-2.5408)**	0.52	0.0000		(0.0328)	0.48
80th to 100th Percentile - SIR	-0.0010		(-0.7937)	0.46	-0.0017		(-1.5546)	0.49
5 Factor								
Zero - SIR	0.0034		(0.9479)	0.65	-0.0005		(-0.6166)	0.62
0 to 20th Percentile - SIR	-0.0020		(-0.8439)	0.67	-0.0003		(-0.4245)	0.68
20th to 40th Percentile - SIR	-0.0006		(-0.3816)	0.78	**-0.0026**	***	**(-2.7686)**	0.65
40th to 60th Percentile- SIR	**-0.0048**	*	**(-1.8858)**	0.66	0.0006		(0.6199)	0.65
60th to 80th Percentile - SIR	**-0.0075**	**	**(-2.494)**	0.48	-0.0006		(-0.6258)	0.51
80th to 100th Percentile - SIR	-0.0017		(-1.1531)	0.49	-0.0019		(-1.5414)	0.50
8 Factor								
Zero - SIR	0.0033		(0.8844)	0.62	-0.0004		(-0.54)	0.62
0 to 20th Percentile - SIR	-0.0021		(-0.8306)	0.65	-0.0001		(-0.2078)	0.67
20th to 40th Percentile - SIR	-0.0006		(-0.3405)	0.76	**-0.0028**	***	**(-2.8808)**	0.64
40th to 60th Percentile- SIR	**-0.0041**	*	**(-1.8835)**	0.66	0.0004		(0.472)	0.65
60th to 80th Percentile - SIR	**-0.0062**	*	**(-1.8936)**	0.50	-0.0006		(-0.6341)	0.50
80th to 100th Percentile - SIR	-0.0016		(-1.1047)	0.48	-0.0021		(-1.6368)	0.50

Table 3.10 Value Weighted Alpha Results for Crisis and Non-Crisis Periods (Global Benchmark)

The table below displays the regression results (alphas) of the monthly returns for the different levels of SIR percentile of firms which had illegal violations/fines during crisis and non-crisis periods. The regressions are run using the Barclays Global Benchmark factors and are value weighted. The crisis periods cover economic recessions for the US of 38 months from 12/2001 until 06/2003 and from 12/2007 until 06/2009. The non recession periods are the other remaining months in the sample from 01/2000 to 12/2013.The table displays the T-statistics in parentheses and the adjusted R-square values for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *, ** and *** for 10%, 5% and 1% significance levels respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Value Weighted - Global Benchmark							
	Recession Periods				**Non - Recession Periods**			
Portfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**				**(2)**			
Zero - SIR	-0.0015		(-0.5347)	0.50	-0.0003		(-0.5002)	0.63
0 to 20th Percentile - SIR	-0.0011		(-0.4719)	0.61	-0.0004		(-0.6279)	0.62
20th to 40th Percentile - SIR	0.0001		(0.0933)	0.74	**-0.0020**	**	**(-2.4499)**	0.64
40th to 60th Percentile- SIR	**-0.0070**	**	**(-2.3606)**	0.56	0.0007		(0.7685)	0.65
60th to 80th Percentile - SIR	**-0.0070**	**	**(-2.5408)**	0.52	0.0000		(0.0328)	0.48
80th to 100th Percentile - SIR	-0.0010		(0.7331)	0.61	-0.0015		(-1.421)	0.51
5 Factor								
Zero - SIR	0.0034		(0.4932)	0.60	-0.0006		(-0.7792)	0.62
0 to 20th Percentile - SIR	-0.0020		(-0.9848)	0.65	0.0002		(0.3656)	0.68
20th to 40th Percentile - SIR	-0.0006		(-0.255)	0.77	**-0.0027**	***	**(-2.8100)**	0.66
40th to 60th Percentile- SIR	-0.0048		(-1.6387)	0.64	0.0004		(0.4769)	0.65
60th to 80th Percentile - SIR	**-0.0075**	*	**(-1.8561)**	0.52	-0.0006		(-0.5744)	0.50
80th to 100th Percentile - SIR	-0.0017		(0.6436)	0.64	-0.0020		(-1.6109)	0.53
8 Factor								
Zero - SIR	0.0033		(-0.0785)	0.60	-0.0006		(-0.8583)	0.63
0 to 20th Percentile - SIR	-0.0021		(-0.5361)	0.67	0.0001		(0.1854)	0.68
20th to 40th Percentile - SIR	-0.0006		(-0.3387)	0.75	**-0.0028**	***	**(-2.9028)**	0.65
40th to 60th Percentile- SIR	**-0.0041**	*	**(-1.7997)**	0.63	0.0003		(0.3775)	0.65
60th to 80th Percentile - SIR	-0.0062		(-0.6565)	0.66	-0.0004		(-0.4598)	0.49
80th to 100th Percentile - SIR	-0.0016		(0.604)	0.62	-0.0019		(-1.5523)	0.52

3.6.3 Liquidity Measure

Bonds are known to be very illiquid in nature and various researches have tried to measure whether liquidity affects bond pricing and yields (Chen, Lesmond et al. 2007; Dick-Nielsen, Feldhütter et al. 2012). There has been no real consensus on a common liquidity measure in bond literature. A recent paper by Schestag, Schuster et al. (2016) was the first to compare all commonly employed liquidity measures based on intraday and daily data for the U.S corporate bonds. They find that high frequency data based on intraday data are very strongly correlated and daily data generally also measure transaction costs well. Based on that, I use intraday data from TRACE to calculate my daily bond volume. TRACE provides intraday volume data of bonds only from July 1, 2002 to December 31, 2015. Nayak (2010) used different liquidity metrics to evaluate whether there is differences in bond liquidity based on investor sentiment. Following his paper, I use the Amihud illiquidity measure based on Amihud (2002) which is a widely used measure. Everything else equal, smaller values would indicate greater liquidity.

$$\mathrm{ILLIQ_{it}} = \frac{1}{DAYS_{it}} \sum_{t=1}^{DAYS_{it}} \frac{\|r_{it}\|}{VOL_{it}} * 10^6 \tag{3.3}$$

where r_{it} is the *i*th bond's return on day t, VOL_{it} is the total daily trading volume in dollars, and $DAYS_{it}$ is the total number of trading days for bond i in the year, respectively. Using the mean Amihud illiquidity measure, I separate the companies above 75th percentile which indicate greater illiquidity and below the 25th percentile for greater liquidity. The results in table 3.11 indicate that my results are robust to even high and low liquidity bonds. I find that there are statistically significant underperformances for the high and low liquidity portfolios at the 60th to 80th and 80th to 100th percentile portfolios, respectively.

Table 3.11 Equal Weighted Alpha Results for High and Low Liquidity

The table below displays the regression results (alphas) of the monthly returns for the different levels of SIR percentile of firms which had illegal violations/fines. The regressions are run using the Barclays US Benchmark factors and are equal weighted. I classify bonds that are above the 75th percentile which indicate greater illiquidity and below the 25th percentile for greater liquidity. The sample period is from 2002 to 2013. The table displays the T-statistics in parentheses and the adjusted R-square values for each portfolio. The regressions are computed with (Newey and West 1987) corrections for serial correlation. Significance levels are presented as *, ** and *** for 10%, 5% and 1% significance levels respectively. All regressions include a series of variables described in the text (but their regression coefficients are not reported in the table).

	Equal Weighted - US Benchmark							
	High Liquidity				**Low Liquidity**			
Portfolio	**Alpha**			**Adj R^2**	**Alpha**			**Adj R^2**
1 Factor	**(1)**			**(2)**	**(3)**			**(4)**
Zero - SIR	-0.0001		(-0.8878)	0.99	-0.0002		(-0.9741)	0.99
0 to 20th Percentile - SIR	-0.0010		(-0.7938)	0.55	-0.0013		(-1.076)	0.60
20th to 40th Percentile - SIR	0.0002		(0.2047)	0.63	0.0010		(0.4661)	0.59
40th to 60th Percentile- SIR	-0.0020		(-0.9239)	0.55	-0.0004		(-0.4753)	0.81
60th to 80th Percentile - SIR	**-0.0019**	*	**(-1.8568)**	0.71	-0.0006		(-0.4899)	0.66
80th to 100th Percentile - SIR	-0.0022		(-1.2167)	0.53	**-0.0024**	***	**(-1.7989)**	0.56
5 Factor								
Zero - SIR	-0.0001		(-0.9239)	0.99	-0.0003		(-1.0111)	0.99
0 to 20th Percentile - SIR	-0.0001		(-0.0724)	0.60	-0.0001		(-0.1591)	0.64
20th to 40th Percentile - SIR	0.0008		(0.8438)	0.65	0.0013		(0.6558)	0.58
40th to 60th Percentile- SIR	-0.0020		(-0.8693)	0.55	-0.0007		(-0.7986)	0.81
60th to 80th Percentile - SIR	**-0.0022**	*	**(-1.7512)**	0.71	-0.0003		(-0.2608)	0.67
80th to 100th Percentile - SIR	-0.0029		(-1.4126)	0.53	**-0.0032**	**	(-2.1489)	0.57
8 Factor								
Zero - SIR	-0.0001		(-0.9043)	0.99	-0.0003		(-0.9855)	0.99
0 to 20th Percentile - SIR	0.0001		(0.0418)	0.60	-0.0001		(-0.0655)	0.64
20th to 40th Percentile - SIR	0.0007		(0.7797)	0.65	0.0011		(0.5956)	0.58
40th to 60th Percentile- SIR	-0.0021		(-1.0092)	0.57	-0.0007		(-0.8239)	0.80
60th to 80th Percentile - SIR	**-0.0021**	*	(-1.7575)	0.71	-0.0001		(-0.0699)	0.67
80th to 100th Percentile - SIR	-0.0029		(-1.4546)	0.52	**-0.0033**	**	**(-2.0974)**	0.57

3.6.4 Additional Analysis

3.6.4.1 Control Sample

The understanding behind the results presented in the previous section is that only companies with fines and settlements demonstrate negative underperformances on bond returns. One can argue that the results are biased only on those specific companies that have illegal violations and the underperformance is driven by bad sentiment caused by the reactions to the fines. Hence, using the similar methodology presented in section 4, I re-estimate my models using all U.S companies in the MSCI Large Cap universe regardless whether they have a fine or settlement. The portfolios are also updated every quarter and held for three months.

The results presented in Table 3.12 are interesting in nature. Firstly, I observe that the portfolio of zero SIR data indicates positive alpha coefficients in all 1, 5 and 8 factor models. This is quite intuitive considering, no short selling would indicate "good" sentiment and hence outperformance. For instance, the 8 factor model shows outperformance of 54 basis points p.m. Secondly, I observe that the lowest SIR portfolio shows negative alpha coefficients in the 5 and 8 factor models. In the 8 factor model, the underperformance is 15 basis points p.m. These results suggest that firms with low short selling ratio have a negative impact on bond performances regardless whether a firm has a fine or settlement. This analysis further strengthens my results as this shows that when a firm has a fine, there is higher short selling which in turn induces larger underperformances on bond returns.

Table 3.12 Control Sample Equal Weighted Results based on Barclays US Index Benchmark (Full Sample Period)

The table below displays the monthly alphas which are adjusted based on Newey-West (1987) standard errors. The tables also indicate the coefficients estimated by model for the duration, default, option, equity, USD-EUR,USD-GBP and USD-YEN. The portfolios are equally weighted. The table displays the R-square and adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics.

Portfolio	Alpha			Market			Adj R^2
1 Factor							
Zero - SIR	**0.0038**	***	**(3.3425)**	**0.6965**	***	**(9.8259)**	0.47
0 to 20th Percentile - SIR	-0.0016		(-1.6223)	**0.9766**	***	**(14.0217)**	0.75
20th to 40th Percentile - SIR	0.0001		(0.2124)	**0.9321**	***	**(15.0525)**	0.85
40th to 60th Percentile- SIR	0.0002		(0.2854)	**0.8320**	***	**(12.93)**	0.74
60th to 80th Percentile - SIR	0.0000		(-0.0259)	**0.8274**	***	**(18.3494)**	0.74
80th to 100th Percentile - SIR	0.0000		(-0.0319)	**0.9457**	***	**(8.0617)**	0.52
5 Factor							
Zero - SIR	**0.0035**	***	**(0.6520)**	**0.8638**	***	**(5.1864)**	0.50
0 to 20th Percentile - SIR	**-0.0017**	*	**(-1.7622)**	**0.8833**	***	**(10.4777)**	0.81
20th to 40th Percentile - SIR	0.0000		(-0.0207)	**0.7728**	***	**(8.4097)**	0.90
40th to 60th Percentile- SIR	0.0001		(0.2493)	**0.8185**	***	**(8.8041)**	0.80
60th to 80th Percentile - SIR	0.0003		(0.4295)	**0.9412**	***	**(8.6362)**	0.75
80th to 100th Percentile - SIR	0.0010		(1.0267)	**0.9577**	***	**(7.9127)**	0.65
8 Factor							
Zero - SIR	**0.0054**	**	**(2.3963)**	**0.9317**	***	**(3.8374)**	0.38
0 to 20th Percentile - SIR	**-0.0015**	*	**(-1.7107)**	**0.8484**	***	**(8.963)**	0.81
20th to 40th Percentile - SIR	0.0000		(-0.0693)	**0.7530**	***	**(7.0604)**	0.90
40th to 60th Percentile- SIR	0.0001		(0.3034)	**0.7773**	***	**(8.741)**	0.80
60th to 80th Percentile - SIR	0.0004		(0.5823)	**0.9268**	***	**(7.913)**	0.75
80th to 100th Percentile - SIR	0.0009		(1.0154)	**0.9789**	***	**(7.4047)**	0.69

3.6.4.2 Inclusion of bonds with all characteristics and features

My early analysis involved only bonds that have non-callable and straight features. This research revolves around understanding whether fines can be information that the market can use in analysis. Thus the previous results should also hold for all bonds regardless of its features. Here I test whether the results would also hold using US dollar bonds that have callable features and the nature of their cash flows vary[40]. The results presented in Table 3.13 confirm my view that companies with fines and high SIR have negative underperformances in bond returns. The results further substantiates my hypothesis as it shows the highest portfolio level of 80th to 100th SIR percentile with underperformances of 25 basis points p.m in the 5 factor model. I note that there is no statistical significance in the 8 factor model; nevertheless the results also still show underperformances in returns. This further affirms my view that fines is a type of information that is robust to even different types of bond features.

[This section has been intentionally left blank]

[40] Bond with Warrant (cash flow depends on a bond plus a call option for an equity), Convertible (cash flow depends on a conversion option), Index Linked (cash flow is adjusted usually in line with a consumer price index), Floating Rate (cash flow are variable)

Table 3.13 Callable and Non-Callable Bonds Equal Weighted Results based on Barclays US Index Benchmark (Full Sample Period)

The table below displays the monthly alphas which are adjusted based on Newey-West (1987) standard errors. The tables also indicate the coefficients estimated by model for the duration, default, option, equity, USD-EUR,USD-GBP and USD-YEN. The portfolios are equally weighted. The table displays the R-square and adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics.

Portfolio	Alpha			Market			Adj R^2
1 Factor							
Zero - SIR	0.0003		(0.289)	**0.9433**	***	(12.7971)	0.59
0 to 20th Percentile - SIR	-0.0002		(-0.1147)	**0.7309**	***	(3.8032)	0.41
20th to 40th Percentile - SIR	-0.0034		(-1.0971)	**1.8961**	**	(2.3815)	0.50
40th to 60th Percentile- SIR	-0.0008		(-0.7941)	**0.6438**	***	(3.6397)	0.43
60th to 80th Percentile - SIR	-0.0005		(-0.4586)	**0.6194**	***	(4.2828)	0.49
80th to 100th Percentile - SIR	**-0.0021**	*	(-1.8)	**0.9743**	***	(9.7033)	0.44
5 Factor							
Zero - SIR	-0.0005		(-0.5949)	**0.8389**	***	(7.9938)	0.66
0 to 20th Percentile - SIR	-0.0016		(-1.2291)	**0.4445**	*	(1.7797)	0.41
20th to 40th Percentile - SIR	-0.0018		(-1.0884)	**3.0072**	**	(2.5482)	0.64
40th to 60th Percentile- SIR	-0.0012		(-1.3263)	**0.3019**	*	(1.7993)	0.59
60th to 80th Percentile - SIR	-0.0014		(-1.3819)	**0.3702**	**	(2.0117)	0.56
80th to 100th Percentile - SIR	**-0.0025**	*	(-1.7276)	**1.1035**	***	(5.933)	0.46
8 Factor							
Zero - SIR	-0.0010		(-0.9791)	**0.8573**	***	(8.1835)	0.67
0 to 20th Percentile - SIR	-0.0012		(-0.9781)	**0.3999**		(1.6532)	0.49
20th to 40th Percentile - SIR	-0.0024		(-1.2243)	**3.1439**	***	(2.6819)	0.66
40th to 60th Percentile- SIR	-0.0012		(-1.4943)	**0.2821**	*	(1.7487)	0.61
60th to 80th Percentile - SIR	-0.0012		(-1.3212)	**0.3277**	*	(1.943)	0.57
80th to 100th Percentile - SIR	-0.0023		(-1.4039)	**1.0808**	***	(6.5652)	0.46

3.7 Summary

Short selling has always been viewed as a controversial activity and short sellers have been blamed for manipulating shares, as evident by the temporary ban in 2008 on financial sector securities by regulators during the financial crisis. However, short selling can be viewed as a strong negative sentiment and evidence in previous literature have highlighted short sellers as being able to detect financial fraud even before revelations. Furthermore, high SIR has also been associated with negative equity performances. Nonetheless, there has so far been no literature to measure the impact of short selling on the performance of bond returns. I study here the effect of short selling on U.S bond returns in the context of fines. Such events of fines are material events as it has also been associated with drop in share prices. Using hand collected data of fines and for a 12 year sample period, I provide evidence high short selling at the 60th to 80th percentile, in the context of fines induces negative underperformances in bond returns by an average of 20 basis points p.m. In short, this means that the 2nd highest SIR portfolio in my sample has negative underperformances. Surprisingly, the 1st highest SIR portfolio does not show any statistical significant results. Interestingly, Karpoff and Lou (2010) find that among firms that have been misrepresenting their financials for 12 months, it is at only the 75th percentile of abnormal short interest will be publically revealed 8 months sooner than a firm at the 25th percentile. This shows that my results also compares to theirs at the 60th to 80th percentile which has negative underperformances. Furthermore, the results for the lower SIR portfolios were expected as they do not also show any statistical significance. This confirms that high short selling in the context of fines has a direct link to bond returns (i.e. higher short selling after a fine induces negative bond returns). In addition, I find that the underperformances are more profound for portfolios with longer remaining years to maturity. This coincides with the view that SRI investors with long-term investment horizon mindset would consider negative events detrimental in bonds that have longer remaining years to maturity.

I also test whether short selling in the context of fines has a larger effect during crisis periods. I can confirm my hypothesis that there is a larger underperformance of bond returns during crisis periods than in non-crisis periods. This conveys that investors find short selling during crisis periods to have more significance, independent from low or high short selling. Thus, negative sentiments of investors during crisis periods are clearly much more detrimental to the performances of company's bond returns.

I also examine firms that have short selling regardless if they have a fine and my results indicate that portfolios with zero short interest outperforms and low short selling (0 to 20th percentile) have underperformances in bond returns. Thus when there is no short selling which in turn would indicate "good" sentiment there is outperformance on the bond returns. The results of the negative underperformances of on the lower SIR portfolio confirm that only higher SIR ratios after fines induce higher negative bond returns. Using also sample of bonds regardless of their cash flow features, I find that now the highest SIR percentile portfolio underperforms by 25 basis p.m. The above results clearly indicate that short selling after fines, especially when it is high, has a negative impact on bond returns. My results are robust to different benchmarks and liquidity levels. Though there are somewhat mixed results when value weighted, overall conclusion still remains unchanged as there are still underperformances after announcements of fines or settlements on bond returns.

This chapter shows that stock market sentiment (using short interest ratios) especially in the context of fines does affect corporate bond returns i.e. high investor sentiment in equities has a direct effect on corporate bond prices. Firms should be aware that their illegal actions during crisis period would be even more detrimental to their bond returns. Investors are less lenient to firms that incur monetary fines during crisis periods than non-crisis periods. This study finds that short selling ratio is a viable indicator to measure the link between sentiment and bond returns. Nevertheless, this study only holds for the US market and whether the results hold in non-US markets warrants further investigation.

[This section has been intentionally left blank]

4. A Comparative Event Study: The Impact of Fines on Credit Default Swaps and Stocks

4.1 Introduction

In 2007, just before the financial crisis, the outstanding notional size of the CDS market was just over $60 trillion[41]. The credit derivatives market was then stained by the financial crisis in 2008, where the majority of the mortgage backed securities were backed by Credit Default Swaps (CDS) as a form of insurance[42]. 10 years later, the CDS market has been hovering just about $10 trillion. Even though the CDS market is not at the level from its former glory days, it is now growing as investors are appealing to CDS for its characteristics of tracking the likelihood of default of a company and also to protect their bonds from losses[43].

In 2015, the automaker Volkswagen was fined by the U.S Environmental Agency for evading government pollution controls. The impact of this fine on Volkswagen was seen twofold, firstly by the drop of their share price by 45% and secondly by widening of their 5 year CDS spreads by 125% from 60 basis points (bps) to 135 bps[44]. This is very similar to British Petroleum (BP) that also had a continued drop of its share price and widening of their CDS price after the explosion at the Gulf of Mexico (Fodor and

---

41 " The rise and fall of the hottest financial product in the world" available at http://www.businessinsider.de/rise-and-fall-of-cds-market?r=US&IR=T (accessed 31st May 2017)

42 The housing market was initially insured by billions of dollars of CDS from AIG. However, following AIG's bailout in September 2008, *"the scrutiny of the CDS market and the manner in which the contracts were written and cleared changed substantially. Specifically, the bailout of AIG led to calls for increased transparency and regulation"* (Jenkins, Kimbrough et al. 2016)

43 "Credit default swap activity heats up" available at https://www.ft.com/content/c47dce8e-ca9f-11e5-be0b-b7ece4e953a0 (accessed 1st March 2017)

44 "Volkswagen credit spreads soar after EPA charges with evading pollution controls" available at http://www.forbes.com/sites/spleverage/2015/09/21/volkswagencreditspreadssoarafterepachargescowithevadingpollutioncontrols/#6d97ac6c3e9e (accessed 20th October 2016)

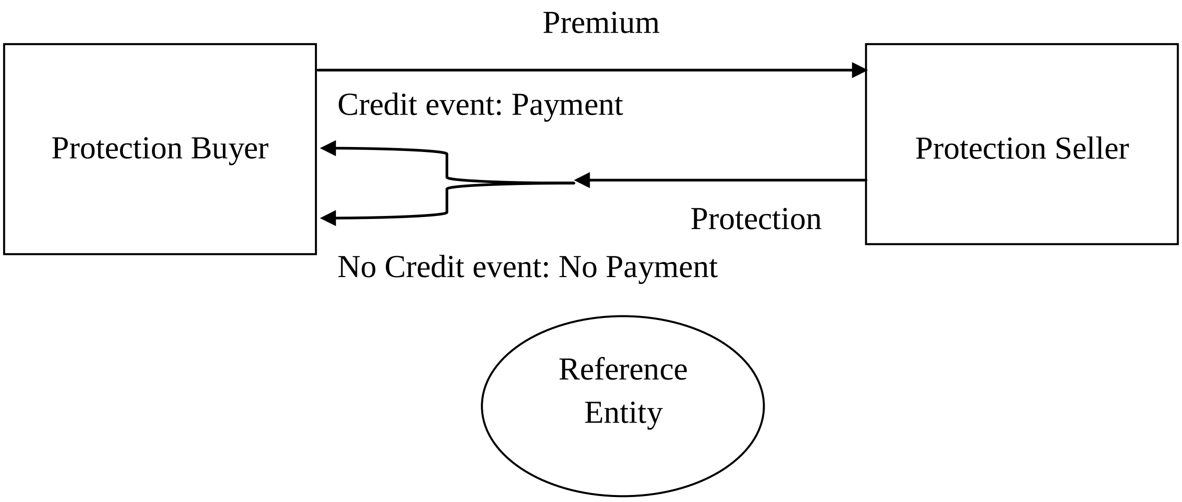
Stowe 2012). There is huge amount of literature that measure the impact of illegalities on stock markets and findings from literature indicate that stock prices do react negatively to announcements of illegal behaviours of companies (Wallace and Worrell 1988; Baucus and Near 1991; Davidson, Worrell et al. 1994; Karpoff, John R. Lott et al. 2005; Karpoff, Lee et al. 2005; Arnold and Engelen 2007; Kouwenberg and Phunnarungsi 2013; Zeidan 2013; Song and Han 2015). Furthermore, in my previous two chapters, I examine the impact of illegalities on both stock and bond markets and also find underperformance after announcement of illegalities[45]. Prior studies have either only examined rating announcement (Hull, Predescu et al. 2004; Micu, Remolona et al. 2004; Norden and Weber 2004; Wengner, Burghof et al. 2015) or earnings announcements (Greatrex 2009; Jenkins, Kimbrough et al. 2016) on CDS prices. I find there is a gap in literature in understanding the impact of illegalities, especially fines on CDS, which I examine in this chapter.

A CDS is essentially an insurance contract in which a protection buyer and seller agree on a premium which is paid on a regular basis until the contract expires or when the credit event actually materializes. The credit event can be a pre-determined event stated in the contract ranging from bankruptcy, default or even to restructuring. When a credit event is triggered, the settlement of this CDS contract depends on the agreed terms between protection buyer and seller. This could range from physical settlement where the protection seller has to buy the underlying security (either a bond or loan) back from the buyer or a cash settlement where the protection buyer receives the difference between the bond value at the time of settlement and the bond's nominal

[45] Even though in my previous chapter on bonds I make a comparison that the bonds also indicates underperformances after illegalities. It is important to note that because of the difference in the sample time frames, there is no arbitrage opportunity which exists when comparing the results in this chapter on CDS with the previous chapter on bonds.

value in cash (Weistroffer, Speyer et al. 2009). The premium of the CDS is called the "spread"[46] and is usually a measure of risk whereby higher spreads indicate higher credit risks associated with the underlying reference entity or firm (Greatrex 2009). In essence, the protection seller assesses the credit risk of the reference entity and decides on the premium accordingly. There is also counterparty risk between the protection seller and buyer[47]. The CDS market has several ways to mitigate this risk post the financial crisis. The most important is the market infrastructure provided by the International Swaps and Derivatives Association (ISDA) which has several frameworks in place and is used by market participants significantly to reduce the potential losses arising from the default of a counterparty in a swap or derivative contract and another way is by collateralization (Arora, Gandhi et al. 2012). Figure 3 below represents a diagram explaining the mechanisms of a CDS payment structure:

Figure 3 CDS payment structure adapted from Weistroffer et al., (2009)



---

[46] *"CDS "prices," as measured in the market, represent the size of the premium paid by the buyer of protection and are generally known as CDS "spreads." CDS spreads change over time based on supply and demand for particular CDS contracts. CDS spreads are analogous to insurance premiums and similarly reflect market participants' assessment of the risk of a default or credit event associated with the underlying obligation"* Flannery, M. J., J. F. Houston, et al. (2010)

[47] Counterparty credit risk is when *"a firm selling credit protection might enter financial distress itself and be unable to meet its contractual obligations, thus there is a risk that the protection seller may not perform"* Longstaff, Mithal et al (2003)

The CDS credit risk profile is known to be similar to corporate bonds where it is exposed to credit risk without owning the underlying bond. Nevertheless, CDS spreads have many advantages over corporate bond yields. Firstly, CDS spreads reflect pure credit risk whereas bond yields take into account interest rate risk, secondly there is no requirement for a benchmark risk-free rate to estimate CDS spreads and finally bonds yields are at times conformed to embedded options such as call features (Callen, Livnat et al. 2009). In addition, Blanco et al.,(2005) find that CDS prices are much better in explaining credit risk than bond spreads and Zhu (2006) discovers that the CDS market often moves ahead of the bond market in price adjustment. Furthermore, Stulz (2010) states that the CDS market is more liquid than the bond market and hence is a better market to investigate a company's credit risk than the bond market.

The illegal behaviours of firms can be considered a default risk because the negative impact of this behaviour results in fines and thereby alsocash flows and firm value. Using four major events[48] from the financial crisis, Huang et al., (2012) find that CDS markets reacts more rapidly to negative shocks than to positive one. Hence, taking into account the growth in the CDS market and that the changes of CDS spreads are deemed as a measure of risk, this study aims to investigate whether illegal behaviours of companies especially after fines affect CDS spreads in the market. This study uses daily CDS quotes from Datastream for a sample of 121 United States (US) large cap firms from the period 2009 to 2012.

[48] They used four key events of the financial crisis during 2007 and 2008 which are 1) the Bear Stearns collapse 2) the acquisition of Bear Stearns by JP Morgan 3) Fannie Mae and Freddie Mac revealed financial difficulties 4) AIG announced serious liquidity difficulty and Lehman Brothers filed for Chapter 11

My study extends the growing empirical research on illegalities especially on CDS. To my knowledge, the paper by Kölbel and Busch (2013) is the only one that measures the impact of illegal behaviors of firms on CDS and they find that negative media attention causes a significant increase in CDS spreads. My paper differs significantly from theirs in several ways. Firstly, their paper is based on negative news retrieved from prominent international newspapers. Instead my study involves a dataset of purely fines taken from the SEC 10-K fillings database for US listed companies. Secondly, their study is based on a panel regression model to find the relationship between CDS spreads and negative news using quarterly and yearly data. Whereas, using daily data, I examine the immediate impact of the fines (pre and post) using an event study methodology which is a widely used methodology to examine price effect after announcements. Thirdly, their study only measures all types of negative news in one category, while I separately measure the impact of different types of ESG plus LT fines including different legal stages of the fines and fines per market cap. Fourthly, their study is based on 5 year and 10 year CDS spreads, while I measure different levels of CDS spreads up to 30 years.

Additionally, the unique aspect of this study is that I measure the impact of illegalities on CDS spreads and also compare it to short-term stock returns. I find two studies which have examined and compared the impacts of events using the traditional event study methodology on both CDS spreads and stock returns (Norden and Weber 2004; Greatrex 2009). My study differs from those studies significantly as I examine impact of announcement of fines whereas those studies examine earnings and ratings announcements. If equity and CDS markets are connected, then informational events should impact both markets as seen with examples from BP and VW (i.e. after the fine, the stock prices drops and CDS spreads increase). Moreover, there is also literature that examines the bi-directional information between these two asset classes. For instance, Norden and Weber (2009), using a VAR model, find that the stock market informs the CDS market whereas Longstaff, Mithal et al.(2003) using a closed-form model for valuing CDS within a reduced-form framework find that both the CDS and stock market inform the bond market.

This study makes a number of contributions. Firstly, I add to the current understanding how the credit market uses announcements of fines as information. While prior event studies have focused on credit market responses to rating or earnings announcements, my focus on the pre and post announcements of fines sheds lights on how the credit market absorbs and reacts to illegality news especially when a monetary fine is imposed. Secondly, this paper also adds to the literature on anticipation as I find that that the credit market anticipates illegality news which would be of interest to regulators. Furthermore, this analysis is beneficial to traders who are interested in fines as an information type and could use this in their analysis and trading. This is also very useful for institutional holders such as pension funds (who have large holdings in US public listed firms) and are interested in understanding the difference in perception of the credit and stock markets reactions on ESG plus LT fines and fines in different industries.

The remainder of this chapter is organized as follows. Section 2 provides an overview of the related literature and the hypotheses development. Section 3 provides description of the fines and CDS data and the event study methodology. Section 4 presents the results of the CDS and stock market responses to illegal behaviours events. Section 4 provides the limitations of this study and Section 5 concludes.

4.2 Literature Review and Hypotheses Development

4.2.1 Related literature of the impact of announcements/news on CDS spreads

It is important to understand the context of probability of default and how it affects firm value and the pricing of CDS. There are two seminal theories which explain this; the Merton structural model and the Efficient Market Hypothesis (EMH) suggests that stock markets always reflects all relevant information especially incorporating default probability information of firms. Merton (1974) introduced his structural model that analyzes credit risk of firm's debt and its probability of meeting financial obligation. This was further enhanced by Black and Scholes (1973) who created the Black and Scholes model which could derive the discount to be applied to a corporate bond because of the possibility of default. In essence, these finance theories indicate that once the condition of a firm deteriorates, this increases the probability of default on the firm's bonds which in turn in an efficient market would lead stock and bond prices to go down and inevitably CDS spreads to increase (Fung, Sierra et al. 2008). Longstaff et al., (2005) find that the majority of the CDS spreads changes are due to changing default risk. In relating this to illegality and CDS, news on fines imposed on companies contains new information about the future cash flow of the firms and thus affects firm value. This would in turn decrease the firm's ability to service its debt obligations as well as its expectations of its future cash flows taking into account that the fines would have to be paid in cash at most times. Thus, the default which is driven by this firm value process would then increase the price of a CDS.

The impact of new information such as ratings announcement on CDS prices has been researched extensively. (Hull, Predescu et al. 2004; Micu, Remolona et al. 2004; Norden and Weber 2004) examined CDS changes and find significant reaction to ratings announcements and reviews for downgrade and that there is already anticipation of these announcements beforehand. Norden and Weber (2004) not only measured CDS market changes to rating announcements but also to the stock market. They find that both the stock and CDS markets not only anticipate rating downgrades, but also review for downgrade by three major rating agencies (S&P, Moody's and Fitch). Contrary to those findings, Finnerty et al., (2013) find that credit rating upgrades have a significant impact on CDS spreads even though they are not as well anticipated as downgrades. The studies above indicate there is anticipation of rating announcements even before the actual announcement, therefore Norden (2008) further investigated if and how exactly public and private information affects the CDS market response to rating announcements.. He finds that the CDS market significantly reacts to rating downgrades and even stronger to reviews of downgrade. He further adds that it is the intensity and content of daily corporate news and private information (under certain conditions) which influences CDS prices. Galil and Soffer (2011) also confirm the previous studies that CDS spreads change abnormally following announcements of rating changes and rating reviews. However, they add that the market is more sensitive to negative news and that CDS spread changes are greater surrounding negative events than surrounding positive events. A more recent study by Wengner et al., (2015) examined the impact of S&P rating events on CDS spreads of firms from 2004 to 2011. They find that both credit downgrades and upgrades have an impact on the CDS spread of event and non-event firms on the event date. However, downgrades are more anticipated than upgrades.

