School of Economics and Finance

Three Essays on Investor Sentiment and Stock Returns

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DECLARATION

To the best of my knowledge and belief this dissertation contains no material previously published by any other person except where due acknowledgment has been made.

This dissertation contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature: ……………………………………………….

Date: 15th of February 2018

ABSTRACT

The aim of this dissertation is to explore the relationship between sentiment and stock returns. As sentiment is unobservable, sentiment in this dissertation is defined as that which is attributed to mood and news which may influence investor behavior in a quasi-rational manner. This dissertation presents three essays on the topic of investor sentiment and stock returns using a text-based measure of sentiment derived from Thomson Reuters News Analytics (TRNA). TRNA utilizes neural linguistic algorithms and machine learning as a more sophisticated text-based sentiment measure than previous methods. This dissertation adds to the strand of sentiment literature that focuses of text-based sentiment measures and examines its impact over multiple countries.

Chapter 1 presents the introduction to this thesis, motivation and summarizes the findings and conclusions of each chapter. The first essay in chapter 2 presents evidence that Japan's dismal returns can be related to negative sentiment both at the aggregate market and individual firm level. The link between mood and sentiment has, to my knowledge, not been examined in Japan previously. The effect of news sentiment is greatest for smaller firms in this sample data set.

Chapter 3 contains the second essay which extends upon analysis in chapter 2 and examines sentiment as an augmentation to the Fama and French three-factor model for Japan. This chapter provides evidence that in this framework sentiment has heterogeneous effects: small stocks and large stocks appear to be most affected by sentiment.

Chapter 4 examines sentiment as an augmentation to the Fama and French five-factor model for Europe. In this chapter I follow common practice in the literature and divide Europe into two distinct groups based on the perceived severity of their exposure to the European debt crisis. I find that sentiment is positively related to portfolio returns in the countries most severely impacted by the debt crisis, and it is not an important factor in those countries not heavily impacted by the crisis.

With regards to publication, material from this dissertation has been published and presented at multiple conferences. Chapter 2 was adapted as part of submission to

The Pacific-Basin Finance Journal. It forms the foundation of the published article "Melancholia and Japanese stock returns – 2003 to 2012" (Khuu et. al 2017) available from: https://doi.org/10.1016/j.pacfin.2016.05.011.

Chapter 3 has been presented at the 6th Behavioral Finance and Capital Markets Conference (2016, Adelaide South Australia) and the 29th PhD Conference in Economics and Business, University of Western Australia (2016, Perth Western Australia). Feedback and commentary has subsequently been included in this dissertation.

During my candidature, I have also co-authored a paper related to my dissertation, "The Validity of Investor Sentiment Proxies" (Chan et al. 2017). This is published in *The International Review of Finance* and is available from: http://dx.doi.org/10.1111/irfi.12102.

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List of Abbreviations

B/M	*Book to market*
CAPM	*Capital asset pricing model*
CBCI	*Conference Board Consumer Index*
CDS	*Credit Default Swaps*
CMA	*Conservative minus aggressive*
CRSP	*The Center for Research in Security Prices*
DJIA	*Dow Jones Industrial Average*
EFC	*European Financial Crisis*
GFC	*Global Financial Crisis*
GMT	*Greenwich Mean Time*
HML	*High minus low*
MCSI	*Michigan Consumer Sentiment Index*
ME	*Market Equity*
NBER	*National Bureau of Economic Research*
Non-PIIGS	*Austria, Belgium, Denmark, France, Germany, Netherlands, Norway, Sweden, Switzerland and United Kingdom*
PIIGS	*Portugal, Italy, Ireland, Greece and Spain.*
RIC	*Reuters Instrument Code (RIC)*
RMW	*Robust minus weak*
SAD	*Seasonal Affective Disorder*
SIRCA	*Securities Industry Research Centre of Asia-Pacific*
SMB	*Small minus big*
TOPIX	*Tokyo Stock Price Index*
TRNA	*Thomson Reuters News Analytics*
VAR	*Vector Autoregressive model*
WSJ	*Wall Street Journal*

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Chapter 1 INTRODUCTION

Sentiment is often referred to anecdotally in finance, and in literature, as the market spirit or *zeitgeist*. This *zeitgeist* is a behavioral phenomenon rooted in human psychology. It attempts to explain why markets may tend to act irrationally against the traditional efficient market hypothesis. In finance the market spirit or mood can be attributed to the overarching market sentiment. A growing body of literature suggests that sentiment impacts stock market behavior and can predict stock returns. These findings are contradictory to the traditional efficient market hypothesis approach in finance and are a behavioral explanation of asset pricing anomalies.

There are broadly three approaches to measuring sentiment currently in the literature. One approach is through the use of macroeconomic or market variables. This approach was made popular by Baker and Wurgler (2006) who use Principal Component Analysis to obtain a sentiment index. Survey based sentiment indices utilize either market or household opinions on a regular basis, examples of these surveys include the Conference Board Consumer Index (CBCI) and Michigan Consumer Sentiment Index (MCSI). Another approach which has gained attention is the construction of sentiment measures through the use of news or text-based measures. These measures can also be extended to areas of social media, internet search engines such as Google or internet news boards. In this dissertation I focus on using news and text-based sentiment measures provided by Thomson Reuters News Analytics. In this dissertation I choose a text-based measure as this allows for the construction of daily sentiment measures at the market and firm level and captures dynamic movement of sentiment at higher frequency than the other two types of measures.

This dissertation's data coverage encompasses the period of 2003 – 2014 and covers two distinct stock market areas. Chapters 2 and 3 focuses on Japan, whilst chapter 4 focuses on stocks from 15 European countries. Data is collected from Bloomberg, Datastream, The Center for Research in Security Prices, and TRNA is obtained through Securities Industry Research Centre of Asia-Pacific (SIRCA).

1.1 Motivation

The aim of this dissertation is to explore the relationship between sentiment and stock returns using multiple countries as a testing ground. As sentiment is unobservable, sentiment in this dissertation is defined as that which is attributed to mood and news which may influence investor behavior in a quasi-rational manner. This dissertation presents three essays on the topic of investor sentiment and stock returns using a text-based measure of sentiment derived from Thomson Reuters News Analytics (TRNA).

The first motivation of this dissertation is to examine the role that market sentiment has on asset pricing and, explore if sentiment can help explain poor Japanese stock returns during part of “the lost decades”. Chapter 2 of this dissertation fills a gap in the literature as traditional models of asset pricing have been so far unable to explain the puzzle that is the lost decades of the Japanese stock market. In addition, the link between mood and sentiment has to my knowledge, not been examined in Japan.

Chapter 3 explores the relationship between sentiment and Japanese stock returns in a more formal empirical asset pricing model, the Fama and French three-factor model. I augment the three-factor model as the five-factor model does not appear to explain the stock returns in Japan better than the three-factor model.

Chapter 4 extends upon findings in chapter 2 and 3 where sentiment appears to help explain Japanese stock returns in periods of recession and market decline. The motivation for this chapter was to examine if the chapter 2 results for Japan could be applicable to countries which had similarly suffered periods of recession and markets decline. I consider whether sentiment can help explain European stock returns for 15 countries within the Fama and French framework, and for countries which were most vulnerable to the European Financial Crisis (EFC). Specifically, this chapter extends upon the analysis in chapter 2, as results for Japan may also be applicable for stocks from Portugal, Ireland, Italy, Greece and Spain, (PIIGS), which I hypothesize will be more sentiment prone than other Eurozone and European Union countries.

1.2 Findings and conclusions

Chapter 2 focuses on examining Japan's "lost decades" which challenge finance's central tenet of a positive expected relationship of return and risk. It presents the background literature and concepts linking mood and sentiment used for much of the dissertation. The background in chapter 2 is applicable to all chapters of the dissertation but is not repeated in full form in each chapter for conciseness. The results in chapter 2 presents evidence that Japan's poor stock returns can be partially attributed to sentiment at both the aggregate market and individual firm level. Utilizing a text-based measure of news sentiment (Thomson Reuters News Analytics) to proxy for investor sentiment, I find that sentiment is predominately negative during the sample period of 2003 to 2012 and is associated with negative returns. The results in chapter 2 suggest that there is an asymmetric effect of news sentiment on stocks based on size, with the effect of news sentiment greatest for small stocks. The findings in this chapter are consistent with US evidence suggesting that sentiment has a greater effect on small "opaque" firms as they may have characteristics such as high information asymmetry, low liquidity and high transaction costs. However, there is still conflicting evidence as to whether the effect is greatest for stocks categorized as value or growth.

Chapter 3 examines sentiment as an addition in the Fama and French three-factor model using Japan as a market setting, as the five-factor model does not appear to work for Japan. This chapter is an extension on the theme of chapter 2 and it utilizes the same text-based sentiment measure derived from Thomson Reuters News Analytics, but in the context of a well-accepted empirical asset pricing model. Similarly, to results in chapter 2, there is evidence that sentiment in this framework has effects on small stocks. However, I also find that large growth stocks are affected, which may have characteristics such as intangibles which make them hard to value and more easily influenced by sentiment. My analyses also present evidence that sentiment may influence stock portfolios *via* the Fama and French factors, or potentially as a separate additional factor.

Chapter 4 extends the analysis of chapters 2 and 3. This chapter examines sentiment as an augmentation to the Fama and French five-factor model for Europe. I follow common practice in the literature and divide Europe into two distinct groups based on the perceived severity of their exposure to the European debt crisis. I find that sentiment is positively related to portfolio returns in the countries most severely impacted by the debt crisis (PIIGS), and it is not an important factor in those countries not heavily impacted by the crisis (Non-PIIGS). I also find that there is an asymmetric effect of sentiment based on size which has been well documented in this dissertation for Japan and confirms a common result in the literature. However, unlike in chapter 3, where there is evidence for large growth stocks being affected by sentiment, in chapter 4 there is also evidence that large value stocks, and value stocks in PIIGS are also affected by sentiment.

Chapter 2 MELANCHOLIA AND JAPANESE STOCK RETURNS – 2003 TO 2012

The material from this chapter was adapted as part of submission to The Pacific-Basin Finance Journal. It forms the foundation of the published article Melancholia and Japanese stock returns – 2003 to 2012 (Khuu et. al 2016) available from: *https://doi.org/10.1016/j.pacfin.2016.05.011*.

2.1 Introduction

A positive relationship between risk and expected return is a central tenet of finance theory (Merton 1973; 1980)[1]. However, Japan's "lost decades" challenge this idea. In the 25 years and counting since the Japanese crash, the Nikkei stock index, which peaked at 38,916 in December 1989,[2] has not "recovered". In the period I consider, average returns have been primarily negative.[3]

Merton's proposition of the positive relationship of returns and risk is based on rational expectations. Japan's *prima facie* violation of Merton's proposition suggests that a quasi-rational, or behavioral, model might help us understand Japanese returns. This chapter examines the relationship between the returns on the Tokyo Stock Exchange (TOPIX)[4] and investor sentiment from January 2003 to October 2012. This time period encompasses part of the "second lost decade of Japan".

I find that sentiment has a significant positive relationship with stock returns, and thus the prolonged downturn in Japanese markets may be attributed to the

1. See Müller et al. (2011) for a review of literature discussing the relationship of risk and expected return.
2. Shiratsuka (2005) described the pre-crash period as one dominated by "euphoria" or "optimism", consistent with Shiller's (2000) "irrational exuberance".
3. I discuss this result in detail below when presenting summary statistics in Table 3.
4. The TOPIX is a free-float adjusted market capitalization-weighted index that is calculated using all the domestic common stocks listed on the TSE First Section. TOPIX shows the measure of current market capitalization assuming that market capitalization as of the base date (January 4 1968) is 100 points. This is a measure of the overall trend in the stock market, and is used as a benchmark for investment in Japan stocks.

prevalent negative mood throughout the period being studied.[5] My analysis uses a text-based measure of news sentiment (Thomson Reuters News Analytics) to proxy for investor sentiment.

I also analyze the role of sentiment at the firm level and find evidence to suggest that the effect of news sentiment is greatest on the stocks of smaller firms, although smaller firms generally have fewer news items. My study fills a gap in the literature on the cross-sectional effect of sentiment; this body of work has largely ignored text-based measures such as that employed here. In addition, the link between mood and sentiment has to my knowledge, not been examined in Japan. My findings are consistent with US evidence suggesting that sentiment has a greater effect on small firms. Baker and Wurgler (2006; 2007) found a size effect, where smaller stocks are more susceptible to "sentiment" and related this to the notion of limits-to-arbitrage. Berger and Turtle (2012) found a similar result, where "sentiment prone" stocks tend to be young, volatile and small firms with "opaque" characteristics. Brown and Cliff (2005), Lemmon and Portniaguina (2006), and Schmeling (2009) also noted that sentiment had a greater influence on small firms, although there is conflicting evidence as to whether the effect is greatest for stocks categorized as value or growth.

My analysis of the association between investor sentiment and Japanese returns contributes to a growing literature (outlined above and, in more detail, in section 2.3) linking returns to sentiment. Further, my findings, presented in Section 2.3, demonstrate that the consideration of sentiment can help us understand the prolonged Japanese bear market. Given that findings related to text-based measures of sentiment are predominately obtained using US data, my analysis provides evidence that sentiment can play an important role in understanding markets outside of the US. Section 2.3 discusses my methodology; in particular, I detail how I construct text-based sentiment measures for the Japanese markets using data from Thomson Reuters News Analytics (TRNA).[6]

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5. García (2013) used a similar psychological framework and stated "human behavior is significantly different in times of anxiety and fear versus periods of prosperity and tranquility". My measure of market sentiment is negative for most years in my sample, which is perhaps one reason why, contrary to the literature, the effects of sentiment identified in Japan are not any stronger at times such as the Global Financial Crisis of 2008-09.

6. TRNA, formerly, the Reuters NewsScope Sentiment Engine.

2.2 Background

Mood has been found to have influencing or conditioning effects on human decision making, perception and behavior (Schwarz and Clore 1983). Johnson and Tversky (1983) found that bad moods could be induced in readers by brief news stories, even if minimal information is disclosed. They theorized that an individual's judgement is influenced by their current mood state, even if the subject matter they are analyzing is unrelated to the cause of their mood. Readers reacted not to the information contained in the article, but the mood which it introduced. This is known as mood misattribution. Loewenstein (2000) found that visceral factors[7] influence an individual's mood or emotion, which in turn acts as a channel influencing preferences. As a result, an individual investor's behavior may not always be rational depending on their conditioning mood. Lucey and Dowling (2005) examined this in detail and developed a theoretical framework for "investor feelings" and the effect that this can have on equity pricing. More broadly, as Kaplanski et al. (2014) describe, this psychological framework examines the effects of non-economic variables on stock markets, which is not consistent with efficient and rational markets.

A growing body of literature suggests that mood, can influence investor decisions and is linked with sentiment, which in turn influences share market behavior, (Baker and Wurgler 2006; Brown and Cliff 2005; Lawrence et al. 2007; Tetlock 2007; Tetlock et al. 2008; Stambaugh et al. 2012). Sentiment is not directly observable: only its effects are visible. Therefore, when analyzing its influence on market behavior I must introduce a proxy. The earliest papers proxy investor sentiment through weather. Saunders (1993) presented an early and influential study that the weather in New York City had a significant effect on stock market performance. Specifically, Saunders argued for the presence of a weather effect on investor psychology, which in turn influenced the behavior of investors and subsequently the stock market. Saunders regressed daily returns on several US stock market indices against measures of sunny days, (positive sentiment days), from 1927 to 1990 and found that sunnier days had a positive correlation to stock market returns. Hirshleifer and Shumway (2003) extended this research using a sample of twenty-six countries from 1982 to 1999 and also found

7. Visceral factors are a series of negative emotions, drive states and feeling states which can alter desires rapidly as they are affected by external and internal stimuli (Lowenstein, 2000).

a significant positive relationship between sunny days and stock returns. Trading on this "sunshine" effect can improve the Sharpe ratio of a trader's investment portfolio, but only if the trader has low transaction costs. Kamstra et al. (2003) and Goetzmann et al. (2014) examined mood fluctuations due to Seasonal Affective Disorder (SAD) and the effects on stock markets. Kamstra et al. (2003) found a relationship between SAD and investor risk aversion. They examined nine stock indices around the world and found seasonality in stock returns. Investors suffering from SAD due to changing seasons, autumn to winter (winter to summer), became more (less) risk averse and sold (bought) stocks, therefore depressing (raising) prices. Goetzmann et al. (2014) also examined the impact of weather induced mood on investor belief and found sunnier (cloudier) days are related to investor optimism (pessimism). They found that institutional investors have an increased propensity to buy on sunnier days, but also an increased propensity to sell due to perceived mispricing on cloudier days. Perceived mispricing in this study was captured through a survey, where investors are asked their opinions about the level of the Dow Jones Industrial Average based on their belief about U.S corporate strength and fundamentals. Goetzmann et al. (2014) also constructed a firm level proxy for investor optimism based on weather. They found a positive correlation between their optimism measure and firm stock returns, with the effect concentrated in stocks which are subject to higher arbitrage costs.

Weather is not the only psychological link between aggregate investor sentiment and stock market returns. The effect of team sports results on market returns has also been discussed in the literature, where a win is generally seen as having a positive effect due to positive sentiment associated with a win, but a loss having a negative sentiment effect. Ashton et al. (2003; 2011) documented a relationship between the performance of Football teams and share prices on various stock exchange. Edmans et al. (2007) examined a similar effect using international soccer results, finding an asymmetric yet statistically significant negative effect for the losing country's stock market. They found evidence for a cross-sectional effect on sentiment with small stocks more susceptible to this negative effect. They showed no statistically positive effect which follows from Prospect Theory (Kahneman and Tversky 1979). Kaplanski and Levy (2010) showed how this relationship between FIFA World Cup soccer matches and the US stock market produces an exploitable effect. The results of the World Cup impact the US stock market due to the presence of foreign investors and the associated sentiment from match outcomes. They theorized that the tournament style format introduces a cumulative negative sentiment effect on the stock market as countries are eliminated and an increasing number of investors, domestic and foreign, become despondent.

A recent study by Kaplanski et al. (2014) argued causality between non-economic "sentiment creating factors" and stock prices through the effect on individual investors. They found that "sentiment"[8] affects expected household investor returns more "intensely than expected risk". They examined the relationship between non-economic "sentiment-creating measures"[9] on investors using survey data from 5,000 households in the Netherlands. These measures comprise mood inducing factors which have been identified in previous literature as having aggregate investor behavior effects on share market returns. They confirmed the existence of an asymmetric effect of mood on expectations, the presence of a SAD and sports team effect on "subjective estimates" of return and risk. A strength of Kaplanski et al. (2014) is that it finds statistically significant relationships between variables believed to influence mood and investors' intentions. A limitation of this chapter is that it cannot link intentions to actions.

There are currently three broad approaches to measuring investor sentiment. One approach is to try and capture market sentiment through the use of macroeconomic and market variables. This approach was popularized by Baker and Wurgler (2006; 2007) and is considered to be a "top down" approach. The Baker and Wurgler (2006) sentiment index is based on the first principal component extracted from a set of six candidate proxies for market sentiment.[10] The six proxies are the NYSE trading volume based on turnover, dividend premium, the closed-end fund discount, equity share in new stock issues and the number and first day returns of initial public

8. They used Baker and Wurgler's (2007) sentiment definition: "investors' belief about future cash flows and risk not justified by the facts at hand" (p. 129).

9. These factors are an individual's contemporaneous general feeling, results of the investor's favorite soccer team, perception of contemporaneous weather in the previous two days and if they perceive themselves as suffering from SAD.

10. Baker and Wurgler (2006) report that the first measure of sentiment explains 49% of the sample variance of the set of candidate sentiment proxies and that the second measure explains 51% of the variance of the orthogonalized proxies. For the second measure, they also report that this is the only component with an eigenvalue greater than one; but they do not report the eigenvalues of the first principal components analysis.

offerings. Baker and Wurgler (2006) also presented a second, but related, sentiment index based on principal components analysis of the candidate proxies orthogonalized to a set of state variables (commonly used in empirical work in intertemporal, or consumption, Capital Asset Pricing Models).[11] These state variables are industrial production, real growth in durable, non-durable, and services consumption, growth in employment and the National Bureau of Economic Research (NBER) recession indicator. Baker and Wurgler's measures are limited to a monthly frequency due to the nature of the data with which they work; other similar measures that utilize macroeconomic data that is released quarterly provide even less frequent measurements of sentiment. Paper which use this style of macro-measure include Tsuji (2006), Yu and Yuan (2011) Baker et al. (2012), Chung et al. (2012) and Stambaugh et al. (2012). On the other hand, the literature (Chen et al. 1993; Lemmon and Portniaguina 2006; Qiu and Welch 2006) notes that proxies used in constructing such measures may not actually be effective in capturing sentiment.

The second approach for quantifying sentiment uses survey-based sentiment indices that poll market or household opinions on a regular basis (Akhtar et al. 2011, 2012; Antoniou et al. 2013; Brown and Cliff 2005; Hengelbrock et al. 2013; Lemmon and Portniaguina 2006). Examples of surveys include the Conference Board Consumer Index (CBCI) and Michigan Consumer Sentiment Index (MCSI). This measurement is limited in that it matches the frequency of a periodic survey and is potentially subject to bias introduced in the design or construction of the underlying survey itself. Boisen et al. (2015) raised the prospect that consumer indices are weak proxies for investor sentiment, finding little to no significant correlation between two consumer sentiment indices and the Baker and Wurgler (2006) measures. If both were appropriate measures of investor sentiment, then I would expect the correlation to be stronger. Lemmon and Portniaguina (2006) found evidence to suggest that "the different measures either capture some unrelated components of investor sentiment or perhaps fail altogether to capture some important aspects of sentiment".

The third approach, which I employ, is the use of text-based sentiment measures (Allen et al. 2015; Dzielinski 2011; García 2013; Groß-Klußmann and Hautsch 2011; Smales 2014a; Tetlock 2007; Tetlock et al. 2008; Uhl 2014). Such

11. See Chen (1991) for a seminal analysis.

measures are increasingly prevalent in the literature and have incorporated articles posted to internet discussion boards (Antweiler and Frank 2004), frequency of entries in search engines and social media posts (Bollen, Mao et al. 2011), in addition to more traditional channels such as newspapers and newswires. One advantage of this measure is that news is released frequently and can be updated frequently, capturing changes in sentiment and the effects on investor behavior. The other two measures are updated at a slower rate and arguably miss this dynamic component of sentiment. Tetlock et al. (2008) also found that information is embedded in news stories, and a quantitative measure of language can capture difficult to measure firm fundamentals.

There is one further advantage of text-based sentiment measures over the others. It is relatively easy to identify a candidate for the mechanism through which the sentiment is identified as the textual analysis "translates" to the mood and feelings of investors. I note, however, that the literature in this area has been silent on this mechanism. Experimental psychology demonstrates how subjects' moods may be manipulated through external stimuli such as sad stories, movies and music (Maymin 2012).[12,13]

The simplest text-based measures use a "bag of words" approach that classifies words as positive or negative to create measures of sentiment (Tetlock 2007) based on the frequency of each word-type. This simple approach may be problematic as there is no guarantee that negative words on their own imply negative sentiment (e.g. double negatives). Contemporary methods utilize computer algorithms, or linguistic pattern analysis, to understand the context in which words are presented. This neatly coincides with the increase in delivery and frequency of news due to technological innovations. The advantage of these methods is a systematic and quantitative approach to assigning and classifying high frequency news in terms of sentiment and relevance. Market vendors of these services include TRNA and Ravenpack.

Tetlock (2007) was the first to formally link "sentiment" resulting from the text of news articles with stock returns. Negative sentiment or pessimism was measured using a text-based program (the General Inquirer) together with the Harvard IV-4

12. To experience the effectiveness of this approach, see either the death of Bambi's mother (https://www.youtube.com/watch?v=-eHr-9_6hCg) or the climactic scene in Old Yeller (https://www.youtube.com/watch?v=fjTJB-_Yd50) (both accessed on July 2 2015).
13. For reviews on mood induction see Gerrards et al. (1994) and Westermann et al. (1996).

Dictionary to classify negative words in the Wall Street Journal's (WSJ) "Abreast of the market" column. Tetlock found that media pessimism predicted lower stock returns on the Dow Jones Industrial Average (DJIA), suggesting a psychological link between the news and market prices. The effect of negative sentiment was found to be concentrated in "extreme values of returns and sentiment" with a reversal to fundamentals slower in smaller stocks. Tetlock argued that "media content is linked to the behavior of individual investors, who own a disproportionate fraction of small stocks" (Tetlock 2007 pg.1166). Tetlock also noted a relationship between sentiment and trading volume, with trading volume increasing with negative sentiment.

García (2013) also analyzed the text of a Wall Street Journal (WSJ) news column and found that the predictive power of such news-sentiment is concentrated in recessions. Such news columns are overviews of market events, summarizing events of the previous day, rather than news that explicitly reveals fundamental information such as earnings reports or forecasts. News columns are likely to contain opinion and speculation and thus be linked to sentiment rather than fundamental information; although the two types of information effects can be difficult to separate. García (2013) also found a relationship between changes in trading volume and days of extreme pessimism or optimism; evidence of an irrational or behavioral reaction to market news, with one possible explanation of naive or noise traders who react to positive and negative news rather than fundamentals.

A more sophisticated branch of text-based analysis has emerged. This branch utilizes advances in computer algorithms to classify news based on linguistic pattern analysis, which captures contextual aspects of text. Groß-Klußmann and Hautsch (2011) demonstrated the efficacy of a computer algorithm generated analysis using TRNA to investigate the effect of non-scheduled news items on 39 stocks listed on the London Stock Exchange from January 2007 to June 2008. They found that news relevance, measured by TRNA classifying filters, is essential to filtering out noise and that sentiment indicators have some predictive power in forecasting future stock returns. Smales (2014b) also confirmed the importance of relevance and sentiment classification indicators using Ravenpack on 33 listed stocks on the Australian Stock Exchange 50 from 2000 to 2011.

Uhl (2014) used TRNA to construct a sentiment measure to test the ability of sentiment to predict the returns of the DJIA. Uhl (2014) found that this measure of sentiment was better able to forecast returns than macroeconomic factors. The study used a Vector Autoregressive (VAR) model finding that news sentiment using the TRNA measure has an effect that can be detected over several months. Uhl (2014) also found that negative sentiment is more persistent than positive sentiment when used as a predictor of stock returns and that bad news is incorporated into stock prices more slowly. Dzielinski (2011) compared positive news days and negative news days using the TRNA dataset and found that US stock returns have above (below) average returns on positive (negative) days.

The research in this chapter adds to the strand of behavioral finance literature that links mood and sentiment to stock prices. In particular, the analysis presented in this chapter links persistent negative stock returns of the Japanese stock market to negative sentiment during the period of 2003-2012.