Since the studies above have only looked at corporate CDS, there are others studies which examines whether the results above also hold for sovereign CDS.

Ismailescu and Kazemi (2010) examined the effect of sovereign credit rating change announcements on the CDS spreads of the event countries, and their spillover effects on other emerging economies' CDS premiums. They find that surrounding a two day period of the event, positive events have a greater impact on CDS markets and are more likely to have a spillover effect on to emerging countries. They also indicate that markets are able to anticipate negative events. Blau and Roseman (2014) investigated a cross-country effect between sovereign US credit rating downgrades with European CDS spreads. They find a surge in European CDS spreads during the ten-day period surrounding the U.S. downgrade. Kim et al.,(2015) measured the impact of domestic and spillover macroeconomic news from U.S, the Eurozone and China on national sovereign CDS spreads and spread volatility over the period from November 2007 to March 2012. Similarly to corporate CDS spreads, they find that better than expected news tend to reduce sovereign CDS spreads, whilst worse than expected news increases spreads.

In addition to credit ratings announcements and macroeconomic news, there is also literature that measure the impact of earnings on CDS spreads. Callen et al., (2009) find that earnings (changes) are negatively correlated with one-year CDS changes but not with longer term changes. Their results suggest that positive (negative) earnings convey favorable (unfavorable) information primarily about short-term default risk. Similar to credit rating announcements, Greatrex (2009) examines the impact of earnings announcements and finds that the CDS market anticipates negative earnings surprises as prices being to adjust prior to the actual announcement date. The market also responds more strongly to negative news than to positive news. This makes sense as CDS is a form of protection, therefore spreads increase quickly during negative news to adjust for the higher risk, whereas during positive news which indicates a better outlook for a firm, the reactions to change might be slower.

Most importantly, I find only Kölbel and Busch (2013) which investigates the effect of negative media regarding CSR on credit risk. Their study is not based on an announcement effect, rather using panel regressions they examine the relationship between credit spreads and news. Their results indicate that negative media attention causes a significant increase in credit default swap spreads.

4.2.2 Related literature on the relationship between CDS and other asset classes

There are also numerous studies that measure the relationship between CDS and other assets classes (i.e. stocks and bonds). Using weekly data, Longstaff et al., (2003) examined the relationship between US firm's CDS spread changes, corporate bond yields and stock returns. They find that CDS spreads and stock returns often lead changes in corporate bond yields, indicating that information reaches first to credit derivatives and stock markets before the corporate bond market. Norden and Weber (2009), using a VAR analysis, measured the relationship between daily and weekly CDS spreads, stock returns and bond yields of European firms. They find that the CDS market is significantly more sensitive to the stock market than the bond market. Using a sample of firms from North America and Europe instead, Forte and Pena (2009) also find that stocks lead CDS and bonds more frequently than vice versa. Fung et al.(2008) examined the U.S stock market and CDS market for the period of 2001 to 2007 and find that lead-lag relationship between the U.S. stock market and the CDS market depends on the credit quality of the underlying reference entity. Using daily and weekly data, Hilscher et al.(2015), find that informed traders are primarily active in the equity market rather than the CDS market.

I find two similar studies that have examined impacts of events on both CDS spreads and stock returns using event study methodology. Norden and Weber (2004) analyzed the response of stock and CDS markets to rating announcements from 2000 to 2002 and find that both markets anticipate rating and reviews of downgrades. Greatrex (2009) measured the reaction of CDS spreads based on earnings announcements from 2001 to 2006 and compared the results with equity returns. She finds that CDS spreads increase (decrease) upon the announcement of unexpected negative (positive) news and that the CDS market anticipates negative earnings. Using a market model, the author also finds that the stock market's reaction to negative earnings surprises is similar to the CDS market.

4.2.3 Hypotheses Development

Pursuant to the studies in the previous section, I find so far no literature that measures the impact of fines on CDS spreads. I find evidence of CDS spread changes after a fine especially from the BP and VW case. Callen et al.(2009), investigated earnings on CDS and they state that *"In structural models, the price of credit derivates is a function of the likelihood and severity of financial distress (the credit event), and the more profitable is the firm, the less likely it is to suffer from financial distress".* Following their reasoning, it can be deduced that illegalities play a role in structural models when a fine is imposed to a firm which in turn reduces cash flows and the profitability of the firm. Depending on the size of the fine, it can have a strong impact on the default risk of the firm. Any negative news due to illegal behaviours of a firm would result in a drop in its share price, consequently a lower firm value and an increase in CDS spread. Thus, my first hypothesis is that CDS in general should react to fines:

H1: *Investors react with increases in CDS spread changes after announcements on illegalities*

Secondly, most of the reviewed studies only measure five year maturity of the senior unsecured CDS changes as they indicate that it is by far the most popular, commonly traded and most liquid (Hull, Predescu et al. 2004; Micu, Remolona et al. 2004; Norden and Weber 2004; Blanco, Brennan et al. 2005; Forte and Pena 2009; Norden and Weber 2009; Ismailescu and Kazemi 2010; Galil and Soffer 2011; Finnerty, Miller et al. 2013). Kölbel and Busch (2013) examined 5 year CDS spreads and 10 years CDS spreads as a robustness and find that their results are similar in indicating that negative media attention to CSR issues raises credit risk spreads. However, Callen et al.(2009), measured the different maturity levels (one year, five year and ten year) of CDS spreads and they find only the levels of one year CDS spreads are inversely related to quarterly earnings. This indicates that higher profits (positive information) signify lower default risk but only in the short run. Thus, as fines relates to negative news, thus signifying higher default risk, the changes in CDS spreads should be more evident with longer term maturities[49]. Furthermore, announcement of illegal violations can be considered as long-term event risks as implications of violations usually have longer time frames for regulatory enforcements. Furthermore, as most of the studies indicate that the CDS market is able to anticipate news before even

[49] Short-term if they have less than 5 years remaining years to maturity, medium term if they have 5 to 10 years remaining years to maturity and long-term if they have more than 10 years remaining to maturity

announcement (Hull, Predescu et al. 2004; Micu, Remolona et al. 2004; Norden and Weber 2004), I also expect the same for news on illegalities. Hence, my second hypotheses are stated as below:

H2a: *Investors react stronger (higher spread changes) on higher CDS maturities compared to lower CDS maturities after announcements on illegalities*

H2b: *Investors in the CDS market are able to anticipate news of illegalities even before announcements*

Third, I also investigate whether firms with higher fines per market cap have a larger reaction compared to firms with lower fines per market cap. Defaults of corporations (reference entity) are the most common events CDS contracts are written against (Cherny and Craig 2009). Thus it is only rational that the CDS market would expect firms with larger fines per market cap to be more in financial distress. Relating this also to my second chapter, I find firms with larger fines to have more underperformances compared to firms with lower fines in the long-term. Thus, it is only rational to assume that this would have a similar reaction in the short-term for both the CDS and stock market. Even Karpoff, John R. Lott et al. (2005) measure the size of the legal penalties imposed on environmental violations and find that firms' losses in share value are related to the size of the fine and damage award eventually imposed by regulators or the courts. Hence, my third hypotheses are stated as below:

H3a: *Investors in the CDS market react negatively (increase in spreads) to firms with higher fines per market cap compared to lower fines per market cap after announcements on illegalities*

H3b: *Investors in the stock market react negatively (decrease in returns) to firms with higher fines per market cap compared to lower fines per market cap after announcements on illegalities*

Fourth, most of the studies examined reactions to announcement of news/ events on CDS prices that are relatively final (i.e. rating/ reviews of downgrades, macroeconomic news, earnings announcements) (Hull, Predescu et al. 2004; Micu, Remolona et al. 2004; Norden 2008; Callen, Livnat et al. 2009; Galil and Soffer 2011; Kim, Salem et al. 2015). However, news of illegalities are unique as they involve various legal stages before a "one-set" final fine amount is either imposed to or accepted by firms. Refer to figure 2 in chapter 2 for the various stages of the legal process. The initial allegation period (Pending) usually involves informing the market of the illegal behaviour of the company with an expected fine amount. However, the allegation could then be pending various legal outcomes (Confirmed Violation but pending other Matters - CVPM) such as a retrial, fairness hearing, resettlement etc. Only at the final stage (Confirmed violation) would the company have either agreed or accepted a set fine amount. Rationally, as CDS is an insurance contract, the spreads should be higher at the initial stage so investors can "prepare" for any possibility of default in the future. Thus on a realistic assumption, it is the initial violation stage that CDS investors would react to (i.e higher spreads) compared to other stages. This reaction would be similar to the one in the stock market as illustrated in Chapter 2.4.3. Though fines are detrimental to stock returns, at times the confirmation of fines may be viewed positively, if the market expected worse and/or the market is relieved to have simply been removed from the uncertainty. Karpoff et al., (2005) find that the stock price reactions to initial announcements on environmental fines capture most of the firm's total loss in market value. Hence my fourth hypotheses are stated as below:

H4a: *Investors in the CDS market react negatively (increase in spreads) at the initial stage of the violations after announcements on illegalities*

H4b: *Investors in the stock market react negatively (decrease in returns) at the initial stage of the violations after announcements on illegalities*

Fifth, it is important to examine market reaction of these CDS prices on different industries. Investors in different industries have different tolerance levels to risk and hence would not have the same reaction to news. There are only a few studies that have measured industry effects on CDS. Jorion and Zhang (2007) examined the impact of Chapter 7 and Chapter 11 bankruptcies on CDS spreads and show that intra-industry effects depend on the type of credit event. Huang et al. (2012), examined the impact of four major events (three negative and one positive) of the financial crisis on the CDS market across two industries, financial and non-financial. They find that CDS spreads of financial firms jump before and after the default events of financial institutions with negative shocks and while negative news continues, the CDS spreads of non-financial firms rises as a result of the key default of financial firms. Wengner et al.(2015), examined the impact of S&P rating events on CDS spreads across industries. Findings in their study suggest that market reaction to rating events should not be generalized but should rather be examined on an industry level. Daniels and Jensen (2005), find that the CDS market is segmented across industries and market reactions to rating announcements differ at the industry level. I assume the same for investors in the stock market. Hence my fifth hypotheses are stated as below:

H5a: *Investors in the CDS market react negatively (increase in spreads) only in certain industries after announcements on illegalities*

H5b: *Investors in the stock market react negatively (decrease in returns) only in certain industries after announcements on illegalities*

Finally, despite the fact that there are numerous event studies that measure the impact of illegalities on stock returns (Wallace and Worrell, 1988, Baucus and Near, 1991, Davidson et al., 1994, Karpoff et al., 2005a, Karpoff et al., 2005b, Zeidan, 2013, Song and Han, 2015, Kouwenberg and Phunnarungsi, 2013, Arnold and Engelen, 2007), I find no studies that have measured the impact of different ESG and LT issues on CDS spreads. I find the study by Sun and Cui (2014) slightly related in linking default risk with Corporate Social Responsibility (CSR). They find that CSR helps firms reduce the risk of falling into default. Nonetheless that study does not measure the actual impact using an event study on CDS spreads. Thus in this study I examine which individual ESG plus LT issue is more of a concern to CDS investors using the European Federation of Financial Analysts Societies (EFFAS) standards. No one to my knowledge has used the EFFAS standards on all four ESG plus LT criteria's to measure violations. I consider the LT issues key to be added to ESG because companies usually pursue corporate sustainability with both an agenda to reduce ESG risk but also to increase their long-term viability i.e. increase their profits. Hence, examining the LT separately from ESG issues would be crucial in understanding whether the CDS market considers LT issues that affect companies as a concern. For example, the LT could relate to innovation (i.e. patents) that would affect the long-term revenue generation of the company. I also measure this to the stock market reaction. Hence my sixth hypotheses are stated as below:

H6a: *Investors in the CDS market react negatively (increase in spreads) only on certain ESG plus LT issues after announcements on illegalities*

H6b: *Investors in the stock market react negatively (decrease in returns) only on certain ESG plus LT issues after announcements on illegalities*

4.3 Data and Methodology

4.3.1 Credit default swap spreads and illegality data

My sample is based on daily corporate CDS data from 2009 to 2012 for U.S firms and is extracted from Thomson Reuters Datastream (Datastream) database. Jenkins et al. (2016), also used CDS prices from Datastream and argue *"it has a better advantage of allowing to capture the change in CDS spreads on individual security basis than the change in issue price on two different CDSs issued on the same reference asset".* Datastream provides CDS spreads for various types of currencies (i.e. USD, Euro Australian, Japanese Yen, Norwegian Krone) and seniority (i.e. Senior unsecured, Subordinated unsecured). As most contracts are U.S dollar dominated, for consistency I removed all other currencies and only retained U.S dollar contracts and only senior unsecured CDS data (Ismailescu and Kazemi 2010). I use the mid-rate spread between the entity and the relevant benchmark curve and the rate is expressed in basis points (bps). Though most literature only use the five-year CDS as it is the most commonly quoted level, in this study I analyze all the various levels of maturities from 6 months to 30 years to understand whether there are any significant variances between these different maturity levels after an event. The CDS spreads are also categorized into seven different industry levels according to Standard Industrial Classification (SIC) codes. The illegal behaviors event dataset is similar to the previous two chapters which is hand collected data of violations of MSCI Large Cap U.S firms from the Securities Exchange Commission (SEC) 10-k fillings. The initial sample from 2009 to 2012 consisted of 164 numbers of firms and 556 numbers of fines. However, once I matched the fines data with the available CDS data, my final sample consisted of 121 numbers of firms and 471 numbers of fines. Refer to table 8.9 in the appendix for a detailed overview of the sample size and table 8.10 for the composition of CDS data per firm.

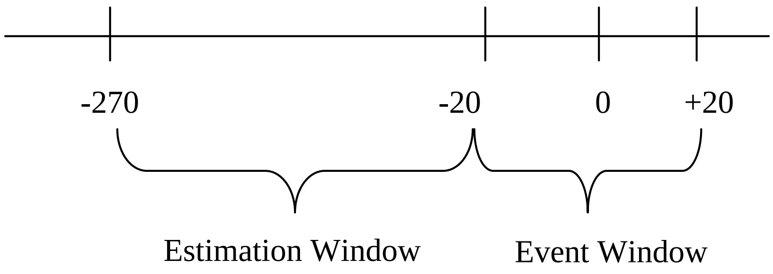
4.3.2 Event Study Methodology

In this section, I explain the methodology used in my analysis to measure the impact of illegal behaviours on the changes of CDS spreads. Following the seminal paper by MacKinlay (1997) who stated that *" the usefulness of the event study…can be constructed using security prices over a relatively short period of time",* I thus conduct the analysis using the traditional event study methodology[50]. Firstly, I define the event which in my case is the daily dates of the violations of firms as per SEC filings. Secondly, I select the estimation window period which is the period prior to the event and the event date is normally not included in the estimation. I have chosen 250 days as the estimation window to obtain the coefficient estimates which is similar to Greatrex (2009) who also used this period to measure CDS spread changes. Finally, an event window is chosen which in my case is 20 days before and 20 days after the event, totaling to 41 days and is referred as [-20,+20]. This is a market model which is

[50] In the previous two chapters, I had used the CAPM, FF and Carhart models using the portfolio method to examine the impact of fines on long-term returns. However, in this chapter as I intend on measuring the short –term impact of fines on both CDS and equities, the standard market model using the event study methodology is the most appropriate. Additionally, this event study model is commonly used in literature (as per section 4.2) where short-term CDS spreads are examined..

commonly used in stock market literature and takes into account. The estimation and observation windows do not overlap as per Figure 4 below which provides the description of the event periods:

Figure 4 Event study timeline adapted from MacKinlay (1997)



I employ a market model that is "*a statistical model which relates the return of any given security to the return of the market portfolio"*(MacKinlay 1997). This means that I regress the daily CDS spread changes on an overall CDS market. The market model is as per below:

$$\Delta CDS_{it} = \alpha_i + \beta_i \Delta MKT_t + \varepsilon_{it} \tag{4.1}$$

where ΔCDS_{it} is the change of the daily CDS spread for the firm *i* at date *t*. ΔMKT_t is the daily change of the CDS market and since I do not have an equivalent CDS index, I calculated my own CDS index by equal weighting the mean CDS spread of all the firms in my sample at date *t*. α_i & β_i are the parameters of the model and ε_{it} is the zero mean disturbance term. I then proceed to calculate the abnormal spread changes (ASC) using the following formula:

$$\Delta ASC_{it} = \Delta CDS_{it} - \hat{\alpha}_i - \hat{\beta}_i \Delta MKT_t \tag{4.2}$$

However, most current CDS literature that employ an event study methodology use instead an index-adjustment based model (Hull, Predescu et al. 2004; Norden and Weber 2004; Greatrex 2009; Ismailescu and Kazemi 2010; Galil and Soffer 2011; Huang, Shen et al. 2012; Finnerty, Miller et al. 2013; Wengner, Burghof et al. 2015). Since CDS spreads are not returns, employing a market model may not be accurate and considering that an overall CDS market exchange index is not accessible and that I have to create my "own" index, Finnerty et al.(2013) and Huang et al., (2012) indicate that using a simple average of CDS spreads would be preferable instead. Thus, I employ a ratings based index-adjustment model which will remove any systematic effects from an individual firm's spread changes. The formula used to calculate the index-adjustment based model is per below:

$$ASC_{it} = (\Delta CDS_{it} \text{-} \Delta INDX_{it}) = (CDS_{it} - CDS_{it-1}) - (INDX_{it} - INDX_{it-1}) \qquad (4.3)$$

where similarly to the market model, ΔCDS_{it} is the change of the daily CDS spread for the firm *i* at date *t*. However, instead the $INDX_{it}$ is now calculated by equal weighting the mean CDS spread level of firms within two separate rating categories for the firms at date *t*. $\Delta INDX_{it}$ is the daily change of the rating based index. Following Huang et al. (2012), I use the credit ratings assigned by S&P to determine the two rating categories, investment grade (AAA to BBB-) and speculative grade (BB+ and below). Finally, cumulative abnormal spread changes (CASC) are calculated by summing up the daily ASC within the event window starting at τ_1 and ending at τ_2 as per the formula below:

$$CASC_{i\tau_i\tau_2} = \sum_{t=\tau_1}^{\tau_2} ASC_{it} \qquad (4.4)$$

I also conducted a short-term event study on stock returns for comparison purposes. Similar to Greatrex (2009) I use a market model and a market adjusted model with an estimation period of 250 days with an event window totaling to 41 days and is referred as [-20,+20]. The market model is estimated as per the model below:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{4.5}$$

where R_{it} is the daily log return of the firm *i* at date *t*. R_{mt} is the market portfolio which I have created by equal weighting the portfolio log returns in the sample portfolio from 2009 to 2012. α_i & β_i are the parameters of the model and ε_{it} is the zero mean disturbance term. The market model abnormal return is estimated as per the model below:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \tag{4.6}$$

where AR_{it} is the abnormal stock return of the firm *i* at date *t*. The market adjusted abnormal returns is estimated as per the model below:

$$AR_{it} = R_{it} - R_{mt} \tag{4.7}$$

Similar to the CDS, cumulative abnormal returns (CARs) are calculated by summing up the daily AR within the event window starting at τ_1 and ending at τ_2 as per the formula below:

$$CAR_{i\tau_i\tau_2} = \sum_{t=\tau_1}^{\tau_2} AR_{it} \tag{4.8}$$

Following Huang, Shen et al.(2012), CASCs and CARs are computed within seven pre and post event windows [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] with cross-sectional test statistics (t-test) by *"dividing average event-period residual by its contemporaneous cross-sectional standard error"(Boehmer, Masumeci et al. 1991).*

4.4 Empirical Results: Analyzing CDS spread changes and stock market returns

4.4.1 Overall Market reaction and by CDS maturity level

In this section, I analyze the impact of illegalities on overall market reaction and on the different maturity levels of CDS. I separate the maturities into six different levels, i) Less than 1 year, ii) between 2 and 5 years iii) between 6 and 10 years iv) above 10 years vi) only 5 years and vii) all maturity levels.

Tables 4.1 to 4.3 report the results of the cumulative abnormal spread changes (CASC) response to illegalities. Examining the results in Table 4.1, I find increase in CDS spread changes (post event) on three out of six levels of maturity. This confirms the first hypothesis that there are increases in CDS spreads after announcements of illegality. CASC for firms with less than 1 year maturity are statistically significant at a 5% and 10% level for the [0, 1] and [0, 2] announcement windows respectively. CASC for firms between 6 and 10 years and All maturity levels are statistically significant at a 10% level at [0, 1] announcement windows. This indicates CDS investors react immediately the day after the news of illegalities. The changes in the spreads for the less than 1 year maturity is +1.6 basis points, between 6 and 10 years maturity is +1.1 basis points and all maturity is +1.1 basis points for the [0, 1] announcement windows.

My second hypothesis is that investors react stronger (higher spread changes) on higher CDS maturities compared to lower CDS maturities after announcements on illegalities. The results show that the increase in CDS spreads is evident in short-term, medium term and on all levels of maturities[51]. Indicating, regardless of the level of maturity, CDS investors react immediately after announcements of fines. This makes sense as CDS has insurance like characteristics and should have a mechanism to protect all types of bonds regardless of maturity.

However, I find that the results are only evident to a market-model and when an index-adjusted model is used, the reactions to the illegal behaviour news (post event) show no statistical significance (as per table 4.2). These results are interesting, as the index adjusted investment grade ratings model indicates that investors do not perceive fines for firms with high quality ratings (i.e. more stable) to be of a concern. This is also evident with the co-efficient sign post event on all levels of maturity being negative. The results on the speculative grade ratings model in table 4.3 also show statistically no significance pre and post events.

Supporting Norden and Weber (2004) I also find that the CDS markets anticipate the news even before announcements on five out of six levels of maturity. This supports my hypothesis 1b that the CDS market anticipates illegality news even before announcements. In the market model, I find statistically significant larger spread changes before announcements at the [-5,-1] announcement window for five different maturity levels[52] and also at the [-10,-1] announcement window for two maturity levels[53]. I observe that the changes in spreads at pre-event announcement for the [-5,-1] announcement window is approximately between +2.1 and +3.5 basis points and for the [-10,-1] announcement window approximately between +4.1 basis points and +5.1 basis points. This is significantly larger than the post-announcement period spread change. I

[51] Short-term if they have less than 5 years remaining years to maturity, medium term if they have 5 to 10 years remaining years to maturity and long-term if they have more than 10 years remaining to maturity
[52] Less than 1 year, between 6 and 10 years, above 10 years, only 5 years and all maturity levels.
[53] Above 10 years and only 5 years maturity levels

find that maturities of only 5 years and above 10 years have statistically significant pre announcement effects but no significant reaction post announcement. However, in the index -adjusted model based on the investment grade ratings, I find that there is only a negative spread change for the less than 1 year maturity pre-event announcement window of [-5,-1] and [-10,-1]. None of the post event announcement window for both the index-adjusted models shows any statistical significance.

[This section has been intentionally left blank]

Table 4.1 Cumulative Abnormal Spread Returns (CASCs) Around Illegal Events based on CDS maturity level (Market Model)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on CDS maturity level of less than 1 year, between 2 and 5 years, between 6 and 10 years, above 10 years, only 5 years and all levels of maturity over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using a market-model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Market - model CASCs									
All	CASCs (bps)	467	2.2114	**2.9070****	1.1241	**1.0568***	1.2403	2.1667	5.6000
	t-test		(1.2283)	**(2.0245)**	(1.4994)	**(1.776)**	(1.3938)	(1.276)	(1.2343)
	t-test *p*-val		0.2193	**0.0429**	0.1338	**0.0757**	0.1634	0.2020	0.2171
Less than 1 Year	CASCs (bps)	467	-5.1673	**2.1082***	1.0145	**1.5814****	**1.0261***	1.8026	5.2600
	t-test		(-1.5895)	**(1.645)**	(1.2382)	**(2.2263)**	**(1.6832)**	(1.6146)	(1.3765)
	t-test *p*-val		0.1119	**0.1000**	0.2157	**0.0260**	**0.0923**	0.1064	0.1687
Between 2 and 5 Years	CASCs (bps)	466	1.9019	2.6849	1.0723	0.9352	0.9821	1.8255	5.2745
	t-test		(0.9431)	(2.0935)	(1.6324)	(1.8381)	(1.3867)	(1.2474)	(1.2094)
	t-test *p*-val		0.3456	0.0363	0.1026	0.0660	0.1655	0.2123	0.2265
Between 6 and 10 Years	CASCs (bps)	467	3.8235	**2.4064***	1.0374	**1.0696***	1.7661	3.1625	6.7644
	t-test		(1.5283)	**(1.7168)**	(1.3665)	**(1.6889)**	(1.3164)	(1.3003)	(1.3044)
	t-test *p*-val		0.1265	**0.0860**	0.1718	**0.0912**	0.1880	0.1935	0.1921
Above 10 Years	CASCs (bps)	467	**5.0774***	**2.6621***	0.9985	0.9882	1.7382	3.1319	6.9440
	t-test		**(1.776)**	**(1.7999)**	(1.2382)	(1.4723)	(1.2046)	(1.231)	(1.3141)
	t-test *p*-val		**0.0757**	**0.0719**	0.2157	0.1410	0.2284	0.2183	0.1888
Only 5 Years	CASCs (bps)	434	**4.0819***	**3.4827****	1.1187	0.9135	1.2615	2.3708	6.2839
	t-test		**(1.6567)**	**(2.2157)**	(1.4807)	(1.5163)	(1.1963)	(1.1495)	(1.2283)
	t-test *p*-val		**0.0976**	**0.0267**	0.1387	0.1294	0.2316	0.2503	0.2193

Table 4.2 Cumulative Abnormal Spread Returns (CASCs) Around Illegal Events based on CDS maturity level (Index Adjusted Model based on Investment Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on CDS maturity level of less than 1 year, between 2 and 5 years, between 6 and 10 years, above 10 years, only 5 years and all levels of maturity over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using a market-model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Index - adjusted model CASCs based on Investment Grade Ratings									
All	CASCs								
	(bps)	404	0.3297	0.5021	-0.2620	-0.2144	-0.3571	-0.2618	-0.4243
	t-test		(0.2477)	(0.5535)	(-0.7427)	(-0.5941)	(-0.8575)	(-0.3918)	(-0.5838)
	t-test *p*-val		0.8044	0.5799	0.4576	0.5524	0.3912	0.6952	0.5593
Less than 1 Year	CASCs								
	(bps)	402	**-2.5405*****	**-0.8847***	-0.4613	-0.0241	-0.3324	-0.5969	-1.2256
	t-test		**(-3.15)**	**(-1.822)**	(-1.4365)	(-0.0711)	(-0.826)	(-0.9446)	(-1.5604)
	t-test *p*-val		**0.0016**	**0.0685**	0.1509	0.9433	0.4088	0.3449	0.1187
Between 2 and 5 Years	CASCs								
	(bps)	404	0.0174	0.3893	-0.2627	-0.1966	-0.3645	-0.2884	-0.7187
	t-test		(0.0129)	(0.4195)	(-0.7533)	(-0.5473)	(-0.8756)	(-0.4279)	(-0.9615)
	t-test *p*-val		0.9897	0.6749	0.4513	0.5842	0.3813	0.6687	0.3363
Between 6 and 10 Years	CASCs								
	(bps)	402	-0.1486	0.0489	-0.3376	-0.0583	-0.1555	0.1969	0.2648
	t-test		(-0.197)	(0.0923)	(-0.9858)	(-0.1682)	(-0.3869)	(0.3345)	(0.3783)
	t-test *p*-val		0.8439	0.9264	0.3242	0.8664	0.6989	0.7380	0.7052
Above 10 Years	CASCs								
	(bps)	402	0.5198	0.4170	-0.3672	-0.1498	-0.2651	0.1693	0.6718
	t-test		(0.6654)	(0.7394)	(-0.9863)	(-0.3968)	(-0.6086)	(0.2737)	(0.8901)
	t-test *p*-val		0.5058	0.4596	0.3240	0.6915	0.5428	0.7843	0.3734
Only 5 Years	CASCs								
	(bps)	368	1.1477	1.1455	-0.1004	-0.0923	-0.1491	0.0829	-0.1052
	t-test		(0.8035)	(1.2134)	(-0.2858)	(-0.2597)	(-0.3653)	(0.1253)	(-0.1593)
	t-test *p*-val		0.4217	0.2250	0.7750	0.7951	0.7149	0.9003	0.8734

Table 4.3 Cumulative Abnormal Spread Returns (CASCs) Around Illegal Events based on CDS maturity level (Index Adjusted Model based on Speculative Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on CDS maturity level of less than 1 year, between 2 and 5 years, between 6 and 10 years, above 10 years, only 5 years and all levels of maturity over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using a market-model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Index - adjusted model CASCs based on Speculative Grade Ratings									
All	CASCs (bps)	33	-61.8609	-12.8976	0.8672	7.3826	17.4896	44.5647	85.5277
	t-test		(-1.0271)	(-1.0593)	(0.0935)	(0.8045)	(0.8259)	(0.9085)	(0.9591)
	t-test *p*-val		0.3044	0.2895	0.9255	0.4211	0.4089	0.3636	0.3375
Less than 1 Year	CASCs (bps)	33	-139.0141	-12.9152	0.0383	12.4300	13.6673	43.6252	84.9165
	t-test		(-1.5869)	(-0.6867)	(0.0047)	(1.2233)	(0.9482)	(1.0807)	(1.002)
	t-test *p*-val		0.1125	0.4923	0.9963	0.2212	0.3430	0.2798	0.3164
Between 2 and 5 Years	CASCs (bps)	33	-63.0424	-15.7365	-0.5896	4.7305	12.6749	37.4036	81.2955
	t-test		(-0.9306)	(-1.0055)	(-0.0583)	(0.5529)	(0.6766)	(0.8189)	(0.9356)
	t-test *p*-val		0.3521	0.3147	0.9535	0.5803	0.4986	0.4129	0.3495
Between 6 and 10 Years	CASCs (bps)	33	-28.3410	-10.6259	2.2227	7.3017	23.1181	50.9760	89.0477
	t-test		(-0.512)	(-1.4325)	(0.2394)	(0.7652)	(0.8702)	(0.9067)	(0.9546)
	t-test *p*-val		0.6086	0.1520	0.8108	0.4441	0.3842	0.3645	0.3398
Above 10 Years	CASCs (bps)	33	-15.8646	-9.4740	3.2540	7.7204	25.3127	53.4151	91.0833
	t-test		(-0.3256)	(-1.3992)	(0.3584)	(0.7917)	(0.9069)	(0.9219)	(0.9661)
	t-test *p*-val		0.7448	0.1617	0.7201	0.4285	0.3645	0.3566	0.3340
Only 5 Years	CASCs (bps)	33	-45.5162	-11.7073	0.4547	5.7417	16.9017	43.2607	85.1354
	t-test		(-0.7485)	(-1.1652)	(0.048)	(0.6373)	(0.7646)	(0.857)	(0.9536)
	t-test *p*-val		0.4542	0.2440	0.9617	0.5239	0.4445	0.3914	0.3403

4.4.2 Market reaction by fines per market cap

In this section, I examine the impacts of different illegalities of firms based on i) high fines per market cap (80^{th} to 100^{th} percentile) and ii) low fines per market cap (0 to 20^{th} percentile). The results in table 4.4 on the CDS spread changes confirms my hypothesis that the CDS market would increase spreads for firms with higher fines per market cap compared to lower fines per market cap. As observed for the high fines per market cap firms, in the market model in Panel A, there are increases of +0.3 basis points and +0.4 basis points at the [0,1] and [0,2] event windows respectively. Additionally, even firms with higher investment grade ratings (Panel B) witness an increases in spreads of +0.4 basis points at the [0,2] event window. However, I do not find any post event CDS market reaction to the speculative grade rating model. In line with expectations, the lower fines per market cap do not exhibit any statistical significance. Even though, the increase in spreads is marginal, these results show that the CDS market reacts more to firms with higher fines per market cap.

When examining the stock market results, one would also expect stock investors to react negatively to fines. The results in table 4.5, confirm my hypothesis that in the short-term there is also larger negative returns to firms with higher fines per market cap compared to lower fines per market cap. As seen in the market model (panel A) and in the market-adjusted model (panel B), the stock immediately decreases in returns in the [0,1] and [0,2],[0,5] event window respectively. Surprisingly, in the market model in panel A I find that firms with lower fines per market cap actually have positive returns. This result indicates that firm losses in share value are dependent on the size of the fine in perspective to size of the firm. In short, it can be observed that stock investors are taking into account the size of the fine when reacting to illegality news.