2.3 Data and Methodology

This study utilizes a text-based sentiment measure to examine the effects of news on Japanese stock markets. The particular sentiment measure that I construct utilizes data provided by TRNA, via SIRCA. TRNA uses machine learning with a neural network to classify the sentiment associated with news stories, primarily by examining sentences rather than individual words. This has the advantage of a contextual word analysis rather than standalone meaning. The word lexicon is triple hand annotated and includes around 16,000 words and 2500 phrases. Training and validation of the neural network was undertaken by using 5,000 news articles from December 2004 to January 2006 annotated by three separate individuals (Thomson Reuters 2013). Recent studies that have utilized this data set include Hendershott et al (2015) and Smales (2014a, 2015a, 2015b). This dataset is chosen for several reasons. Firstly, unlike sentiment measures constructed using macroeconomic or survey data, this data is available at a higher frequency, allowing for the construction of daily sentiment measures at the market and firm-level. Secondly, Johnson and Tversky (1983) found that even minor news may influence investor mood and investor perceptions; it is therefore possible that news in addition to major macroeconomic events, or earning announcements, will influence an investor's mood, impacting their judgement and subsequently influencing trading behavior. Finally, the TRNA algorithm allows us to consider the potential impact of news that is categorized as "good", "bad" or "neutral".

As I have highlighted, TRNA uses a linguistic algorithm to analyze the content of news messages in individual news items delivered across the Thomson Reuters Newswire; this service is used by a substantial number of investors. The algorithm assigns a sentiment score of positive (1), negative (-1) or neutral (0) to each news item. Each news item is accompanied by a GMT date and time stamp to the nearest millisecond as well as a Reuters Instrument Code (RIC) code which links the news item to the relevant firm. It is possible for one news item to be linked to multiple RIC codes; however, the sentiment measure associated may not be the same for each individual firm. For example, one news item may be linked to a positive sentiment score for one firm but be linked to a negative or neutral sentiment score for another firm.

The relevant information fields that I use to construct my time series daily sentiment measures are:

1. *Sentiment*: The measure of the sentiment of the news article that is categorized as positive (1), negative (-1) or neutral (0). TRNA also indicates the probability that the particular news item will fall into each category. For example, if the TRNA algorithm assigns an 80% probability that a news item is positive, 16% neutral, and 4% negative, then the sentiment for that news item would be characterized as positive (+1), while the probability weighted sentiment score would be +0.8 (i.e. +1 x 80%).

2. *Relevance*: A rating between 0 and 1 that indicates how relevant the news item is to a specific firm. A score of 1 (0) means the news item is highly relevant (irrelevant). In my primary analysis I limit my sample to those news articles with a relevance score above 0.8 to ensure that the sentiment measure I construct is relevant[14] to stock prices and returns. Groß-Klußmann and Hautsch (2011) and Smales (2014b) find that relevance is highly important in

14. If investors have limited attention I expect that they will focus only on relevant information.

identifying information and filtering “noise”. Dzielinski (2011) employs an even stricter filter than I do, only considering news items with relevance equal to 1. Owing to the limited attention of investors, I focus only on relevant articles since these are most likely to influence investor behavior.

3. *Novelty*: Measures how unique a particular news item is when compared to previous similar news items within a defined period. The time frame for this measure can be split into five different historical periods. Since I are interested in unique news, I filter for content that is considered “novel”, that is news items that are not similar to previous articles.

Table 1 illustrates the effect of my filtering process for news related to Japanese stocks in the TRNA dataset over my sample period, which runs from 1st of January 2003 – 31st of October 2012, coinciding with data availability for TRNA. Initially, I have 971,290 news items for stocks traded on the Tokyo Stock Exchange, of which 363,574 are novel. If I only filter for news classified as relevant, there are 474,414 news items. Filtering for both novel and relevant news items leaves us with 220,784 unique news items that are used to construct the sentiment measures utilized in my analysis.

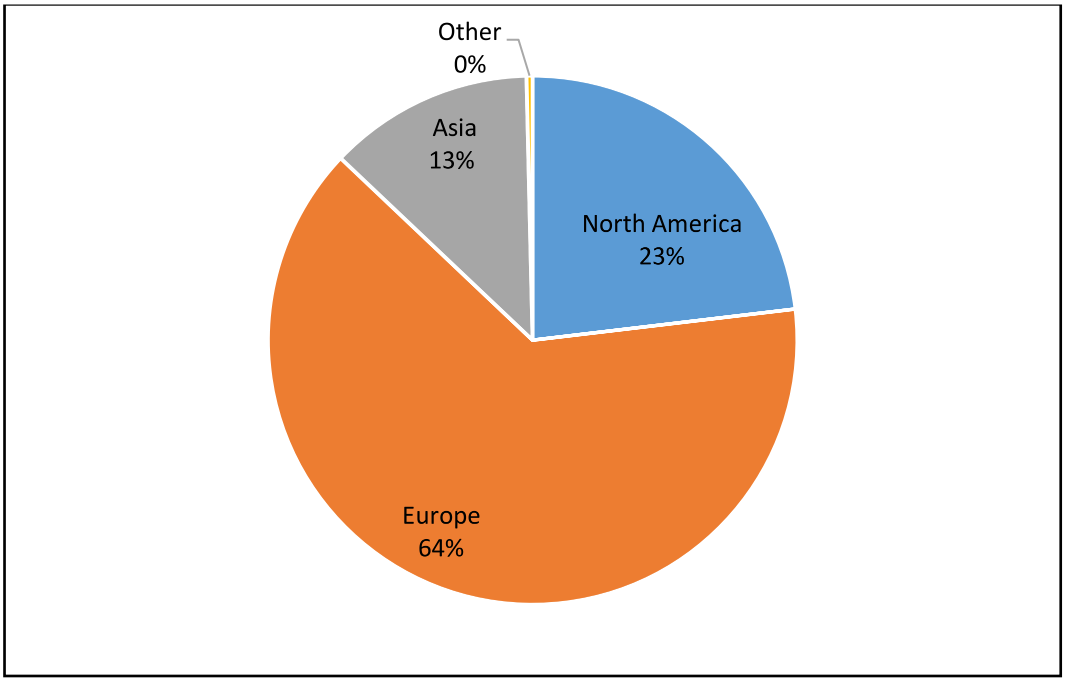
Table 1. Summary of Filtering Process for News Items

	All News Items for the Tokyo Stock Exchange	**News Observations After Filters**
Time Period	01 Jan 2003 -31 October 2012	01 Jan 2003 -31 October 2012
Individual News Observations	971,290	363,574
Only Relevant News Sentiment $\geq \pm 0.8$	474,414	220,784

Note: This table shows the filtering process for news related to Japanese stocks in the TRNA dataset over my sample period, which runs from 1st of January 2003 – 31st of October 2012, coinciding with data availability for TRNA.

Data provided by TRNA is presented in English, not Japanese, and it is worth considering if the use of TRNA-based sentiment metrics presents a challenge for the interpretation of my results. I am unable to distinguish between translated news (news written in Japanese and translated to English) and news originally published in English; it is possible that the context of such news may be lost in the translation process. The interpretation of news presented in English may also be subject to cultural differences in interpretation by investors. At the daily frequency I am studying, it is unlikely that the tone of stories will be uncorrelated: any such systematic bias in tone should lead to arbitrage opportunities. Foreign investors account for a significant proportion of stock market activity in Japan: 43% by volume and 51% by value in 2012. Near the beginning of the sample period this was 22% by volume and 28% by value.[15] Figure 1 presents the breakdown of foreign ownership by region.[16] Analogous arguments justifying sentiment proxies have been utilized in related studies. For example, Kaplanski and Levy (2010) used FIFA world cup results as a proxy for sentiment on US stock returns. It is argued that even though football is not a particularly popular sport in the US the presence of foreign investors who may be affected by the results has an effect on the market.

Figure 1 Investments in Listed Stocks by Non-residential Investors (by region) 2012



Note: Figure 1 presents the breakdown of foreign ownership by region. Source: Japan Exchange Group: http://www.jpx.co.jp/english/markets/statistics-equities/investor-type/07.html.

15. This refers to the year 2005, as data provided by Japan Exchange Group begins here.

16. Total foreign ownership of Japanese shares has grown over the sample period analyzed from over 15% at the start of my sample period to approximately 30% in 2014. This is reported to be steadily increasing each year (Fujikawa 2014).

In a similar vein to Allen et al. (2015), Smales (2014a) and Uhl (2014) I construct a daily sentiment measure by aggregating the sentiment for all news items on the particular day. If an individual firm has more than one unique news item per trading day, then the average of that is found to construct that firm's daily sentiment score. I calculate two types of averages described by equations (1) and (2).

The first method uses a simple average of the daily sentiment scores, and the second method uses a probability weighted sentiment average. The simple average method is described below by equation (1). Each firm's sentiment scores are measured and then I take the simple average of those scores to form a daily market wide level sentiment measure:

$$Asent_{mkt} = \frac{\sum(1)\cdot sentiment_{positive} + \sum(-1)\cdot sentiment_{negative}}{nsentiment_{positive} + nsentiment_{negative} + nsentiment_{netural}} \in [-1;1] \tag{1}$$

where $Asent_{mkt}$ is the average sentiment of the market, *sentiment* is the sentiment score associated with a news item, positive or negative, and *nsentiment* is the number of sentiment news items with corresponding positive, negative or neutral scores. For example, if there are two unique firm news items on a day, with one signed as being positive (1) and one being neutral (0), then the average market sentiment for that day using equation (1) is 0.5. By construction, this measure is bounded by ±1. Neutral news items (sentiment = 0) have no effect on the numerator, but do affect the denominator, and hence the prevailing market sentiment measure for each day.

To construct the probability weighted average market sentiment score, the sentiment attached to a news item is multiplied by the TRNA assigned probability that it is correctly categorized. In this instance, the equation is as follows:

$$Psent_{mkt} = \frac{\sum(1)\cdot Psentiment_{positive} + \sum(-1)\cdot Psentiment_{negative}}{nsentiment_{positive} + nsentiment_{negative} + nsentiment_{netural}} \in [-1;1] \tag{2}$$

where $Psent_{mkt}$ is the probability weighted sentiment of the market, *Psentiment* is the probability sentiment score associated with a news item positive or negative and *nsentiment* is the number of sentiment news items with corresponding positive, negative or neutral scores. Table 2 shows summary information for the news items in each year, along with the measures of market sentiment calculated using equations (1) and (2). The number of firms increases over time, as does the total number of news items. 2012 has fewer observations as the sample ends in October.

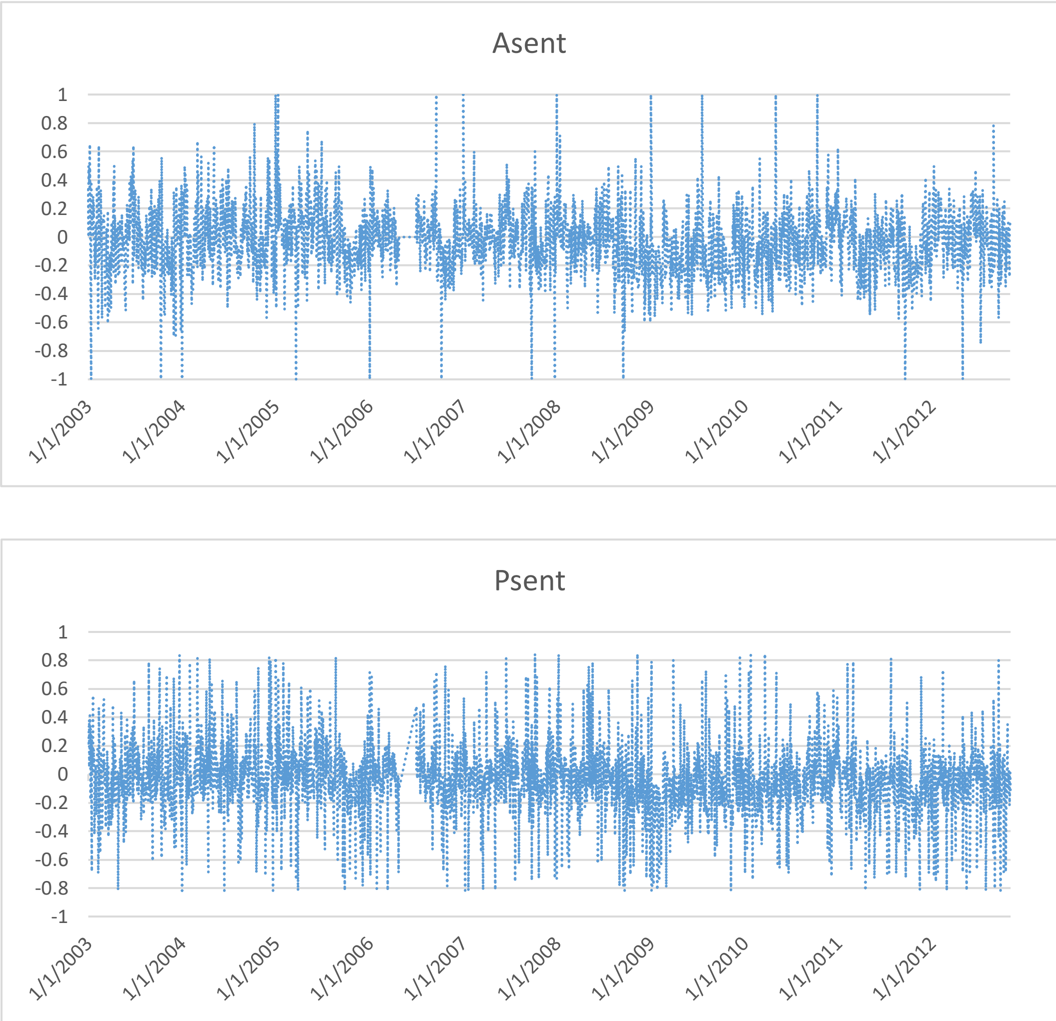
Table 2. Breakdown of News Items by Year and Market Sentiment Measures

Year	Number of News Items	Number of Firms	Simple Average Market Sentiment	Probability Weighted Market Sentiment	Standard Deviation TOPIX
2003	15,210	2,084	-0.05950	-0.0573	0.0123
2004	15,351	2,160	-0.01459	-0.0182	0.0101
2005	15,838	2,233	-0.00581	-0.0190	0.0078
2006	15,758	2,318	-0.03389	-0.0331	0.0117
2007	19,476	2,362	-0.02870	-0.0328	0.0118
2008	20,125	2,383	-0.05511	-0.0597	0.0259
2009	47,686	2,404	-0.18441	-0.1616	0.0149
2010	24,871	2,430	-0.07744	-0.0844	0.0107
2011	26,083	2,467	-0.08235	-0.0878	0.0140
2012	20,386	2,496	-0.00358	-0.0412	0.0098
Total	220,784	23,337	-0.05454	-0.0595	0.0138

Note: This table presents the number of news items in my data set after filtering and corresponding sentiment measures as well as the standard deviation of the TOPIX.

Figure 2 illustrates the time series of my daily market sentiment measure for the TOPIX for my sample period. I drop all non-trading days from my dataset and sentiment scores are constructed only from news that is released during trading hours. If news on a trading day is released after trading hours, for example 19:00 Tuesday, that news item is assigned to the following trading day. There is a break in the TRNA data set from the 24th of April 2006 to the 2nd of July 2006, where there were no relevant sentiment news items after I filter for relevant and novel news items relating to Japan. Rather than winsorize my sample, the effect of weighting the sentiment measure by probability in equation (2) truncates the daily market sentiment measures, removing extremely positive or negative sentiment scores. In the probability weighted measures there are no “days” with completely positive (1) or negative (-1) sentiment. There is no agreement in the literature as to whether or not sentiment should be weighed by probability, hence I use both sentiment measures in this analysis.

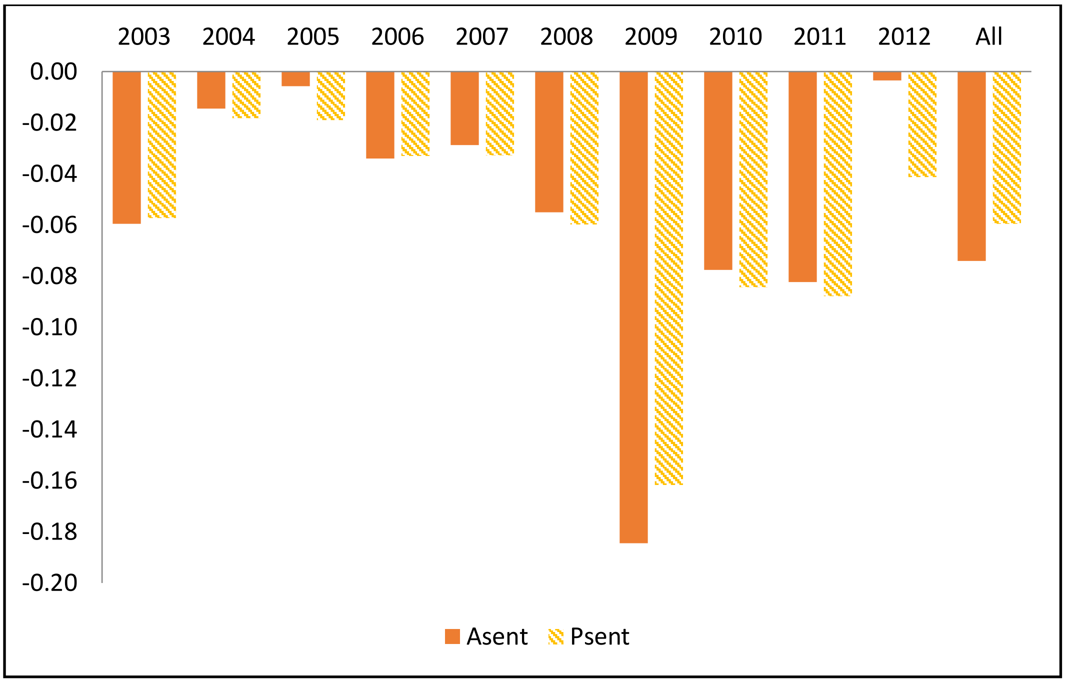
Figure 2 Daily Market Sentiment for the TOPIX 2003 - 2012



Note: This figure presents a time series plot of constructed sentiment measures.

Figure 3 illustrates the average of the constructed news sentiment for the Tokyo Stock Market (TOPIX) over the sample period, including non-trading days, where *Asent* is the simple sentiment average for the year and *Psent* is the probability weighted average sentiment score.

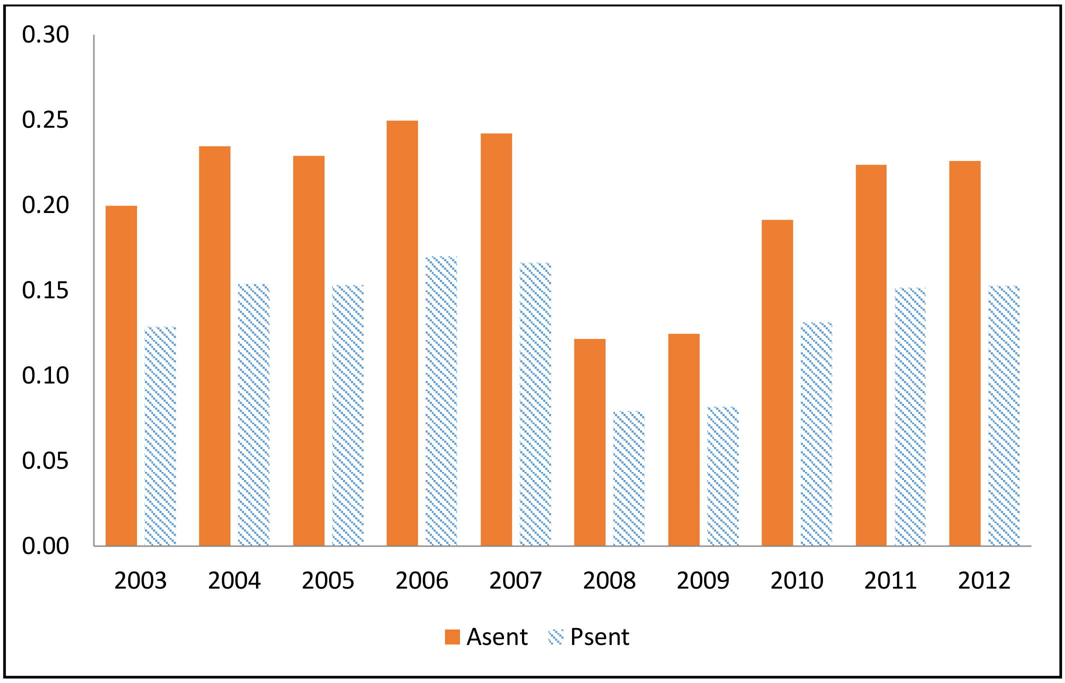
Figure 3 Yearly Market Sentiment for the TOPIX - Including Non-Trading Days 2003 - 2012



Note: This figure shows the average yearly sentiment for the TOPIX using the same method I use to calculate my sentiment measures for Japan. The data is sourced from the same TRNA dataset used in this dissertation.

It is apparent that the average sentiment for the TOPIX is negative in each year of the sample period: this is in contrast to evidence for the U.S. markets that finds sentiment is always positive, even during the Global Financial Crisis (GFC) of 2008 to 2009 (see Figure 4). Note that, for Japan, market sentiment is more negative during the crisis period.

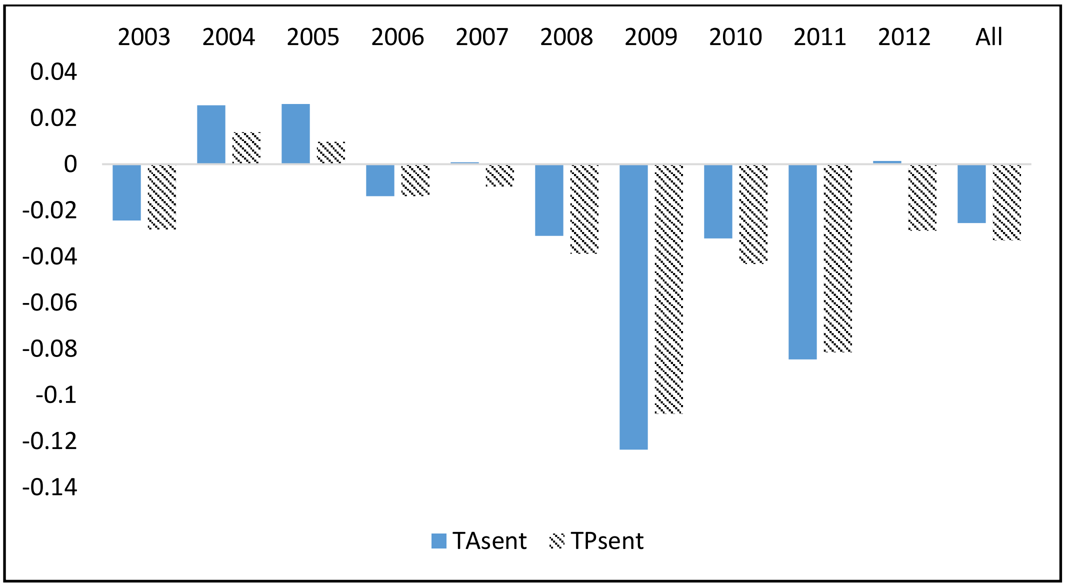
Figure 4 Average Yearly Sentiment for the New York Stock Exchange 2003 – 2012



Note: This figure shows the average yearly sentiment for the NYSE using the same method I use to calculate my sentiment measures for Japan.

Figure 5 shows the sentiment measures constructed in equation (1) and (2) for the TOPIX for trading days (only) which correspond to trading days in the DataStream data set. Once non-trading days are removed from the dataset the average yearly sentiment shifts upwards, indicating that weekend news and non-trading day sentiment is typically negative. The pattern in the yearly sentiment remains the same with negative sentiment most prominent in the years surrounding the financial crisis.

Figure 5 Yearly Market Sentiment for the TOPIX - Trading Days Only 2003 – 2012



Note: This figure shows the average yearly sentiment for trading days for the TOPIX using the same method I use to calculate my sentiment measures for Japan.

A similar measure is constructed for each firm in my sample. Based on a firm's RIC code on any given day, I take each unique news item and assign the associated sentiment score of -1, 0 and 1 to the firm. If a firm has multiple news items per day, I find the average of the sentiment scores attached to each unique firm news item to construct the firm level sentiment measure:

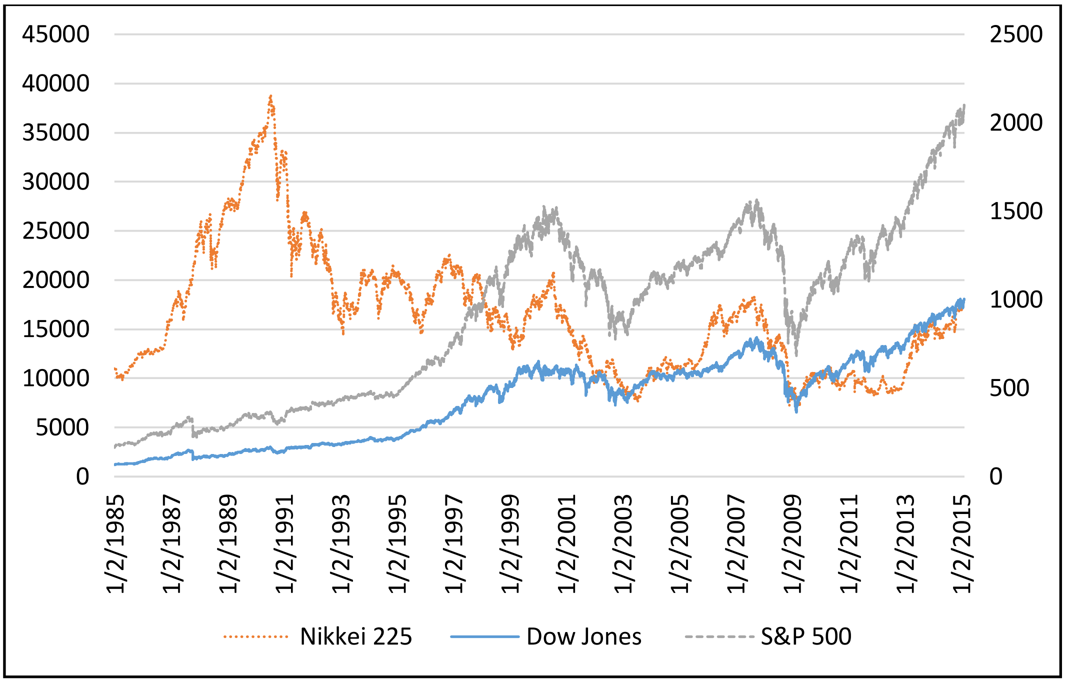
$$Asent_{firm} = \frac{\sum(1)\cdot sentiment_{positive} + \sum(-1)\cdot sentiment_{negative}}{nsentiment_{positive} + nsentiment_{negative} + nsentiment_{netural}} \in [-1;1] \qquad (3)$$

where $Asent_{firm}$ is the average sentiment of the firm, *sentiment* is the sentiment score associated with an individual firm news item, positive or negative, and *nsentiment* is the number of firm sentiment news items with corresponding positive, negative or neutral scores. If a firm has no news items on any given day then the firm is assigned a sentiment score of 0 for that day, indicating neutral sentiment. This means that a firm with no news may potentially have the same sentiment scores as a firm that did have a news item (if the associated sentiment of that news item is neutral or 0). To control for this effect, I include a firm news dummy. The dummy variable takes on a value of 1 if there was a unique firm news event on a given day, and zero if there was no news. A probability-weighted sentiment measure is also constructed at the firm-level:

$$Psent_{firm} = \frac{\sum(1) \cdot Psentiment_{positive} + \sum(-1) \cdot Psentiment_{negative}}{nsentiment_{positive} + nsentiment_{negative} + nsentiment_{netural}} \in [-1;1] \quad (4)$$

I construct a series of daily log returns for TOPIX and individual firms using data from Thomson Reuters DataStream. One of the distinguishing characteristics of Japan's prolonged downwards trend is the near zero equity returns and flat growth compared to other equity markets around the world, particularly when contrasted with other developed markets. Figure 6 shows the Historical Adjusted Price Chart for the Nikkei 225, Dow Jones and S&P 500 from 1985 – 2015. Given that there appears to be variation in TOPIX returns, I would expect to see positive returns based on Merton's (1980) relationship of risk and expected returns.