Table 4.4 Cumulative Abnormal Spread Returns (CASCs) Around Illegal Events based on Fines per Market Cap (Market, Index Adjusted Model based on Investment and Speculative Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on low fines per market cap and high fines per market cap over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using a market-model (Panel A), Index Adjusted Investment Grade model (Panel B) and Speculative Grade model (Panel C). N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Panel A: Market - model CASCs									
Low Fines per Market Cap (0 to 20th Percentile)	CASCs (bps)	277	0.0343	-0.3191	-0.0406	-0.1595	-0.1851	-0.3465	-0.3948
	t-test		(0.0954)	(-1.2538)	(-0.252)	(-0.5248)	(-0.5876)	(-0.8985)	(-1.1763)
	t-test *p*-val		0.9240	0.2099	0.8010	0.5997	0.5568	0.3689	0.2395
High Fines per Market Cap (80th to 100th Percentile)	CASCs (bps)	352	0.1905	0.3375	0.2524	**0.2547***	**0.3670***	0.1910	-0.0208
	t-test		(0.4904)	(1.2612)	(1.48)	**(1.7116)**	**(1.8021)**	(0.7287)	(-0.0487)
	t-test *p*-val		0.6239	0.2072	0.1389	**0.0870**	**0.0715**	0.4662	0.9611
Panel B: Index - adjusted model CASCs based on Investment Grade Ratings									
Low Fines per Market Cap (0 to 20th Percentile)	CASCs (bps)	273	0.0500	-0.3719	-0.0524	-0.2028	-0.2005	-0.4249	-0.3854
	t-test		(0.1564)	(-1.4624)	(-0.2814)	(-0.5984)	(-0.5745)	(-0.997)	(-1.0473)
	t-test *p*-val		0.8757	0.1436	0.7784	0.5496	0.5657	0.3188	0.2949
High Fines per Market Cap (80th to 100th Percentile)	CASCs (bps)	201	0.2482	**0.5307****	0.1382	0.2219	**0.3719***	0.2098	-0.1559
	t-test		(0.5661)	**(1.9709)**	(0.7963)	(1.4247)	**(1.6522)**	(0.7439)	(-0.3191)
	t-test *p*-val		0.5713	**0.0487**	0.4259	0.1542	**0.0985**	0.4570	0.7496
Panel C: Index - adjusted model CASCs based on Speculative Grade Ratings									
Low Fines per Market Cap (0 to 20th Percentile)	CASCs (bps)	16	**-1.7692****	**-1.4265***	-0.0984	0.4612	-0.2173	0.8731	-0.1193
	t-test		**(-2.2092)**	**(-1.7429)**	(-1.3818)	(1.2737)	(-0.2025)	(0.8121)	(-0.0907)
	t-test *p*-val		**0.0272**	**0.0814**	0.1670	0.2028	0.8395	0.4168	0.9278
High Fines per Market Cap (80th to 100th Percentile)	CASCs (bps)	17	-1.0469	**-2.0160***	0.9289	0.6042	0.4390	1.0233	1.6199
	t-test		(-0.9987)	**(-1.8327)**	(1.1542)	(0.7527)	(0.5101)	(1.3692)	(1.554)
	t-test *p*-val		0.3180	**0.0668**	0.2484	0.4516	0.6100	0.1710	0.1202

Table 4.5 Cumulative Abnormal Returns (CARs) around Illegal Events based on Fines per Market Cap (Market-model and Market-adjusted)

The table below provides the cumulative abnormal returns (CARs) around illegal events based on low fines per market cap and high fines per market cap over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal returns are calculated using a market-model (Panel A) and market-adjusted model (Panel B). N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Panel A: Market - model CARs									
Low Fines per Market Cap (0 to 20th Percentile)	CARs (in %)	277	-0.0028	**0.0051***	0.0047	**0.0075***	**0.0074***	-0.0062	0.0007
	t-test		(-0.5909)	**(1.8076)**	(1.2002)	**(1.7947)**	**(1.7515)**	(-0.8346)	(0.0782)
	t-test *p*-val		0.5546	**0.0707**	0.2301	**0.0727**	**0.0799**	0.404	0.9377
High Fines per Market Cap (80th to 100th Percentile)	CARs (in %)	352	0.0025	0.0011	-0.0013	**-0.0027***	-0.0016	-0.0028	-0.0008
	t-test		(0.5911)	(0.3694)	(-0.7816)	**(-1.792)**	(-0.954)	(-1.1463)	(-0.2443)
	t-test *p*-val		0.5544	0.7118	0.4344	**0.0731**	0.3401	0.2517	0.807
Panel B: Market- adjusted model CARs									
Low Fines per Market Cap (0 to 20th Percentile)	CARs (in %)	277	-0.0079	0.0009	0.0036	0.0055	0.0044	-0.012	-0.0082
	t-test		(-1.3668)	(0.2956)	(0.9032)	(1.3122)	(1.0265)	(-1.4898)	(-0.8063)
	t-test *p*-val		0.1717	0.7675	0.3664	0.1895	0.3047	0.1363	0.4200
High Fines per Market Cap (80th to 100th Percentile)	CARs (in %)	352	0.0039	0.0002	-0.001	-0.0028	**-0.0039***	**-0.0053***	-0.0046
	t-test		(0.8375)	(0.0732)	(-0.5962)	(-1.6078)	**(-1.8656)**	**(-1.824)**	(-1.1132)
	t-test *p*-val		0.4023	0.9416	0.5511	0.1079	**0.0621**	**0.0681**	0.2656

4.4.3 Market reaction by stages of legal process

Here, I examine the impact of illegalities by the different legal stages on both CDS spreads and stock returns. I have three different categories i) Pending, ii) Confirmed but pending other matters (CVPM) and iii) Confirmed.

The findings here are unusual, as pursuant to the results in table 4.6, I do not find as per my hypothesis that the pending stage for CDS has increases in spreads. In the market model, it is the confirmed stage which has an increase in spread of +2.1 basis points at the [0,1] event window. In the investment grade model, the pending stage has a significant negative change at the [0,1] and [0,2] event window with-1.6 basis and -1.6 basis points respectively. The CVPM has an increase in spread at the [0,1], [0,2] and [0,3] event window with +1.1, +1.0 and +1.4 basis points respectively. Subsequently, when the fine is at the CVPM and confirmed stage, the CDS market then reacts to the announcements with an increase in spreads to cover for any further losses. I find no statistically significant results after announcements for the index-adjusted speculative grade model as per table 4.7.

On the stock market results, the CAR as per table 4.8 supports my hypothesis as in the market adjusted model, I find significant negative return at the pending stage in the [0,5] event window. In the market-model, I find a significant positive return at the confirmed stage in both [0,5] and [0,10] event window which is also as expected.

Table 4.6 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on legal stages of illegalities (Market –model and Index Adjusted Model based on Investment Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) and cumulative abnormal returns (CARs) around illegal events based on three (Pending, Confirmed but Pending other Matters and Confirmed) legal stages of illegalities over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using a market-model (Panel A), an index-adjusted model based on investment grade ratings (Panel B). N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		N	(-10,-1)	(-5,-1)	(-1,0)	(0,1)	(0,2)	(0,5)	(0,10)
Panel A: Market - model CASCs									
Pending	CASCs (bps)	180	4.1894	3.7773	1.4613	0.4198	0.2263	1.4569	0.7397
	t-test		(1.0146)	(1.4236)	(1.0157)	(0.4234)	(0.2203)	(0.8014)	(0.434)
	t-test *p*-val		0.3103	0.1545	0.3098	0.672	0.8257	0.4229	0.6643
Confirmed but Pending other Matters	CASCs (bps)	119	0.9675	0.9062	-0.2166	0.5752	0.3177	0.2781	-0.5982
	t-test		(0.8263)	(1.1833)	(-0.5511)	(1.5618)	(0.7679)	(0.3912)	(-0.5316)
	t-test *p*-val		0.4086	0.2367	0.5816	0.1183	0.4426	0.6956	0.595
Confirmed	CASCs (bps)	173	1.0392	3.4559	1.7733	**2.0631***	2.9884	4.3816	15.1618
	t-test		(0.4818)	(1.3141)	(1.3481)	**(1.7028)**	(1.3665)	(1.0178)	(1.2276)
	t-test *p*-val		0.63	0.1888	0.1776	**0.0886**	0.1718	0.3088	0.2196
Panel B: Index - adjusted model CASCs based on Investment Grade Ratings									
Pending	CASCs (bps)	161	1.5252	1.9311	-0.8065	**-1.6354****	**-1.5615****	-0.9512	-0.8694
	t-test		(0.518)	(0.9671)	(-1.2)	**(-2.3459)**	**(-1.9992)**	(-0.6912)	(-0.5881)
	t-test *p*-val		0.6045	0.3335	0.2301	**0.019**	**0.0456**	0.4895	0.5565
Confirmed but Pending other Matters	CASCs (bps)	101	0.4276	-0.1958	-0.1683	**1.0965*****	**0.9398****	**1.4398****	1.266
	t-test		(0.2227)	(-0.1461)	(-0.2395)	**(2.8944)**	**(2.1656)**	**(2.306)**	(1.5608)
	t-test *p*-val		0.8238	0.8838	0.8107	**0.0038**	**0.0303**	**0.0211**	0.1186
Confirmed	CASCs (bps)	142	-1.0954	-0.6218	0.2887	0.4643	0.086	-0.6903	-1.122
	t-test		(-0.9406)	(-0.785)	(0.6865)	(0.7978)	(0.1201)	(-0.6978)	(-1.054)
	t-test *p*-val		0.3469	0.4324	0.4924	0.425	0.9044	0.4853	0.2919

Table 4.7 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on legal stages of illegalities (Index Adjusted Model based on Speculative Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on three (Pending, Confirmed but Pending other Matters and Confirmed) legal stages of illegalities over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using an index-adjusted model based on speculative grade ratings (Panel C). N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Panel A: Index - adjusted model CASCs based on Speculative Grade Ratings									
Pending	CASCs (bps)	12	-58.1692	-15.5115	-2.5319	-8.7861	-11.1516	-16.1411	8.8128
	t-test		(-1.0414)	(-0.8244)	(-0.7035)	(-1.3161)	(-1.1886)	(-1.1509)	(0.7316)
	t-test *p*-val		0.2977	0.4097	0.4818	0.1882	0.2346	0.2498	0.4644
Confirmed but Pending other Matters	CASCs (bps)	7	**-4.8138***	-1.2214	1.1907	-0.1705	-0.0188	0.3662	-1.5854
	t-test		**(-1.6526)**	(-0.5585)	(0.3911)	(-0.0351)	(-0.0039)	(0.0617)	(-0.3003)
	t-test *p*-val		**0.0984**	0.5765	0.6957	0.972	0.9969	0.9508	0.7639
Confirmed	CASCs (bps)	14	-93.5488	-16.4953	3.6188	25.0181	50.7934	118.6976	194.8399
	t-test		(-0.6991)	(-0.6943)	(0.1674)	(1.2094)	(1.0327)	(1.0328)	(0.9279)
	t-test *p*-val		0.4845	0.4875	0.8671	0.2265	0.3017	0.3017	0.3535

Table 4.8 Cumulative Abnormal Returns (CARs) around Illegal Events based on industry categories (Market-model and Market-adjusted)

The table below provides the cumulative abnormal returns (CARs) around illegal events based on three (Pending, Confirmed but Pending other Matters and Confirmed) legal stages of illegalities over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal returns are calculated using a market-model (Panel A) and market-adjusted model (Panel B). N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Panel A: Market - model CARs									
Pending	CARs (in %)	180	0.0026	0.001	-0.0005	0.0002	0.0000	-0.0043	-0.0019
	t-test		(0.739)	(0.3825)	(-0.2092)	(0.0946)	(-0.0016)	(-1.0635)	(-0.3613)
	t-test p-val		0.4599	0.7021	0.8343	0.9246	0.9987	0.2876	0.7179
Confirmed but Pending other Matters	CARs (in %)	119	-0.0027	**-0.0062*****	-0.0001	0.0007	0.001	-0.0011	-0.0044
	t-test		(-0.7952)	**(-2.9129)**	(-0.0724)	(0.4669)	(0.6333)	(-0.4984)	(-1.4209)
	t-test p-val		0.4265	**0.0036**	0.9423	0.6406	0.5265	0.6182	0.1553
Confirmed	CARs (in %)	173	**0.0078***	0.0033	0.0023	0.0021	0.0027	**0.0047***	0.0113
	t-test		**(1.9511)**	(1.3522)	(1.2336)	(1.1104)	(1.131)	**(1.6501)**	(2.6048)
	t-test p-val		**0.051**	0.1763	0.2173	0.2668	0.2581	**0.0989**	0.0092
Panel B: Market- adjusted model CARs									
Pending	CARs (in %)	180	0.0017	-0.0019	-0.0008	-0.0016	-0.003	**-0.0098****	-0.0079
	t-test		(0.401)	(-0.6981)	(-0.3438)	(-0.7758)	(-1.1628)	**(-2.2607)**	(-1.4133)
	t-test p-val		0.6884	0.4851	0.731	0.4379	0.2449	**0.0238**	0.1576
Confirmed but Pending other Matters	CARs (in %)	119	-0.0029	**-0.0083*****	-0.0024	-0.0006	-0.0008	-0.0032	-0.005
	t-test		(-0.7209)	**(-2.847)**	(-1.2354)	(-0.3035)	(-0.3952)	(-1.1409)	(-1.2303)
	t-test p-val		0.471	**0.0044**	0.2167	0.7615	0.6927	0.2539	0.2186
Confirmed	CARs (in %)	173	0.0044	0.0016	0.0004	0.0003	-0.0004	0.0002	0.0032
	t-test		(1.0842)	(0.6024)	(0.1893)	(0.1637)	(-0.1424)	(0.0701)	(0.6969)
	t-test p-val		0.2783	0.5469	0.8498	0.8699	0.8868	0.9441	0.4858

4.4.4 Market reaction by industry

In this section, I analyze the impact of illegalities on different industries on both CDS spreads and stock returns. I have seven different industry categories i) mining, ii) manufacturing, iii) transportation & public utilities, iv) wholesale trade, v) retail trade, vi) finance, insurance and real estate and vii) services.

Overall, I find supporting evidence in respect to both hypothesis 5a and 5b. Tables 4.9 to table 4.11 report the results of the cumulative abnormal spread changes (CASC) response and tables 4.12 to 4.13 report the cumulative abnormal returns (CAR) to illegalities. Following the assumption that illegalities would drive CDS prices to rise, at both market and speculative grade model, I find only the mining industry CASC post announcement results has an increase in spreads with statistically significant results. In the market model, this is quite evident with increases on all the post announcement event windows of approximately between +4.9 and +7.3 basis points It is important to note that for lower quality credit ratings in the mining sector, the increase in spreads is larger between +9.8 basis points and +12.9 basis points for the [0,1],[0,2] and [0,5] announcement windows. I find no statistical significance in the index adjusted model based on the investment grade ratings. This shows that investors in the CDS market react negatively to illegalities in the mining industry, and even more so on firms with lower grade credit ratings.

On the other hand, I observe that the services, wholesale trade, transportation & public utilities and surprisingly the finance industry have decreases in CDS spreads. In the market-model, services industry is significantly negative at the event window [0,5]. In the index-adjusted model based on investment grade ratings, I find significantly negative results for wholesale trade and finance, insurance and real estate at the event window [0,2] and [0,10] respectively. In the index-adjusted model based on speculative grade ratings, I find transportation and public utilities to have significantly negative results at the [0,10] event window.

On the stock market, examining the market-model CAR post announcement results, I find that it is only the manufacturing industry which has a short-term reaction to announcements of fines. There is significantly negative CAR at the [0,5] and [0,10] event window and at the [0,2] [0,5] and [0,10] event window in the market and market-adjusted model respectively. On the other hand, the mining, transportation & public utilities and finance, insurance and real estate exhibit increases in share prices.

Comparing the CASC and CAR results, it is observed that investors in both the CDS and stock market react differently in industries. Norden and Weber, (2004) argue that both markets do not react identically because stocks and CDS differ in several ways (i.e. cash vs derivatives, risk-return profile, exchange vs over the counter, market participant structure, etc.). This further supports Wengner et al.,(2015) and Jorion and Zhang (2007) that CDS market reaction should not be generalized but should rather be examined on an industry level.

[This section has been intentionally left blank]

Table 4.9 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on industry categories (Market – model)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on seven (Mining, Manufacturing, Transportation & Public Utilities, Wholesale Trade, Retail Trade, Finance, Insurance and Real Estate and Services) industry categories over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using a market-model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Market - model CASCs									
Mining	CASCs (bps)	27	1.6727	2.5449	1.4447	**4.9503****	**5.4983****	**7.3339*****	**6.4554***
	t-test		(0.4105)	(1.0056)	(0.9045)	**(2.4489)**	**(2.3777)**	**(2.7303)**	**(1.6739)**
	t-test *p*-val		0.6815	0.3146	0.3657	**0.0143**	**0.0174**	**0.0063**	**0.0942**
Manufacturing	CASCs (bps)	247	2.3262	**4.0885***	1.7849	1.6021	2.1125	3.9697	11.6202
	t-test		(1.0467)	**(1.9162)**	(1.3687)	(1.5646)	(1.3028)	(1.2443)	(1.3463)
	t-test *p*-val		0.2952	**0.0553**	0.1711	0.1177	0.1926	0.2134	0.1782
Transportation & Public Utilities	CASCs (bps)	66	-0.662	-0.0487	-0.3661	0.3345	-0.2171	-0.7687	-1.6565
	t-test		(-0.7036)	(-0.1023)	(-0.7577)	(0.7038)	(-0.272)	(-0.4598)	(-0.6713)
	t-test *p*-val		0.4817	0.9185	0.4486	0.4815	0.7856	0.6457	0.502
Wholesale Trade	CASCs (bps)	11	1.565	-0.3119	0.5592	-4.2295	-3.6461	-2.9214	0.6446
	t-test		(0.5833)	(-0.1433)	(0.418)	(-0.6984)	(-0.5859)	(-0.3832)	(0.0805)
	t-test *p*-val		0.5597	0.8861	0.676	0.4849	0.5579	0.7016	0.9359
Retail Trade	CASCs (bps)	27	**6.6309***	4.2396	0.6885	-0.3751	-0.5733	0.1068	0.5074
	t-test		**(1.651)**	(1.4186)	(0.7084)	(-1.0584)	(-0.8826)	(0.1597)	(0.4094)
	t-test *p*-val		**0.0987**	0.156	0.4787	0.2899	0.3775	0.8731	0.6823
Finance, Insurance and Real Estate	CASCs (bps)	87	3.34	2.3278	0.7918	0.0537	-0.0496	-0.3225	-3.2334
	t-test		(0.4704)	(0.5215)	(0.6067)	(0.0702)	(-0.0566)	(-0.2308)	(-1.5894)
	t-test *p*-val		0.6381	0.602	0.5441	0.944	0.9549	0.8175	0.112
Services	CASCs (bps)	6	-2.4806	**-1.1232****	**-1.1799***	-0.1007	-0.5805	**-3.5887*****	-0.8108
	t-test		(-0.7855)	**(-2.2508)**	**(-1.8684)**	(-0.1459)	(-1.2909)	**(-2.7296)**	(-0.3115)
	t-test *p*-val		0.4322	**0.0244**	**0.0617**	0.884	0.1967	**0.0063**	0.7554

Table 4.10 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on industry categories (Investment Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on seven (Mining, Manufacturing, Transportation & Public Utilities, Wholesale Trade, Retail Trade, Finance, Insurance and Real Estate and Services) industry categories over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using an Index - adjusted model based on Investment Grade Ratings. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Index - adjusted model CASCs based on Investment Grade Ratings									
Mining	CASCs (bps)	20	-2.6689	0.1897	-1.1985	-0.2848	0.1807	0.9188	1.4373
	t-test		(-1.1976)	(0.1393)	(-0.9358)	(-0.2058)	(0.1654)	(0.7497)	(0.4294)
	t-test *p*-val		0.2311	0.8892	0.3494	0.8369	0.8686	0.4534	0.6676
Manufacturing	CASCs (bps)	217	0.0391	0.5066	-0.19	-0.0986	-0.2442	0.2541	0.6285
	t-test		(0.049)	(0.9352)	(-0.4185)	(-0.2424)	(-0.5033)	(0.3407)	(0.7278)
	t-test *p*-val		0.9609	0.3497	0.6756	0.8084	0.6148	0.7333	0.4668
Transportation & Public Utilities	CASCs (bps)	58	-0.7639	0.2632	-0.182	0.0338	0.575	0.8182	1.0062
	t-test		(-1.0685)	(0.5829)	(-0.5684)	(0.0766)	(1.1006)	(1.1358)	(1.0472)
	t-test *p*-val		0.2853	0.56	0.5698	0.9389	0.2711	0.256	0.295
Wholesale Trade	CASCs (bps)	7	0.0653	-0.7457	**-0.5557****	-0.6802	**-0.9378***	0.2045	0.5344
	t-test		(0.0263)	(-0.2802)	**(-2.4889)**	(-1.5206)	**(-1.745)**	(0.1125)	(0.503)
	t-test *p*-val		0.979	0.7793	**0.0128**	0.1284	**0.081**	0.9104	0.6149
Retail Trade	CASCs (bps)	18	10.1112	6.3686	1.6499	0.0304	-0.0439	1.6465	2.9813
	t-test		(1.4139)	(1.2842)	(1.0646)	(0.0544)	(-0.0451)	(1.0635)	(1.5486)
	t-test *p*-val		0.1574	0.1991	0.2871	0.9566	0.964	0.2875	0.1215
Finance, Insurance and Real Estate	CASCs (bps)	81	0.623	-0.2418	-0.7751	-0.7957	-1.5937	-3.229	**-5.7044****
	t-test		(0.1031)	(-0.0587)	(-0.6677)	(-0.5883)	(-1.0374)	(-1.261)	**(-2.2944)**
	t-test *p*-val		0.9179	0.9532	0.5043	0.5563	0.2996	0.2073	**0.0218**
Services	CASCs (bps)	3	-3.5116	-5.3296	2.2941	2.3906	2.7338	1.2502	3.2459
	t-test		(-0.7696)	(-1.0695)	(1.092)	(1.1105)	(1.226)	(0.3546)	(1.2172)
	t-test *p*-val		0.4415	0.2849	0.2748	0.2668	0.2202	0.7229	0.2235

Table 4.11 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on industry categories (Index Adjusted Model based on Speculative Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on six (Mining, Manufacturing, Transportation & Public Utilities, Wholesale Trade, Retail Trade, Finance, Insurance and Real Estate) industry categories over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using an Index - adjusted model based on Speculative Grade Ratings. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Index - adjusted model CASCs based on Speculative Grade Ratings									
	CASCs (bps)	7	-2.9358	3.675	2.7826	**9.7800****	**10.0548***	**12.8469***	6.7783
Mining	t-test		(-0.526)	(0.6079)	(0.8281)	**(2.1227)**	**(1.6741)**	**(1.7015)**	(0.8449)
	t-test *p*-val		0.5989	0.5433	0.4076	**0.0338**	**0.0941**	**0.0888**	0.3982
	CASCs (bps)	6	-326.2115	-81.1312	4.4974	41.867	97.5302	249.0491	478.5759
Manufacturing	t-test		(-0.9852)	(-1.2246)	(0.0889)	(0.8519)	(0.8425)	(0.9254)	(0.9766)
	t-test *p*-val		0.3245	0.2207	0.9292	0.3943	0.3995	0.3548	0.3288
	CASCs (bps)	4	3.6619	0.7333	-5.1343	-3.1406	0.3483	3.4966	**-13.584***
Transportation & Public Utilities	t-test		(0.7194)	(0.2606)	(-1.042)	(-1.484)	(0.2126)	(1.0743)	**(-1.9445)**
	t-test *p*-val		0.4719	0.7944	0.2974	0.1378	0.8316	0.2827	**0.0518**
	CASCs (bps)	4	-3.7343	-2.0298	2.7269	-8.8475	-6.8582	-2.7852	7.058
Wholesale Trade	t-test		(-0.5989)	(-1.2583)	(0.8791)	(-0.6232)	(-0.4697)	(-0.1484)	(0.337)
	t-test *p*-val		0.5493	0.2083	0.3793	0.5332	0.6386	0.882	0.7361
	CASCs (bps)	10	-2.989	4.7902	0.8699	-1.1928	-2.5469	-5.6213	-5.1149
Retail Trade	t-test		(-0.8377)	(1.1677)	(0.3668)	(-0.4677)	(-0.7569)	(-0.7844)	(-0.8341)
	t-test *p*-val		0.4022	0.2429	0.7138	0.64	0.4491	0.4328	0.4042
	CASCs (bps)	2	-3.7186	3.5906	-0.6583	-3.3222	-4.9416	-17.106	-6.4801
Finance, Insurance and Real Estate	t-test		(-1.3375)	(1.0499)	(-0.3163)	(-1.471)	(-1.4705)	(-1.2579)	(-0.7181)
	t-test *p*-val		0.1811	0.2938	0.7518	0.1413	0.1414	0.2084	0.4727

Table 4.12 Cumulative Abnormal Returns (CARs) around Illegal Events based on industry categories (Market–model)

The table below provides the cumulative abnormal returns (CARs) around illegal events based on seven (Mining, Manufacturing, Transportation & Public Utilities, Wholesale Trade, Retail Trade, Finance, Insurance and Real Estate and Services) industry categories over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal returns are calculated using a market-model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Market - model CARs									
Mining	CARs (in %)	27	-0.011	**-0.0096****	-0.0019	-0.0004	0.0014	-0.0012	**0.0164***
	t-test		(-1.5536)	**(-1.6896)**	(-0.5148)	(-0.1094)	(0.3305)	(-0.2208)	**(1.9111)**
	t-test *p*-val		0.1203	**0.0911**	0.6067	0.9129	0.7411	0.8253	**0.056**
Manufacturing	CARs (in %)	247	0.0016	**-0.0032***	-0.0018	-0.0001	-0.0014	**-0.0058***	**-0.0068***
	t-test		(0.5271)	**(-1.6488)**	(-1.0891)	(-0.036)	(-0.6935)	**(-1.8904)**	**(-1.8107)**
	t-test *p*-val		0.5981	**0.0992**	0.2761	0.9713	0.488	**0.0587**	**0.0702**
Transportation & Public Utilities	CARs (in %)	66	**0.0069***	0.0019	**0.0034****	0.0035	0.0048	0.0056	**0.0081***
	t-test		**(1.8159)**	(0.7394)	**(2.0303)**	(1.0497)	(1.4368)	(1.5323)	**(1.6866)**
	t-test *p*-val		**0.0694**	0.4597	**0.0423**	0.2939	0.1508	0.1254	**0.0917**
Wholesale Trade	CARs (in %)	11	0.01	0.0063	0.0021	0.0056	0.0048	-0.0024	0.0011
	t-test		(0.808)	(0.5425)	(0.2606)	(0.7826)	(0.7115)	(-0.4159)	(0.1049)
	t-test *p*-val		0.4191	0.5875	0.7944	0.4338	0.4767	0.6775	0.9164
Retail Trade	CARs (in %)	27	0.0132	0.0014	0.0006	-0.0031	-0.0033	0.0019	0.0105
	t-test		(1.6053)	(0.2536)	(0.2158)	(-0.9257)	(-0.8272)	(0.3842)	(1.315)
	t-test *p*-val		0.1084	0.7998	0.8292	0.3546	0.4081	0.7009	0.1885
Finance, Insurance and Real Estate	CARs (in %)	87	0.0018	**0.0064***	**0.0036***	0.0023	**0.0057****	**0.0084****	**0.0137****
	t-test		(0.3345)	**(1.722)**	**(1.8065)**	(0.9739)	**(2.0115)**	**(2.333)**	**(2.4448)**
	t-test *p*-val		0.738	**0.0851**	**0.0708**	0.3301	**0.0443**	**0.0196**	**0.0145**
Services	CARs (in %)	6	0.0275	0.016	0.0126	0.0056	0.0062	0.012	0.0156
	t-test		(1.0484)	(1.1587)	(0.812)	(0.6175)	(0.5242)	(0.6264)	(0.4783)
	t-test *p*-val		0.2944	0.2466	0.4168	0.5369	0.6002	0.531	0.6324

Table 4.13 Cumulative Abnormal Returns (CARs) around Illegal Events based on industry categories (Market-adjusted model)

The table below provides the cumulative abnormal returns (CARs) around illegal events based on seven (Mining, Manufacturing, Transportation & Public Utilities, Wholesale Trade, Retail Trade, Finance, Insurance and Real Estate and Services) industry categories over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal returns are calculated using a market-adjusted model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Market- adjusted model CARs									
Mining	CARs (in %)	27	-0.0099	**-0.0099****	-0.0016	-0.001	-0.0006	-0.0051	0.0125
	t-test		(-1.4279)	**(-1.6977)**	(-0.4491)	(-0.256)	(-0.1264)	(-0.9588)	(1.4047)
	t-test *p*-val		0.1533	**0.0896**	0.6534	0.7979	0.8994	0.3376	0.1601
Manufacturing	CARs (in %)	247	0.0000	**-0.0053****	**-0.0031***	-0.0015	**-0.004***	**-0.0104*****	**-0.0126*****
	t-test		(0.0082)	**(-2.2692)**	**(-1.6982)**	(-0.9262)	**(-1.8786)**	**(-3.0561)**	**(-2.9445)**
	t-test *p*-val		0.9935	**0.0233**	**0.0895**	0.3544	**0.0603**	**0.0022**	**0.0032**
Transportation & Public Utilities	CARs (in %)	66	0.0073	-0.0007	0.0011	-0.0001	0.0008	0.0024	0.0061
	t-test		(1.2522)	(-0.2106)	(0.4631)	(-0.015)	(0.2104)	(0.5054)	(1.0123)
	t-test *p*-val		0.2105	0.8332	0.6433	0.988	0.8334	0.6133	0.3114
Wholesale Trade	CARs (in %)	11	0.0027	0.0018	0.0031	0.0063	0.0033	-0.008	-0.0048
	t-test		(0.1944)	(0.1244)	(0.3753)	(0.7467)	(0.3961)	(-0.8459)	(-0.349)
	t-test *p*-val		0.8458	0.901	0.7074	0.4553	0.692	0.3976	0.7271
Retail Trade	CARs (in %)	27	0.0082	-0.003	-0.0042	-0.0063	-0.0061	-0.0044	0.0045
	t-test		(0.9077)	(-0.5016)	(-0.9635)	(-1.5562)	(-1.3365)	(-0.763)	(0.4484)
	t-test *p*-val		0.364	0.616	0.3353	0.1197	0.1814	0.4455	0.6538
Finance, Insurance and Real Estate	CARs (in %)	87	-0.0018	0.004	0.0029	0.0016	0.0035	0.0052	0.0069
	t-test		(-0.3428)	(1.0948)	(1.4991)	(0.657)	(1.1937)	(1.351)	(1.161)
	t-test *p*-val		0.7318	0.2736	0.1338	0.5112	0.2326	0.1767	0.2456
Services	CARs (in %)	6	0.0276	0.0153	0.0097	0.0031	0.0021	0.0064	0.0045
	t-test		(1.2645)	(1.292)	(0.6569)	(0.395)	(0.207)	(0.398)	(0.154)
	t-test *p*-val		0.2061	0.1964	0.5112	0.6929	0.836	0.6906	0.8776

4.4.5 Market reaction by ESG plus LT

Finally, in this section I analyze the impact of illegalities on ESG plus LT issues on both the CDS and stock market. Refer to table 4.14 to table 4.18 for the results of the CASC and CAR on each individual E,S,G and LT issue. Overall, I find supporting evidence in respect to both hypothesis 6a and 6b. Reviewing the market model for the CASC post event, I find environment to have a significantly positive change of +2.9 basis points at [0,1] event window and governance a +2.0 basis points change at [0,5] event window. On the other hand, the CDS market reacts positively to long-term illegalities with LT having a significantly negative change of -1.6 and – 3.3 basis points at the [0,2] and [0,5] event window. These results are also only robust to the market-model and when an index adjusted model is used, I find no significant reactions in any of the E,S,G or LT issue post announcement.

The CAR results indicate that in the market-model post announcement, only LT is significantly positive at both [0,1] and [0,2] event window. In the market-adjusted model, I find significantly negative reactions for environment at the [0,1] and [0,1] event window and also for social at the [0,5] event window.

[This section has been intentionally left blank]

Table 4.14 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on ESG and LT issues (Market–model)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on Environmental, Social, Governance and Long-Term issues over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using a market-model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Market - model CASCs									
	CASCs (bps)	164	3.7508	**6.0346****	2.4392	**2.8983****	3.8896	7.3502	19.6496
Environment	t-test		(1.1255)	**(1.8838)**	(1.2418)	**(1.8639)**	(1.5881)	(1.5359)	(1.5159)
	t-test *p*-val		0.2604	**0.0596**	0.2143	**0.0623**	0.1123	0.1246	0.1295
	CASCs (bps)	105	-0.0387	0.5319	0.2041	-0.0594	-0.1186	-0.2003	-0.6669
Social	t-test		(-0.0319)	(0.6783)	(0.5865)	(-0.2194)	(-0.3198)	(-0.2939)	(-0.569)
	t-test *p*-val		0.9746	0.4976	0.5575	0.8263	0.7491	0.7688	0.5693
	CASCs (bps)	101	**-2.5924****	-0.9824	0.3156	1.1897	1.2591	**1.9845***	-0.1225
Governance	t-test		**(-2.1849)**	(-1.1891)	(0.4835)	(1.5901)	(1.4662)	**(1.7423)**	(-0.0868)
	t-test *p*-val		**0.0289**	0.2344	0.6287	0.1118	0.1426	**0.0815**	0.9308
	CASCs (bps)	101	6.9182	4.3154	0.8804	-0.8948	**-1.5849****	**-3.3255****	**-4.6568****
Long-Term	t-test		(1.137)	(1.1301)	(0.8496)	(-1.289)	**(-1.9857)**	**(-2.273)**	**(-2.1881)**
	t-test *p*-val		0.2555	0.2584	0.3955	0.1974	**0.0471**	**0.023**	**0.0287**

Table 4.15 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on ESG and LT issues (Investment Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on Environmental, Social, Governance and Long-Term issues over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using an index-adjusted model based on investment grade ratings. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Index - adjusted model CASCs based on Investment Grade Ratings									
	CASCs (bps)	146	-0.9214	0.8533	**-1.1864****	-0.9108	-1.0363	-0.2204	0.5346
Environment	t-test		(-1.0794)	(1.2546)	**(-1.9652)**	(-1.569)	(-1.5637)	(-0.2136)	(0.4412)
	t-test *p*-val		0.2804	0.2096	**0.0494**	0.1166	0.1179	0.8308	0.6591
	CASCs (bps)	92	-0.1936	0.1854	0.3861	0.3901	0.5515	0.9868	0.661
Social	t-test		(-0.1469)	(0.2146)	(0.9145)	(1.2041)	(1.2863)	(1.5627)	(0.7036)
	t-test *p*-val		0.8832	0.8301	0.3605	0.2286	0.1983	0.1181	0.4817
	CASCs (bps)	90	**-4.9977****	**-2.862***	-0.9812	0.0869	-0.5772	-0.9628	-2.77
Governance	t-test		**(-2.2969)**	**(-1.8634)**	(-1.1054)	(0.0799)	(-0.4566)	(-0.5406)	(-1.3425)
	t-test *p*-val		**0.0216**	**0.0624**	0.269	0.9364	0.6479	0.5888	0.1794
	CASCs (bps)	76	9.6753	4.1945	**1.5811***	0.0349	0.1085	-1.0225	-0.8024
Long-Term	t-test		(1.5799)	(1.0158)	**(1.8068)**	(0.0442)	(0.1235)	(-0.5322)	(-0.5372)
	t-test *p*-val		0.1141	0.3097	**0.0708**	0.9647	0.9017	0.5946	0.5911

Table 4.16 Cumulative Abnormal Spread Returns (CASCs) around Illegal Events based on ESG and LT issues (Speculative Grade Ratings)

The table below provides the cumulative abnormal spread changes (CASCs) around illegal events based on Environmental, Social, Governance and Long-Term issues over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal spread changes are calculated using an index-adjusted model based on speculative grade ratings. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Index - adjusted model CASCs based on Speculative Grade Ratings									
	CASCs (bps)	11	-176.4736	-41.5564	2.8755	26.5522	58.3607	143.1357	262.5631
Environment	t-test		(-0.9769)	(-1.1452)	(0.1037)	(0.9927)	(0.9241)	(0.975)	(0.982)
	t-test *p*-val		0.3286	0.2521	0.9174	0.3208	0.3554	0.3296	0.3261
	CASCs (bps)	3	-1.4831	-2.9473	-6.414	-12.5935	-12.7395	-12.458	-10.1936
Social	t-test		(-0.4694)	(-1.0014)	(-1.0441)	(-1.1909)	(-1.2039)	(-1.0397)	(-1.1344)
	t-test *p*-val		0.6388	0.3166	0.2964	0.2337	0.2286	0.2985	0.2566
	CASCs (bps)	6	-2.1519	1.6166	0.2217	6.035	4.8979	8.858	6.8128
Governance	t-test		(-0.3889)	(0.4451)	(0.0676)	(1.2611)	(0.8569)	(1.1471)	(1.0619)
	t-test *p*-val		0.6973	0.6562	0.9461	0.2073	0.3915	0.2513	0.2883
	CASCs (bps)	13	**-6.3723****	2.357	1.146	-3.606	-4.3062	-9.2023	-5.852
Long-Term	t-test		**(-2.3869)**	(0.8457)	(0.8063)	(-0.8209)	(-0.9152)	(-1.2487)	(-0.8847)
	t-test *p*-val		**0.017**	0.3977	0.4201	0.4117	0.3601	0.2118	0.3763

Table 4.17 Cumulative Abnormal Returns (CARs) around Illegal Events based on ESG and LT issues (Market-model)

The table below provides the cumulative abnormal returns (CARs) around illegal events based on Environmental, Social, Governance and Long-Term issues over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal returns are calculated using a market-model. N is the number of fines in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Market - model CARs									
	CARs (in %)	154	0.0038	-0.0004	-0.0019	-0.0013	-0.0027	-0.0003	0.0024
Environment	t-test		(0.9999)	(-0.1624)	(-1.2698)	(-0.8693)	(-1.0832)	(-0.1158)	(0.5803)
	t-test *p*-val		0.3174	0.871	0.2042	0.3847	0.2787	0.9078	0.5617
	CARs (in %)	105	0.0004	**-0.0054****	**-0.0024****	-0.0013	-0.001	-0.0032	-0.0007
Social	t-test		(0.1441)	**(-2.5211)**	**(-1.9986)**	(-0.9013)	(-0.5803)	(-1.3142)	(-0.211)
	t-test *p*-val		0.8854	**0.0117**	**0.0457**	0.3675	0.5617	0.1888	0.8329
	CARs (in %)	101	0.0044	0.0053	0.002	-0.001	0.0012	0.0017	0.0037
Governance	t-test		(1.0384)	(1.6215)	(1.1475)	(-0.4865)	(0.4727)	(0.5588)	(0.7757)
	t-test *p*-val		0.2991	0.1049	0.2512	0.6266	0.6364	0.5763	0.4379
	CARs (in %)	101	0.0037	0	0.0049	**0.0074****	**0.008****	0.0009	0.0039
Long-Term	t-test		(0.6669)	(0.0087)	(1.4078)	**(2.2869)**	**(2.3665)**	(0.1607)	(0.5166)
	t-test *p*-val		0.5048	0.9931	0.1592	**0.0222**	**0.018**	0.8723	0.6054

Table 4.18 Cumulative Abnormal Returns (CARs) around Illegal Events based on ESG and LT issues – (Market-adjusted model)

The table below provides the cumulative abnormal returns (CARs) around illegal events based on Environmental, Social, Governance and Long-Term issues over the [-10,-1], [-5,-1], [-1, 0], [0, 1], [0, 2], [0, 5] and [0, 10] event windows. The abnormal returns are calculated using a market-adjusted model. N is the number of firms in the sample. Cross sectional t-statistics are reported in parentheses and the p-values are reported below the CASCs. The superscripts ***,**, and * indicate significance at 1%,5% and 10% levels, respectively.