Figure 6 Historical Adjusted Price Chart for the Nikkei 225, Dow Jones and S&P 500 1985 - 2015



Note: This figure presents a comparison of the adjusted historical prices of the Nikkei 225, Dow Jones and S&P 500. Source: DataStream. Nikkei on the left axis, Dow Jones and S&P 500 on the right axis.

News articles may affect the market through additional channels besides sentiment. The effect of news is not limited to sentiment, as the presence of news can have other behavioral effects. For example, news may have limited attention effects. Therefore, I include trading volume to proxy for the market's limited attention. I obtain data on trading volume and the number of news items in order to control for this potential effect. Limited attention affects investor behavior since investors tend to buy rather than sell stocks with media coverage or large price movements (Barber and Odean 2008, Hirshleifer and Teoh 2003). The concept of limited attention may not be, in itself, a complete model of how investors' cognitive capacity is directed. Durand et al. (2014) highlight and utilize Broadbent's (1957, 1958) notion of selective and limited attention in their analysis of sell-side analysts' herding. An important feature of their study is introducing the distinction between selective attention – an endogenous feature of individual behavior – and limited attention which exogenously determines the cognitive effort of investors. The distinction between selective and limited attention is well-known to Psychology but hitherto ignored by Finance. Durand et al. (2014) provide evidence that both trading volume and the number of news stories are proxies for limited attention. Durand et al. (2014) argue, however, that market capitalization is a proxy for investors' selective attention. Accordingly, to capture this, I will form portfolios based on firm size to further analyze if sentiment is in some way associated with limited attention.[17]

If salience has an effect on the Japanese share market, I would expect to see cross sectional effects in returns based on firm size and the number of firm news items. This occurs as investors are easily able to process more prominent information first which relates to large companies with more information. Stocks with more news stories gain more coverage and investors react to this public information (Klibanoff et al. 1998). da Silva Rosa and Durand (2008) found that the choice of portfolio stocks is mainly affected by salience, as proxied by national news coverage in the month prior to portfolio formation. In addition, investors may have more difficulty in reacting to news that is less prominent and harder to digest. If this is the case, I would see a cross sectional effect of news stories in smaller stocks.

17. Tversky and Kahneman (1973) introduce the availability heuristic in the litany of tools investors might use in decision making. da Silva Rosa and Durand (2008) present a study of the availability heuristic in financial decision-making utilizing market capitalization as a proxy for the availability, or salience, of information about firms. I do not believe that they would do so again today. A point of contrast between da Silva Rosa and Durand (2008) and Durand et al. (2014) is that the latter make the claim that firm size is associated with salience by assertion whereas the latter argue, using empirical evidence, that size is related to selective attention.

Table 3 shows the summary statistics for the main variables used in my regression analyses. *N* represents the common observations used in the regression analyses. Panel A shows summary statistics for daily data at the *market* level. TOPIX returns were, on average, negative for the entire sample period. If I relate negative sentiment to negative (low) returns the two different sentiment measures are also negative for the sample period. This occurs in the presence of positive risk as measured by standard deviation and is contrary to what I would expect, given standard Finance's belief in a positive relationship of return and risk.

Panel B shows summary statistics for daily data at the *firm* level. The average firm return in most years is close to 0. The two firm sentiment measures are marginally negative and are smaller than those reported for the market in Panel A of Table 3. This is due to the many neutral firm sentiment scores, as a firm with no news is assigned a neutral sentiment score of 0. I also conduct Augmented-Dickey Fuller tests and reject the null of non-stationarity at the 1% level for all my main time series variable. Table 4 presents these results.

Table 3. Summary Statistics

Panel A	Mean	Median	SD	Skewness	Kurtosis	N
TOPIX Return	-0.0002	0.0000	0.0140	-0.76	8.88	2,248
Average Market Sentiment	-0.0272	-0.0294	0.2030	0.06	3.38	2,248
Probability Weighted Sentiment	-0.0343	-0.0357	0.1425	0.03	3.39	2,248
Log(Volume)	0.0010	-0.0008	0.6421	0.00	10.16	2,248
Log(Number_Of_News)	4.0654	3.9512	0.8131	0.39	3.84	2,248
Panel B	**Mean**	**Median**	**SD**	**Skewness**	**Kurtosis**	**N**
Firm Return	0.0000	0.0000	0.0276	-2.70	801.73	5,021,095
Average Firm Sentiment	-0.0028	0.0000	0.1109	-2.10	79.05	5,021,095
Probability Weighted Sentiment	-0.0024	0.0000	0.0750	-3.70	91.89	5,021,095
Log(Volume)	0.0009	-0.0009	0.6463	0.01	10.06	5,021,095
Log(Number_Of_News)	4.0908	3.9890	0.8155	0.40	3.78	5,021,095

Note: This table shows summary statistics for the common variables used in regression analysis over a period of 1st of January 2003 – 31st of October 2012. Panel A shows summary statistics for daily data at the market level. Panel B shows summary statistics for daily data at the firm level for the time period 1st of April 2003 – 31st of October 2012. TOPIX Return is the daily log return of the TOPIX. Log(Volume) is the change in trading volume by value of the TOPIX, Log(Number_Of_News) is the number of news articles on the TOPIX, Average Market Sentiment is the average market sentiment for the TOPIX calculated via equation (1), probability weighted sentiment is calculated in equation (2), average firm sentiment is calculated in equation (3), Probability Weighted Sentiment for the firm is calculated in equation (4)

Table 4 Panel Unit Root Test for Firm Level Variables using Augmented Dickey-Fuller test.

Null: Unit root (assumes common unit root process)								
	Log(Returns)		Sentiment		Log(Volume)		Log(Number_Of_News)	
	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	-3234.48	0.00	-2286.13	0.00	4256.35	0.00	-273.87	0.00
Null: Unit root (assumes individual unit root process)								
Im, Pesaran and Shin W-stat	-2720	0.00	-2005.28	0.00	-807.38	0.00	-451.287	0.00
ADF - Fisher Chi-square	71213.6	0.00	265847.	0.00	384477	0.00	195740	0.00
PP - Fisher Chi-square	71011.4	0.00	78350.5	0.00	44379.1	0.00	481833	0.00

Note: this table presents unit root tests checking for stationarity in data. ** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

2.4 Empirical Analysis

I begin by examining the effects of sentiment on the Japanese stock market as a whole. I run the following regression, with both average and probability weighted proxies of market sentiment, to estimate the effect that the average market sentiment has on daily returns:

$$\begin{aligned} R_{mkt_t} &= \alpha + \delta avgsentiment_{mkt_t} + \gamma logvolume_{mkt_t} \\ &+ \lambda lognews_{mkt_t} + \varepsilon_t \end{aligned} \tag{5}$$

$Rmkt_t$ is the log daily market return of the TOPIX on day t and $avgsentimentmkt_t$ is the contemporaneous sentiment of the TOPIX on day t. As I highlighted previously, sentiment *per se* may not be the only effect news articles may have on the market. Therefore, I include trading volume and the number of news items to proxy for the market's limited attention. $logvolumemkt_t$, is the change in trading volume by value of the TOPIX on day t and $lognewsmkt_t$, is the number of news articles on the TOPIX on day t.

Sentiment in equation (5) is both contemporaneous and exogenous to the market. This differs from Dzielinski (2011), Tetlock (2007), and Uhl (2014) where returns were found to affect sentiment and, accordingly, methodologies such as Vector Autoregression (VAR) were utilized. The Japanese data does not support a similar approach. Unreported analyses[18] showed that both contemporaneous and lagged returns were insignificant in models of both the simple average and probability weighted sentiment. Therefore, neither a two-stage least squares analysis or VAR analysis, such as that presented in Tetlock (2007) or Uhl (2014) is appropriate.

18. Available on request.

Table 5. Market sentiment effects on TOPIX Returns

This table reports the relationship between the average market sentiment at time t on the TOPIX. The regression model is as follows:

$$R_{mkt_t} = \alpha + \delta avgsentiment_{mkt_t} + \gamma logvolume_{mkt_t} + \lambda lognews_{mkt_t} + \varepsilon_t$$

$Rmkt_t$ is the daily log market return of the TOPIX on day t, *avgsentimentmkt,* $_{t}$ *is* the contemporaneous sentiment of the TOPIX on day t. I include trading volume, and the number of news items to capture the market's limited attention. $logvolumemkt_t$, is the change in trading volume by value of the TOPIX on day t and $lognewsmkt_t$, is the number of news articles on the TOPIX on day t. The regressions use Newey-West Serial Correlation Consistent Standard Errors. (1) presents results based on an average sentiment measure equation (1), whilst (2) presents results based on a probability weighted sentiment measure equation (2).

	(1)	(2)
Sentiment	0.0046***	0.0075***
	(3.05)	(3.38)
Log Volume	-0.0004	-0.0004
	(-1.20)	(-1.17)
Log News	-0.0005	-0.0004
	(-1.43)	(-1.11)
α	0.0020	0.0017
	(1.38)	(1.17)
Adjusted R^2	0.005	0.006
AIC	-5.696	-5.367
Durbin-Watson	1.971	1.97
F-statistic	4.691***	5.619***
Prob(F-statistic)	0.003	0.000
Quandt-Andrews	1.43	1.49

Superscripts ** and *** indicate significance at the 5% and 1% levels respectively. t-statistics are in parentheses ().

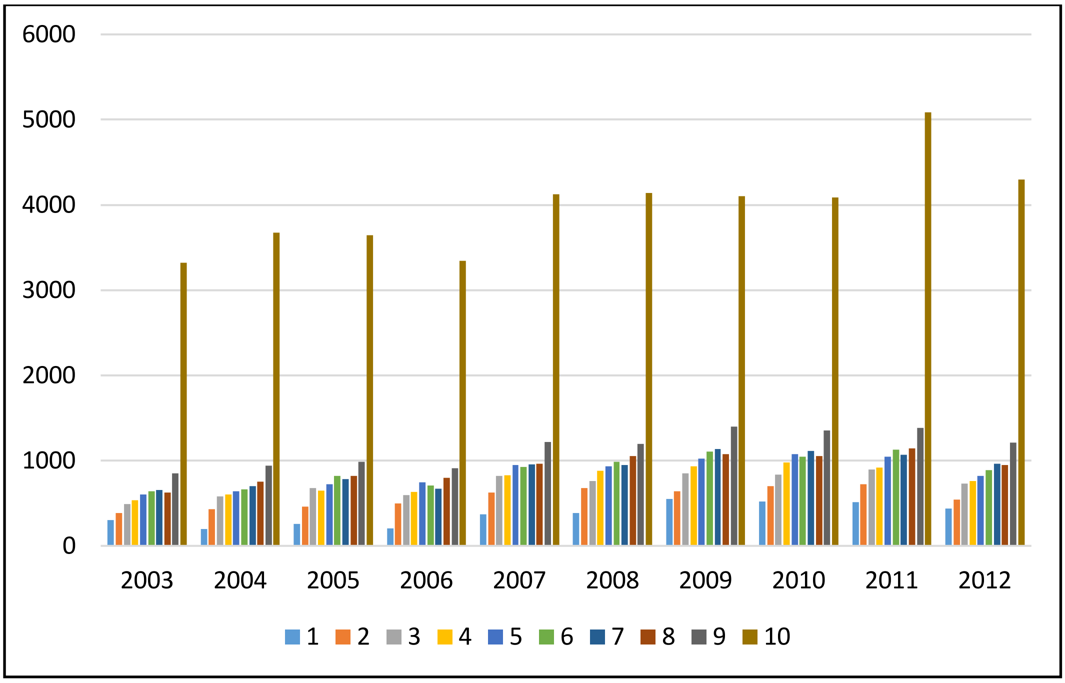
Table 5 (1) presents the results of the market level sentiment effects on TOPIX returns using the market sentiment measure described in equation (1). The results indicate that market sentiment is positively significant at the 1% level with a coefficient of 0.0046. As the average sentiment is mostly negative or close to 0 for the TOPIX over my sample period, I argue that sentiment is a potential explanation of the disconnection between Merton's (1980) theory of a positive expected risk-return relationship and the returns of the Japanese share market. This result is consistent with other results in the literature that find a positive relationship between sentiment and share market returns (Allen et al. 2014; García 2013; Tetlock 2007; Uhl 2014). The other coefficients are insignificant, suggesting that returns in the Japanese share market are not being driven by news related proxies for limited attention: trading volume or the number of news articles of the day. A Quandt-Andrews Breakpoint Test was conducted which did not detect any structural breaks in my data set. This result is different to García (2013) who found that the effect of sentiment is greater during recessions.

I repeat the above regression using a weighted probability sentiment measure. Table 5 (2) presents the probability weighted sentiment score for equation (2). There is a similar pattern with a significant positive coefficient for market sentiment of 0.0075. This measure's construction is similar to the simple average sentiment measure used previously in this chapter and also in the literature (Allen et al. 2015; Dzielinski 2011; Smales 2014a). A Wald test indicates that the two coefficients are significantly different from each other, indicating that the method of constructing the sentiment variable impacts the magnitude of the coefficient, although the direction of the effect is unchanged.   As with the analysis using *Asent*, the Quandt-Andrews Breakpoint Test could not reject the null of no structural breaks when *Psent* is used.

The above analysis highlights the potential effects that news sentiment has on investor decision making in the Japanese stock market and provides *prima facie* evidence that negative sentiment provides one explanation for consistently low returns in the market. I explore the firm-specific effect of sentiment on firm returns to examine if these effects are asymmetric in the cross-section. This also allows us to separate firms by the number of news items given that I have

5,021,095 firm-level daily return observations but only 220,784 individual news items. I sort my sample into deciles based on market capitalization on the 1st of April each year. I choose this date as the majority of firms on the Tokyo Stock Exchange have their financial year-end on the 31st of March. Figure 7 illustrates the composition of news by decile and year. News is concentrated in decile 10 which comprises the largest stocks sorted by market capitalization.

Figure 7 Count of Firm News Items by Decile



Note: This figure presents the split of news by decile. Decile 1 consists of counts of news items associated with small stocks. Decile 10 consists of news items associated with the largest stocks.

In order to investigate the firm-level relationship between news sentiment and returns, I specify the regression model as follows:

$$\begin{aligned} r_{firm_{i,t}} &= \alpha + \beta sentiment_{firm_{i,t}} + \delta logvolume_{mkt_t} \\ &+ \gamma negativenews_{i,t} + \varphi\, firmnews_{i,t} + \lambda lognews_{mkt_t} + \varepsilon_{i,t}\, i \end{aligned} \tag{6}$$

where $r_{firmi,t}$ is the daily log adjusted firm return of day t, $sentiment_{firmi,t}$, is the contemporaneous sentiment of firm i on day t, which I run with both *Asent* and *Psent* measures; $logvolume_{mkt,t}$, is the change in trading volume by value of the TOPIX on day t; $negativenews_{i,t}$, is a dummy variable that takes the value of 1 if a firm had a negative news item on day t; $firmnews_{i,t}$, is a dummy variable that takes on a value of 1 if a firm had a news item on day t; and $lognews_{mkt,t}$, is the total number of firm news articles on the TOPIX on day t. The firm level analysis has an important difference to the market-level analyses presented in Table 5. The firm level data is a panel and, accordingly, I use panel estimation in my analysis. I conducted a Hausman test for model specification using one-way fixed (i.e., firm) and random effects, with the null hypothesis of random effects. Using this test, I reject the null hypotheses at 1% and therefore use a fixed effects model. Results for this are presented in Table 6.

Table 6 Hausman-test in cross section.

Correlated Random Effects - Hausman Test
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	271.101033	5	0.0000

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
Asent	0.003427	0.003083	0.0000	0.0000
LogVolume	-0.000303	-0.000303	0.0000	0.0000
Negative News Dummy	0.000491	0.000046	0.0000	0.0000
Firm News Dummy	0.002649	0.002498	0.0000	0.0000
LogNumberofNews	-0.000925	-0.000924	0.0000	0.5264

Note: This table presents results for a Hausman-test. The null hypothesis is that a random effects model is appropriate. The alternative is that fixed effects model is appropriate.

Table 7. Firm Level Sentiment on Firm Returns

This table presents results for the cross-sectional panel regression looking at the relationship between firm sentiment and firm returns. The regression model is as follows:

$$r_{firm_{i,t}} = \alpha + \beta sentiment_{firm_{i,t}} + \delta logvolume_{mkt_t} + \gamma negativenews_{i,t} + \varphi firmnews_{i,t} + \lambda lognews_{mkt_t} + \varepsilon_{i,t}\ i$$

Where r_{firm} is the daily adjusted log firm return of day t, $sentiment_{firm}$ is the contemporaneous sentiment of firm i on day t, $logvolume_{mkt}$, is the change in trading volume by value of the TOPIX on day t, $negativenews$ is a dummy variable that takes the value of 1 if a firm had a negative news item on day t, $firmnews$, is a dummy variable that takes on a value of 1 if a firm had a news item on day t, and $lognews$ is the total number of firm news articles on the TOPIX on day t. The regression is run with White cross-section standard errors for heteroscedasticity. Panel A presents results based on an average firm sentiment which is calculated in equation (3), Panel B presents results using Probability Weighted Sentiment for the firm, and is calculated in equation (4)

Panel A		Smallest									Largest
Decile	All	1	2	3	4	5	6	7	8	9	10
$sentiment_{firm}$	0.0031**	0.0145**	0.0119**	0.0089**	0.0090**	0.0050**	0.0068**	0.0066**	0.0050**	0.0054**	0.0020**
	(7.81)	(2.86)	(4.24)	(4.27)	(4.79)	(3.42)	(5.01)	(5.07)	(4.10)	(5.91)	(4.87)
$logvolume_{mkt}$	-0.0003	-0.0000	-0.0002	-0.0002	-0.0002	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005
	(-1.25)	(-0.09)	(-1.01)	(-0.76)	(-1.03)	(-1.34)	(-1.48)	(-1.34)	(-1.50)	(-1.24)	(-1.55)
$negativenews_{i,t}$	0.0000	0.0052	0.0087**	0.0067**	0.0080**	0.0055**	0.0049**	0.0050**	0.0017	0.0012	-0.0032**
	(0.07)	(0.84)	(2.63)	(2.64)	(3.45)	(2.90)	(2.58)	(2.67)	(0.97)	(0.80)	(-4.08)
$firmnews_{i,t}$	0.0025**	0.0095**	0.0052**	0.0040**	0.0036**	0.0020**	0.0022**	0.0022**	0.0021**	0.0017**	0.0014**
	(7.33)	(4.93)	(5.47)	(5.11)	(5.10)	(2.72)	(3.00)	(3.15)	(2.86)	(2.66)	(4.25)
$lognews_{mkt_t}$	-0.0009**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0010**	-0.0009**	-0.0009**	-0.0008*	-0.0007	-0.0007
	(-3.42)	(-4.21)	(-4.81)	(-4.81)	(-4.54)	(-3.86)	(-3.28)	(-2.79)	(-2.32)	(-1.92)	(-1.88)
α	0.004**	0.005**	0.004**	0.005**	0.005**	0.004**	0.004**	0.003**	0.003**	0.003	0.003
	(3.30)	(4.31)	(4.51)	(4.67)	(4.38)	(3.72)	(3.16)	(2.67)	(2.20)	(1.78)	(1.72)
Adj R^2	0.0010	0.0007	0.0011	0.0014	0.0015	0.0013	0.0013	0.0012	0.0011	0.0012	0.0020
AIC	-4.341	-3.607	-4.059	-4.317	-4.405	-4.507	-4.581	-4.574	-4.607	-4.685	-4.747
Durbin–Watson	2.01	2.09	2.11	2.00	1.99	1.95	1.92	1.96	1.97	2.00	2.00
F-statistic	990.69	71.91	106.44	140.71	154.44	129.91	135.40	124.91	108.11	120.52	201.28
Prob (F-statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B

Decile	All	Smallest 1	2	3	4	5	6	7	8	9	Largest 10
$sentiment_{firm}$	0.0074**	0.0385**	0.0309**	0.0235**	0.0204**	0.0147**	0.0174**	0.0194**	0.0143**	0.0142**	0.0049**
	(11.93)	(4.40)	(6.08)	(6.04)	(5.63)	(5.56)	(6.76)	(7.70)	(6.48)	(9.82)	(8.37)
$logvolume_{mkt}$	-0.0003	0.0000	-0.0002	-0.0002	-0.0002	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005
	(-1.25)	(-0.09)	(-1.01)	(-0.75)	(-1.03)	(-1.34)	(-1.48)	(-1.33)	(-1.49)	(-1.24)	(-1.55)
$negativenews_{i,t}$	0.0026**	0.0207**	0.0200**	0.0152**	0.0137**	0.0112**	0.0105**	0.0125**	0.0072**	0.0063**	-0.0014
	(4.04)	(2.81)	(4.83)	(4.87)	(4.72)	(5.07)	(4.75)	(5.67)	(3.58)	(4.24)	(-1.83)
$firmnews_{i,t}$	0.0019**	0.0086**	0.0047**	0.0035**	0.0034**	0.0014*	0.0017*	0.0012	0.0012	0.0006	0.0008*
	(5.81)	(4.69)	(5.02)	(4.62)	(4.87)	(1.96)	(2.37)	(1.74)	(1.70)	(0.92)	(2.34)
$lognews_{mkt_t}$	-0.0009**	-0.0011**	-0.0011**	-0.0011**	-0.0011**	-0.0010**	-0.0009**	-0.0009**	-0.0008*	-0.0007	-0.0007
	(-3.40)	(-4.19)	(-4.66)	(-4.77)	(-4.52)	(-3.84)	(-3.26)	(-2.75)	(-2.29)	(-1.88)	(-1.86)
α	0.004**	0.005**	0.004**	0.005**	0.005**	0.004**	0.004**	0.003**	0.003**	0.002	0.003
	(3.28)	(4.29)	(4.49)	(4.64)	(4.35)	(3.70)	(3.13)	(2.63)	(2.17)	(1.75)	(1.70)
Adj R2	0.0010	0.0008	0.0012	0.0015	0.0016	0.0014	0.0015	0.0015	0.0013	0.0015	0.0022
AIC	-4.341	-3.607	-4.059	-4.318	-4.405	-4.507	-4.581	-4.57	-4.607	-4.685	-4.747
Durbin–Watson	2.01	2.09	2.11	2.00	1.99	1.95	1.92	1.96	1.97	2.00	1.99
F-statistic	1050.05	80.49	121.87	155.97	164.97	141.97	152.20	153.84	127.42	152.77	220.71

Superscripts * and ** indicate significance at the 5% and 1% levels respectively. t-statistics are in parentheses ( ).

I observe that the sentiment coefficients have different effects across the different portfolios, with the smallest portfolio having the largest coefficients when compared to the other deciles. Decile 1 in both Panel A and B of Table 7 have the highest positive coefficients at 0.0145 for *Asent* and 0.0385 for *Psent* respectively. This is compared to the highest decile 10, which has 0.0020 for A*sent* and 0.0049 for *Psent*, and the pooled firm sentiment coefficients of 0.0031 and 0.0074. On average Panel B, which uses the probability weighted sentiment measure, has larger coefficients for sentiment. One reason could be that the probability score is effective in capturing the accuracy of classification of news in the TRNA dataset. These results confirm what has been observed in other studies (Baker and Wurgler 2006, Baker et al. 2012), that there are cross-sectional variations in the effects of sentiment. I also confirm Baker and Wurgler's (2006) result that sentiment typically has a greater effect on small stocks. Baker and Wurgler's hypothesis predict that stocks with opaque characteristics, which are difficult to value, are those which are most influenced by sentiment due to the limits to arbitrage. Unlike García (2013), I do not find evidence of differences in news sentiment effects dependent on market conditions as I did not detect any structural breaks in my data set. One of the reasons could be the noise in daily returns and therefore the lack of power due to the high proportion of unexplained variation.

I also see evidence for news and limited attention when I examine the firm news dummies, which are positively significant for all size deciles. This is something that I would expect to find given Barber and Odean (2008). Barber and Odean (2008) found that individuals are more likely to purchase stocks which are attention grabbing. In Panel A of Table 7, I find that the firm news dummy is significant for all deciles, which indicates that the presence of firm news itself is significant and has effects on stock returns. However, in Panel B, which includes the probability weighted sentiment measure, I find that the effect of news is mostly significant, although this is only concentrated in the smaller and highest decile only. Interestingly, as discussed above, Panel B had generally higher and significant coefficients on sentiment. One interpretation of this is that in the higher deciles, the effects of sentiment capture the effects of firm news. So, in the larger deciles, sentiment rather than the presence of firm news is important. Another interpretation of the firm news dummy is that limited attention affects an investor's ability to process large volumes of information (Hirshleifer and Teoh 2003) or salience. If salience has an effect on the Japanese share market, I would expect to see cross sectional effects in returns based on firm size and the number of firm news items that I observe. I do find this effect, with variation in the size of these coefficients, however they are relatively small compared to the others.

One result in Table 7 is, to my mind, difficult to explain. I observe significant coefficients on the negative news firm dummies in Table 7. This dummy indicated whether or not the news item that was included was negative for the firm. In Panel B these coefficients are all positively significant except for decile 10. In the pooled firm analysis this effect is only significant in Panel B. This result does not imply that negative news has a positive impact on returns, instead this coefficient offsets the effect of the coefficient estimated for sentiment, indicating that, for the majority of stocks, the effect of negative news is weaker than that of positive news. While I have adopted panel methodology for examining firm level effects, I have closely followed the approach for the market-level analysis. This may be problematic for the panel in that I have assumed that my treatment of sentiment as contemporaneous and exogenous applies in this panel as well. It may be the case, however, that sentiment is endogenous at the firm level. Therefore, I repeat the analysis using firm level instruments for sentiment; I model firm sentiment with lagged values using one-way panel fixed effects. The results are presented in Table 8 and are substantively unchanged except for the negative news dummy, where I find evidence of asymmetry in the expected direction except for the middle decile.