Event Window		**N**	**(-10,-1)**	**(-5,-1)**	**(-1,0)**	**(0,1)**	**(0,2)**	**(0,5)**	**(0,10)**
Market- adjusted model CARs									
	CARs (in %)	154	0.0034	-0.002	-0.0026	**-0.0027***	**-0.0051***	-0.0039	-0.0034
Environment	t-test		(0.7804)	(-0.7063)	(-1.5873)	**(-1.7568)**	**(-1.9331)**	(-1.2909)	(-0.7456)
	t-test *p*-val		0.4352	0.48	0.1124	**0.0789**	**0.0532**	0.1968	0.4559
	CARs (in %)	105	-0.0012	**-0.0062***	-0.0025	-0.0015	-0.0026	**-0.0078****	-0.0022
Social	t-test		(-0.2661)	**(-1.8331)**	(-1.1952)	(-0.771)	(-1.1386)	**(-2.3726)**	(-0.4533)
	t-test *p*-val		0.7901	**0.0668**	0.232	0.4407	0.2549	**0.0177**	0.6503
	CARs (in %)	101	0.0025	0.0044	0.0012	-0.0029	-0.0019	-0.003	-0.0039
Governance	t-test		(0.5377)	(1.3232)	(0.6616)	(-1.402)	(-0.7051)	(-0.8975)	(-0.7582)
	t-test *p*-val		0.5908	0.1858	0.5082	0.1609	0.4808	0.3694	0.4483
	CARs (in %)	101	0.0005	-0.0054	0.0011	0.0046	0.0042	-0.0034	-0.0025
Long-Term	t-test		(0.0974)	(-1.6021)	(0.2957)	(1.3592)	(1.2222)	(-0.5466)	(-0.3218)
	t-test *p*-val		0.9224	0.1091	0.7675	0.1741	0.2216	0.5847	0.7476

4.5 Limitations

Nevertheless, this study has its limitations. When running a traditional event study model, it is assumed that the events or information is usually an unexpected or unpredictable event which then produces a “shock” factor either positive or negative (McWilliams and Siegel 1997). This event is presumed to provide new information which would affect the health of the company i.e. the future profitability of the company. However, MacKinlay (1997) state it might be difficult to identify the exact date of announcements as one cannot be certain if the market was informed prior to the close of the market the prior trading date. The event data is also assumed to be accurate and precise and is not affected by other concurrent announcement. On the other hand, de Jong and Naumovska (2016) finds that there is a challenge in identifying (systematic) confounding events especially in event study methodologies when testing theories about investor’s reactions in finance and management research. As I do not have data prior to the fines i.e. rumors or information that might indicate or speculate a fine, in this chapter I run the event study models assuming that the fines are information that are exogenous, in short unforeseeable or unpredictable to measure the “shock” factor post the announcement of the fine. Though, I define here the announcements of fines as new information that would impact CDS spreads and equity returns, I am aware of the limitations that this brings. McWilliams, Siegel et al.(1999) state it is at times difficult for researchers to determine what prior information investors might have had and if there were any speculations prior to announcements and thus by the time of an actual announcement, investors would have already capitalized information into the stock price. They further add that this can be mitigated though by examining “leakage events” information such as shareholder meetings, public forums, press releases and news articles that might hint or indicate any potential discussion of the event. Therefore, this calls for further research to examine rumors priors to the fines data to examine whether the results in this study still hold and if investors react to these rumors. Additionally, due to CDS data availability only from 2009 to 2012, I note the limitations of the sample size and I am also unable to examine the effects of illegalities pre the financial crisis period, which would be another avenue for further research.

4.6 Summary

In this study, I examined the short-term impacts of illegalities on both the CDS market and stock market. Previous studies have measured the impact of CDS spread changes mostly on earnings announcements and negative credit rating events. I find only a few studies that comparatively measure the impact of events on both CDS and stock markets, furthermore to my knowledge none measured the impact of fines yet. Using my unique dataset of illegalities from the period of 2009 to 2012, I was able to run analyses to examine six different hypotheses.

On overall I find the CDS market reacts to announcements of illegality with increases of CDS spreads. However, I find that the increase in CDS spreads is evident in short-term, medium term and even on all levels of maturities. This indicates that CDS investors react immediately after announcements of fines. Interestingly, I also find that the CDS markets anticipate the news even before announcements, as I observed larger spread changes pre–event. Hence, this supports studies that indicate CDS markets are able to anticipate news even before it happens. I am the first to examine CDS market anticipation of illegality news. I also examine the impact of fines per market cap and I observe that even though the results are marginal in terms of economic significance, both the CDS market and stock market reacts more to higher fines per market cap than lower fines per market cap. This indicates that it is the higher fines that markets are concerned about.

I also examine the different stages of legal processes on both the CDS and stock market. In the CDS market, I find negative spread changes at the initial stage and increase in spreads at the CVPM stage of the illegalities in the investment grade model. These results show that for companies with higher quality grade credit ratings, investors are more concerned when the allegations are being examined legally i.e. at the confirmed but pending other legal matters stage. Comparing the results in the stock market, I find a drop in stock returns at the pending stage and increase in stock price at the CVPM and Confirmed stage. This supports the rational that there is “shock” factor at the initial stage in the stock market.

My results support my hypotheses that reactions of both CDS and stock investors are significant only in certain industries after announcements on illegalities. My post event results show that investors in the CDS market react negatively to illegalities in the mining industry, and even more so on mining firms with lower grade credit ratings. On the other hand, stock market investors react negatively more towards manufacturing firms.

Finally, I am the first to examine the impact of E, S, G plus LT issues on CDS markets. I find that investors in the CDS and stock market react only on certain ESG plus LT issues after announcements on illegalities. Specifically, the CDS spreads increase for environment and governance issues, whereas for stock returns a decrease in returns for environment and social issues is observed. This shows that both the CDS and stock market reacts negatively to environmental issues. Interestingly, both CDS and stock markets also react similarly to LT issues but with positive reactions. Zeume (2014

)find that firms actually benefit from the ability to use bribes. Therefore contrary to expectations that investors would react negatively to LT violation issues and this finding indicates that both the markets feel that LT violations are instead “beneficial” for the company in the short-term.

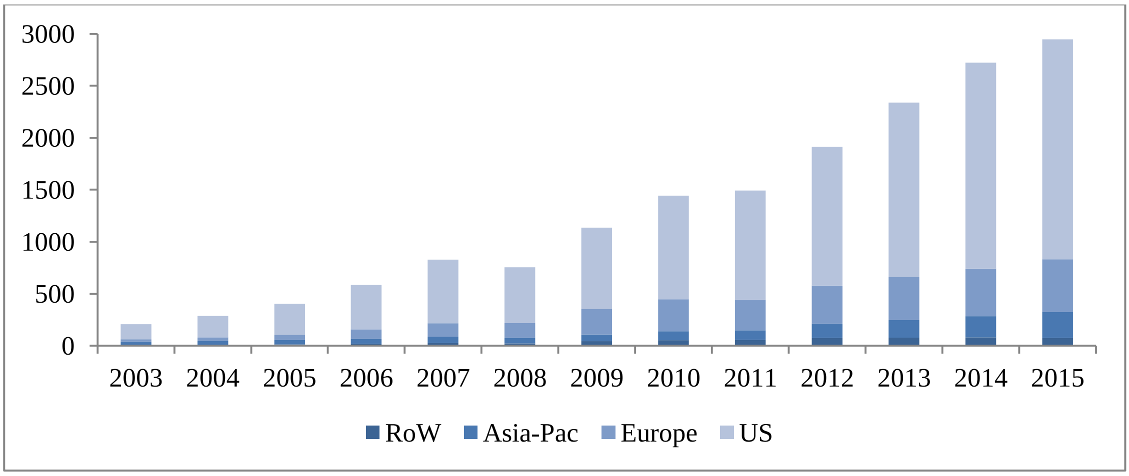
Overall, I find similar to Greatrex (2009) that these results are sensitive to the choice of model used. The findings of this research are very interesting. Firstly, it shows that when examining impact of illegalities especially fines in the CDS market, it is important to examine individually the different stages of the illegalities. For instance, when examining overall illegalities by maturity type, the CDS market reacts negatively to all types of maturity level. However, when the fine is broken down into the types of legal stages, the CDS market instead does not react negatively on all the stages. Thus, this result is valuable for research in illegalities especially for academics, indicating that it is important to examine the different legal stages of illegalities. Secondly, as the CDS market is able to anticipate news, investors in other markets should look to the CDS market first when examining illegalities. Regulators also could use this information to detect illegal behaviours of companies. Thirdly, the results on the ESG and LT issues, further affirm that environmental issues are a key concern to investors in both markets. However, LT issues on the other hand indicate that markets perceive this to benefit the company. Finally, firms should be aware that their illegal behaviours impacts their company value by drop in share prices and also increases in credit spreads which affects their credit worthiness and their future credit borrowing activities.

5. ETF Fund Flows and Index Returns: A Global Multi Asset Class Analysis

5.1 Introduction

The three previous chapters have examined three different asset classes (i.e. equity, bonds and credit default swaps). Those chapters have used a type of information specifically fines, to examine the impact investors have on returns and spreads. It is from this information of fines that has led investors to react. For that reason, information is deemed to be vital. Thus in this chapter I proceed to use another unique set of information, fund flow data, to examine the relationship between Exchange Traded Fund (ETFs) flows on returns on multi asset classes. The financial market has always been innovative with the creation of various products such as derivates, alternative risk transfer products, variants of tax-deductible equity and ETFs (Tufano 2003). It is argued that the creation of new financial products is usually aimed at circumventing regulatory constraints (Silber 1983). The growth of Exchange Traded Products (ETPs) which constitutes ETFs, exchange traded commodities (ETCs) and exchange traded notes (ETNs), have been popular in the recent years as seen in Figure 5 due to their benefits such as intraday trading, tax efficiency, low expense ratios and cost transparency in comparison to conventional mutual funds and closed-end funds (Charupat and Miu 2013).

Figure 5 Global ETP regional asset growth historically (AUM$bn)



Source: ETF Annual Review and Outlook (Deutsche Bank Markets Research, 2016)

In this study, I examine ETFs which permit investors to invest in portfolios that provide passive exposure to various asset classes while having intra-day pricing and efficient tax management (Svetina 2015). Demand for ETFs has grown in the last decade with assets in ETFs accounting to nearly 13% of total net assets managed by investment companies in 2016[54]. The growth of ETFs indicates that more and more investors are looking at this as a way of investment. ETFs have been around since 1993, with the very first known US ETF - Standard & Poor's Depositary Receipts (SPDR) which tracked the S&P 500 index. The US has the largest ETF market constituting nearly 73% of total $3.5 trillion in ETF assets worldwide, followed by Europe with 16%, Africa and Asia Pacific with 9% and other Americas with 3%[55]. ETFs can be traded throughout the day on the stock exchange which is in contrast to mutual funds which can only be purchased at the end of the day.

[54] "2017 Investment Company Fact Book – A review of Trends and Activities in the Investment Company Industry" pg 67 Available at https://www.ici.org/pdf/2017_factbook.pdf (accessed 1st June 2017)

[55] "2017 Investment Company Fact Book – A review of Trends and Activities in the Investment Company Industry" pg 58 Available at https://www.ici.org/pdf/2017_factbook.pdf (accessed 1st June 2017) Note: Components do not add to 100 percent because of rounding

ETFs are based on performances of an underlying index and not based on managerial expertise. Many investors choose to buy ETFs as a way to diversify portfolios. *"ETFs are a great way to capture sector or asset-class exposure with very little expense,"* quoted from the president and chief investment officer of Napa Valley Wealth Management[56]. One could hold ETFs in various different asset classes from stocks, bonds, commodities and currencies. ETFs were developed to allow investors to track the performances of an underlying index by buying or selling the ETF. The objective of the portfolio manager is to passively track the index and to ensure there is very low error (performance difference between the ETF fund and the underlying benchmark) with minimal cost to investors (Gallagher and Segara 2005). This passive ownership structure has been growing in the last 15 years and the demand from investors for a multi asset solution product has been growing tremendously[57]. Additionally, passive funds have been popular in recent years because of the high fees of active funds which at times provide dismal portfolio return[58].Though there are some similarities between ETFs and mutual funds, such as both are passive in nature; investors are able to short sell an ETF which in contrary is not possible with index funds.

It is important to understand that the key difference between ETFs and mutual funds lies in its mechanisms. The main difference is that ETFs allows a combination of creation and redemption of shares via an in-kind redemption feature. ETF shares are

[56] "Why financial advisers prefer ETFs over mutual funds" Available at http://www.marketwatch.com/story/why-financial-advisers-prefer-etfs-over-mutual-funds-2017-06-09 (accessed 11th June 2017)

[57] Special ETF Research (Deutsche Bank Markets Research, 2015)

[58] " The end of active investing?" available at https://www.ft.com/content/6b2d5490-d9bb-11e6-944b-e7eb37a6aa8e accessed 11 June 2017

created when an Authorized Participant (AP), which is typically a large financial institution (i.e. self-clearing broker-dealers) and are the only ones that is authorized to deal with the fund, submits an order for units. In short, it is exchanging the underlying index assets for an equivalent share of the ETF. The redemption process is then the opposite, where the share of the ETF is given to the fund and receives in turn the underlying index assets. The in-kind feature basically means that it is a barter of equivalent securities and it is important to note that the APs have to buy (sell) the underlying assets before creating (redeeming) the ETF shares (Staer 2014). APs then sell the ETF shares in a secondary market to investors in the stock exchange.

ETFs are supposed to track an underlying security and in theory not deviate from the underlying value. However, as it is traded on a stock exchange, the price of the ETF share is influenced by supply and demand and at times deviates from its underlying value. This creates actions where investors *"may buy (sell) ETF shares or sell (buy) the underlying securities or do both when an ETF is trading at a discount (premium)*[59]*"* which in turn brings the price of the ETF closer to its underlying value. It is basically arbitrage that sets the price back to equilibrium.

In explaining the link between ETFs flows and returns I draw on traditional mutual fund literature to explain this relationship. There is extensive literature that explains the relationship between mutual fund flows and returns. For instance, Warther (1995), using monthly data cash flows on US mutual funds, find that aggregate security returns are highly correlated with concurrent unexpected cash flows into mutual funds,

[59] "2017 Investment Company Fact Book – A review of Trends and Activities in the Investment Company Industry" pg 64 Available at https://www.ici.org/pdf/2017_factbook.pdf (accessed 1st June 2017)

though unrelated to concurrent expected flows. Edelen and Warner (2001) find positive association between aggregate daily flow and concurrent market returns in mutual funds[60]. They also find aggregate flow follows market returns with a one-day lag. Both those studies show that there can be a relation between fund flows and returns Staer (2014) explains that these relation between fund flows and returns can be explained using information and price pressure hypothesis. The information hypothesis explains more on concurrent flows, where positive (negative) information shock positively (negatively) affects both flows and returns simultaneously. In terms of lagged flows, the price pressure hypothesis states that a contemporaneous price shock will be followed by a price reversal which would turn into a negative relation between past flows and returns[61]. Thus, in this study, I examine two research questions. Considering that ETFs track the market very closely, the first research question is to understand how much of the variation of market returns can be explained by fund flows into the respective ETF. My second research question aims at examining the relationship between lagged ETF fund flows and market returns. This study uses data of yearly fund flows from 51 countries into ETFs in US, Europe, Asia Pacific and Rest of the World (RoW) from the period 2011 to 2015.

I find two papers by Kalaycıoğlu (2004) and Staer (2014) which are closely related in examining ETF fund flows and its underlying returns. However, my study differs from theirs significantly in several ways. Firstly, Kalaycıoğlu (2004) examines the impact of ETF flows on aggregrate and individual levels for five major ETF indices in the US and Staer (2014) only uses data from U.S ETFs. Instead, I am the first to my

[60] For example, days with positive (negative) unexpected flow have estimated abnormal market returns of 25 (-25) basis points

[61] "The price pressure hypothesis involves finding that there is a positive relation between the ETF flows and the concurrent underlying asset returns while also finding a negative relation between lagged flows and returns." pg 3 Staer (2014)

knowledge to use a unique set of ETF fund flow data provided by Deutsche Bank which provides data of yearly fund flows from 51 countries into ETFs in US, Europe, Asia Pacific and Rest of the World (RoW). Secondly, both the studies only measure the relationship on equity indices returns, whereas this study examines three different asset classes, namely i) equity ii) bond and iii) future indices. Thirdly, the data period for Kalaycıoğlu (2004) is from 2000 to 2003 and Staer (2014) is from 1993 to 2010, whereas this study is based on a more recent dataset from 2011 to 2015.

Using panel data regressions, I find the explanatory power of ETF fund flows is similar to macro-economic variables in explaining indices returns. I use macro-economic variables as a comparison because they are widely used in asset pricing literature to explain stock returns (Asprem 1989; Wasserfallen 1989; Durham 2001; Flannery and Protopapadakis 2002; Rapach, Wohar et al. 2005; Birz and Lott Jr 2011). Secondly, I find that on equity indices based on statistical significance, lagged ETF fund flows into Europe have a positive relationship with equity index returns. On the contrary, I find a negative relationship between lagged ETF fund flows in the US with equity index returns. I find similar negative relationship of the lagged ETF fund flows into the US market for future indices which indicates a price pressure reversal effect. On the other hand, I find there is statistically no significant relationship between ETFs fund flows and bond index returns.

This paper contributes to the growing literature on ETFs in numerous ways. Firstly, this paper adds to current ETF fund flow literature that to date only measures the relationships of ETFs in the US. This study provides global scale trading reactions of ETFs especially into other regions. These results would be interesting for traders especially those who are interested in understanding the movements of ETFs not just in the US but also globally. Secondly, this study adds to literature on asset allocation and pricing especially on variability. The results explains that ETF fund flows even on a global scale explain only about 18 percent of variability in returns for equity indices, 60 percent on bond indices and 14 percent on future indices, which is comparable to the variability of macro-economic news.

The remainder of the chapter is organized as follows. Section 2 is a literature review on ETF performance, asset allocation and variability, on price movements and macro-economic variables. In this section, I also describe in detail my research questions. Section 3 is the data and methodology. Section 4 reports the empirical results and section 5 concludes.

5.2 Related Literature and Research Question Development

5.2.1 Literature on ETFs and Performances

There has been growing literature on ETFs in comparison to mutual funds. Elton, Gruber, Comer, & Li (2002) and Gastineau (2004) examined the performances of conventional indexed mutual funds relative to ETFs and they both indicate that there is relative performance weakness in ETFs due to inadequate information provided to portfolio managers and due to dividend reinvestments, where the dividends received are not reinvested but are held in non-interest bearing accounts. This underperformance is also confirmed by Rompotis (2008) who regressed 16 ETFs from 2001 to 2002 and index funds return on his / her underlying benchmarks and finds that they do not achieve any excess return. This underperformance is even more evident when using

ETFs bid-ask return on the index return. The author indicates that ETFs and index funds are chosen by investors with different sets of behaviours. Conservative stock investors and institutional investors who do not use financial derivatives for hedging purposes might end up choosing ETFs instead of index funds.

However, using ETFs and index funds data prior to 2006 from Vanguard , Rompotis (2009) finds that on average they present similar return and risk records. Using a sample size and time frame of 230 paired ETFs and index funds from 2002 to 2010 respectively, Sharifzadeh & Hojat (2012) find that although 50 percent of the selected ETFs outperformed their index mutual fund counterparts, this outperformance was not statistically significant. They also conclude investor's preference to choose either ETFs or index funds boils down to product characteristics and tax preferences. Svetina (2015) examined 629 ETFs in existence at the end of 2007 and find that 83% of all ETFs track indices which do not have corresponding index funds and on average also underperform benchmark indices. However, only 17% of ETFs which directly compete with index funds provide slightly better performances when compared to retail index funds and equivalent performance when compared to institutional index funds.

The rational that investor preferences exist when choosing whether to use ETFs is tested by Huang & Guedj (2009). They compared ETFs with Open-Ended Mutual Funds (OEF) from 1992 to 2006 and find that both OEFs and ETFs do coexist in equilibrium but with different liquidity clienteles. ETFs are suited more for investors with longer term horizons who prefer narrower and less liquid underlying indexes. Agapova (2011), using monthly data of U.S funds from 2000 to 2004, measured whether ETFs and mutual funds act as substitutes. Using aggregate fund flows, the study found that the substitute effect exists (though not perfect) and can also be explained by clientele effect. Their results suggest that ETFs may be preferred by tax-sensitive investors while conventional funds would be preferred by tax-exempt investors or those insensitive to taxes. In addition, they indicate that on average, the flows to ETFs are positive and much higher compared to conventional index funds.

A recent study by Staer (2014) investigates the relation between ETF flows and their underlying securities returns for 286 U.S equity ETFs. Using Bloomberg data from 1993 to 2010, he finds that there is a strong positive relation between daily contemporaneous ETF flows and underlying stock returns. The magnitude of the relation as a response to one standard deviation flow shock varies between 7 to 52 basis points in the sub samples. The paper concludes that there is a price pressure effect related to flow activity. This study is contradictory to the findings by Kalaycıoğlu (2004) who also investigated the return flow relationship of ETFs and found no price pressure effect.

The studies above have only been on US ETFs, but do the same hold for European ETFs? Blitz, Huij, & Swinkels (2012) investigated European index mutual funds and ETFs and found that they underperform their benchmarks by 50 to 150 basis points per annum. They indicate that it is the fund expenses and dividend taxes which result in the drag in the fund performances. This result is similar to US ETF fund performances. On the other hand, Gallagher & Segara (2005) find that Australian ETFs are able to closely track their respective benchmarks. They find that the variation between the net asset values and the traded price of the ETFs is small. However, they indicate there is a lack of trading activity in Australian ETFs due to several reasons (i.e. ETF vehicles could erode fund managers market share if the distribution function is controlled by an independent party and an upfront fee requirement to enter the fund).

5.2.2 Literature on Asset Allocation and Variability

ETFs and their growth are based on underlying indices and the growth of multi-asset ETFs has increased in the past years due to growing demand from investors. Thus, the link between ETFs and asset classes is inevitable. Investors are leaning towards a more diversified portfolio that would benefit them in reducing their portfolio risk. The diversified portfolio can be based on different asset allocation. Investor's preferences to different assets are based on their own mix of risk and return characteristics. Markowitz (1952) introduced the concept of portfolio theory whereby investors should actually not consider look at individual risk and returns of investments but only the incremental risk and return the investment adds to its portfolio. The theory indicates that there is a possible efficient frontier where investors are able to create maximum return given any preferred level of risk. Determining how much exposure an investor should have in each proponent of asset class is a crucial factor. This information is important to determine an investors overall effective asset mix (Sharpe 1992).

An investor's asset mix is derived from the various main asset classes such as equity, fixed income, private equity and even venture capital. Within these asset classes there are also sub-classes. For fixed income there are bills which are usually less than a year in maturity, medium term government bonds that are less than 10 years in maturity, long-term government bonds that are more than 10 years in maturity and corporate bonds with also different maturities. For equity there are small, medium and large capitalized stocks which carry different market sizes according to their inclusion in a particular equity index or universe. There are also value stocks that are based on high book to market ratios and growth stocks with low book to market ratios. Choosing these different classes of assets even amongst its sub-classes is called “style investing”. Barberis & Shleifer (2003) indicate that investors pursue style investing because allocating funds in asset styles is much easier and less intimidating than choosing from thousands of listed securities and that the creation of various styles allows for comparison of the performances amongst similar money managers.

How does an investor choose a certain style or determine which asset suits their portfolios? Canner, Gregory, & David (1994) examined advise on portfolio allocation amongst cash, bonds and stocks and find that the advice is inconsistent with mutual fund separation theorem (investors should hold portfolios comprised of risky assets with some percentage of risk-free assets). They rather find there is a human capital influence whereby aggressive investors are recommended to hold lower ratios of bonds to stocks than conservative investors. They also find an absence of the risk free asset and deviation from mean-variance preferences. Though in theory an optimal portfolio solution exists, in reality it is difficult to fully understand the rationale behind investors reasoning in choosing their asset mix.

Asset allocation has always been in the forefront of investors mind. The next valuable question is how much variation in asset allocation explains its performance? The seminal paper by Gary et al. (1986) was the first to answer that question. They find that investment policies dominate investment strategies, explaining on average 93.6 percent of variation in total plan return. Ibbotson & Kaplan (2000) argue that Gary, Hood, & Gilbert, (1986) results were not sensitive to each funds allocation policy. Hence, Ibbotson & Kaplan (2000) using cross section returns of 10 years of US mutual funds, found 90 percent of the variability in returns of a typical fund across time is explained by policy, about 40 percent of the variation of returns among funds is explained by policy, and on average about 100 percent of the return level is explained by the policy return level. Ibbotson (2010) indicates that asset allocation is important, though it is difficult in explaining 90 percent of variation returns is caused by specific asset allocation mix. Ibbotson & Kaplan (2000) and Hensel, Ezra, & John (1991) also stated that most time-series variations come from a general market movement.

5.2.3 Literature on Price Movement and Macro-economic Variables

There is vast amount of literature that measures price movements of stocks and other asset classes due to macro-economic variables. Economic news has always been deemed to affect asset prices. The news of the changes to the macro-economic variables would have an impact on stock returns as it would affect firm's fund flows and risk-adjusted discount rates. Ross (1976) seminal paper introduced Arbitrage Pricing Theory (APT), which is a general asset pricing theory and was proposed as an alternative to the Capital Asset Pricing Model (CAPM). The APT model states that asset prices can be predicted by measuring its asset return with various other common risk factors. The model uses linear combinations of independent macro-economic variables to predict the relationship between a portfolios returns and a return of a single asset. The conclusion that state variables relating to the economy would be able to affect asset prices is also consistent with other asset-pricing theories from (Merton 1973; Cox, Ingersoll et al. 1985). Hence, it is common understanding that the returns of an asset are influenced by systematic economic variables.

Chen et al., (1986) investigated which specific economic news (i.e the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high- and low- grade bonds) is likely to affect assets. They found that several of those economic variables[62] were significant in explaining expected stock returns and conclude that stock returns are exposed to systematic economic news and are priced according to their exposures. Various other researchers also find there is a relationship and link between macroeconomic variables and stock price returns (Asprem 1989; Wasserfallen 1989; Durham 2001; Flannery and Protopapadakis 2002; Rapach, Wohar et al. 2005; Birz and Lott Jr 2011). Nonetheless, there still is a lack of common consensus of which macro-economic variables are the most important indicator. For instance, Flannery and Protopapadaki (2002) find no evidence of Industrial Production which is a popular measure to have predictive ability, yet they find other six variables that do. Birz and Lott Jr, (2011) find that Gross Domestic Product (GDP) and unemployment do affect stock returns, yet on the contrary Ghent (2010) find no statistical significant effect.

The above research has indicated that macro-economic variables are significant and can to a certain extent explain stock returns. However, Chan et al.(1998), find otherwise. They find the performance of macro-economic factors to be disappointing and explain return co-variations poorly with the exception of default premium and term premium. Importantly, how much variability can economic variables actually explain stock price movement? Cutler et al. (1989), using structured Vector autoregressions (VAR), analyzed monthly stock returns from 1926 to 1985 to explore whether unexpected macroeconomic news can explain share price movements. Using seven different macro-economic variables[63], they use the VAR models to identify the

[62] "*Several of these economic variables were found to be significant in explaining expected stock returns, most notably, industrial production, changes in the risk premium, twists in the yield curve, and, somewhat more weakly, measures of unanticipated inflation and changes in expected inflation during periods when these variables were highly volatile"(p402)*

[63] Real dividend payments on the value-weighted New York Stock Exchange portfolio(deflated by monthly Consumer Price Index),logarithm of industrial production, logarithm of real money supply, the nominal interest rate, nominal short-term interest rate, the monthly CPI rate, logarithm of stork market volatility

unexpected component of each time series and to consider the explanatory powers of these "news" measures to explain stock returns. Their results indicated that macro-economic news was only able to explain one fifth of the movements in stock prices. Their results are robust to even increasing the number of lagged values in the VARs. They further examine whether market moves are coincident with major world and political events and their results indicate that there is only a small effect on non-economic news. They conclude their paper by stating that *"it is difficult to explain as much as half of the variance in stock prices on the basis of publically available news bearing on fundamental values"(p14).*

5.2.4 Research Question Development

This study contributes to literature by extending previous research which only looked at individual and aggregate ETF flows and index returns to a broader link between country ETF fund flows and index returns.

These studies are important as they question the variability's of returns to understand asset allocation in depth. Firstly, I intend to measure whether ETF fund flows have a better power to explain market movements in different asset classes than commonly used macroeconomic variables do. Cutler et al., (1989) find that it is difficult to explain more than one third of the return variance from macroeconomic news. I find that their paper confirms my notion that macro-economic variables alone are unable to fully explain the variations of stock price movements. Hence my first research question intends to find out the following:

Research question 1: *How much of the return variation of equity, bond and future indices can be explained by ETF fund flows compared to macroeconomic variables?*

Staer (2014) examined the relation between ETF flows and their underlying securities returns using U.S equity ETFs and finds a strong positive relation. Kalaycıoğlu (2004) on the other hand finds a negative correlation between ETF flows and market returns based on five major US index ETFs. However, none of the studies have measured the relation between ETF fund flows and index returns on a global level as well on different asset classes. Thus, in my next research question, I intend on understanding whether last year's ETF fund flows are able to predict next year's index market movement based on global ETF fund flow data on equities, bonds and future indices. Hence my second research question intends to find out the following:

Research question 2: *What is the relationship between last year ETF fund flows and next year's market returns on equities, bonds and future indices?*

5.3 Data and Methodology

My data set contains ETF fund flow data, return indexes and macro-economic variables. The period of my data is yearly from 2011 to 2015. I retrieve my ETF fund flow data from Deutsche Bank Markets Research Synthetic Equity & Index Strategy, ETF Annual Review & Outlook 2014, 2015 and 2016 report. The report is publically available online at the Deutsche Asset Management website[64] and is published yearly from 2014 onwards. Each year their report provides data of 3 prior years. The ETF report provides an industry overview of ETFs and the growth of the market. I use the ETF fund flow data provided in their report for developed and emerging markets which is also sourced from Reuters and Bloomberg. I use the ETF fund flows that were provided for 51 countries in Europe, Americas, Asia, Israel, BRIC (Brazil, Russia, India and China) and Latin America. The report extensively provides ETF fund flow data of

[64] "ETF Annual Review" available at https://etf.deutscheam.com/GBR/ENG/Downloadcenter/ETF-Research (accessed 24 February 2016)

US, Europe, Asia Pacific and the Rest of the World (RoW) investors into other countries.