Table 8. Two Stage Least Squares Firm Level Sentiment on Firm Returns Using Predicted Values of Sentiment as an Instrument

This table presents results for the cross-sectional panel regression which examines the relationship between firm sentiment using predicted values of sentiment, and firm returns sorted into deciles based on market capitalization. The regression model is as follows:

$$r_{firm_{i,t}} = \alpha + \beta sentiment_{instrument_{i,t}} + \delta logvolume_{mkt_t} + \gamma negativenews_{i,t} + \varphi firmnews_{i,t} + \lambda lognews_{mkt_t} + \varepsilon_{i,t}\ i$$

Where *rfirm*$_{i,t}$ is the daily adjusted log firm return of day t, , *sentiment*$_{instrumenti,t}$ is the predicted value of sentiment of firm i on day t, *logvolume*$_{mkt,t}$, is the change in trading volume by value of the TOPIX on day t, *negativenews*$_{i,t}$ is a dummy variable that takes the value of 1 if a firm had a negative news item on day t, *firmnews*$_{i,t}$,is a dummy variable that takes on a value of 1 if a firm had a news item on day t, and *lognews*$_{mkt,t}$, is the total number of firm news articles on the TOPIX on day t. The regression is run with White cross-section standard errors for heteroscedasticity.

Panel A		Smallest									Largest
Decile	All	1	2	3	4	5	6	7	8	9	10
$Sentiment_{instrument}$	0.1043**	0.3441**	0.2239**	0.2187**	0.1781**	0.1675**	0.1266**	0.1120**	0.0895**	0.0822**	0.0090
	(8.38)	(6.33)	(5.56)	(6.24)	(5.85)	(3.89)	(3.21)	(3.92)	(3.13)	(3.91)	(1.01)
$Logvolume_{mkt}$	-0.0003	-0.0000	-0.0002	-0.0002	-0.0002	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005
	(-1.24)	(-0.07)	(-0.10)	(-0.76)	(-1.02)	(-1.33)	(-1.48)	(-1.33)	(-1.50)	(-1.25)	(-1.55)
Negativenews	-0.0040**	-0.0122**	-0.0053**	-0.0036**	-0.0027**	-0.0007	-0.0037**	-0.0034**	-0.0048**	-0.0061**	-0.0060**
	(-12.69)	(-5.45)	(-4.33)	(-3.47)	(-2.73)	(-0.84)	(-4.20)	(-3.77)	(-5.23)	(-7.19)	(-13.82)
Firmnews	0.0039**	0.0124**	0.0074**	0.0055**	0.0053**	0.0032**	0.0039**	0.0041**	0.0037**	0.0038**	0.0027**
	(14.64)	(6.59)	(7.86)	(7.41)	(7.53)	(4.71)	(6.16)	(6.67)	(6.02)	(7.65)	(11.43)
$Lognews_{mkt}$	-0.0009**	-0.0010**	-0.0010**	-0.0011**	-0.0011**	-0.0010**	-0.0009**	-0.0008**	-0.0007*	-0.0007	-0.0007
	(-3.37)	(-3.94)	(-4.46)	(-4.55)	(-4.30)	(-3.68)	(-3.09)	(-2.64)	(-2.24)	(-1.87)	(-1.90)
α	0.0039**	0.0051**	0.0046**	0.0050	0.0048**	0.0044**	0.0039**	0.0036**	0.0031*	0.0027	0.0026
	(3.45)	(4.71)	(4.78)	(4.90)	(4.54)	(3.89)	(3.21)	(2.71)	(2.27)	(1.86)	(1.74)
Adj R2	0.0010	0.0008	0.0013	0.0022	0.0025	0.0023	0.0024	0.0018	0.0017	0.0013	0.0018
AIC	-4.341	-3.606	-4.058	-4.317	-4.404	-4.506	-4.580	-4.573	-4.607	-4.684	-4.746
Durbin–Watson	2.01	2.04	2.06	1.96	1.94	1.91	1.89	1.92	1.93	1.95	1.94
F-statistic	990.69	1.81	1.94	2.43	2.54	2.48	2.62	2.27	2.41	2.37	3.68
Prob(F-statistic)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Superscripts * and ** indicate significance at the 5% and 1% levels respectively. t-statistics are in parentheses ().

2.5 Conclusion

Japan's historically poor stock returns challenge a central idea in the field of finance, which is that there exists a positive relationship between returns and risk. I use the psychological links between mood, sentiment and investor decision making to examine if there is any relationship between sentiment and Japanese stock returns. Taking advantage of sentiment classified news as a proxy for investor sentiment, I find that sentiment and, in particular, negative sentiment, can explain these returns.

I find that Japanese returns have a positive association with sentiment. The low returns I observe in Japan are a function of pervasive negative sentiment about the market. Sentiment derived from newswire messages for Japan is on average negative during my sample period. Analyzing the relationship of market sentiment to market level returns, I find that sentiment is the only significant coefficient in my model. My results add to the literature which supports the link between sentiment and stock returns.

Examining the relationship between sentiment at the firm level and firm returns based on portfolios formed on market capitalization, I find that the effect of sentiment is greater for smaller firms than for larger firms. This confirms a result in the literature that sentiment has cross sectional effects on returns and, in particular, size. I also find evidence for the role of limited attention and news when examining sentiment and the cross section of firms. The presence of news in the market matters, as news is positively significant for all size deciles, and smaller stocks are more affected by news releases than larger stock.

Chapter 3 INVESTOR SENTIMENT AND JAPANESE STOCK RETURNS

This chapter has been presented at the 6th Behavioral Finance and Capital Markets Conference (2016, Adelaide South Australia) and the 29th PhD Conference in Economics and Business, University of Western Australia (2016, Perth Western Australia). Feedback and commentary has subsequently been included in this dissertation.

3.1 Introduction

Augmentations to the Fama and French three-factor model (1993; 1996) such as momentum (Carhart, 1997), profitability and investment (Fama and French 2015a), have achieved varied success in explaining US and global stock market returns (Fama and French 2015a). However, these additional factors have notably, and repeatedly, "failed" in the Japanese context (Cakici 2015; Fama and French 2017).[19]

This chapter considers the role of sentiment in explaining Japanese stock returns and I find that sentiment plays a small but important role in an augmented asset pricing framework. My finding contributes to the growing literature which suggests that sentiment can influence individuals in decision making and as a result market behavior and stock returns (Baker and Wurgler 2006; Brown and Cliff 2005; Lawrence et al. 2007; Tetlock 2007; Tetlock et al. 2008; Stambaugh et al. 2012). It is therefore a natural extension to consider, as a behavioral explanation of stock markets, that sentiment may also provide a useful addition to the Fama and French three-factor model. There are two potential pathways

19. Chang et al. (2018) find residual momentum in Japan for short term holding periods and present evidence that this phenomenon is associated with a profitable trading strategy. They argue that their observations are consistent with investor under-reaction. I note, however, that the residuals they analyze are obtained after returns are adjusted for expected returns using the Fama and French three-factor model. As such, their study is very different from those which examine momentum as a potential priced factor which might be included in an asset pricing model. Chang et al. present potentially important evidence regarding asset pricing in Japan but their analysis does not warrant reconsideration of my reliance on the three-factor model in the analysis I present in this chapter.

through which sentiment might affect returns. The first is that sentiment may have market wide effects and could influence returns *via* the Fama and French factors. Alternatively, sentiment may act as a separate, additional factor.

There is good reason to consider sentiment as a candidate for inclusion in a model of Japanese returns. Chapter 2 of this dissertation[20] found that news sentiment can help explain the prolonged negative average stock returns in Japan – a phenomenon which challenges the positive relationship between risk and expected returns. They find a positive relationship between news sentiment and stock returns, where on average the market exhibited negative sentiment which was linked to poor market returns in aggregate. They also document a relation between sentiment and firm size that is a common finding in the sentiment literature. Smaller stocks seem to be more susceptible to "sentiment" with "limits-to-arbitrage" presenting one explanation (Baker and Wurgler 2006; 2007).[21] Size appears to be an important characteristic when examining the effects of sentiment and is explicitly priced in the Fama and French empirical framework through *SMB*. The common variable in size suggests that sentiment might be associated with *SMB* for Japan. As results in Chapter 2 suggest that prolonged periods of negative sentiment can help explain poor stock market returns in Japan, I expect that *Rm-Rf* (which represents the market premium), may also be influenced by sentiment.

The Fama and French (1993) three-factor model provides an empirically-based explanation for patterns in stock returns that were not captured by the single factor Capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965). In addition to the market risk premium, the three-factor model includes two other factors, *SMB* and *HML*. *SMB* captures a size premium where stocks with lower market capitalization earn higher returns, than stocks with higher market capitalization. *HML* captures a value premium, where higher returns are related to stocks with high book values of assets to market values than stocks which have

20. Published as Khuu et al. (2017).
21. A common explanation in the literature is that "sentiment prone" stocks are young, volatile, small firms with "opaque" characteristics (Berger and Turtle 2012). Brown and Cliff (2005), Lemmon and Portniaguina (2006), and Schmeling (2009) also note that sentiment has a larger influence on small firms. There is mixed evidence as to whether the effect is greatest for stocks categorized as value or growth, however "opaque characteristics" are associated with small growth firms.

low book values to market values. The excess returns equation of this model is as follows:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) \\ +\delta_p SMB_t + \gamma_p HML_t + \varepsilon_{pt} \tag{7}$$

where R_{pt} is the return of the portfolio; R_{ft} is the return of a risk-free asset; R_{mt} is the return of a market portfolio; HML_t is the difference between a portfolio of high book to market (B/M) and low B/M; SMB_t is the return of a portfolio of small minus big stocks; ε_{pt} is the error term. α_p represents the intercept or abnormal return of the expected return, which would be expected to be equal to zero if the factors capture all the variation in expected returns. In this model, the factor loadings represent risk premia associated with sensitivity to *HML* and *SMB*. As Japanese stock returns are highly correlated to book to market (B/M) (Chan et al. 1991), I expect this to be captured by *HML*. Although this model is often augmented by a momentum factor (Carhart 1997), I do not employ it here given that momentum effects are commonly regarded as absent in Japan (Fama and French 2012). Recent evidence also suggests that the new profitability and investment factors (Fama and French 2015) add little to the three-factor model when applied to Japan (Cakici 2015; Fama and French 2017)[22]. Both rational and behavioral explanations have been offered for the pattern of Japanese stock returns. In this chapter, I consider the addition of sentiment as a behavioral aspect of asset pricing in addition to the three-factors.

Sentiment is not directly observable but is often associated with the market "mood" or "feeling". While sentiment itself is not observable, the effects of sentiment can be observed, and this requires a proxy (Chan et al. 2016). While there is no common definition for sentiment, there are three common approaches which I now briefly discuss. One popular sentiment proxy includes Baker and Wurgler's (2006; 2007) macroeconomic based measure which captures market

22. Different explanations have been put forward for the pattern of Japanese stock returns. Daniel et al. (2001) argued that a characteristics-based model rather than a risk factor based model is more suitable for Japan. Chiao and Hueng (2005) find evidence for overreaction in Japan (Chang et al, 1995; Gunaratne and Yonesawa, 1997), which is independent of the characteristics and risk factor hypotheses. However, I do not focus on these explanations here.

sentiment through the use of macroeconomic and market variables. Papers which employ this metric include Baker and Wurgler (2006; 2007), Tsuji (2006), Yu and Yuan (2011), Baker et al. (2012), Chung et al. (2012) and Stambaugh et al. (2012). However, there is debate as to whether these proxies are effective when compared to other sentiment proxies (Chen et al. 1993; Lemmon and Portniaguina 2006).

The second popular approach is to try to capture sentiment using periodic survey-based indices (Akhtar et al. 2011; Antoniou et al. 2013; Brown and Cliff 2005; Lemmon and Portniaguina 2006). Examples include the Conference Board Consumer Index (CBCI) and Michigan Consumer Sentiment Index (MCSI), which poll market or household opinions on a regular basis.

The third approach, which I employ in this chapter, utilizes text-based analysis to try to capture sentiment inherent in text. There are varying approaches to this in the literature, however they all attempt to proxy sentiment via text sources (Allen et al. 2015; Dzielinski 2011; García 2013; Groß-Klußmann and Hautsch 2011; Smales 2014; Tetlock 2007; Tetlock et al. 2008; Uhl 2014). In this chapter I utilize one of these approaches and employ Thomson Reuters News Analytics (TRNA) as a news and text-based proxy of sentiment.[23] News has been linked to sentiment and an advantage of using a proxy which is linked to news is that it may be able to capture dynamic changes in sentiment given the high frequency of news releases. As news is released and updated, this would elicit changes in sentiment and influences investor behavior. Studies suggestive of this link and the effect on stock markets include Tetlock (2007) who found that media pessimism predicted lower stock returns on the Dow Jones Industrial Average (DJIA). A similar analysis of text by García (2013) using a Wall Street Journal (WSJ) news column finds similar results. There is evidence of an irrational reaction to market news on days of both pessimism and optimism. A distinct finding of this study is that the predictive power of sentiment is concentrated in recessions and periods of pessimism. Uhl (2014) finds that news sentiment is more accurate than macroeconomic factors when it comes to explaining and predicting stock returns for the DJIA. Distinguishing between positive and negative news

23. TRNA currently reports news in English, however there is a high level of foreign investor activity in Japan. See chapter 2.2 for a more thorough discussion.

days using TRNA, Dzielinski (2011) found that US stock returns have above (below) average returns on positive (negative) days. More specifically to Japan, Aman (2013) identifies a potential relationship between active media coverage (newspaper articles) and extreme and large market volatility (crashes) in Japan. He finds that investors have extreme and large reactions to increased intensity of news coverage.

My findings using the TRNA sentiment proxy indicate that the addition of sentiment to the Fama and French three-factor model contributes to my understanding of Japanese asset pricing. Sentiment appears to work both through the factors and in some cases, as an independent priced factor. Sentiment appears to improve the model, with one model satisfying the standard asset pricing test, the Gibbons, Ross and Shanken (GRS) test. The remainder of this chapter is structured as follows:3.2 describes the data and methodology utilized in this chapter, 3.3 presents my results and 3.4 concludes.

3.2 Data

My study utilizes daily data for common stocks that are listed on the Tokyo Stock Exchange (TSE) from January 2003 to July 2014.[24] I choose daily data as it is more likely to capture the dynamic relationship of sentiment on stock prices which would otherwise be lost by using monthly data.