Each respective country's equity, bond and futures index returns were retrieved from Datastream. Firstly, I retrieved each countries yearly bond index returns using the Total Return Index (RI) code which calculates the effect of re-investing all the gross coupons received back into the bonds of the index. For the yearly equity index returns, I also used RI which represents the theoretical aggregate growth in value of the constituents of the index. The index constituents are deemed to return an aggregate daily dividend which is included as an incremental amount to the daily change in price index. However, for the futures index returns, I used the yearly settlement price which is the price at which a contract is settled at the end of the trading day and is issued by the exchange. From the 51 countries, I was able to locate all equity indices but only and 49 and 34 bond and future indices respectively. Secondly, I then converted each of these returns to continuously compounded returns using the following formula:

$$\mathrm{R_{it}} = \ln\left(\frac{\mathrm{P_{i,t}}}{\mathrm{P_{i,t-1}}}\right) \tag{5.1}$$

The above formula indicates that the natural logarithm (ln) is taken by dividing the index' price in that year by the price of the previous year. Table 8.11 in the appendix provides the list of codes and names of the indices of the three different asset classes retrieved from Datastream.

I used yearly data of macro-economic variables from the World Economic Outlook (WEO) database provided by the International Monetary Fund (IMF)[65]. The data from WEO is available from 1980 to the present year and is released in April and

[65] "IMF Macro-economic data" available at https://www.imf.org/external/pubs/ft/weo/2016/01/weodata/weoselgr.aspx (accessed 20 July 2016)

September/October each year. The database has a list of 31 macro-economic variables. For the purpose of this analysis, I used 7 macro-economic variables; Gross domestic product, current prices (U.S. dollars) (GDP), Gross domestic product based on purchasing-power-parity (PPP) valuation of country GDP (GDP based on PPP), Implied PPP conversion rate (IMPLIED PPP), Inflation, average consumer prices in index (INFLATION), Volume of imports of goods and services in percent change (VOLUME of IMPORTS), Unemployment rate as a percent of total labor force (UNEMPLOYMENT), Current account balance in U.S. dollars (CURRENT BALANCE). Refer to table 8.12 in the appendix for the definitions of each of the variables. The final country-year observation of the sample consisted of a balanced panel data set with 204 country-year observations (N= 51 different countries and a period of T=4 years). Various subsets of these macroeconomic variables have been used in earlier studies (Chen, Roll et al. 1986; Asprem 1989; Cutler, James M. Poterba et al. 1989; Wasserfallen 1989; Chan, Karceski et al. 1998; Flannery and Protopapadakis 2002; Green 2004; Love and Payne 2009; Christiansen, Schmeling et al. 2012).

As mentioned in the previous section in the research questions, I will be measuring four different types of models:

Model 1: Log(Excess Index$_{i,t}$)= f(Marcoeconomic variables$_{i,t-1}$) (5.2)

Model 2: Log(Excess Index$_{i,t}$)= f(ETF Fund Flows$_{i,t-1}$) (5.3)

Model 3:Log(Excess Index$_{i,t}$)= f(ETF Fund Flows$_{i,t-1,}$Marcoeconomic variables$_{i,t-1}$) (5.4)

I use three types of indices; equity, bond and future indices separately as the dependent variable. The Log (Excess Index$_{i,t}$) is calculated using the log of the return of the index minus the global market which is the MSCI World Index[66]. The lagged macroeconomic variables and the ETF fund flows have already been described previously. The rational for having lagged variables is because I am measuring the causal effect of the ETF fund flows and with excess returns on indices, whereby the excess returns on indices are the effect and the ETF fund flows are the cause. In essence, it allows explanatory variables to have effects that extend beyond the current period and can also serve as a control for serial correlation. Staer (2014) also used lagged ETF flows to examine the effect on underlying stock returns. I use the macro-economic as control variables.

I run my analysis using panel data estimations (i.e cross-sectional time series data) with combinations of parametric approaches to ensure robustness of estimates. Before running my regressions, I have to choose either a fixed or random effects model. The fixed effect model assumes that there is only one true effect size whereas the random effect model allows the true effect size to differ (Borenstein, Hedges et al. 2010). There has always been a debate on choosing the relevant model in econometrics. Allison (2006) state that there can be disadvantages of using a fixed effect model as *"fixed effects estimates may have substantially larger standard errors than random-effects estimates, leading to higher p-values and wider confidence intervals"(p.2).* Furthermore, Baltagi (1988) state that both the *"random and fixed effects models yield different estimation results, especially if T is small and N is* large*"(p.6).* It is evident that both the fixed effects and random effects model represent different assumptions of data and therefore it is important that the appropriate model is chosen beforehand to ensure that the statistics is estimated correctly (Borenstein, Hedges et al. 2010). To

[66] The MSCI World Index, which is part of The Modern Index Strategy, is a broad global equity benchmark that represents large and mid-cap equity performance across 23 developed markets countries. https://www.msci.com/world (accessed 20 May 2016)

ensure I choose the right model, I proceed by conducting Hausman tests developed by (Hausman 1978). I run the Hausman test where the null hypothesis indicates that the random effect model is appropriate and the alternative hypothesis is that the fixed effect model is appropriate. This is a test to check whether the error terms in regressions are correlated with the regressors. The null hypothesis is that they are not related. If the p-value provided is statistically significant then a fixed effect model shall be used. In table 5.1, I find that running the equity, future and bond returns on macroeconomics variables is appropriate under a random effect model. Referring to table 5.2 and 5.3, I find that the equity and future returns is appropriate under a fixed effects model, whereas for bond returns a random effects model is correct. In table 5.4, I find a random effect model is appropriate. In addition as there is a cross-section component to panel data, it can be deemed that they will be heteroscedasticity. Hence, I use the White diagonal robust coefficient covariance estimator (adjusted for panel data) to adjust for heteroscedasticity. I account for time effects in the model by adding fixed effects (dummy variables) to ensure there are unbiased standard errors.

Table 5.1 Hausman Test Results on Excess Equity, Future and Bond Index on Macroeconomic Variables

As per equation 5.2, the table below explains the three different dependent variables (excess equity, excess future and excess bond indices) with explanatory macroeconomic variables run under a Hausman Test. The first column is the dependent variables, the second column is the Chi-Sq Statistic and the third column is the Probability. *, **, *** indicate statistical significance at the 10 %, 5 % and 1 % levels, respectively.

	Chi-Sq. Statistic	Prob.
Ln Excess Equity	0.5587	0.4548
Ln Excess Future	0.5892	0.4427
Ln Excess Bond	0.0142	0.9050

Table 5.2 Hausman Test Results on Excess Equity, Future and Bond Index on ETF Fund Flows

As per equation 5.3, the table below explains the three different dependent variables (excess equity, excess future and excess bond indices) with explanatory ETF fund flow variables run under a Hausman Test. The first column is the dependent variables, the second column is the Chi-Sq Statistic and the third column is the Probability. *, **, *** indicate statistical significance at the 10 %, 5 % and 1 % levels, respectively.

	Chi-Sq. Statistic		Prob.
Ln Excess Equity	9.4118	*	0.0516
Ln Excess Future	15.2817	***	0.0042
Ln Excess Bond	1.4343		0.8382

Table 5.3 Hausman Test Results on Excess Equity, Future and Bond Index on ETF Fund Flows and Macroeconomic Variables

As per equation 5.4, the table below explains the three different dependent variables (excess equity, excess future and excess bond indices) with explanatory ETF fund flow variables and Macreconomic control variables run under a Hausman Test. The first column is the dependent variables, the second column is the Chi-Sq Statistic and the third column is the Probability. *, **, *** indicate statistical significance at the 10 %, 5 % and 1 % levels, respectively.

	Chi-Sq. Statistic		Prob.
Ln Excess Equity	9.8009	*	0.0811
Ln Excess Future	12.8747	**	0.0246
Ln Excess Bond	1.1812		0.9467

5.4 Empirical Results

5.4.1 Descriptive and Correlation Analysis

Table 5.4 presents the descriptive statistics analysis for the main variables which includes the dependent and independent variables. The dependent variables on the excess equity, excess bond and excess future returns all have very similar ranging values for the mean returns. The standard deviations values also indicate good variability in returns. Comparing the mean variables for the fund flows for the four regions, I find that Rest of the World (RoW) mean values are very low compared to the other three regions. This is due to the lack of many of the values for the individual countries. Looking at the macro-economic variables, two variables (inflation and unemployment rate) have minimum values of zero. This is also due the lack of information provided for individual countries inflation figures from Argentina for two years (2014 and 2015) and unemployment rate from India, Bangladesh, Qatar and United Arab Emirates.

Table 5.4 Descriptive Statistics

The table below provides the descriptive statistics of the number of observations (Obs), the mean, the standard deviations (Std), the minimum and maximum values of the main variables examined

Variable	**Obs.**	**Mean**	**Std.**	**Min**	**Max**
Current account balance	255	7.91	88.97	-484.08	293.20
Asia Pacific	255	376.05	2875.07	-14030.60	31348.20
Europe	255	223.09	1901.85	-9937.50	18347.10
RoW	255	19.80	269.95	-1881.30	2066.80
US	255	309.90	1720.97	-3656.10	17313.50
Excess Bond	255	-0.07	0.19	-1.89	0.68
Excess Equity	255	-0.10	0.27	-3.14	0.40
Excess Future	255	-0.10	0.15	-0.88	0.36
GDP	255	1397.61	2675.36	120.68	17947.00
GDP based on PPP	255	1821.62	3278.95	-1.59	19392.36
Implied PPP	255	273.80	1151.53	0.13	7682.40
Inflation	255	148.45	154.57	0.00	1410.97
Unemployment rate (%)	255	7.57	5.30	0.00	27.48
Volume of imports of goods and services	255	4.25	6.84	-28.26	40.79

.

Table 5.5 examines the correlations between the main variables and independent variables. Overall the results show not very high values (more than 0.8) to indicate any multicollinearity, with the exception to GDP based on PPP variable which has a value of 0.9. However, I proceed to use this variable as the GDP based on PPP is an important variable to measure GDP not only per country but also how it compares to other countries and considering that in this study I am measuring the impact on different regions ETF fund flows. The GDP per PPP is used by the IMF to generate the World Economic outlook country group composites. Nevertheless, I still conducted a robustness test by removing the GDP per PPP on each of the individual regression analysis. I find that the results are similar in terms of the signs, size and statistical significances on the main ETF fund flow variables for all four regions which are the main variables that are being examined in this study.

[This section has been intentionally left blank]

Table 5.5 Correlation Analysis

The table below describes the correlation matrix for the dependent variables excess equity, excess bond and excess future. It also provides the independent variables correlation matrix for the ETF Asia Pacific, ETF Europe, ETF RoW (Rest of the World) and ETF US figures. Furthermore, it also provides the correlation matrix results for the macro-economic variables GDP, GDP based on PPP, Implied PPP, Inflation, Unemployment rate and Volume of imports of goods and services.

Correlation	Current account balance	Excess Bond	Excess Equity	Excess Future	Asia Pacific	Europe	RoW	US	GDP	GDP based on PPP	Implied PPP	Inflation	Unemployment rate	Volume of imports of goods and services
Current Account Balance	1.00													
Excess Bond	0.02	1.00												
Excess Equity	0.05	0.10	1.00											
Excess Future	0.06	0.25	0.40	1.00										
Asia Pacific	0.10	-0.03	0.06	0.05	1.00									
Europe	-0.28	0.14	0.04	0.08	0.20	1.00								
RoW	-0.18	0.05	-0.22	0.04	0.00	0.10	1.00							
US	-0.28	-0.04	0.09	0.21	0.44	0.51	0.18	1.00						
GDP	-0.40	0.02	0.07	0.15	0.13	0.39	0.18	0.58	1.00					
GDP based on PPP	-0.23	0.03	0.05	0.11	0.10	0.30	0.14	0.48	0.94	1.00				
Implied PPP	-0.02	0.05	-0.02	0.04	-0.02	-0.02	0.00	-0.03	-0.09	-0.05	1.00			
Inflation	-0.14	0.00	-0.14	-0.24	-0.02	-0.02	0.05	-0.07	0.05	0.06	-0.04	1.00		
Unemployment rate	-0.17	-0.05	-0.03	-0.17	-0.10	-0.01	-0.01	-0.05	-0.09	-0.10	-0.14	-0.05	1.00	
Volume of imports of goods and services	0.06	0.12	0.01	0.05	0.01	0.01	0.04	-0.04	0.02	0.04	0.26	-0.09	-0.15	1.00

5.4.2 Regression Analysis

5.4.3 Effects of Index Returns on Macroeconomic Variables and ETF Fund Flows

Table 5.6 provides the results of the effects of the lagged macroeconomic variables on the logged excess equity, bond and future index returns respectively. All regressions are run using White diagonal standard errors to adjust for heteroscedasticity. Observing the results on the effect on excess equity returns, I find that GDP (US Dollars), GDP based on PPP and Inflation are all statistically significant. The lagged regressors have an explanatory return based on adjusted R-squared values of 5% and when there is a time effect it goes up to 19%. For excess bond returns, I find that GDP and Current account balance are statistically significant. The explanatory power of the adjusted R-squared value is only 2% but increases dramatically to 62% with a time effect. For excess future returns, I find GDP, Inflation and Current account balance are statistically significant. The explanatory power of the adjusted R-squared value is 13% and increases to 21% with a time effect.

Table 5.7 provides the results of the lagged ETF fund flows on logged excess equity, bond and future index returns respectively. Observing the results on the effect on excess equity, I find that ETF Europe and ETF US are both statistically significant with adjusted R-squared value of 5%. With a fixed time effect, I find that the adjusted R-squared values increases to 17% but the significances disappear. For excess bond returns, I find that only ETF Asia Pacific is significant and the adjusted R-squared value is very low at 1%. Similarly to the excess equity, the adjusted R-squared value increases with a time fixed effect to 59% and the significances also disappears. For excess future returns, ETF Asia Pacific, ETF Europe and ETF US are significant and the adjusted R-squared value is 3%. As anticipated with a fixed effect, the adjusted R-squared value increases to 14% and only ETF US has statistical significance. Though, it is important to note that the explanatory power of the model is evidently due to the fixed effect applied. Therefore, ETF fund flows could by themselves provide very little explanation to the variation in returns.

Thus, it can be observed that ETF fund flows provide a similar explanatory power of return variation compared to macroeconomic variables when measuring effects on return indices, nevertheless it should be noted the limitation that it is perhaps the fixed effect model that induces the explanatory power to increase. However, if I were to consider r-squared (instead of adjusted r-squared) values, then ETF fund flows would have a slightly higher variation in returns for equity and future indices at approximately 40 percent compared to macroeconomic variables explaining approximately 20 percent. Nevertheless, adjusted r-squared values are important in regressions as "*it takes into account the loss of degrees of freedom associated with adding extra variables"p.110* (Brooks 2008).

[This section has been intentionally left blank]

Table 5.6 Panel Regression Results of Excess (Equity, Bond and Future) Indices on Macroeconomic Variables

The table below reports the estimated coefficients from equation 5.2 using Random Effect Panel on the dependent variable which is the logged excess equity (Panel A), bond (Panel B) and future(Panel C) returns and independent variables which is the lagged macro-economic independent variables (GDP, GDP based on PPP, Implied PPP, Inflation, Volume of imports of goods and services, unemployment rate and current account balance) and t-statistics in parentheses. The regressions are run using white diagonal standard errors & covariance. The sample runs from FY2011 to FY2015. Panel A represents the results run without a period effect and Panel B represents the results with a period effect. Robust standard errors are shown in brackets. *, **, *** indicate statistical significance at the 10 %, 5 % and 1 % levels, respectively. The number of observations (N) is also listed below.

Independent Variables	**Panel A: Ln Excess Equity**		**Panel B: Ln Excess Bond**		**Panel C: Ln Excess Future**	
	(1)	(2)	(1)	(2)	(1)	(2)
Constant	-0.06275**	-0.04786*	-0.08346***	-0.07256***	-0.08202***	-0.07469***
	(-2.0726)	(-1.6811)	(-3.9394)	(-4.5957)	(-3.4281)	(-3.2149)
GDP (U.S. dollars)(-1)	0.00004**	0.00003*	-0.00004***	-0.00004***	0.00004***	0.00004**
	(2.43450)	(1.9341)	(-3.1023)	(-4.2647)	(2.6023)	(2.467)
GDP based on PPP(-1)	-0.00002**	-0.00002	0.00003	0.00003	-0.00002	-0.00002
	(-2.0868)	(-1.5876)	(2.9342)	(4.3769)	(-1.6199)	(-1.5575)
Implied PPP(-1)	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000
	(-0.135)	(0.3881)	(0.3298)	(1.2974)	(0.1185)	(0.4973)
Inflation, average consumer prices(Index) (-1)	0.00000***	0.00000***	0.00000	0.00000	0.00000***	0.00000***
	(-3.0589)	(-3.2246)	(-0.7585)	(-0.8585)	(-3.1047)	(-3.2707)
Volume of imports of goods and services(-1)	-0.00197	-0.00585*	-0.00034	-0.00300	-0.00003	-0.00202
	(-0.6223)	(-1.8715)	(-0.2012)	(-2.3736)	(-0.0161)	(-1.2616)
Unemployment rate(Percent of total labor) force (-1)	-0.00213	-0.00248	-0.00037	-0.00060	-0.00376	-0.00387
	(-0.7715)	(-0.901)	(-0.1984)	(-0.3461)	(-1.4343)	(-1.4379)
Current account balance(U.S. dollars)(-1)	0.00018	0.00019	-0.00028**	-0.00028***	0.00027*	0.00028*
	(1.1874)	(1.1524)	(-2.4077)	(-2.935)	(1.9126)	(1.9591)
R-squared	0.08365	0.23227	0.05655	0.64374	0.16474	0.25420
Adjusted R-squared	0.04801	0.18889	0.01986	0.62361	0.13226	0.21206
Cross-Section Fixed Effects or Random Effects	Random	Random	Random	Random	Random	Random
Period Effects (Time)	N	Y	N	Y	N	Y
Number of Observations (N)	188	188	188	188	188	188

Table 5.7 Panel Regression Results of Excess (Equity, Bond and Future) Indices on ETF Fund Flows

The table below reports the estimated coefficients from equation 5.3 using Fixed and Random Effect Panels on the dependent variable which is the logged excess equity (Panel A), bond (Panel B) and future (Panel C) returns and independent variables which is the lagged ETF fund flows (Asia Pacific, Europe, RoW and US) and t-statistics in parentheses. The regressions are run using white diagonal standard errors & covariance. The sample runs from FY2011 to FY2015. Column (1) represents the results run without a period effect and Column (2) represents the results with a period effect. Robust standard errors are shown in brackets. *, **, *** indicate statistical significance at the 10 %, 5 % and 1 % levels, respectively. The number of observations (N) is also listed below.

Independent Variables	**Panel A: Ln Excess Equity**		**Panel B: Ln Excess Bond**		**Panel C: Ln Excess Future**	
	(1)	(2)	(1)	(2)	(1)	(2)
Constant	-0.07405***	-0.07425***	-0.09221***	-0.09373***	-0.09140***	-0.09243***
	(-5.6714)	(-5.9932)	(-10.6077)	(-17.464)	(-8.714)	(-9.0655)
Asia Pacific(-1)	0.00000	0.00000	-0.00001**	0.00000	-0.00001***	-0.00001
	(-0.4503)	(-0.2933)	(-2.0066)	(-1.2667)	(-4.5596)	(-3.1242)
Europe(-1)	0.00001***	0.00000	0.00000	0.00000	0.00001***	0.00000
	(3.2524)	(1.3269)	(1.4208)	(0.8147)	(2.7456)	(1.6014)
RoW(-1)	0.00005	0.00003	-0.00002	0.00001	0.00002	0.00003
	(1.4646)	(1.0994)	(-0.6308)	(0.8608)	(0.6226)	(1.063)
US(-1)	-0.00001**	-0.00001	0.00000	0.00000	-0.00001*	-0.00001***
	(-2.2941)	(-1.5953)	(0.1502)	(-0.668)	(-1.745)	(-1.5997)
R-squared	0.30342	0.40504	0.02789	0.60384	0.28893	0.37817
Adjusted R-squared	0.05097	0.17276	0.00836	0.58969	0.03122	0.13540
Cross-Section Fixed Effects or Random Effects	Fixed	Fixed	Random	Random	Fixed	Fixed
Period Effects (Time)	N	Y	N	Y	N	Y
Number of Observations (N)	51	51	51	51	51	51

5.4.4 Effects of ETF Fund Flows on the movements of Index Returns

The results of the previous section indicate that ETF fund flows and macroeconomic variables have a comparable power in explaining the return variability of equity, bond and future indices. In this section, I analyse the panel regression results to measure the relationship between last year's ETF fund flows and next year's movements on equities, bonds and future indices. This is to understand the effects of ETF fund flows into different regions (Asia Pacific, Europe, Rest of the World, and US) and the performance of the markets (return indices). I use macro-economic variables as control variables in the panel data regression analysis.

As per table 5.8 I find that in the equity indices, the adjusted r-squared values without and with a period effect are relatively low at 0.10 and 0.22 respectively. Analyzing the results with the period effect, ETF Europe fund flows have a positive coefficient sign indicating that when there is more fund flow into European ETFs, the market is positive in the next year. On the other hand, I find a negative coefficient sign for US ETF fund flows indicating that when there are more fund flows into the US, the market is negative in the next year. This result is quite interesting as one would expect intuitively if there are more fund flows into the market, the market should react also positively in the next year. A potential explanation could be similar to Staer (2014) who examined US equity ETFs and found a strong positive relation between daily contemporaneous ETF flows and underlying stock returns suggesting price pressure effect related to flow activity, but most importantly he found that 38% of the flows shock's price change is reversed after five days which supports the price pressure causing the return effect. This suggests that negative relation between lagged fund flows and returns in the US market is consistent with the price pressure hypothesis. This is however contradictory to Kalaycıoğlu (2004) who found no price pressure effects on market returns originating from US ETF flows. He states due to the small portion of the ETF market (in the year 2004), it would be unlikely to cause price impact flow[67]. Similarly, I find this result in Europe where a potential explanation is that ETFs in Europe only constitute 16% of the ETF market where else the US has the largest ETF market of 73%[68].

For the bond indices I find the adjusted r-squared values without a period effect are relatively low at 0.03 and with a period effect high at 0.62. Analyzing the results with the period effect, I find there is statistically no significant relationship between ETFs fund flows and bond index returns. Here, I find there is no significant relationship between ETF fund flows and performances on a bond level.

Reviewing the results on future indices, I find the adjusted r-squared values without and with a period effect are relatively low at 0.09 and 0.17 respectively. Similar to the results in the equity index with a period effect, I find a negative coefficient sign for US ETF fund flows indicating that when there are more fund flows into the US, the market is negative in next year's future indices. In an efficient market, the returns on stock indices and stock index future should be correlated (Stoll and Whaley 1990). Here I find similar reactions of the ETF fund flows into the US market for both equity indices and future indices. This indicates that there is a price pressure effect causing the return effect in the following year.

[67] It is important to note that his study was based on 2004 and the US ETF market has since then grown.
[68] "2017 Investment Company Fact Book – A review of Trends and Activities in the Investment Company Industry" pg 58 Available at https://www.ici.org/pdf/2017_factbook.pdf (accessed 1st June 2017)

Table 5.8 Panel Regression Results of Excess (Equity, Bond and Future) Indices on ETF Fund Flows and Macro-Variables

The table below reports the estimated coefficients using equation 5.4 from Fixed and Random Effect Panels on the dependent variable which is the logged excess equity (Panel A), bond (Panel B) and future (Panel C) returns and independent variables which are the lagged ETF fund flows (Asia Pacific, Europe, RoW and US) and control variables which are the macro-economic variables and t-statistics in parentheses. The regressions are run using white diagonal standard errors & covariance. The sample runs from FY2011 to FY2015. Column (1) represents the results run without a period effect and Column (2) represents the results with a period effect. Robust standard errors are shown in brackets. *, **, *** indicate statistical significance at the 10 %, 5 % and 1 % levels, respectively.

Independent Variables	**Panel A: Ln Excess Equity**		**Panel B: Ln Excess Bond**		**Panel C: Ln Excess Future**	
	(1)	(2)	(1)	(2)	(1)	(2)
Constant	0.53638***	0.24919	-0.08336***	-0.07228***	0.09139	0.00628
	(3.0852)	(1.3609)	(-3.91)	(-4.5714)	(0.5447)	(0.0363)
Asia Pacific(-1)	-0.00001**	0.00000	-0.00001*	0.00000	-0.00001**	-0.00001
	(-2.0178)	(-0.7924)	(-1.7961)	(-1.2115)	(-2.3003)	(-1.4218)
Europe(-1)	0.00001***	0.00001**	0.00000	0.00000	0.00001*	0.00000
	(3.9707)	(2.1203)	(1.5534)	(1.3313)	(1.7109)	(1.1116)
RoW(-1)	0.00006	0.00004	-0.00002	0.00001	0.00003	0.00003
	(1.5864)	(1.3404)	(-0.527)	(0.8569)	(0.9053)	(1.1564)
US(-1)	-0.00002***	-0.00002***	0.00001	0.00000	-0.00002**	-0.00002*
	(-2.7829)	(-2.9384)	(1.0129)	(-0.0899)	(-1.9804)	(-1.8814)
GDP (U.S. dollars)(-1)	-0.00013*	-0.00018*	-0.00004***	-0.00004***	-0.00008	-0.00006
	(-1.8799)	(-1.9175)	(-3.4851)	(-4.4749)	(-0.7968)	(-0.5331)
GDP based on PPP(-1)	0.00001	0.00011*	0.00003***	0.00003***	0.00011	0.00010
	(0.1544)	(1.6609)	(3.7669)	(4.7007)	(1.552)	(1.3317)
Implied PPP(-1)	-0.00012	0.00006	0.00000	0.00001	0.00009	0.00013
	(-1.0874)	(0.6356)	(0.3021)	(1.2849)	(0.8675)	(1.5684)
Inflation, average consumer prices(Index) (-1)	0.00000	0.00000	0.00000	0.00000	0.00000*	0.00000**
	(-1.523)	(-1.5096)	(-0.5959)	(-0.8247)	(-1.7811)	(-2.1719)
Volume of imports of goods and services(-1)	-0.00153	-0.00480	-0.00022	-0.00301**	0.00056	-0.00153
	(-0.4312)	(-1.4441)	(-0.1289)	(-2.369)	(0.2792)	(-0.7848)
Unemployment rate(Percent of total labor) force (-1)	-0.04796***	-0.03231**	-0.00042	-0.00066	-0.03327**	-0.02554*
	(-3.1265)	(-1.9892)	(-0.2233)	(-0.3789)	(-2.3209)	(-1.6931)
Current account balance(U.S. dollars)(-1)	0.00106	0.00089	-0.00018*	-0.00024**	0.00016	-0.00001
	(1.3818)	(1.0933)	(-1.7413)	(-2.572)	(0.1866)	(-0.0068)
Adjusted R-squared	0.07691	0.22074	0.02733	0.61898	0.08291	0.16261
Cross-Section Fixed Effects or Random Effects	Fixed	Fixed	Random	Random	Fixed	Fixed
Number of Observations (N)	188	188	188	188	188	188

5.5 Summary

In this chapter, I extended the literature on ETF fund flows and return performance. I study ETF fund flows on a global level using 51 different countries from 2011 to 2015 to understand whether they provide a better explanation of variation of index returns than macro-economic variables and I also examine the relationship between last year's ETF fund flows and next year's market returns on indices. I am the first to my knowledge to use a unique set of ETF fund flow data on a global level provided by Deutsche Bank.

My first research question sets to explain whether ETF fund flows have better explanatory powers in explaining index returns compared to macroeconomic variables. Most of the reviewed literature on returns and macro-economic variables indicate that macro-economic news is only able to explain very little of the movements in stock prices. My findings indicate that using a panel data model, the explanatory powers of ETF fund flows are similar to macro-economic variables in explaining indices returns.

My second research question is aimed at analyzing the relationship between last year's ETF fund flows and next year's market returns on equities, bonds and future indices. I find that on equity indices based on statistical significance, lagged ETF fund flows into Europe have a positive relationship with equity index returns. I find a negative relationship between ETF fund flows in the US with equity index returns. I find similar negative relationship of the ETF fund flows into the US market for future indices. However, in examining the bond indices, I find there is statistically no significant relationship between ETFs fund flows and bond index returns, but the macro-economic variables have a 60% explanatory power. A potential explanation is that the bond ETF fund flows are considerably lower compared to the ETF equity market[69].

The findings show that ETF fund flows are also quite comparable to macro-economic variables in explaining indices returns. Thus, investors could use ETF as information to understand market movements especially globally. Additionally, when other regions invest into ETFs in the US, the equity and future market moves in the opposite direction is interesting as it shows there is a price pressure causing a return effect in the US market. However, this is not seen with the European market, whereby there is still a positive effect between lagged ETF fund flows and next year's equity market movements. This indicates that the European market does not have any price pressure reversal effect. ETF traders could use this information especially on equity and future indices, as it shows the different impact ETF fund flows have on regional indices. In addition, due to the benefits of ETFs, regulators should also learn how and if flows shift markets and ease the creation of ETFs (approval for ETF sponsors have taken about a year[70]) to ensure the growth of ETF products in the market and to promote the benefits of ETFs. This study though has some limitations as my data is only yearly and I do not claim that I have exhausted all the significant macro-variables that are influential, though the variables chosen in this study have also been used in various other studies. In addition, the potential reverse causality between ETF fund flows and returns have not been investigated. This can be an area for future research to understand if a two-way causal relationship between ETF fund flows and returns exists.

[69] In 2015, US ETF equity cash flows was $173,920 million and ETF fixed income was $59,944 million (source: ETF Annual Review 2016" available at https://etf.deutscheam.com/GBR/ENG/Downloadcenter/ETF-Research (accessed 24 February 2016)

[70] "Here Come ETF regulations and why the Industry is happy about it" Available at https://www.wsj.com/articles/here-come-etf-regulations-and-why-the-industry-is-happy-about-it-1488770041 (accessed 11 June 2017)

6. Conclusion

6.1 Summary of the findings of the thesis

The core question that is addressed in this thesis relates to understanding new information types which would help investors to understand the impact on their portfolios especially on different asset classes. In this thesis, I answer that question using four empirical analyses based on unique hand-collected data on fines and on ETF flow data which to my knowledge is the first to be examined. I examine fines as new information because illegal behaviors of companies have clear detrimental impact on company reputation resulting even in resignations of senior management such as the case of VW. I also examine fines as important information because it relates closely to the area of Responsible Investment (RI). RI has grown in the last few years in an astonishing rate evident by the huge scale of investors signing up to the UNPRI. The UNPRI has grown consistently since it started in 2006 from initially only 100 numbers of signatories to 1500 in April 2016 with assets under management amounting to USD 62 trillion[71]. Therefore, more and more investors are keen on incorporating ESG issues into investment analysis and decision-making processes. This indicates that investors are now more inclined to understand the impact ESG issues have on their portfolio returns. Thus, understanding the impact ESG fines have on portfolios would benefit investors tremendously. I also examine ETF fund flows as information because it would be keen to understand the relationship between ETFs and various global indices especially on different asset types. Investor behavior has also been changing towards a more long-term focused horizon rather than short-term. From those four empirical studies, I examine five major questions. 1) Do fines have a long-term negative impact

[71] https://www.unpri.org/about accessed 29 April 2017

on equity return? 2) What is the impact on returns of ESG plus LT fines? 3) Is there an inter-link effect in the context of fines between equity and fixed income? 4) What is the short-term impact of fines on CDS spreads and equity returns? 5) What is the relationship between last year ETF fund flows and next year's market returns on indices?

I answer questions (1) and (2) in the empirical Chapter 2. The study in this chapter examines the impact of fines on long-term returns using hand-collected data from SEC filings from the period 1994 to 2012 for US large capitalization companies. Time-series regressions were run using both equal and value weighted portfolios following CAPM, Fama-French and Carhart models. The main findings of this chapter suggests that when holding shares of firms with monetary fines for one year there are negative underperformances of between 29 and 57 basis points p.m and the results are robust to different weighting metrics. Most importantly, I find that firms with higher fines per firm size (based on market capitalization) have a larger underperformance compared to firms with lower fines. I also investigate the different legal stages of the fines and find that initial announcements of the violations have larger negative returns compared to other legal stages. What is even more interesting is that using classifications of ESG and LT aspects, I find investors perceive environmental issues on all different legal stages of violations to be a cause of concern and with larger underperformances compared to social, governance and long-term issues. Furthermore, not all not all ESG plus LT issues are relevant in all industries. However, it is important to note that I find the manufacturing industry exhibits outperformance with statistical significance on the confirmed violations but still pending other matters legal stage. A potential explanation could be that the market perceives a better outcome on the fines on manufacturing companies when the violation is subject to legal procedures. Overall, from the findings from this chapter I advocate that companies should be more legally responsible.

My empirical chapter 3 answers the major question (3) about the link between equity and fixed income in the context of fines and further adds to the originality contributions of this thesis. In this study, I use short selling after announcements of illegal violations to a sample of 691 US firms on 4661 bond returns from the period 2000 to 2012 using a multi-index bond model. Using different levels of quintiles, I find that the second highest percentile, after a fine or settlement induces negative underperformances in non-callable bond returns by an average of 20 basis points p.m. However, when I split the sample in the middle into two time periods, I find that it is the first half of the period that induces the negative underperformances. I also examine whether there is a difference between periods of crisis and non-crisis and the investment horizons of the bonds in terms of their remaining years to maturities to provide an accurate description of the relationship between these two asset classes. Firstly, the results are interesting as it indicates that investors penalize companies more during crisis periods indicating that illegalities are more detrimental to companies during periods of uncertainty. Secondly, I find that bonds with longer years to maturities exhibit underperformances compared to bonds with lower years to maturities which actually outperforms. This finding coincides with the understanding that RI investors are more concerned about the performances of longer term bonds.

These results are robust to different benchmarks, value weightings and also liquidity measures. Moreover, I also run a series of additional analysis. Firstly, using a control sample which includes all companies regardless if it has a fine, I find that there is outperformance on companies that have no short selling and underperformances only with companies with lowest short selling. Thus when there is no short selling which in turn would indicate "good" sentiment there is outperformance on the bond returns. The underperformance on the lowest short selling portfolio results, affirms the main findings as it shows that only higher short selling in the context of fines induces larger underperformances on bond returns. Secondly, as I had only examined non-callable bonds, I test whether the results would hold with bonds with all characteristics and features. The results indicate that the highest short selling portfolio underperforms at 25 basis p.m.

Similar to the results in the preceding chapter 2 on equity returns, overall I also find underperformances in the context of fines on bond returns. The findings in this chapter are interesting to investors who are keen to understand the inter-market link between assets. More importantly, in this chapter it shows that not only equity investors are feeling the pinch of illegal behaviors of companies but bond investors too. Inter-market theory states that at times of panic or uncertainty, both bonds and stocks fall. Here I show, there is evidence of a direct relationship between bonds and stocks after violations.

. In chapter 4 I examine the impact of fines on risk, specifically credit risk. I answer the major questions (2) and (4) which relate to understanding the impacts of fines on CDS spreads and also the impact on different ESG plus LT issues on 121 US large capitalization companies from the period 2009 to 2012 using event study models. Most importantly, I comparatively measure the impact of events on CDS spreads and equity returns. This study is highly interesting as I find no literature in the area of illegalities that have directly measured the impact of fines on CDS spreads. Firstly, the empirical results show that the CDS market reacts to news of illegalities on short-term, medium term and even on all levels of maturities. Secondly, most studies indicate CDS markets are able to anticipate news which is also corroborated by my results that indicate the CDS market anticipates illegality news even before announcements. Thirdly, I also find that both the CDS and stock market reacts more to firms with higher fines per market cap. Fourthly, based on the different legal stages of the fines, CDS markets reacts negatively at the final stage (confirmed) compared to the stock market which reacts negatively at the initial stage (pending) of the fine. Fifthly, in terms of industry expectations, CDS and stock markets react only negatively to fines in mining and manufacturing companies respectively. Both the CDS and stock markets react negatively to environmental issues. However, for long-term issues, surprisingly both markets react positively.

On an overall perspective, these results verify the notion that illegal behaviors can induce a strong perception of default risk of a company which results in increases in spreads after announcements of fines. These results are especially interesting for academics who are interested in research on illegalities. Furthermore, investors in other markets should look to the CDS market first especially when there are increases in spreads even before any illegality announcements are made. This is a possible hint that the CDS market is already aware of potential defaults and thus has factored this into CDS prices.

The previous three empirical chapters have all looked at fines as information for investors. In chapter 5, I examine the relationship between ETF fund flows and returns on indices as information that investors could use to track their fund performances. I also examine whether ETF fund flows provide better explanation of market return variations than commonly used macro-economic variables. Using a novel set of ETF fund flow data retrieved from Deutsche Bank, I was able to run analysis using panel data estimations on 51 countries worldwide.

Firstly, examining the empirical results, my findings indicate that the explanatory powers of ETF fund flows are similar to macro-economic variables in explaining indices returns. In essence they both provide similar adjusted r-squared values indicating similar goodness fit to the model. Secondly, when examining the relationship between ETF fund flow data on different regions, the empirical results are on overall mixed. For instance, on equity indices returns, the results show that when there is an increase of fund flow into Europe ETFs, the equity market returns increase in the next year. However, this is the opposite for lagged ETF fund flows into the US, where I find an inverse relationship for both equity and future indices returns. There are no statistically significant results for ETF fund flows and bond indices. The overall results here are quite interesting for investment managers as this provides information that indicates ETFs are very similar to macro-economic variables and managers can use ETF fund flows movements to examine possible future movements of indices.

In summary, the main findings of this thesis have great implications for institutional investors, companies, researchers and also regulators. The most important conclusion that can be drawn from this thesis is that fines are detrimental not only on the short run but also long run to the performances of company returns. Review of the empirical studies indicates a strong investor reaction to corporate illegalities and institutional investors should be aware of the negative impacts of having companies with fines in their portfolios. Additionally, investors could look at CDS market behavior when examining illegalities as they are able to anticipate news. Regulators should ensure that adequate controls and procedures are in place to deter corporate illegalities. Furthermore, information on global ETF fund flows provides a better understanding on the movements of various global indices especially on different asset classes. Overall, this thesis contributes to the growing literature on corporate illegalities and on ETFs.

This thesis shows that the impact of fines is not just limited to one asset class such as equities but extends to the bond and credit default markets. This research would especially benefit RI investors who are not only keen on understanding the impact external information has on their portfolios but to also advocate a sense of corporate legal responsibility which would hopefully lead to the betterment of company behavior.

6.2 Suggestion for future research

Even though there is vast amount of literature in the area of illegalities that intends to measure the impact violations have on short-term equity returns, there still seems to lack attention and research on long-term returns. With the exception of Baucus and Near (1991) and Baucus and Baucus (1997) that measured long-term impact of illegalities, though their papers differ from mine in various ways. Firstly, their data is based only on convicted firms. Secondly, they measure accounting data and market returns using covariance procedures and thirdly their data sample is from 1963 to 1981. I not only examine equity returns but also extend the analysis to bond returns. My methodology is based on Carhart models and multi-index bond models. Academics could further examine the long-term impacts using panel data regressions and having dependent variables and independent variables to measure what actually drives fines on companies instead of a portfolio method. This calls for future research to further enhance my understanding of the long-term impact of illegalities.

In an efficient market, prices would reflect all relevant information in any point of time. However, if there is a semi-strong form view in the markets, then any new additional information would results in prices changes. Following the information content hypothesis, there should be price reactions on the daily basis of excess returns if there is a new risk level associated with the new announcement of violation. In this thesis, I also measure daily announcements of CDS spread changes and equity returns and I find immediate reactions. As in my CDS results, I find that the CDS market has already anticipated illegal announcement news even before announcements. However, as I do not have data prior to fines due to dataset limitations to examine rumors or speculations using news data, this would be an interesting avenue in research to understand what kind of rumors prior to fines are investors more concerned about and also how strong is the impact of rumors or even private information compared to actual announcements.

The underlying datasets of this thesis is purely based on publicly available information. Most of the information given is for large public listed companies and thus another intriguing area to examine would be if the reactions of investors on illegal behaviors of companies are the same for non-public listed companies. This would be interesting to measure the reputation differences companies have being listed or non-listed and the tolerance levels of investors. Thus, measuring corporate reputation based on the types of disclosure requirements of companies especially on their illegal behaviors would be a fascinating area for academics to research on.

Although I have examined the impact of new information such as fines and flows on overall market reactions, I have not measured whether this information has different reactions by different types of investors, i.e. institutional or individual. Investor trading behavior has always been an interest both academically and practically especially by the type of investors. Public information is always available to investors thus investigating the trading behaviors and patterns of different types of investors would be beneficial in understanding which type of investors is actually more concerned about violations of companies and also fund flows into ETFs. Inferring the different types of trading behaviors of various types of investors can be accomplished using either trading size, by institutional ownership or even by actual trades (Nofsinger 2001).

[This section has been intentionally left blank]

7. References

Adamsson, H. and A. G. F. Hoepner (2015). "The 'Price of Sin' Aversion: Ivory Tower Illusion or Real Investable Alpha?" Available at SSRN: http://ssrn.com/abstract=2659098

Agapova, A. (2011). "Conventional mutual index funds versus exchange-traded funds." Journal of Financial Markets **14**(2): 323-343.

Allison, P. D. (2006). "Fixed effects regression methods in SAS." Thirty-first Annual SAS.

Amihud, Y. (2002). "Illiquidity and stock returns: cross-section and time-series effects." Journal of Financial Markets **5**(1): 31-56.

Arnold, M. and P.-J. Engelen (2007). "Do financial markets discipline firms for illegal corporate behaviour." Management & Marketing **2**(4): 103-110.

Arora, N., P. Gandhi, et al. (2012). "Counterparty credit risk and the credit default swap market." Journal of Financial Economics **103**(2): 280-293.

Ashbaugh-Skaife, H., D. W. Collins, et al. (2006). "The effects of corporate governance on firms' credit ratings." Journal of Accounting and Economics **42**(1–2): 203-243.

Asprem, M. (1989). "Stock prices, asset portfolios and macroeconomic variables in ten European countries." Journal of Banking & Finance **13**(4): 589-612.

Asquith, P., P. A. Pathak, et al. (2005). "Short interest, institutional ownership, and stock returns." Journal of Financial Economics **78**(2): 243-276.

Baker, M. and J. Wurgler (2006). "Investor Sentiment and the Cross-Section of Stock Returns." The Journal of Finance **61**(4): 1645-1680.

Balduzzi, P., E. J. Elton, et al. (2001). "Economic News and Bond Prices: Evidence from the U.S. Treasury Market." Journal of Financial and Quantitative Analysis **36**(04): 523-543.

Baltagi, B. H. (1988). "Panel Data Methods." Handbook of Applied Economic Statistics(A. Ullah and D.E.A. Giles (eds), Marcel Dekker, New York.).

Barber, B. M. and J. D. Lyon (1997). "Detecting long-run abnormal stock returns: The empirical power and specification of test statistics." Journal of Financial Economics **43**(3): 341-372.

Barberis, N. and A. Shleifer (2003). "Style investing." Journal of Financial Economics **68**(2): 161-199.

Baucus, M. S. and D. A. Baucus (1997). "Paying the Piper: An Empirical Examination of Longer-Term Financial Consequences of Illegal Corporate Behavior." The Academy of Management Journal **40**(1): 129-151.

Baucus, M. S. and J. P. Near (1991). "Can Illegal Corporate Behavior Be Predicted? An Event History Analysis." The Academy of Management Journal **34**(1): 9-36.

Becker, G. S. (1968). "Crime and Punishment: An Economic Approach." Journal of Political Economy **76**(2): 169-217.

Bender, J. (2012). "Demystifying Equal Weighting " MSCI Research Insights, June 2012. Available at SSRN: http://ssrn.com/abstract=2543983 or http://dx.doi.org/10.2139/ssrn.2543983.

Bhojraj, S. and P. Sengupta (2003). "Effect of Corporate Governance on Bond Ratings and Yields: The Role of Institutional Investors and Outside Directors." The Journal of Business **76**(3): 455-475.

Birz, G. and J. R. Lott Jr (2011). "The effect of macroeconomic news on stock returns: New evidence from newspaper coverage." Journal of Banking & Finance **35**(11): 2791-2800.

Black, F. and M. Scholes (1973). "The Pricing of Options and Corporate Liabilities." Journal of Political Economy **81**(3): 637-654.

Blake, C. R., E.J. Elton, et al. (1993). "The Performance of Bond Mutual Funds." Journal of Business **Vol. 66**: pp. 371–403.

Blanco, R., S. Brennan, et al. (2005). "An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps." Journal of Finance **60**(5): 3-32.

Blau, B. M. and B. S. Roseman (2014). "The reaction of European credit default swap spreads to the U.S. credit rating downgrade." International Review of Economics & Finance **34**: 131-141.

Blitz, D., J. Huij, et al. (2012). "The Performance of European Index Funds and Exchange-Traded Funds." European Financial Management **18**(4): 649-662.

Boehmer, E., Z. R. Huszar, et al. (2010). "The good news in short interest." Journal of Financial Economics **96**(1): 80-97.

Boehmer, E., C. M. Jones, et al. (2008). "Which Shorts Are Informed?" The Journal of Finance **63**(2): 491-527.

Boehmer, E., C. M. Jones, et al. (2013). "Shackling Short Sellers: The 2008 Shorting Ban." Review of Financial Studies **26**(6): 1363-1400.

Boehmer, E., J. Masumeci, et al. (1991). "Event-study methodology under conditions of event-induced variance." Journal of Financial Economics **30**(2): 253-272.

Bondt, W. F. and R. Thaler (1985). "Does the stock market overreact?" The Journal of Finance **40**(3): 793-805.

Borenstein, M., L. V. Hedges, et al. (2010). "A basic introduction to fixed-effect and random-effects models for meta-analysis." Research Synthesis Methods **1**(2): 97-111.

Bosch, J.-C. and E. W. Eckard, Jr. (1991). "The Profitability of Price Fixing: Evidence From Stock Market Reaction to Federal Indictments." The Review of Economics and Statistics **73**(2): 309-317.

Boyce, W. M. and A. J. Kalotay (1979). "Tax Differentials and Callable Bonds." The Journal of Finance **34**(4): 825-838.

Brooks, C. (2008). Introductory Econometrics for Finance.

Brown, G. W. and M. T. Cliff (2004). "Investor sentiment and the near-term stock market." Journal of Empirical Finance **11**(1): 1-27.

Brown, S. J., W. Goetzmann, et al. (1992). "Survivorship Bias in Performance Studies." Review of Financial Studies **5**(4): 553-580.

Callen, J. L. and X. Fang (2015). "Short interest and stock price crash risk." Journal of Banking & Finance **60**: 181-194.

Callen, J. L., J. Livnat, et al. (2009). "The impact of earnings on the pricing of credit default swaps." The Accounting Review **84**(5): 1363-1394.

Campbell, J. L. (2007). "Why Would Corporations Behave in Socially Responsible Ways? An Institutional Theory of Corporate Social Responsibility." The Academy of Management Review **32**(3): 946-967.

Campbell, J. Y. and G. B. Taksler (2003). "Equity Volatility and Corporate Bond Yields." The Journal of Finance **58**(6): 2321-2350.

Canner, N. N., M. Gregory, et al. (1994). "An asset allocation puzzle." No. w4857. National Bureau of Economic Research.

Capelle-Blancard, G. and M.-A. Laguna (2010). "How does the stock market respond to chemical disasters?" Journal of Environmental Economics and Management **59**(2): 192-205.

Carhart, M. M. (1997). "On Persistence in Mutual Fund Performance." The Journal of Finance **52**(1): 57-82.

Chan, L. K. C., J. Karceski, et al. (1998). "The Risk and Return from Factors." Journal of Financial and Quantitative Analysis **33**(2): 159-188.

Charupat, N. and P. Miu (2013). "Recent developments in exchange-traded fund literature." Managerial Finance **39(5), 427-443**.

Chen, L., D. A. Lesmond, et al. (2007). "Corporate Yield Spreads and Bond Liquidity." The Journal of Finance **62**(1): 119-149.

Chen, N.-F., R. Roll, et al. (1986). "Economic Forces and the Stock Market." The Journal of Business **59**(3): 383-403.

Cherny, K. and B. R. Craig (2009). "Credit default swaps and their market function." Economic Commentary.

Choi, S. and A. Pritchard (2012). "SEC Investigations and Securities Class Actions: An Empirical Comparison." Law & Economics Working Papers. Paper 55.

Christiansen, C., M. Schmeling, et al. (2012). "A comprehensive look at financial volatility prediction by economic variables." Journal of Applied Econometrics **27**(6): 956-977.

Chung, Y.-T., T. L. Liao, et al. (2015). "The selection of popular trading strategies." Managerial Finance **41**(6): 563 - 581.

Cohen, M. A. (1996). "Theories of Punishment and Empirical Trends in Corporate Criminal Sanctions." Managerial and Decision Economics **17**(4): 399-411.

Coleman, L. (2011). "Losses from Failure of Stakeholder Sensitive Processes: Financial Consequences for Large US Companies from Breakdowns in Product, Environmental, and Accounting Standards." Journal of Business Ethics **98**(2): 247-258.

Cox, J. C., J. E. Ingersoll, et al. (1985). "An Intertemporal General Equilibrium Model of Asset Prices." Econometrica **53**(2): 363-384.

Cutler, D. M., James M. Poterba, et al. (1989). "What Moves Stock Prices?" Journal of Portfolio Management **15**(3): 4-12.

Daniels, K. N. and M. S. Jensen (2005). "The effect of credit ratings on credit default swap spreads and credit spreads." The Journal of Fixed Income **15**(3): 16-33.

Datta, S. and U. S. Dhillon (1993). "Bond and Stock-Market Response to Unexpected Earnings Announcements." Journal of Financial and Quantitative Analysis **28**(4): 565-577.

Davidson, W. N., III, D. L. Worrell, et al. (1994). "Stock Market Reactions to Announced Corporate Illegalities." Journal of Business Ethics **13**(12): 979-987.

de Jong, A. and I. Naumovska (2016). "A Note on Event Studies in Finance and Management Research*." Review of Finance **20**(4): 1659-1672.

DeFond, M. L. and J. Zhang (2008). "The Information Content of Earnings Surprises in the Corporate Bond Market " Available at SSRN: http://ssrn.com/abstract=1157489 or http://dx.doi.org/10.2139/ssrn.1157489.

Defond, M. L. and J. Zhang (2014). "The Timeliness of the Bond Market Reaction to Bad Earnings News." Contemporary Accounting Research **31**(3): 911-936.

Derwall, J. and K. Koedijk (2009). "Socially Responsible Fixed-Income Funds." Journal of Business Finance & Accounting **36**(1-2): 210-229.

Desai, H., K. Ramesh, et al. (2002). "An Investigation of the Informational Role of Short Interest in the Nasdaq Market." The Journal of Finance **57**(5): 2263-2287.

Dichev, I. D. and J. D. Piotroski (2001). "The Long-Run Stock Returns Following Bond Ratings Changes." The Journal of Finance **56**(1): 173-203.

Dick-Nielsen, J., P. Feldhütter, et al. (2012). "Corporate bond liquidity before and after the onset of the subprime crisis." Journal of Financial Economics **103**(3): 471-492.

Diether, K. B., K.-H. Lee, et al. (2009). "Short-Sale Strategies and Return Predictability." Review of Financial Studies **22**(2): 575-607.

Drut, B. (2010). "Sovereign Bonds and Socially Responsible Investment." Journal of Business Ethics **92**(1): 131-145.

Durham, J. B. (2001). "The effects of monetary policy on monthly and quarterly stock market returns: Cross-country evidence and sensitivity analyses." Finance and Economics Discussion Series Paper 2001-42(Federal Reserve Board of Governors).

Dyck, A., A. Morse, et al. (2010). "Who Blows the Whistle on Corporate Fraud?" The Journal of Finance **65**(6): 2213-2253.

Eaglesham, J. and A. Fuller (2015) "Wall Street’s Top Cop Takes Harder Line."

Edelen, R. M. and J. B. Warner (2001). "Aggregate price effects of institutional trading: a study of mutual fund flow and market returns." Journal of Financial Economics **59**(2): 195-220.

Edmans, A. (2011). "Does the stock market fully value intangibles? Employee satisfaction and equity prices." Journal of Financial Economics **101**(3): 621-640.

Elton, E. J., M. J. Gruber, et al. (2002). "Spiders: Where are the bugs?" The Journal of Business **75**(3): 453-472.

English, S. (2014) "The rising costs of non-compliance."

Fabozzi, F. J., K. C. Ma, et al. (2008). "Sin stock returns." Journal of Portfolio Management: 82-94.

Fama, E. F. (1998). "Market efficiency, long-term returns, and behavioral finance." Journal of Financial Economics **49**(3): 283-306.

Fama, E. F. and K. R. French (1993). "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Financial Economics

33:1: 3–56.

Fama, E. F. and K. R. French (1996). "Multifactor Explanations of Asset Pricing Anomalies." Journal of Finance **51:1**: 55–84.

Fama, E. F. and K. R. French (2004). "The Capital Asset Pricing Model: Theory and Evidence." The Journal of Economic Perspectives **18**(3): 25-46.

Finnerty, J. D., C. D. Miller, et al. (2013). "The impact of credit rating announcements on credit default swap spreads." Journal of Banking & Finance **37**(6): 2011-2030.

Flannery, M. J. and A. A. Protopapadakis (2002). "Macroeconomic Factors Do Influence Aggregate Stock Returns." Review of Financial Studies **15**(3): 751-782.

Fleming, M. J. and E. M. Remolana (1997). "What moves the bond market?" Federal Reserve Bank of New York. Economic Policy Review 3 (4).

Fodor, A. and J. Stowe (2012). "Financial Market Reactions to a Company Disaster: The BP Case." Journal of Applied Finance **22**(1): 88.

Forte, S. and J. I. Pena (2009). "Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS." Journal of Banking & Finance **33**(11): 2013-2025.

Freeman, R. (1984). "Strategic Management: a Stakeholder Approach." Pitman, Marshall, MA.

Fung, H.-G., G. E. Sierra, et al. (2008). "Are the US stock market and credit default swap market related? Evidence from the CDX indices." The Journal of Alternative Investments **11**(1): 43-61.

Galil, K. and G. Soffer (2011). "Good news, bad news and rating announcements: An empirical investigation." Journal of Banking & Finance **35**(11): 3101-3119.

Gallagher, D. R. and R. Segara (2005). "The performance and trading characteristics of exchange-traded funds." University of New South Wales.

Gary, P. B., L. R. Hood, et al. (1986). "Determinants of Portfolio Performance." Financial Analysts Journal **42**(4): 39-44.

Gastineau, G. L. (2004). "The benchmark index ETF performance problem." Journal of Portfolio Management **30**(2): 96-103.

Ghent, A. C. (2010). " Why Do Markets React Badly to Good News? Evidence from Fed Funds Futures." Available at SSRN: http://ssrn.com/abstract=1153122 or http://dx.doi.org/10.2139/ssrn.1153122.

Gibson , R. and P. Krueger (2017). "The Sustainability Footprint of Institutional Investors " Swiss Finance Institute Research Paper No. 17-05(Available at SSRN: https://ssrn.com/abstract=2918926 or http://dx.doi.org/10.2139/ssrn.2918926).

Gillan, S. L. and L. T. Starks (2000). "Corporate governance proposals and shareholder activism: The role of institutional investors." Journal of Financial Economics **57**(2): 275-305.

Goh, J. C. and L. H. Ederington (1993). "Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders?" The Journal of Finance **48**(5): 2001-2008.

Greatrex, C. A. (2009). "The credit default swap market's reaction to earnings announcements." Journal of Applied Finance **19**(1): 193-216.

Green, T. C. (2004). "Economic News and the Impact of Trading on Bond Prices." The Journal of Finance **59**(3): 1201-1233.

Grinblatt, M. and S. Titman (1989). "Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings." The Journal of Business **62**(3): 393-416.

Hausman, J. A. (1978). "Specification Tests in Econometrics." Econometrica **46**(6): 1251-1271.

Henke, H.-M. a. Maehlmann, et al. (2014). "The Effect of Social Screening on Bond Mutual Fund Performance " SSRN: http://ssrn.com/abstract=2429221 or http://dx.doi.org/10.2139/ssrn.2429221.

Henry, T. R., D. J. Kisgen, et al. (2015). "Equity short selling and bond rating downgrades." Journal of Financial Intermediation **24**(1): 89-111.

Hensel, C. R., D. D. Ezra, et al. (1991). "The Importance of the Asset Allocation Decision." Financial Analysts Journal **47**(4): 65-72.

Hilscher, J., J. M. Pollet, et al. (2015). "Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets." Journal of Financial and Quantitative Analysis **50**(03): 543-567.

Hoepner, A. G. F. and M. A. Nilsson (2015). "ESG Expertise & Fixed Income " Available at SSRN: http://ssrn.com/abstract=2517057 or http://dx.doi.org/10.2139/ssrn.2517057.

Hoepner, A. G. F., H. G. Rammal, et al. (2011). "Islamic mutual funds' financial performance and international investment style: evidence from 20 countries." The European Journal of Finance **17**(9-10): 829-850.

Hoepner, A. G. F. and L. Schopohl (2016). "On the Price of Morals in Markets: An Empirical Study of the Swedish AP-Funds and the Norwegian Government Pension Fund." Journal of Business Ethics: 1-28.

Hoepner, A. G. F. and S. Zeume (2013). "Fiduciary Duty and Sin Stocks: Is Vice Really Nice? ." Handbook of Institutional Investment and Fiduciary Duty, 2014. Available at SSRN: http://ssrn.com/abstract=1485846.

Hong, H. and M. Kacperczyk (2009). "The price of sin: The effects of social norms on markets." Journal of Financial Economics **93**(1): 15-36.

Hopewell, M. H. and G. G. Kaufman (1973). "Bond Price Volatility and Term to Maturity: A Generalized Respecification." The American Economic Review **63**(4): 749-753.

Hribar, P. and D. W. Collins (2002). "Errors in Estimating Accruals: Implications for Empirical Research." Journal of Accounting Research **40**(1): 105-134.

Huang, A. Y., C. Shen, et al. (2012). "The impact of major events from the recent financial crisis on credit default swaps." The Journal of Fixed Income **21**(3): 31-43.

Huang, J.-Z., M. Rossi, et al. (2015). "Sentiment and Corporate Bond Valuations Before and After the Onset of the Credit Crisis." Journal of Fixed Income, Forthcoming. Available at SSRN: http://ssrn.com/abstract=2298491 or http://dx.doi.org/10.2139/ssrn.2298491.

Huang, J. C. and I. Guedj (2009). "Are ETFs Replacing Index Mutual Funds? ." AFA 2009 San Francisco Meetings Paper. Available at SSRN: http://ssrn.com/abstract=1108728 or http://dx.doi.org/10.2139/ssrn.1108728.

Hull, J., M. Predescu, et al. (2004). "The relationship between credit default swap spreads, bond yields, and credit rating announcements." Journal of Banking & Finance **28**(11): 2789-2811.

Ibbotson, R. G. (2010). "The Importance of Asset Allocation." Financial Analysts Journal **66**(2): 18-20.

Ibbotson, R. G. and P. D. Kaplan (2000). "Does Asset Allocation Policy Explain 40, 90, or 100 Percent of Performance?" Financial Analysts Journal **56**(1): 26-33.

Ismailescu, I. and H. Kazemi (2010). "The reaction of emerging market credit default swap spreads to sovereign credit rating changes." Journal of Banking & Finance **34**(12): 2861-2873.

Izraeli, D. and M. S. Schwartz (1998). "What Can We Learn from the U.S. Federal Sentencing Guidelines for Organizational Ethics." Journal of Business Ethics **17**(9): 1045-1055.

Jacobs, B. W., V. R. Singhal, et al. (2010). "An empirical investigation of environmental performance and the market value of the firm." Journal of Operations Management **28**(5): 430-441.

Jain, A., P. K. Jain, et al. (2013). "Worldwide reach of short selling regulations." Journal of Financial Economics **109**(1): 177-197.

Jegadeesh, N. and S. Titman (1993). "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." The Journal of Finance **48**(1): 65-91.

Jenkins, H. and N. Yakovleva (2006). "Corporate social responsibility in the mining industry: Exploring trends in social and environmental disclosure." Journal of Cleaner Production **14**(3–4): 271-284.

Jenkins, N. T., M. D. Kimbrough, et al. (2016). "The extent of informational efficiency in the credit default swap market: evidence from post-earnings announcement returns." Review of Quantitative Finance and Accounting **46**(4): 725-761.

Jensen, M. C. (1968). "THE PERFORMANCE OF MUTUAL FUNDS IN THE PERIOD 1945–1964." The Journal of Finance **23**(2): 389-416.

Jensen, M. C. and W. H. Meckling (1976). "Theory of the firm: Managerial behavior, agency costs and ownership structure." Journal of Financial Economics **3**(4): 305-360.

Jorion, P. and G. Zhang (2007). "Good and bad credit contagion: Evidence from credit default swaps." Journal of Financial Economics **84**(3): 860-883.

Kahneman, D. and A. Tversky (1979). "Prospect theory: An analysis of decision under risk." Econometrica: Journal of the econometric society: 263-291.

Kalaycıoğlu , S. (2004). "Exchange Traded Fund Flows " Available at SSRN: http://ssrn.com/abstract=881108 or http://dx.doi.org/10.2139/ssrn.881108.

Karpoff, J. M., D. Scott Lee, et al. (1999). "Defense Procurement Fraud, Penalties, and Contractor Influence." Journal of Political Economy **107**(4): 809-842.

Karpoff, J. M. and John R. Lott, Jr. (1993). "The reputational penalty firms bear from committing criminal fraud." Journal of Law and Economics **36**: 757 to 802.

Karpoff, J. M., John R. Lott, Jr., et al. (2005). "The Reputational Penalties for Environmental Violations: Empirical Evidence." Journal of Law and Economics **48**(2): 653-675.

Karpoff, J. M., A. Koester, et al. (2014). "Database Challenges in Financial Misconduct Research." Georgetown McDonough School of Business Research Paper No. 2012-15.

Karpoff, J. M., D. S. Lee, et al. (2005). "The Cost to Firms of Cooking the Books." Journal of Financial and Quantitative Analysis **43**: 581-611.

Karpoff, J. M., D. S. Lee, et al. (2007). "The legal penalties for financial misrepresentation." Available at SSRN: https://ssrn.com/abstract=933333. or http://dx.doi.org/10.2139/ssrn.933333.

Karpoff, J. M. and X. Lou (2010). "Short Sellers and Financial Misconduct." The Journal of Finance **65**(5): 1879-1913.

Karpoff, J. M., D. Scott Lee, et al. (2008). "The consequences to managers for financial misrepresentation." Journal of Financial Economics **88**(2): 193-215.

Kennedy, C. (1985). "Criminal Sentences for Corporations: Alternative Fining Mechanisms." California Law Review **73**(2): 443-482.

Kim, S.-J., L. Salem, et al. (2015). "The role of macroeconomic news in sovereign CDS markets: Domestic and spillover news effects from the U.S., the Eurozone and China." Journal of Financial Stability **18**: 208-224.

Kölbel, J. F. and T. Busch (2013). "The effect of bad news on credit risk: a media based view of the pricing of corporate social responsibility." Policy Paper(40).

Konar, S. and M. A. Cohen (2001). "Does the market value environmental performance?" Review of economics and statistics(83.2): 281-289.

Kothari, S. and J. B. Warner (1997). "Measuring long-horizon security price performance." Journal of Financial Economics **43**(3): 301-339.

Kouwenberg, R. and V. Phunnarungsi (2013). "Corporate governance, violations and market reactions." Pacific-Basin Finance Journal **21**(1): 881-898.

Langus, G. and M. Motta (2006). "The effect of antitrust investigations and fines on the firm valuation." Manuscript, European University Institute, Florence.

Leon, B., M. P. Devereux, et al. (2010). "Corporate tax harmonization in the EU [with Discussion]." Economic Policy **25**(63): 537-590.

Lintner, J. (1965). "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." Review of Economics and Statistics **47:1**: 13–37.

Longstaff, F. A., S. Mithal, et al. (2003). "The credit-default swap market: is credit protection priced correctly?" Working Paper.

Longstaff, F. A., S. Mithal, et al. (2005). "Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market." The Journal of Finance **60**(5): 2213-2253.

Lott, J. R., Jr. (1996). "Corporate Criminal Penalties." Managerial and Decision Economics **17**(4): 349-350.

Love, R. and R. Payne (2009). "Macroeconomic News, Order Flows, and Exchange Rates." Journal of Financial and Quantitative Analysis **43**(2): 467-488.

MacKinlay, A. C. (1997). "Event Studies in Economics and Finance." Journal of Economic Literature **35**(1): 13-39.

Marcus, A. A. and R. S. Goodman (1991). "Victims and shareholders: The dilemmas of presenting corporate policy during a crisis." Academy of Management Journal **34**(2): 281-305.

Markowitz, H. (1952). "Portfolio Selection." The Journal of Finance **7**(1): 77-91.

McWilliams, A. and D. Siegel (1997). "Event Studies in Management Research: Theoretical and Empirical Issues." The Academy of Management Journal **40**(3): 626-657.

McWilliams, A., D. Siegel, et al. (1999). "Issues in the use of the event study methodology: A critical analysis of corporate social responsibility studies." Organizational Research Methods **2**(4): 340-365.

Menz, K. M. (2010). "Corporate Social Responsibility: Is it Rewarded by the Corporate Bond Market? A Critical Note." Journal of Business Ethics **96**(1): 117-134.

Merton, R. C. (1973). "Theory of Rational Option Pricing." The Bell Journal of Economics and Management Science **4**(1): 141-183.

Merton, R. C. (1974). "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." The Journal of Finance **29**(2): 449-470.

Micu, M., E. Remolona, et al. (2004). "The price impact of rating announcements: evidence from the credit default swap market." BIS Quarterly Review **2**(June): 55-65.

Mongin, P. (1997). "Expected utility theory." Handbook of economic methodology: 342-350.

Murphy, J. J. (2011). "Intermarket analysis: Profiting from Global Market Relationships." Wiley Trading Series.

Narayanan, M. P. (1985). "Managerial Incentives for Short-term Results." The Journal of Finance **40**(5): 1469-1484.

Nayak, S. (2010). "Investor Sentiment and Corporate Bond Liquidity." Journal of International Management Studies **5.2**: 227.

Nayak, S. (2010). "Investor sentiment and corporate bond yield spreads." Review of Behavioral Finance **2**(2): 59-80.

Newey, W. and K. West (1987). "A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix." Econometrica **55**: 703–708.

Newey, W. K. and K. D. West. (1986). "A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix."

Nofsinger, J. and A. Varma (2014). "Socially responsible funds and market crises." Journal of Banking & Finance **48**: 180-193.

Nofsinger, J. R. (2001). "The impact of public information on investors." Journal of Banking & Finance **25**(7): 1339-1366.

Norden, L. (2008). "Credit derivatives, corporate news, and credit ratings." Mannheim, Department of Banking and Finance, University of Mannheim.–May **28**.

Norden, L. and M. Weber (2004). "Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements." Journal of Banking & Finance **28**(11): 2813-2843.

Norden, L. and M. Weber (2009). "The co-movement of credit default swap, bond and stock markets: An empirical analysis." European Financial Management **15**(3): 529-562.

Oikonomou, I., C. Brooks, et al. (2014). "The Effects of Corporate Social Performance on the Cost of Corporate Debt and Credit Ratings." Financial Review **49**(1): 49-75.

Patten, D. M. (2002). "The relation between environmental performance and environmental disclosure: a research note." Accounting, Organizations and Society **27**(8): 763-773.

Piotroski, J. D. and D. T. Roulstone (2004). "The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices." The Accounting Review **79**(4): 1119-1151.

Plyakha, Y., R. Uppal, et al. (2012). "Why does an equal-weighted portfolio outperform value- and price-weighted portfolios?" Working Paper, EDHEC Business School: 1-48.

Rapach, D. E., M. E. Wohar, et al. (2005). "Macro variables and international stock return predictability." International Journal of Forecasting **21**(1): 137-166.

Renneboog, L., J. Ter Horst, et al. (2008). "The price of ethics and stakeholder governance: The performance of socially responsible mutual funds." Journal of Corporate Finance **14**(3): 302-322.

Rompotis, G. G. (2008). "An Empirical Comparing Investigation on Exchange Traded Funds and Index Funds Performance " European Journal of Economics, Finance and Administrative Studies **13**: 7–17.

Rompotis, G. G. (2009). "Interfamily competition on index tracking: The case of the vanguard ETFs and index funds." Journal of Asset Management **10**(4): 263-278.

Ross, S. A. (1976). "The arbitrage theory of capital asset pricing." Journal of Economic Theory **13**(3): 341-360.

Sapp, T. and A. Tiwari (2004). "Does Stock Return Momentum Explain the “Smart Money” Effect?" The Journal of Finance **59**(6): 2605-2622.

Scharfstein, D. S. and J. C. Stein (1990). "Herd Behavior and Investment." The American Economic Review **80**(3): 465-479.

Schestag, R., P. Schuster, et al. (2016). "Measuring Liquidity in Bond Markets." Review of Financial Studies.

Schnatterly, K. (2003). "Increasing firm value through detection and prevention of white-collar crime." Strategic Management Journal **24**(7): 587-614.

Seneca, J. J. (1967). "Short Interest: Bearish or Bullish?" The Journal of Finance **22**(1): 67-70.

Sharifzadeh, M. and S. Hojat (2012). "An analytical performance comparison of exchange-traded funds with index funds: 2002–2010." Journal of Asset Management **13**(3): 196-209.

Sharpe, W. F. (1964). "Capital asset prices: A theory of market equilibrium under conditions of risk*." The journal of finance **19(3)**: 425-442.

Sharpe, W. F. (1992). "Asset allocation: Management style and performance measurement." The Journal of Portfolio Management **18**(2): 7-19.

Shimshack, J. P. and M. B. Ward (2005). "Regulator reputation, enforcement, and environmental compliance." Journal of Environmental Economics and Management **50**(3): 519-540.

Silber, W. L. (1983). "The Process of Financial Innovation." The American Economic Review **73**(2): 89-95.

Song, C. and S. H. Han (2015). "Stock Market Reaction to Corporate Crime: Evidence from South Korea." Journal of Business Ethics: 1-29.

Staer, A. (2014). "Fund Flows and Underlying Returns: The Case of ETFs " Available at SSRN: http://ssrn.com/abstract=2158468 or http://dx.doi.org/10.2139/ssrn.2158468.

Stellner, C., C. Klein, et al. (2015). "Corporate social responsibility and Eurozone corporate bonds: The moderating role of country sustainability." Journal of Banking & Finance **59**: 538-549.

Stoll, H. R. and R. E. Whaley (1990). "The Dynamics of Stock Index and Stock Index Futures Returns." The Journal of Financial and Quantitative Analysis **25**(4): 441-468.

Stulz, R. M. (2010). "Credit Default Swaps and the Credit Crisis." The Journal of Economic Perspectives **24**(1): 73-92.

Sun, W. and K. Cui (2014). "Linking corporate social responsibility to firm default risk." European Management Journal **32**(2): 275-287.

Svetina, M. (2015). "Exchange Traded Funds: Performance and Competition." Journal of Applied Finance (Formerly Financial Practice and Education), Vol. 20, No. 2, 2010. Available at SSRN: http://ssrn.com/abstract=2693060.

Thomas, A. (2001). "Corporate environmental policy and abnormal stock price returns: An empirical investigation." Business Strategy and the Environment **10**(3): 125-134.

Tufano, P. (2003). "Financial innovation." Handbook of the Economics of Finance **1**: 307-335.

Tully, S., ed. (2005). "Research Handbook on Corporate Legal Responsibility." Edward Elgar Publishing.

Ulen, T. S. (1996). "The Economics of Corporate Criminal Liability." Managerial and Decision Economics **17**(4): 351-362.

Von Neumann, J. and O. Morgenstern (1944). Theory of games and economic behavior, Princeton university press.

Wallace, N. D., III and D. L. Worrell (1988). "The Impact of Announcements of Corporate Illegalities on Shareholder Returns." The Academy of Management Journal **31**(1): 195-200.

Warther, V. A. (1995). "Aggregate mutual fund flows and security returns." Journal of Financial Economics **39**(2): 209-235.

Wasserfallen, W. (1989). "Macroeconomics news and the stock market." Journal of Banking & Finance **13**(4): 613-626.

Weber, J. (2006). "Discussion of the effects of corporate governance on firms' credit ratings." Journal of Accounting and Economics **42**(1–2): 245-254.

Weistroffer, C., B. Speyer, et al. (2009). "Credit default swaps." Deutsche bank research **27**.

Wengner, A., H.-P. Burghof, et al. (2015). "The impact of credit rating announcements on corporate CDS markets—Are intra-industry effects observable?" Journal of Economics and Business **78**: 79-91.

Zeidan, M. J. (2013). "Effects of Illegal Behavior on the Financial Performance of US Banking Institutions." Journal of Business Ethics **112**(2): 313-324.

Zeume, S. (2014). "Bribes and Firm Value." Available at SSRN: http://ssrn.com/abstract=2179437.

Zhu, H. (2006). "An empirical comparison of credit spreads between the bond market and the credit default swap market." Journal of Financial Services Research **29**(3): 211-235.

Ziegler, A., M. Schröder, et al. (2007). "The effect of environmental and social performance on the stock performance of european corporations." Environmental and Resource Economics **37**(4): 661-680.

Zyglidopoulos, S. (2016). "Toward a Theory of Second-Order Corruption." Journal of Management Inquiry **25**(1): 3-10.

Zyglidopoulos, S. C. and P. Fleming (2016). "Organizational self-restraint." In: Van Slyke, S. R., Benson, M. L. and Cullen, F. T. (eds.) The Oxford Handbook of White-Collar

Crime. Series: The Oxford handbooks in criminology and criminal justice. Oxford University Press: Oxford: 463-475.

8. Appendix

8.1 Appendix to Chapter 1

Table 8.1 Overview of Dataset, Source, Sample Size and Frequency in each Chapter

The table below provides a detailed description of the data used in each chapter as well as the source, sample size (period) and the frequency of the data

Chapter	Chapter Title	Main Data	Source of Data	Sample Size (Period)	Frequency
2	Corporate Legal Responsibility and Stock Returns	Monetary Fines	SEC 10-K Fillings	1994 to 2012	Yearly
2	Corporate Legal Responsibility and Stock Returns	Equity Returns (Returns Index)	Datastream	1994 to 2012	Monthly
2	Corporate Legal Responsibility and Stock Returns	Market Capitalization (Market Value)	Datastream	1994 to 2012	Monthly
2	Corporate Legal Responsibility and Stock Returns	ESG plus Long-Term criteria	EFFAS	1994 to 2012	-
2	Corporate Legal Responsibility and Stock Returns	Short Interest Ratios	Bloomberg	2002 to 2012	Monthly
3	Inter-market Link of Illegality: Measuring the Effect of Short Selling in the context of Fines on Fixed Income	Short Interest Ratios	Bloomberg	2000 to 2012	Monthly
3	Inter-market Link of Illegality: Measuring the Effect of Short Selling in the context of Fines on Fixed Income	Bond Returns (Total Return Index)	Datastream	2000 to 2012	Monthly
3	Inter-market Link of Illegality: Measuring the Effect of Short Selling in the context of Fines on Fixed Income	Bond Volume	TRACE	2002 to 2012	Intraday
4	A Comparative Event Study: The Impact of Fines on Credit Default Swaps and Stocks	CDS Spreads	Datastream	2009 to 2012	Daily
4	A Comparative Event Study: The Impact of Fines on Credit Default Swaps and Stocks	Equity Returns (Returns Index)	Datastream	2009 to 2012	Daily
5	ETF Fund Flows and Index Returns: A global multi asset class analysis	ETF Fund Flows	Deutsche Bank	2011 to 2015	Yearly
5	ETF Fund Flows and Index Returns: A global multi asset class analysis	Macroeconomic Variables	World Economic Outlook (WEO)	2011 to 2015	Yearly

8.2 Appendix to Chapter 2

Table 8.2 Sample Size and % of US Firms in the MSCI World Large Cap Universe

The table below describes the number of US firms per year in the sample and the columns "% of US firms" is in comparison to the rest of the firms in the MSCI World Large Constituents

Year	Number of Firms	% US firms
1994 to 1997	1452	29.3%
1998 to 2001	1516	36.4%
2002 to 2005	844	38.9%
2006 to 2009	1036	36.1%
2010 to 2012	825	36.9%
Subtotal	**5673**	

Table 8.3 List of relevant SIC codes

The table below depicts the type of industry based on the Standard Industrial Classification (SIC) Code

2 Digit SIC Code	Industry
[10xx-14xx]	Mining
[20xx-39xx]	Manufacturing
[40xx-49xx]	Transportation and Public Utilities
[50xx-59xx]	Retail and Wholesale Trade
[60xx-67xx]	Finance, Insurance, and Real Estate
[70xx-89xx]	Services

Table 8.4 Total Number of Violations per Industry

The table below reports the total number of violations by the type of industry. The type of industry is based on the Standard Industrial Classification (SIC) Code. These violations are categorized according to the two digit SIC code and are based on the hand-collected data from the SEC filings.

2 Digit SIC Code	Industry	Total Violations	1994	1995	1996	1997	1998	1999	2000	2001	2002
[10xx-14xx]	Mining	84	22	12	17	2	6	4	8	9	4
[20xx-39xx]	Manufacturing	544	91	61	71	51	41	53	59	62	55
[40xx-49xx]	Transportation and Public Utilities	249	43	34	28	18	18	27	43	18	20
[50xx-59xx]	Retail and Wholesale Trade	31	2	2	1	4	3	8	2	4	5
[60xx-67xx]	Finance, Insurance, and Real Estate	114	12	10	8	5	12	16	13	14	24
[70xx-89xx]	Services	44	2	1	1	3	8	9	8	9	3
	Total	1066	172	120	126	83	88	117	133	116	111

2 Digit SIC Code	Industry	Total Violations	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
[10xx-14xx]	Mining	86	5	4	3	9	18	7	3	12	18	7
[20xx-39xx]	Manufacturing	603	53	60	46	59	63	48	70	80	62	62
[40xx-49xx]	Transportation and Public Utilities	188	16	13	14	18	19	19	16	27	28	18
[50xx-59xx]	Retail and Wholesale Trade	84	2	8	7	11	15	4	6	8	12	11
[60xx-67xx]	Finance, Insurance, and Real Estate	265	28	27	23	23	19	30	13	34	36	32
[70xx-89xx]	Services	78	7	11	18	7	6	10	5	3	5	6
	Total	1304	111	123	111	127	140	118	113	164	161	136
	Subtotal	2370	283	243	237	210	228	235	246	280	272	136

Table 8.5 Total Number of Violations per Stage (Initial Allegations)

The table below reports the total number of violations by the type of stage (initial allegations). The type of industry is based on the Standard Industrial Classification (SIC) Code. These violations are categorized according to the two digit SIC code and are based on the hand-collected data from the SEC filings.

2 Digit SIC Code	Industry	Total Violations	1994	1995	1996	1997	1998	1999	2000	2001	2002
[10xx-14xx]	Mining	35	14	5	4	2	3	3	3	0	1
[20xx-39xx]	Manufacturing	197	50	18	15	10	18	20	24	18	24
[40xx-49xx]	Transportation and Public Utilities	121	20	15	14	6	6	12	23	13	12
[50xx-59xx]	Retail and Wholesale Trade	9	1	0	0	2	0	2	0	3	1
[60xx-67xx]	Finance, Insurance, and Real Estate	32	6	1	2	0	3	9	3	6	2
[70xx-89xx]	Services	17	1	1	0	2	6	3	0	4	0
	Total	411	92	40	35	22	36	49	53	44	40

2 Digit SIC Code	Industry	Total Violations	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
[10xx-14xx]	Mining	38	2	2	2	4	2	5	0	7	10	4
[20xx-39xx]	Manufacturing	211	21	18	13	24	23	19	32	26	13	22
[40xx-49xx]	Transportation and Public Utilities	91	8	7	3	8	10	12	9	15	12	7
[50xx-59xx]	Retail and Wholesale Trade	28	0	2	2	5	4	2	1	0	6	6
[60xx-67xx]	Finance, Insurance, and Real Estate	83	11	8	2	4	4	6	3	18	12	15
[70xx-89xx]	Services	11	0	1	3	3	2	0	1	0	0	1
	Total	462	42	38	25	48	45	43	46	67	53	55
	Subtotal	873	134	78	60	70	81	92	99	111	93	55

Table 8.6 Total Number of Violations per Stage (Confirmed but Pending other Matters)

The table below reports the total number of violations by the type of stage (Confirmed but Pending other Matters). The type of industry is based on the Standard Industrial Classification (SIC) Code. These violations are categorized according to the two digit SIC code and are based on the hand-collected data from the SEC filings.

2 Digit SIC Code	Industry	Total Violations	1994	1995	1996	1997	1998	1999	2000	2001	2002
[10xx-14xx]	Mining	14	2	1	4	0	1	0	2	3	1
[20xx-39xx]	Manufacturing	73	10	12	7	5	4	5	10	10	10
[40xx-49xx]	Transportation and Public Utilities	26	1	3	3	1	2	6	8	1	1
[50xx-59xx]	Retail and Wholesale Trade	0	0	0	0	0	0	0	0	0	0
[60xx-67xx]	Finance, Insurance, and Real Estate	25	3	2	1	3	3	3	4	2	4
[70xx-89xx]	Services	9	1	0	0	0	1	2	3	1	1
	Total	149	17	18	16	9	11	17	27	17	17

2 Digit SIC Code	Industry	Total Violations	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
[10xx-14xx]	Mining	8	2	0	0	0	2	0	0	1	3	0
[20xx-39xx]	Manufacturing	154	8	8	10	6	16	12	15	23	31	25
[40xx-49xx]	Transportation and Public Utilities	29	2	1	3	3	3	2	3	2	3	7
[50xx-59xx]	Retail and Wholesale Trade	18	2	3	3	2	2	2	2	0	0	2
[60xx-67xx]	Finance, Insurance, and Real Estate	44	0	3	8	4	4	3	0	3	8	11
[70xx-89xx]	Services	25	1	4	6	1	2	5	1	1	1	3
	Total	278	15	19	30	16	29	24	21	30	46	48
	Subtotal	427	32	37	46	25	40	41	48	47	63	48

Table 8.7 Total Number of Violations per Stage (Confirmed)

The table below reports the total number of violations by the type of stage (Confirmed). The type of industry is based on the Standard Industrial Classification (SIC) Code. These violations are categorized according to the two digit SIC code and are based on the hand-collected data from the SEC filings

2 Digit SIC Code	Industry	Total Violations	1994	1995	1996	1997	1998	1999	2000	2001	2002
[10xx-14xx]	Mining	35	6	6	9	0	2	1	3	6	2
[20xx-39xx]	Manufacturing	274	31	31	49	36	19	28	25	34	21
[40xx-49xx]	Transportation and Public Utilities	102	22	16	11	11	10	9	12	4	7
[50xx-59xx]	Retail and Wholesale Trade	33	1	2	0	2	3	0	2	1	4
[60xx-67xx]	Finance, Insurance, and Real Estate	57	3	7	5	2	6	4	6	6	18
[70xx-89xx]	Services	18	0	0	1	1	1	4	5	4	2
	Total	519	63	62	75	52	41	46	53	55	54

2 Digit SIC Code	Industry	Total Violations	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
[10xx-14xx]	Mining	40	1	2	1	5	14	2	3	4	5	3
[20xx-39xx]	Manufacturing	238	24	34	23	29	24	17	23	31	18	15
[40xx-49xx]	Transportation and Public Utilities	68	6	5	8	7	6	5	4	10	13	4
[50xx-59xx]	Retail and Wholesale Trade	64	0	3	3	4	9	1	3	7	6	3
[60xx-67xx]	Finance, Insurance, and Real Estate	138	17	16	13	15	11	21	10	13	16	6
[70xx-89xx]	Services	42	6	6	9	3	2	5	3	2	4	2
	Total	590	54	66	57	63	66	51	46	67	62	33
	Subtotal	1109	117	128	132	115	107	97	99	122	116	33

Table 8.8 Total Number of Firms with Violations per Industry

The table below reports the total number of firms with violations per Industry. The type of industry is based on the Standard Industrial Classification (SIC) Code. These violations are categorized according to the two digit SIC code and are based on the hand-collected data from the SEC filings.

2 Digit SIC Code	Industry	Total Firms	1994	1995	1996	1997	1998	1999	2000	2001	2002
[10xx-14xx]	Mining	51	8	7	12	2	5	3	6	4	4
[20xx-39xx]	Manufacturing	396	53	49	50	38	37	42	42	46	39
[40xx-49xx]	Transportation and Public Utilities	174	26	26	21	13	16	19	24	15	14
[50xx-59xx]	Retail and Wholesale Trade	51	2	1	1	4	3	7	2	2	5
[60xx-67xx]	Finance, Insurance, and Real Estate	96	12	8	6	5	10	13	12	11	19
[70xx-89xx]	Services	39	2	1	1	3	7	8	7	8	2
	Total	807	105	93	92	69	81	99	95	87	86

2 Digit SIC Code	Industry	Total Firms	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
[10xx-14xx]	Mining	72	5	3	3	9	16	3	2	10	15	6
[20xx-39xx]	Manufacturing	396	37	44	33	44	46	33	41	48	41	29
[40xx-49xx]	Transportation and Public Utilities	156	13	8	12	17	16	16	15	20	22	17
[50xx-59xx]	Retail and Wholesale Trade	117	2	5	7	9	11	6	3	7	9	11
[60xx-67xx]	Finance, Insurance, and Real Estate	185	19	17	16	19	17	23	11	19	24	20
[70xx-89xx]	Services	63	5	10	13	7	3	8	4	3	5	5
	Total	989	82	89	87	111	116	92	78	113	123	98
	Subtotal	1796	187	182	179	180	197	191	173	200	209	98

Figure 6 Detailed EFFAS Classification Explanation

The figure below depicts examples of the KPIs provided in the EFFAS KPIs version 3.0. The objective of the KPIs is to propose the basis for the integration of ESG data into corporate performance reporting. The KPIs sets out overall requirements for the presentation of ESG guidelines for the presentation and structure as well as minimum requirements for content to be disclosed. For each of the 114 subsectors following the Dow Jones Industry Classification Benchmark (ICB) lists of KPIs were defined. The first column provides the name of the KPI, the second column identifies the specific KPI whereby E would relate to Environmental, S for Social, G for Governance and V for Long-Term (LT) Viability. The third column indicates the level of company disclosure where Scope 1 (Entry level), Scope II (Mid level) and Scope III (High Level). The fourth column is the specification which provides a detailed explanation of the KPI. For the purpose of this study, I use the KPI identifiers (E,S,G and LT) to match my dataset of violations.

KPI	**Spez.-ID**	**SCOPE**	**Specification**
Accidental oil/gas spills	E25-02	III	Total amount of costs incurred through accidental oil spills amount including remediation and fines
Fatalities & Injuries	S04-03	II	Total number of fatalities in relation to FTEs
Dimensions of pending legal proceedings	G01--1	II	Amount in monetary terms i.e. currency in controversy, dispute from legal proceedings
Litigation Risk	V01.01	I	Expenses and fines on filings, law suits related to anti-competitive behaviour, anti-trust and monopoly practices

Name of KPI

Identifier of KPI

Level of Disclosure

Specification of KPI

Table 8.9 Variable Description and Data Sources

The table below describes in the first column the variable name, second column the description as provided by the data provider, the third column the data provider and the last column in the code used to extract the information

Variable	**Description**	**Data Source**	**Code**
Short Interest Ratio	The total number of shares an investor has sold short divided by the average daily trading volume for a specific time period	Bloomberg	Short_Int_Ratio
Total Assets	Represent the sum of total current assets, long-term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.	Datastream	WC02999
Institutional Ownership	The percentage of total shares in issue of holdings of 5% or more held as long-term strategic holdings by investment banks or institutions seeking a long-term return. Note that holdings by Hedge Funds are not included.	Datastream	NOSHIC
Turnover by Volume	This shows the number of shares traded for a stock on a particular day. The figure is always expressed in thousands.	Datastream	VO
Cash & Equivalents	Represents Cash & Due from banks for banks, cash for insurance firms and cash & short-term investments for all other industries	Datastream	WC02005
Current Assets	Represents cash and other assets that are reasonably expected to be realized in cash, sold or consumer within one year or one operating cycle.	Datastream	WC02201
Current Liabilities	Represent debt or other obligations that the company expects to satisfy within one year	Datastream	WC03101
Short-Term Debt	Represents that portion of debt payable one year including current portion of long-term debt and sinking fund requirements of preferred stock or debentures	Datastream	WC03051
Depreciation, Depletion and Amortization	i) Depreciation represents the process of allocating the cost of a depreciable asset to the accounting periods covered during its expected useful life to a business. It is a non-cash charge for use and obsolescence of an asset. ii) Depletion refers to cost allocation for natural resources such as oil and mineral deposits. iii) Amortization relates to cost allocation for intangible assets such as patents and leasehold improvements, trademarks, bookplates, tools and film cost.	Datastream	WC01151

8.3 Appendix to Chapter 3

Table 8.10 Description of Number of Bonds and Firms by Remaining Years to Maturity

The table below provides the number of bonds and unique firms in each level of Short Interest Ratio Percentile by the different remaining years to maturity for each bond. All bonds are in U.S dollars and have no callable features (call, put, sinking fund, and convertibility)

Years to Maturity	**Zero**	**0 to 20th**	**20th to 40th**	**40th to 60th**	**60th to 80th**	**80th to 100th**	**Total**
	Panel A: Breakdown by Number of Bonds						
Low (Less than 2 years)	126	84	155	119	107	81	672
Short(2 to 7 years)	189	264	419	293	233	206	1604
Medium(7 to 15 years)	150	197	413	275	154	78	1267
Long (15 years and above)	33	197	308	264	166	150	1118
Total	**498**	**742**	**1295**	**951**	**660**	**515**	**4661**
	Panel B: Breakdown by Number of Unique Firms						
Low (Less than 2 years)	9	23	34	26	31	19	142
Short(2 to 7 years)	11	42	52	49	45	37	236
Medium(7 to 15 years)	10	31	43	39	32	22	177
Long (15 years and above)	5	24	28	31	28	20	136
Total	**35**	**120**	**157**	**145**	**136**	**98**	**691**

Table 8.11 Overview of Barclays US Indices

The table below displays the codes and source for each US index used in the model.

Code	**Source**	**Index**
LHAGGBD	Datastream	Barclays United States Aggregate
LHTR20Y	Datastream	Barclays United States Treasury 20 or More Year
LHUT1T3	Datastream	Barclays United States Treasury 1-3 Years
LHYIELD	Datastream	Barclays United States Corporate High Yield
LHMNBCK	Datastream	Barclays United States Mortgage Backed Securities
LHIGAAA	Datastream	Barclays United States Aggregate Corporate AAA
MSUSAML	Datastream	MSCI USA
S&PCOMP	Datastream	S&P 500
USEURSP	Datastream	USD-EUR exchange rate
UKDOLLR	Datastream	USD-GBP exchange rate
JAPYNUS	Datastream	USD-JPY exchange rate
FRTCM3M	Datastream	US Treasury 3 Month - Middle Rate

Table 8.12 Overview of Barclays Global Indices

The table below displays the codes and source for each Global index used in the model.

Code	**Source**	**Index**
LHMGAGG	Datastream	Barclays Global Aggregate
LHTR1T3	Datastream	Barclays Treasury 1-3Y
LHMGHYD	Datastream	Barclays Global High Yield
LHGAAAA	Datastream	Barclays Global AGG AAA
LHGAMOR	Datastream	Barclays Global AGG Mortgages
LHT7T20	Datastream	Barclays Treasury 7-20 Years

Table 8.13Equal Weighted Results (Full Sample and First Half from 2000 to 2006 period)

The table below displays the regression results of the 8 factor monthly alphas, market, duration, default, option, equity, USD-EUR, USD-GBP and USD-YEN variables which are adjusted based on Newey-West (1987) standard errors. The portfolios are equally weighted. The table displays the adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics

Portfolio	**Alpha**	**Market**	**Duration**	**Default**	**Option**	**MSCI USA**	**USD-EUR**	**USD-GBP**	**USD-YEN**	**Adj R^2**
EW Full Sample Period										
Zero - SIR	-0.0005	**0.8173** ***	0.0963	0.0099	-0.0884	0.0389	0.0694	-0.0646	0.0153	0.71
	(-0.6823)	**(6.3057)**	(1.424)	(0.1981)	(-0.3592)	(1.6001)	(1.4235)	(-1.2891)	(0.5608)	
0 to 20th Percentile - SIR	-0.0014	**1.0695** ***	-0.0705	-0.1116	-0.0146	-0.0134	-0.0325	0.0599	0.0751	0.57
	(-1.2293)	**(4.1258)**	(-0.9082)	(-1.6365)	(-0.0549)	(-0.3042)	(-0.549)	(0.8884)	(1.3263)	
20th to 40th Percentile - SIR	-0.0008	**1.0850** ***	-0.0321	-0.0538	0.2561	-0.0128	-0.0056	-0.0433	-0.0173	0.66
	(-1.0219)	**(3.5857)**	(-0.4127)	(-0.7002)	(0.7939)	(-0.3437)	(-0.1471)	(-0.7969)	(-0.3965)	
40th to 60th Percentile- SIR	-0.0010	**0.9459** ***	-0.0365	-0.0625	0.2749	0.0195	0.0091	-0.0378	**-0.0665** *	0.66
	(-1.2958)	**(7.927)**	(-0.6912)	(-1.5764)	(1.3377)	(0.6681)	(0.1639)	(-0.9124)	**(-1.7297)**	
60th to 80th Percentile - SIR	**-0.0020** *	**0.6427** ***	0.0887	0.0872	0.1512	0.0192	-0.0290	0.0619	0.0190	0.55
	(-1.9389)	**(4.5429)**	(1.1166)	(1.1705)	(0.4864)	(0.6508)	(-0.5247)	(1.5172)	(0.3829)	
80th to 100th Percentile - SIR	-0.0003	**0.9258** ***	-0.0722	0.0595	0.1338	-0.0088	**-0.1044** *	0.0130	0.0116	0.49
	(-0.2527)	**(7.6092)**	(-1.371)	(0.9192)	(0.5294)	(-0.2083)	**(-1.9258)**	(0.2213)	(0.3044)	
EW First Half 2000 to 2006										
Zero - SIR	-0.0010	**0.5323** *	-0.0104	0.0917	0.5769	-0.0274	-0.0620	0.0880	-0.0078	0.54
	(-0.9051)	**(1.9463)**	(-0.1153)	(0.9392)	(1.2357)	(-0.9541)	(-1.0611)	(1.4785)	(-0.2614)	
0 to 20th Percentile - SIR	-0.0008	**1.0995** ***	-0.0047	-0.0213	-0.0993	-0.0746	-0.1396 *	0.0548	**0.2243** **	0.58
	(-0.5488)	**(3.4049)**	(-0.0291)	(-0.1771)	(-0.2432)	(-1.1021)	(-1.7435)	(0.5434)	**(2.2765)**	
20th to 40th Percentile - SIR	-0.0012	**0.8576** ***	0.0444	-0.0631	0.4468	0.0297	-0.0532	0.0456	-0.0205	0.71
	(-1.2215)	**(2.8864)**	(0.3706)	(-0.5454)	(0.7787)	(0.6549)	(-0.4885)	(0.5877)	(-0.3355)	
40th to 60th Percentile- SIR	-0.0003	**0.4728** ***	0.0383	0.0319	**0.8077** ***	-0.0466	0.0069	0.0002	-0.0150	0.81
	(-0.3149)	**(2.7739)**	(0.5762)	(0.7249)	**(3.0202)**	(-1.5718)	(0.1324)	(0.0041)	(-0.475)	
60th to 80th Percentile - SIR	-0.0024	**0.6773** **	0.2354 *	0.2176 *	-0.2905	-0.0346	0.0649	0.0141	0.0152	0.57
	(-1.6273)	**(2.4383)**	(1.7464)	(1.8291)	(-0.7444)	(-0.8637)	(0.577)	(0.1532)	(0.2013)	
80th to 100th Percentile - SIR	-0.0032	**1.6802** ***	-0.3773 *	0.0725	0.1459	0.0554	-0.1841	0.0939	-0.0451	0.41
	(-1.4378)	**(3.3925)**	(-1.7937)	(0.5229)	(0.2943)	(0.7926)	(-1.2377)	(0.8593)	(-0.538)	

Table 8.14Equal Weighted Results (Second Half 2007 to 2012 and Crisis Period)

The table below displays the regression results of the 8 factor monthly alphas, market, duration, default, option, equity, USD-EUR, USD-GBP and USD-YEN variables which are adjusted based on Newey-West (1987) standard errors. The portfolios are equally weighted. The table displays the adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics

Portfolio	Alpha		Market		Duration		Default		Option		MSCI USA		USD-EUR		USD-GBP		USD-YEN		Adj R^2
EW Period 2007 to 2012																			
Zero - SIR	-0.0003		**1.0266**	***	**0.1140**	*	-0.0094		**-0.4480**	**	0.0341		**0.1183**	***	**-0.1118**	**	0.0446		0.85
	(-0.2482)		**(9.8215)**		**(1.731)**		(-0.1861)		**(-2.0236)**		(1.1104)		**(3.055)**		**(-2.0711)**		(1.3714)		
0 to 20th Percentile - SIR	-0.0014		**1.0171**	***	-0.1201		**-0.2154**	**	0.0907		0.0358		-0.0171		0.0905		-0.0079		0.58
	(-0.7096)		**(3.0091)**		(-1.2579)		**(-2.2661)**		(0.2611)		(0.6449)		(-0.2741)		(1.2601)		(-0.1392)		
20th to 40th Percentile - SIR	0.0001		**1.2579**	***	-0.0682		-0.0475		0.0097		-0.0786		0.0514		-0.0982		-0.0277		0.61
	(0.082)		**(3.116)**		(-0.6309)		(-0.4613)		(0.0256)		(-1.5401)		(1.2322)		(-1.3797)		(-0.4673)		
40th to 60th Percentile- SIR	-0.0013		**1.0429**	***	-0.0381		-0.0926		0.1074		0.0527		0.0000		-0.0819		-0.0918		0.60
	(-1.0929)		**(9.0829)**		(-0.6541)		(-1.45)		(0.3164)		(1.463)		(0.0003)		(-1.399)		(-1.4752)		
60th to 80th Percentile - SIR	-0.0019		**0.5684**		0.0182		-0.0195		0.5169		0.0879		-0.0907		0.1058		-0.0130		0.57
	(-1.0175)		**(3.6333)**		(0.2774)		(-0.3911)		(1.2119)		(2.374)		(-1.7401)		(2.196)		(-0.1792)		
80th to 100th Percentile - SIR	0.0008		**0.9996**	***	-0.0977	**	0.0102		-0.1286		-0.0573		-0.0710	*	0.0248		0.0146		0.70
	(0.7462)		**(8.9096)**		(-2.1972)		(0.1438)		(-0.4327)		(-1.3325)		(-1.7865)		(0.4302)		(0.3458)		
EW Recession Periods																			
Zero - SIR	0.0003		**0.8057**	***	**0.1843**	*	0.0015		-0.2734		0.0529		0.0273		-0.0162		-0.0099		0.76
	(0.1106)		**(5.3867)**		**(1.9887)**		(0.0331)		(-0.9357)		(1.4975)		(0.2863)		(-0.2295)		(-0.1893)		
0 to 20th Percentile -SIR	**-0.0099**	*	**1.5561**	***	-0.1038		-0.105		-0.6066		**-0.1787**	***	-0.0355		-0.0182		0.1304		0.5
	(-1.9609)		**(4.104)**		(-0.5949)		(-1.0113)		(-1.2498)		**(-3.3401)**		(-0.176)		(-0.1027)		(0.812)		
20th to 40th Percentile - SIR	-0.0002		**0.8227**	***	-0.0463		**-0.1044**	*	0.3758		-0.0363		0.1126		-0.0522		**-0.1349**	***	0.8
	(-0.0912)		**(4.9237)**		(-0.575)		**(-1.729)**		(0.8658)		(-0.7483)		(1.272)		(-0.5899)		**(-3.7647)**		
40th to 60th Percentile- SIR	**-0.0039**	*	**1.0851**	***	0.0341		-0.0732		0.2878		0.0082		-0.089		-0.0037		-0.0701		0.61
	(-1.7263)		**(3.3197)**		(0.268)		(-1.3421)		(0.5463)		(0.2044)		(-0.6885)		(-0.0407)		(-0.737)		
60th to 80th Percentile - SIR	**-0.0065**	**	**0.7456**	**	**0.2602**	*	0.1141		0.2333		-0.0095		**-0.2619**	*	**0.2656**	***	0.1365		0.59
	(-2.2428)		**(2.6835)**		**(1.7804)**		(0.9481)		(0.39)		(-0.2159)		**(-1.9333)**		**(3.8964)**		(1.1994)		
80th to 100th Percentile - SIR	0.0007		**0.7561**	**	-0.1532		0.0663		0.6355		-0.0099		-0.0492		-0.028		0.0019		0.51
	(0.2074)		**(2.5169)**		(-1.0599)		(0.6064)		(1.3255)		(-0.1363)		(-0.3553)		(-0.2493)		(0.0246)		

Table 8.15Equal Weighted Results (Non-Crisis Periods and Low Years to Maturity (YTM))

The table below displays the regression results of the 8 factor monthly alphas, market, duration, default, option, equity, USD-EUR, USD-GBP and USD-YEN variables which are adjusted based on Newey-West (1987) standard errors. The portfolios are equally weighted. The table displays the adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics

Portfolio	Alpha		Market		Duration		Default		Option		MSCI USA		USD-EUR		USD-GBP		USD-YEN		Adj R^2
EW Non - Recession Periods																			
Zero - SIR	-0.0005		**0.8201**	***	0.032		0.0683		0.0906		-0.0085		0.0369		-0.0573		0.0481		0.63
	(-0.5903)		**(3.2578)**		(0.3912)		(0.6475)		(0.1957)		(-0.2667)		(0.7459)		(-0.8615)		(1.4923)		
0 to 20th Percentile - SIR	-0.0001		**0.7908**	***	-0.0109		-0.0782		**0.3772**	*	**0.0597**	**	-0.0366		0.0287		0.0466		0.75
	(-0.2)		**(6.6795)**		(-0.2105)		(-1.1906)		**(1.7455)**		**(2.4688)**		(-0.7443)		(0.7238)		(1.2195)		
20th to 40th Percentile -SIR	**-0.0027**	**	**1.6242**	***	-0.0709		0.1246		-0.1632		-0.0279		-0.0848		0.0175		0.0104		0.7
	(-2.518)		**(3.1808)**		(-0.5717)		(0.912)		(-0.3046)		(-0.5723)		(-1.633)		(0.305)		(0.2361)		
40th to 60th Percentile-SIR	0		**0.9042**	***	-0.0657		0.0092		0.2671		-0.0202		-0.0188		-0.008		-0.0308		0.69
	(0.0246)		**(5.183)**		(-1.2278)		(0.154)		(1.0554)		(-0.6199)		(-0.4634)		(-0.186)		(-1.1993)		
60th to 80th Percentile - SIR	-0.0005		**0.5693**	***	0.0915		**0.1656**	**	0.1262		-0.0037		0.007		0.001		0.0259		0.51
	(-0.4774)		**(4.4677)**		(1.1133)		**(1.9865)**		(0.5793)		(-0.1746)		(0.1115)		(0.0196)		(0.8125)		
80th to 100th Percentile - SIR	-0.0014		**1.2732**	***	-0.0288		0.0103		**-0.5545**	**	0.0469		-0.1073		0.068		-0.0117		0.48
	(-0.9478)		**(4.932)**		(-0.3427)		(0.1585)		**(-2.1339)**		(1.1101)		(-1.2098)		(0.8568)		(-0.2233)		
EW-LOW YTM																			
Zero - SIR	0		**0.8463**	***	-0.0472		0.0086		0.0132		0.0198		-0.0132		-0.0217		0.0169		0.78
	(0.0422)		**(11.237)**		(-1.353)		(0.3257)		(0.0997)		(1.0761)		(-0.3839)		(-0.6142)		(0.7101)		
0 to 20th Percentile - SIR	-0.0002		**0.3189**	**	0.1126	**	**0.1358**	***	**0.3909**	**	**-0.0585**	***	0.0478		0.0182		-0.0309		0.68
	(-0.2208)		**(2.4171)**		(2.5797)		**(2.9069)**		**(2.4213)**		**(-3.0854)**		(1.5894)		(0.6652)		(-1.0291)		
20th to 40th Percentile - SIR	0.0015		**0.5233**	***	-0.0945	***	-0.0402		0.0587		-0.017		**-0.0588**	*	0.0142		0.0321		0.4
	(1.6165)		**(3.8472)**		(-2.679)		(-1.0276)		(0.3523)		(-0.8263)		**(-1.8428)**		(0.4976)		(0.8777)		
40th to 60th Percentile- SIR	**0.0016**	**	**0.7524**	***	-0.1906	***	**-0.1315**	**	-0.1335		0.0184		-0.0175		**-0.0561**	*	0.0555	*	0.49
	(2.2346)		**(4.6028)**		(-3.8342)		**(-2.1085)**		(-0.5822)		(0.7534)		(-0.7454)		**(-1.854)**		(1.6883)		
60th to 80th Percentile - SIR	0.0001		**0.6106**	***	-0.0222		0.0429		0.0039		0.001		0.0617		-0.0632		-0.0428		0.57
	(0.1027)		**(4.6128)**		(-0.5413)		(1.0807)		(0.0228)		(0.0431)		(1.6205)		(-1.4467)		(-1.2205)		
80th to 100th Percentile -SIR	0		**0.9001**	***	-0.0413		-0.0413		-0.0898		**0.0554**	**	0.0066		-0.0404		**-0.0432**	*	0.79
	(-0.0062)		**(9.0965)**		(-1.2279)		(-1.1418)		(-0.5441)		**(2.0698)**		(0.2184)		(-1.2252)		**(-1.7075)**		

Table 8.16 Equal Weighted Short and Medium Years to Maturity (YTM)

The table below displays the regression results of the 8 factor monthly alphas, market, duration, default, option, equity, USD-EUR, USD-GBP and USD-YEN variables which are adjusted based on Newey-West (1987) standard errors. The portfolios are equally weighted. The table displays the adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics

Portfolio	**Alpha**		**Market**		**Duration**		**Default**		**Option**		**MSCI USA**		**USD-EUR**		**USD-GBP**		**USD-YEN**	**Adj R^2**
EW Short YTM																		
Zero - SIR	-0.0002		**0.8864**	***	-0.0296		0.0094		0.2535		0.0091		-0.0036		0.0357		0.0032	0.68
	(-0.2418)		**(10.3813)**		(-0.8658)		(0.1855)		(1.2799)		(0.4739)		(-0.1131)		(1.0316)		(0.1433)	
0 to 20th Percentile - SIR	-0.0005		**0.728**	***	-0.0345		-0.045		0.289		0.0282		**-0.0653**	*	0.0703		0.0194	0.67
	(-0.6686)		**(5.1566)**		(-0.6871)		(-0.9071)		(1.6526)		(1.1438)		**(-1.6714)**		(1.2983)		(0.5806)	
20th to 40th Percentile - SIR	-0.0002		**0.6061**	***	-0.0127		-0.0139		**0.2916**	*	0.0119		-0.0363		0.0679		-0.0019	0.7
	(-0.3425)		**(5.16)**		(-0.2884)		(-0.3057)		**(1.771)**		(0.6201)		(-0.9437)		(1.3731)		(-0.0653)	
40th to 60th Percentile- SIR	-0.0004		**0.7846**	***	-0.0867	***	**-0.1316**	***	**0.2522**	*	**0.0281**	*	0.0297		-0.0478		-0.0392	0.71
	(-0.5818)		**(8.1044)**		(-2.6835)		**(-3.8399)**		**(1.9399)**		**(1.9531)**		(0.7706)		(-1.0096)		(-1.507)	
60th to 80th Percentile - SIR	-0.0005		**0.7736**	***	-0.131	**	-0.0097		0.2502		0.0319		**-0.0872**	**	0.0409		0.0263	0.55
	(-0.6745)		**(6.6536)**		(-2.3013)		(-0.1786)		(0.928)		(1.4063)		**(-2.3739)**		(0.9494)		(0.578)	
80th to 100th Percentile - SIR	**0.0015**	*	**1.1243**	***	-0.1711	***	-0.0567		-0.0804		0.014		**-0.1581**	***	0.0482		0.0555	0.54
	(1.7324)		**(6.5958)**		(-3.0767)		(-0.8651)		(-0.2751)		(0.2721)		**(-2.6252)**		(0.764)		(1.3664)	
EW Medium YTM																		
Zero - SIR	-0.0003		**0.7762**	***	**0.2039**	***	0.0528		-0.0285		**0.0371**	*	0.0416		-0.0399		-0.0082	0.82
	(-0.642)		**(4.8583)**		**(3.6928)**		(1.2668)		(-0.0934)		**(1.8255)**		(1.2625)		(-0.8992)		(-0.2656)	
0 to 20th Percentile - SIR	-0.0021		**1.0772**	***	0.0275		0.0155		-0.0336		-0.0437		-0.0104		-0.0036		0.1109	0.46
	(-1.3483)		**(3.9915)**		(0.2944)		(0.1245)		(-0.1055)		(-0.8543)		(-0.143)		(-0.0678)		(0.9611)	
20th to 40th Percentile - SIR	0		**1.4171**	***	-0.0418		-0.111		-0.0824		-0.0186		0.0887		**-0.1602**	*	-0.0446	0.7
	(-0.0375)		**(3.8343)**		(-0.4138)		(-1.2652)		(-0.2305)		(-0.3356)		(1.3278)		**(-1.9234)**		(-0.6218)	
40th to 60th Percentile- SIR	-0.0016		**1.015**	***	0.0602		**-0.1334**	**	-0.0601		0.0379		0.021		-0.0017		-0.0053	0.63
	(-1.5016)		**(6.9017)**		(0.9691)		**(-1.99)**		(-0.1695)		(1.4401)		(0.352)		(-0.0299)		(-0.1001)	
60th to 80th Percentile - SIR	-0.0007		**0.7142**	***	**0.2142**	**	0.0894		0.1749		0.0227		-0.0212		0.0554		-0.0443	0.59
	(-0.7308)		**(5.0362)**		**(2.4385)**		(1.1398)		(0.6495)		(0.9479)		(-0.5318)		(1.62)		(-1.4833)	
80th to 100th Percentile - SIR	0.0008		**1.0939**	***	**-0.1336**	***	-0.0216		-0.0319		-0.0103		-0.12	**	0.0245		0.0207	0.62
	(1.0119)		**(9.4684)**		**(-2.9183)**		(-0.3911)		(-0.1334)		(-0.2938)		(-2.3707)		(0.4281)		(0.6203)	

Table 8.17 Equal Weighted Long Years to Maturity (YTM)

The table below displays the regression results of the 8 factor monthly alphas, market, duration, default, option, equity, USD-EUR, USD-GBP and USD-YEN variables which are adjusted based on Newey-West (1987) standard errors. The portfolios are equally weighted. The table displays the adjusted R-square for each portfolio. Significance levels are presented as *,** and *** for 10%,5% and 1% significance level respectively. The value in the parentheses represents the values of the T-statistics

Portfolio	Alpha		Market		Duration		Default		Option		MSCI USA		USD-EUR		USD-GBP		USD-YEN	Adj R^2
EW Long YTM																		
Zero – SIR	-0.0013		**0.5987**	**	0.1889		**0.0907**	**	**0.3095**	**	-0.0058		**0.1207**	**	**-0.0763**	*	0.0215	0.86
	(-1.6523)		**(2.4746)**		(1.625)		**(2.2214)**		**(2.3633)**		(-0.3384)		**(2.5274)**		**(-1.8344)**		(0.557)	
0 to 20th Percentile - SIR	-0.0016		**1.4177**	***	0.0252		-0.1957		-0.558		0.0234		0.0455		0.027		0.0611	0.57
	(-1.1139)		**(3.6436)**		(0.2003)		(-1.4602)		(-1.2861)		(0.4132)		(0.8295)		(0.4704)		(1.0098)	
20th to 40th Percentile - SIR	0.0009		**1.43**	*	0.2075		-0.0478		-0.204		0.0587		0.0356		-0.1704		0.0722	0.6
	(0.4435)		**(1.8761)**		(1.0269)		(-0.3006)		(-0.3142)		(0.9212)		(0.367)		(-1.5164)		(0.6882)	
40th to 60th Percentile- SIR	**-0.0026**	**	**1.3644**	***	0.1236		0.0935		0.4286		0.0164		0.0727		-0.1175		-0.1095	0.6
	(-2.2483)		**(3.5354)**		(0.8475)		(1.4373)		(1.0679)		(0.3656)		(0.4636)		(-0.95)		(-1.3843)	
60th to 80th Percentile - SIR	**-0.0031**	**	**1.0026**	***	**0.2616**	***	0.0384		-0.2535		**0.0974**	**	0.0218		0.0586		0.0453	0.62
	(-2.2349)		**(5.8287)**		**(2.9254)**		(0.3774)		(-0.6125)		**(2.2539)**		(0.3916)		(1.1383)		(0.707)	
80th to 100th Percentile - SIR	-0.0011		**0.8966**	***	**0.15**	**	**0.1754**	**	-0.059		0.0067		0.0376		-0.0735		0.0074	0.47
	(-0.5065)		**(6.5635)**		**(2.3338)**		**(1.9993)**		(-0.2034)		(0.1368)		(0.5789)		(-0.8863)		(0.1454)	

8.4 Appendix to Chapter 4

Table 8.18 Frequency of Illegal Announcements

Panel A: Number of Unique Firms and Announcements of Violations in each Industry

The table below depicts the type of industry based on the Standard Industrial Classification (SIC) Code and the number of unique firms in each industry with the number of violations

2 Digit SIC Code	**Industry**	**Number of Firms**	**Number of Violations**
[10xx-14xx]	Mining	9	27
[20xx-39xx]	Manufacturing	47	247
[40xx-49xx]	Transportation & Public Utilities	23	66
[50xx-51xx]	Wholesale Trade	3	11
[52xx-59xx]	Retail Trade	13	27
[60xx-67xx]	Finance, Insurance and Real Estate	21	87
[70xx-89xx]	Services	5	6
	Subtotal	**121**	**471**

Panel B: Number ESG and Long-Term Violations per Year

The table below depicts the number of violations in each respective environmental, social, governance and long-term violations.

	Number of Violations per Year				
Type	**2009**	**2010**	**2011**	**2012**	**Subtotal**
Environmental	36	45	45	38	164
Social	13	35	26	31	105
Governance	8	27	30	36	101
Long-Term	20	22	27	32	101

Table 8.19: Composition of the CDS data set by Firm

No.	Company Name	No of CDS Spreads
1	3M CO	20
2	ABBOTT LABORATORIES	20
3	AES CORP	20
4	AETNA	20
5	AGILENT TECHNOLOGIES	18
6	AIR PRODUCTS & CHEMICALS	20
7	ALCOA	10
8	ALLERGAN	20
9	ALTRIA GRP(PHILIP MORRIS)	30
10	AMAZON.COM	10
11	AMERICAN ELECTRIC POWER	30
12	AMERICAN EXPRESS	30
13	AMERICAN TOWER CORP A	30
14	ANADARKO PETROLEUM CORP	20
15	APACHE CORP	20
16	AT&T	20
17	BAKER HUGHES	20
18	BANK NEW YORK CO	2
19	BANK OF AMERICA CORP	30
20	BAXTER INTERNATIONAL	20
21	BECTON DICKINSON	20
22	BERKSHIRE HATHAWAY B	20
23	BEST BUY CO	20
24	BOSTON SCIENTIFIC CORP	30
25	CARDINAL HEALTH	30
26	CATERPILLAR	20
27	CHESAPEAKE ENERGY CORP	30
28	CHEVRON CORP	20
29	CHUBB CORP	20
30	CITIGROUP	30
31	COLGATE-PALMOLIVE	30
32	CONOCOPHILLIPS	20
33	COSTCO WHOLESALE CORP	20
34	CVS/CAREMARK	20
35	DELL	30
36	DISNEY (WALT)	30

No.	Company Name	No of CDS Spreads
37	DOLLAR GENERAL CORP	10
38	DOMINION RESOURCES	20
39	DOW CHEMICAL CO	30
40	DU PONT (E.I) DE NEMOURS	30
41	DUKE ENERGY CORP	20
42	EBAY	16
43	EXELON CORP	20
44	EXXON MOBIL CORP	20
45	FEDEX CORP	20
46	FIRSTENERGY CORP	20
47	FORD MOTOR CO	20
48	FPL GROUP	40
49	FREEPORT MCMORAN C & G B	18
50	GENERAL ELECTRIC CO	29
51	GOLDMAN SACHS GROUP	27
52	HALLIBURTON CO	20
53	HERSHEY CO (THE)	20
54	HESS	20
55	HOME DEPOT	20
56	HONEYWELL INTERNATIONAL	20
57	IBM CORP	30
58	INTEL CORP	30
59	INT'L PAPER CO	30
60	JOHNSON & JOHNSON	20
61	JPMORGAN CHASE & CO	40
62	KIMBERLY-CLARK CORP	20
63	L-3 COMMUNICATIONS HLDGS	20
64	LOCKHEED MARTIN CORP	20
65	LORILLARD	20
66	LOWE'S COS	20
67	MARATHON OIL CORP	20
68	MARSH & MCLENNAN COS	20
69	MCKESSON CORP	30
70	MEDCO HEALTH SOLUTIONS	30
71	MEDTRONIC	30
72	MERCK & CO	40
73	MERRILL LYNCH & CO	30
74	METLIFE	30
75	MICROSOFT CORP	30

No.	Company Name	No of CDS Spreads
76	MONSANTO CO	20
77	MORGAN STANLEY	27
78	MOTOROLA	59
79	NOBLE ENERGY	20
80	NORFOLK SOUTHERN CORP	30
81	NORTHROP GRUMMAN CORP	20
82	OCCIDENTAL PETROLEUM	20
83	ORACLE CORP	20
84	PEABODY ENERGY CORP	20
85	PEPSICO	20
86	PFIZER	22
87	PG&E CORP	20
88	PHILIP MORRIS INT	10
89	PNC FINL SERVICES GROUP	20
90	PPL CORP	10
91	PRAXAIR	20
92	PROCTER & GAMBLE CO	30
93	PROGRESS ENERGY	20
94	QUEST DIAGNOSTICS	20
95	QWEST COMMUNI. INT'L	20
96	RAYTHEON	20
97	REPUBLIC SERVICES	20
98	REYNOLDS AMERICAN	40
99	SARA LEE CORP	20
100	SCHERING-PLOUGH CORP	40
101	SCHWAB (CHARLES) CORP	20
102	SEMPRA ENERGY	20
103	SLM CORP	1
104	SOUTHERN CO	20
105	STAPLES	20
106	TARGET CORP	20
107	TJX COS	20
108	UNION PACIFIC CORP	30
109	UNITEDHEALTH GROUP	30
110	US BANCORP	27
111	VALERO ENERGY CORP	20
112	VERIZON COMMUNICATIONS	30
113	VIACOM B (NEW)	30
114	WALGREEN CO	10

No.	Company Name	No of CDS Spreads
115	WAL-MART STORES	20
116	WASTE MANAGEMENT	30
117	WELLPOINT	20
118	WELLS FARGO & CO	30
119	WILLIAMS COS	30
120	XCEL ENERGY	20
121	XEROX CORP	30

8.5 Appendix to Chapter 5

Table 8.20 List of Codes and Name of Indices

The table below provides description of the country and full name of the respective index, the source of the data and code retrieved and the associated asset class of the index. (NA indicates data that was not available)

Country	Full Name	Source	Code	Asset Class
Austria	ATX - Austrian Traded Index	Datastream	ATXINDX	Equity Index
Belgium	MSCI BELGIUM	Datastream	MSBELGL	Equity Index
Denmark	OMX Copenhagen (OMXC20)	Datastream	DKKFXIN	Equity Index
Finland	OMX Helsinki (OMXH)	Datastream	HEXINDX	Equity Index
France	France CAC 40	Datastream	FRCAC40	Equity Index
Germany	DAX 30 Performance	Datastream	DAXINDX	Equity Index
Greece	Athex Composite	Datastream	GRAGENL	Equity Index
Ireland	Ireland Stock Exchange Overall (Iseq)	Datastream	ISEQUIT	Equity Index
Italy	FTSE MIB Index	Datastream	FTSEMIB	Equity Index
Netherlands	AEX Index (AEX)	Datastream	AMSTEOE	Equity Index
Norway	Oslo Exchange All Share	Datastream	OSLOASH	Equity Index
Portugal	Portugal PSI-20	Datastream	POPSI20	Equity Index
Spain	IBEX 35	Datastream	IBEX35I	Equity Index
Sweden	OMX Stockholm 30 (OMXS30)	Datastream	SWEDOMX	Equity Index
Switzerland	Swiss Market (SMI)	Datastream	SWISSMI	Equity Index
UK	FTSE 100	Datastream	FTSE100	Equity Index
US	Standard and Poor's 500 Composite	Datastream	S&PCOMP	Equity Index
Canada	Standard and Poor's / Toronto Stock Exchange 60 Index	Datastream	TTOCOMP	Equity Index
Australia	Standard and Poor's / Australian Stock Exchange 200	Datastream	ASX200I	Equity Index
Hong Kong	Hang Seng	Datastream	HNGKNGI	Equity Index
Japan	TOPIX	Datastream	TOKYOSE	Equity Index
New Zealand	Standard and Poor's / NZX 50	Datastream	NZ50CAP	Equity Index
Singapore	Straits Times Index Local Currency	Datastream	SNGPORI	Equity Index
Israel	FTSE Israel	Datastream	WIISRLL	Equity Index
Brazil	Brazil Bovespa	Datastream	BRBOVES	Equity Index
Russia	Russia RTS Index	Datastream	RSRTSIN	Equity Index
India	CNX Nifty (50)	Datastream	INNSE50	Equity Index
China	FTSE China	Datastream	WICINAL	Equity Index
Argentina	MSCI Argentina	Datastream	MSARGTL	Equity Index
Chile	MSCI Chile	Datastream	MSCHILL	Equity Index
Colombia	MSCI Colombia	Datastream	MSCOLML	Equity Index
Mexico	Mexico IPC (Bolsa)	Datastream	MXIPC35	Equity Index
Peru	MSCI All Peru	Datastream	MSAPRUL	Equity Index
Bangladesh	Standard and Poor's Bangladesh Broad Market Index (BMI)	Datastream	IFFMBGL	Equity Index
Indonesia	MSCI Indonesia	Datastream	MSINDFL	Equity Index
Malaysia	FTSE Bursa Malaysia KLCI	Datastream	FBMKLCI	Equity Index
Pakistan	MSCI Pakistan	Datastream	MSPAKIL	Equity Index
Philippines	MSCI Philippines	Datastream	MSPHLFL	Equity Index
South Korea	MSCI Korea	Datastream	MSKOREL	Equity Index
Taiwan	Taiwan Stock Exchange Weighed TAIEX	Datastream	TAIWGHT	Equity Index
Thailand	Bangkok S.E.T.	Datastream	BNGKSET	Equity Index

Country	Full Name	Source	Code	Asset Class
Vietnam	MSCI Vietnam	Datastream	MSVIETL	Equity Index
Egypt	MSCI Egypt	Datastream	MSEGYTL	Equity Index
Kuwait	Standard and Poor's Kuwait Shariah Kuwait Dinar	Datastream	SPSKWDL	Equity Index
Nigeria	MSCI Nigeria	Datastream	MSNGRAL	Equity Index
Poland	MSCI Poland	Datastream	MSPLNDL	Equity Index
Qatar	Standard and Poor's Qatar Shariah Qatar Riyal	Datastream	SPSQARL	Equity Index
South Africa	FTSE / JSE All Share	Datastream	JSEOVER	Equity Index
Saudi Arabia	MSCI Saudi Arabia Domestic Investable Market	Datastream	MSISADL	Equity Index
Turkey	MSCI Turkey	Datastream	MSTURKL	Equity Index
UAE	FTSE United Arab Emirates	Datastream	WIUAEIL	Equity Index
Austria	OTOB-ATX INDEX CONT. INDEX DEAD	Datastream	VTXCS04	Future Index
Belgium	Belfox-Bel20 Index Continuous	Datastream	BFXCS00	Future Index
Denmark	OMX-OMXC20CAP Index Continuous Index	Datastream	DCXCS04	Future Index
Finland	NA	Datastream	NA	Future Index
France	MONEP-CAC 40 Index Continuous	Datastream	FCXCS00	Future Index
Germany	EUREX-DAX Index Continuous	Datastream	GDXCS00	Future Index
Greece	ADEX-FTSE / ASE-20 Continuous	Datastream	ASICS00	Future Index
Ireland	NA	Datastream	NA	Future Index
Italy	Idem-FTSE MIB Continuous Index	Datastream	MSMCS04	Future Index
Netherlands	AEX-AEX Index Continuous	Datastream	ETICS00	Future Index
Norway	Oslo-OBX Index Continuous	Datastream	OSXCS00	Future Index
Portugal	BDP-PSI 20 Index Continuous	Datastream	PSXCS00	Future Index
Spain	MEFF-IBEX 35 Plus Index Continuous	Datastream	MBXCS00	Future Index
Sweden	OMX-OMXS30 Index Continuous	Datastream	OMFCS00	Future Index
Switzerland	EUREX-SMI Continuous Index	Datastream	NA	Future Index
UK	LIFFE-FTSE 100 Index Continuous	Datastream	NA	Future Index
US	CME-S&P 500 Index Continuous	Datastream	ISPCS00	Future Index
Canada	ME-S&P/TSX 60 Index Standard Futures (SXF) Continuous Index	Datastream	CDDCS04	Future Index
Australia	SFE-SPI 200 Index Continuous	Datastream	AAPCS00	Future Index
Hong Kong	HKFE-Hang Seng Index Continuous	Datastream	HSICS00	Future Index
Japan	TSE-TOPIX Index Continuous	Datastream	JSXCS00	Future Index
New Zealand	NA	Datastream	NA	Future Index
Singapore	SGX DT-Straits Times Index Continuous	Datastream	SSTCS00	Future Index
Israel	Tase-TA25 Index Continuous	Datastream	TLVCS00	Future Index
Brazil	BMF-Bovespa Index Continuous	Datastream	BMICS00	Future Index
Russia	RTS-RTS Index Continuous	Datastream	RTSCS00	Future Index
India	NSE-S&P CNX Nifty Continuous Index	Datastream	INICS04	Future Index
China	CFFEX-CSI 300 Index Continuous Index	Datastream	CIFCS04	Future Index
Argentina	NA	Datastream	NA	Future Index
Chile	NA	Datastream	NA	Future Index
Colombia	NA	Datastream	NA	Future Index
Mexico	Mexder-IPC Index Continuous Index	Datastream	MIECS04	Future Index
Peru	NA	Datastream	NA	Future Index
Bangladesh	NA	Datastream	NA	Future Index
Indonesia	SGX - MSCI Indonesia Index	Datastream	SID1215	Future Index
Malaysia	Klse-KLCI Continuous	Datastream	KLCCS00	Future Index
Pakistan	NA	Datastream	NA	Future Index
Philippines	NA	Datastream	NA	Future Index

Country	Full Name	Source	Code	Asset Class
South Korea	KSE-KOSPI 200 Index Continuous Index	Datastream	KKXCS04	Future Index
Taiwan	TAIFEX-Taiwan 50 Index Continuous Index	Datastream	TFTCS04	Future Index
Thailand	SGX-MSCI Thailand Index Continuous	Datastream	NA	Future Index
Vietnam	NA	Datastream	NA	Future Index
Egypt	NA	Datastream	NA	Future Index
Kuwait	NA	Datastream	NA	Future Index
Nigeria	NA	Datastream	NA	Future Index
Poland	WSE-WIG 40 Continuous Index	Datastream	WFOCS04	Future Index
Qatar	NA	Datastream	NA	Future Index
South Africa	SAFEX-All Share 40 Index Continuous Index	Datastream	SALCS04	Future Index
Saudi Arabia	NA	Datastream	NA	Future Index
Turkey	Turkdex-ISE 30 Continuous	Datastream	TRTCS00	Future Index
UAE	NA	Datastream	NA	Future Index
Austria	JPM GBI Austria 1 - 10 Years (United States Dollar)	Datastream	JGOEEU$	Bond Index
Belgium	JPM GBI Belgium 1 - 10 Years (United States Dollar)	Datastream	JGBGEU$	Bond Index
Denmark	JPM GBI Denmark 1 - 10 Years (United States Dollar)	Datastream	JGDKEU$	Bond Index
Finland	JPM GBI Finland 1 - 10 Years (United States Dollar)	Datastream	JGFNEU$	Bond Index
France	JPM GBI France 1 - 10 Years (United States Dollar)	Datastream	JGFREU$	Bond Index
Germany	JPM GBI Germany 1 - 10 Years (United States Dollar)	Datastream	JEBDEU$	Bond Index
Greece	JPM GBI Greece 1 - 10 Years (United States Dollar)	Datastream	JGGREU$	Bond Index
Ireland	JPM GBI Ireland 1 - 10 Years (United States Dollar)	Datastream	JGIREPE	Bond Index
Italy	JPM GBI Italy 1 - 10 Years (United States Dollar)	Datastream	JGITEU$	Bond Index
Netherlands	JPM GBI Netherlands 1 - 10 Years (United States Dollar)	Datastream	JGNLEU$	Bond Index
Norway	Bank Of America Merrill Lynch Norway Government 1 - 10 Years (United States Dollar)	Datastream	MLNW110	Bond Index
Portugal	JPM GBI Portugal 1 - 10 Years (United States Dollar)	Datastream	JGPTEU$	Bond Index
Spain	JPM GBI Spain 1 - 10 Years (United States Dollar)	Datastream	JGESEU$	Bond Index
Sweden	JPM GBI Sweden 1 - 10 Years (United States Dollar)	Datastream	JGSDEU$	Bond Index
Switzerland	Bank Of America Merrill Lynch Swiss Government 1 - 10 Years (United States Dollar)	Datastream	MLSF110	Bond Index
UK	JPM GBI United Kingdom 1 - 10 Years (United States Dollar)	Datastream	JGUKEU$	Bond Index
US	JPM GBI United States 1 - 10 Years (United States Dollar)	Datastream	JGUSEU$	Bond Index
Canada	JPM GBI Canada 1 - 10 Years (United States Dollar)	Datastream	JGCNEU$	Bond Index
Australia	JPM GBI Australia 1 - 10 Years (United States Dollar)	Datastream	JGAUEU$	Bond Index
Hong Kong	JPM GBI Hong Kong 1 - 10 Years (United States Dollar)	Datastream	JGHKEU$	Bond Index
Japan	JPM GBI Japan 1 - 10 Years (United States Dollar)	Datastream	JGJPEU$	Bond Index
New Zealand	JPM GBI New Zealand 1 - 10 Years (United States Dollar)	Datastream	JGNZEU$	Bond Index
Singapore	JPM GBI Singapore 1 - 10 Years (United States Dollar)	Datastream	JGSGEU$	Bond Index
Israel	JPM ELMI + Israel (United States Dollar)	Datastream	JGISEU$	Bond Index
Brazil	JPM EMBI Global Brazil	Datastream	JPMGBRA	Bond Index
Russia	JPM EMBI Global Russia	Datastream	JPMGRUS	Bond Index
India	JPM GBI-Emerging Markets Broad India (United States Dollar)	Datastream	JGE$BIN	Bond Index
China	JPM EMBI Global China	Datastream	JPMGCHN	Bond Index
Argentina	JPM EMBI Global Argentina	Datastream	JPMGARG	Bond Index
Chile	JPM EMBI Global Chile	Datastream	JPMGCHI	Bond Index
Colombia	JPM EMBI Global Colombia	Datastream	JPMGCOL	Bond Index
Mexico	JPM GBI Mexico 1 - 10 Years (United States Dollar)	Datastream	JGMXEU$	Bond Index

Country	Full Name	Source	Code	Asset Class
Peru	JPM EMBI Global Peru	Datastream	JPMGPER	Bond Index
Bangladesh	NA	Datastream	NA	Bond Index
Indonesia	JPM EMBI Global Indonesia	Datastream	JPMGIND	Bond Index
Malaysia	JPM EMBI Global Malaysia	Datastream	JPMGMAL	Bond Index
Pakistan	JPM EMBI Global Pakistan	Datastream	JPMGPAK	Bond Index
Philippines	JPM EMBI Global Philippines	Datastream	JPMGPHL	Bond Index
South Korea	JPM GBI Korea 1 - 10 Years (United States Dollar)	Datastream	JGKREU$	Bond Index
Taiwan	JPM ELMI + Taiwan (United States Dollar)	Datastream	JPMPTA$	Bond Index
Thailand	JPM ELMI + Thailand (United States Dollar)	Datastream	JPMPTH$	Bond Index
Vietnam	JPM EMBI Global Vietnam	Datastream	JPMGVIE	Bond Index
Egypt	JPM ELMI + Egypt (United States Dollar)	Datastream	JPMPEG$	Bond Index
Kuwait	NA	Datastream	NA	Bond Index
Nigeria	JPM EMBI Global Nigeria	Datastream	JPMGNIG	Bond Index
Poland	JPM GBI Poland 1 - 10 Years (United States Dollar)	Datastream	JGPOEU$	Bond Index
Qatar	Citigroup Emusdgbi Qatar	Datastream	CGESQAL	Bond Index
South Africa	JPM GBI South Africa 1 - 10 Years (United States Dollar)	Datastream	JGSAEU$	Bond Index
Saudi Arabia	Bank Of America Merrill Lynch Saudi Riyal Spot Currency (United States Dollar)	Datastream	MLSRY	Bond Index
Turkey	JPM EMBI Global Turkey	Datastream	JPMGTUR	Bond Index
UAE	Bank Of America Merrill Lynch Emerging Markets Corporate Plus UAE Issuers (United States Dollar)	Datastream	MLEAEZ$	Bond Index

Table 8.21 Definition of Macro-Economic Variables

The table below provides description of the macro-economic variables including the abbreviations used in the panel data estimations and the full definitions of the variables. The data is retrieved from the IMF database.

Variable	**Abbreviation**	**Definition**
Gross domestic product, current prices (U.S. dollars) (in Billions)	GDP	Values are based upon GDP in national currency converted to U.S. dollars using market exchange rates (yearly average). Exchange rate projections are provided by country economists for the group of other emerging market and developing countries. Exchanges rates for advanced economies are established in the WEO assumptions for each WEO exercise. Expenditure-based GDP is total final expenditures at purchasers' prices (including the f.o.b. value of exports of goods and services), less the f.o.b. value of imports of goods and services.
Gross domestic product based on purchasing-power-parity (PPP) valuation of country GDP (Current international dollar) (in Billions)	GDP based on PPP	These data form the basis for the country weights used to generate the World Economic Outlook country group composites for the domestic economy.
Implied PPP conversion rate (National currency per current international dollar)	IMPLIED PPP	Expressed in national currency per current international dollar. These data form the basis for the country weights used to generate the World Economic Outlook country group composites for the domestic economy.
Inflation, average consumer prices (Index)	INFLATION	Expressed in averages for the year, not end-of-period data. A consumer price index (CPI) measures changes in the prices of goods and services that households consume. Such changes affect the real purchasing power of consumers' incomes and their welfare. As the prices of different goods and services do not all change at the same rate, a price index can only reflect their average movement. A price index is typically assigned a value of unity, or 100, in some reference period and the values of the index for other periods of time are intended to indicate the average proportionate, or percentage, change in prices from this price reference period. Price indices can also be used to measure differences in price levels between different cities, regions or countries at the same point in time. [CPI Manual 2004, Introduction] For euro countries, consumer prices are calculated based on harmonized prices. For more information see http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-BE-04-001/EN/KS-BE-04-001-EN.PDF.]
Volume of imports of goods and services (Percent change)	VOLUME of IMPORTS	Percent change of volume of imports refers to the aggregate change in the quantities of total imports whose characteristics are unchanged. The goods and services and their prices are held constant, therefore changes are due to changes in quantities only. [Export and Import

Variable	Abbreviation	Definition
		Price Index Manual: Theory and Practice, Glossary]
Unemployment rate (Percent of total labor force)	UNEMPLOYMENT	Unemployment rate can be defined by either the national definition, the ILO harmonized definition, or the OECD harmonized definition. The OECD harmonized unemployment rate gives the number of unemployed persons as a percentage of the labor force (the total number of people employed plus unemployed). [OECD Main Economic Indicators, OECD, monthly] As defined by the International Labour Organization, unemployed workers are those who are currently not working but are willing and able to work for pay, currently available to work, and have actively searched for work. [ILO, http://www.ilo.org/public/english/bureau/stat/res/index.htm]
Current account balance (U.S. dollars) (in Billions)	CURRENT BALANCE	Current account is all transactions other than those in financial and capital items. The major classifications are goods and services, income and current transfers. The focus of the BOP is on transactions (between an economy and the rest of the world) in goods, services, and income.