I compute my sentiment measure, *Psent*, using data obtained from TRNA. TRNA provides text-based news analytics which utilizes neural linguistic algorithm and machine learning to categorize sentiment associated with news stories. These are news which are delivered via Reuters and other third parties. Each news item is categorized as “positive” (1), “negative” (-1) and “neutral” (0).[25] News items are date and time stamped (GMT) and identified via a Reuters Instrument Code (RIC). This allows for identification of the stock that the news item is related to (each news item can relate to multiple stocks). For example, a

24. My sample period is limited by the availability of the TRNA data provided by SIRCA used to construct my sentiment time series.

25. Studies that have utilized this data set include Hendershott et al. (2015) and Smales (2014).

single piece of news relating to a weather event may affect multiple stocks in the agricultural sector.

To create my sentiment proxy, I aggregate all daily news items, relating to Japanese stocks, released during trading hours. If news articles are released after the close of trading. They are then allocated to the following trading day's sentiment measure - that is when such news will be able to impact prices and returns. TRNA also provides other information about individual news items which I use to filter the sample of news articles. I utilize the following information fields in the construction of my sentiment measure:

1. *Sentiment and sentiment probability*: TRNA categorizes news item as positive (+1), neutral (0) or negative (-1). In addition to this more detailed sentiment indication is provided using a probability. This is done using a neural linguistic algorithm.[26] For example, if there is an 80% probability that a news item is positive, the news item would be identified as positive (+1), with 80% probability. From this a *probability weighted* sentiment score can be constructed by multiplying the probability that a news item was intended as (+1), (0) or (-1). For example, +0.8 (i.e. +1 x 80%).[27] I utilize probability-weighted scores in this study.

2. *Relevance*: I filter for news articles with a relevance score above 0.8 to ensure that the sentiment measure I construct is relevant[28] to stock prices and returns (Groß-Klußmann and Hautsch 2011; and Smales 2014) while filtering out noise. This field is an indicator of relevance with values between 0 and 1. This field indicates how relevant the news item is to a specific firm. A score of 1 (0) means the news item is highly relevant (irrelevant). This filter does not necessarily

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26. Further information regarding this can be found via: https://financial.thomsonreuters.com/en/products/data-analytics/financial-news-feed/world-news-analysis.html.

27. The TRNA sentiment scores provide measures of positivity (+1) and negativity (-1) of any news signal, as well as the magnitude (probability). TRNA analysis provides an analysis of the sentiment likely opined from the perspective of the author of the News item for consistency, not how the market perceives the news item.

28. Not all news items referring to a firm may be directly relevant to it. For example, a discussion about Firm A may also mention Firm B in passing. TRNA provides information on relevancy to ensure that the sentiment being distilled from a news article is not mistakenly associated with firms which are not necessarily the focus of the article.

mean that the news contains fundamental information, as this field does not distinguish between the content or topic of the news articles.

3. *Novelty*: I filter for news content that is “novel”, i.e. news items that are not similar to previous articles which would indicate “stale news”. This field identifies the uniqueness of a news item when compared to previous news items within a defined period of time

After filtering news for the above criteria, I construct my sentiment proxy using the remaining news items. I use sentiment classifications (positive +1, negative -1, or neutral 0) attached to a news item and multiply by the TRNA assigned probability that the classification is correct. This provides a probability-weighted sentiment score *Psent*:

$$Psent = \frac{\sum(1)\cdot(P)sentiment_{positive} + \sum(-1)\cdot(P)sentiment_{negative}}{nsentiment_{positive} + nsentiment_{negative} + nsentiment_{netural}} \in [-1;1] \tag{8}$$

where *Psent* is the sentiment of the market; *P* is the TRNA probability of classification; and *nsentiment* is the number of sentiment news items with corresponding positive, negative or neutral scores. As each trading day has its own set of news from which I construct a sentiment measure, each *Psent* observation relates to one trading day. Thus, the *Psent* measure is rebalanced daily. One thing to note is that as neutral news items have a (0), or zero, sentiment classification the denominator of this measure is weighted towards neutral sentiment as the number of neutral news items increases.

Stock market and accounting data are taken from Thomson Reuters Datastream and Bloomberg. The risk-free rate R_f used in this study is the 30-day Gensaki repo rate which is one of the most liquid proxies for the Japanese risk-free rate and is commonly used in the literature (Daniel et al., 2001). The market return R_m is the average return of the TOPIX. I exclude stocks which do not have 24 months of returns before portfolio formation dates, as well as stocks with negative book equity. Unlike firms in the United States, firms in Japan tend to have fiscal years ending March 31st. As a result, I follow Daniel et al. (2001) and

Chiao and Hueng (2005), in the timing of all my portfolio formations, rather than following the traditional June to December formation periods.

Return portfolios are held for one year from the 1st trading day of October each year to the next. For firms sorted in to these portfolios I use the book equity (BE) for each firm using the Japanese fiscal year which is April in the previous year *t-1* to the end of March in the following year *t*. B/M is BE divided by market equity (ME) on the last trading day of March year *t*, size, is taken as the ME of a firm on the last trading day of September year *t*. The 6-month lag between portfolio formation and fiscal year end is commonly used to ensure that accounting information is publicly available and has been disseminated.

I follow Fama and French (1993) in constructing daily Japanese specific Fama French Factors, size (*SMB*) and B/M (*HML*) factors. I first construct six (2x3) size and B/M return portfolios from the intersection of two ME and three B/M independent sorts. Stocks are first sorted into two portfolios by median market capitalization at the end of March year *t*. I then independently sort stocks into three portfolios by B/M using a split of 30:40:30 percentiles. I define the bottom 30th percentile as low, the middle 40th percentile as medium and the top 30th percentile as high. These portfolios are rebalanced every year. The *SMB* factor is then constructed as the average return on the three small portfolios minus the average return of the three big portfolios. The *HML* factor is constructed as the average return on the two high *HML* portfolios, minus the average return of the two low *HML* portfolios. Table 9 presents the number of stocks in the six (2x3) size and B/M return portfolios formed from the intersection of two ME and three B/M independent sorts.

Table 9 Average Number of Stocks in Portfolio 2x3 B/M and ME

B/M	Low	Med	High
Small	278	435	550
Big	480	577	208

Note: this table presents the average number of stocks in each portfolio used to create Fama and French factors.

I also form twenty-five (5x5) size and B/M return portfolios from the intersection of stocks sorted into quintiles by size and B/M. Stocks in my sample are first sorted into ME quintiles from small to large and then again independently sorted into B/M quintiles from low to high. The value weighted daily returns are calculated from the first trading day in October and held for one year.[29] Table 10 displays the number of stocks sorted in to the (5x5) portfolios.

Table 10 Average Number of Stocks in Portfolios 5x5 B/M and ME

B/M	Low	2	3	4	High
Small	75	66	73	98	189
2	76	70	87	117	154
3	85	86	107	126	99
4	109	113	130	105	46
Big	159	168	108	57	14

Note: This table presents the average number of stocks in each portfolio.

Table 11 presents the average excess returns and statistics for the 5x5 size and B/M portfolios. These results demonstrate the puzzle of Japan's stock market in recent times. The average excess returns for the majority of the 5x5 portfolios are close to zero, however despite this there is a significantly large variation in returns. The relationship of positive risk yet zero return contradicts Merton's proposition of positive risk and positive expected return. Given findings in chapter 2 sentiment has a role in explaining this phemonemon and may have two potential mechanisms.

29. As a check, I first download CRSP and Compustat data to replicate a subsample of Fama and French's daily factors. Once I have confirmed replication, I make the required adjustments to my programming code for Japanese data.

Table 11 Average Daily Excess Returns for 5x5 portfolios formed on B/M and ME

B/M	Low	2	3	4	High
	Excess Returns				
Small	0.0005	-0.0005	-0.0003	-0.0003	-0.0003
2	-0.0006	0.0000	-0.0001	0.0000	0.0000
3	-0.0005	-0.0001	0.0000	0.0000	0.0001
4	-0.0002	0.0000	0.0000	0.0001	0.0001
Big	-0.0002	0.0000	0.0001	0.0002	0.0002
	Std. Dev.				
Small	0.0338	0.0126	0.0115	0.0108	0.0099
2	0.0148	0.0129	0.0109	0.0108	0.0109
3	0.0157	0.0128	0.0117	0.0118	0.0123
4	0.0141	0.0133	0.0129	0.0132	0.0146
Big	0.0138	0.0141	0.0141	0.0150	0.0165
	Min				
Small	-0.2283	-0.1770	-0.1799	-0.1748	-0.1658
2	-0.2047	-0.1747	-0.1473	-0.1658	-0.1616
3	-0.1714	-0.1459	-0.1495	-0.1590	-0.1331
4	-0.1361	-0.1373	-0.1319	-0.1438	-0.1431
Big	-0.0971	-0.1058	-0.1253	-0.1262	-0.1138
	Max				
Small	0.9103	0.0859	0.1016	0.0962	0.0921
2	0.1120	0.1197	0.1006	0.1044	0.1060
3	0.1169	0.1212	0.1034	0.0937	0.0928
4	0.1107	0.1171	0.1063	0.1065	0.0939
Big	0.1003	0.1231	0.1073	0.1251	0.1089

Note: This table presents the average excess returns in each of the 5x5 portfolios in my sample.

There are two potential channels through which sentiment could influence asset prices: the first is by acting through or influencing the Fama and French factors themselves (*SMB* and *HML* are negatively correlated and statistically significant). Alternatively, sentiment could present as a separate additional factor itself. Therefore, to remove the influence of market wide sentiment I consider orthogonalizing my Japanese factors to *Psent*. This allows us to separate the effect of sentiment from the factors. To obtain the orthogonalized factors I follow Durand et al. (2016) and regress each Fama and French factor against *Psent*, utilizing the residuals as orthogonalized factors in the following analysis:

$$\begin{aligned} (Rm - Rf)_t &= \alpha + Psent_t + \varepsilon_t \\ SMB_t &= \alpha + Psent_t + \varepsilon_t \\ HML_t &= \alpha + Psent_t + \varepsilon_t \end{aligned} \tag{9}$$

These factors are denoted by $^{\text{orthog}}$ in Table 12 presents summary statistics of my constructed factors. Panel A of Table 12 presents the summary statistics for the constructed factors and the sentiment measure. Panel B presents correlations of the factors. Panel B of Table 12 indicates that there are correlations between the factors and sentiment. Sentiment is positively and statistically significantly correlated with the market premium (0.2838), and negatively related to *SMB* (-0.1176) and *HML* (-0.03715). The reported correlations may indicate that positive (negative) sentiment is related to positive (negative) premiums. Results in chapter 2 link positive sentiment to positive market premiums. Periods of high (low) sentiment have also been associated with future reversals in the size premium (Baker and Wurgler 2006), with exuberance and over confidence (Yu and Yuan 2011) providing one explanation. The positive correlation with the market premium suggests that sentiment has market wide effects.

Table 12 Summary Statistics for Constructed Factors

Panel A: Summary Statistics		Factors			Orthogonalized Factors		
	Psent	SMB	HML	(Rm-Rf)	SMB^{Orthog}	HML^{Orthog}	$(Rm\text{-}Rf)^{Orthog}$
N	2,822	2,822	2,822	2,822	2,822	2,822	2,822
Mean	-0.0501	-0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
Sd	0.1389	0.0085	0.0073	0.0143	0.0084	0.0073	0.0137
Min	-0.5016	-0.0654	-0.2463	-0.1053	-0.0680	-0.2466	-0.1045
Max	0.3658	0.1654	0.0340	0.1207	0.1649	0.0331	0.1264
Panel B: Correlation Matrix							
SMB	-0.1176**						
HML	-0.03715*	-0.4529**					
(Rm-Rf)	0.2838**	-0.4858**	-0.0968**				
SMB^{Orthog}	0	0.9931**	-0.4605**	-0.4556**			
HML^{Orthog}	0	-0.4576**	0.9993**	-0.0863**	-0.4608**		
$(Rm\text{-}Rf)^{Orthog}$	0	-0.4718**	-0.0900**	0.9590**	-0.4751**	-0.0902**	

Note: This table present summary statistics of my constructed factors. Panel A of presents the summary statistics for constructed factors, and sentiment measure. Panel B presents correlations of the factors. ** denotes significance at the 1% level, * 5% level

To assess if sentiment is potentially useful I examine six different model specifications centered around the three-factor Fama and French model. These models are run with and without the orthogonalized factors. The first model is the standard three-factor model (excess returns):

$$\begin{aligned} &R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) \\ &+\delta_p SMB_t + \gamma_p HML_t + \varepsilon_{pt} \end{aligned} \tag{10}$$

where R_{pt} is the return of the portfolio on day t; R_{ft} is the return of the risk-free asset on day t; α_p is the intercept term of the portfolio p; R_{mt} is the market return on day t; *SMB* is the size factor on day t; *HML* is the B/M factor on day t and ε_{pt} is the error term for the portfolio.

The second specification includes the addition of *Psent*. I run this for both un-orthogonal and orthogonalized factors:

$$\begin{aligned} &R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) \\ &+\delta_p SMB_t + \gamma_p HML_t + \kappa_p Psent_t + \varepsilon_{pt} \end{aligned} \tag{11}$$

where R_{pt} is the return of the portfolio on day t; R_{ft} is the return of the risk-free asset on day t; α_p is the intercept term of the portfolio p; R_{mt} is the market return on day t; *SMB* is the size factor on day t; *HML* is the B/M factor on day t; *Psent* is sentiment on day t and ε_{pt} is the error term for the portfolio.

The final specification includes consideration for calendar and day of the week effects. Whilst not central to my chapter it is reasonable to control for these document effects. I include dummy variables for January, March and July and day of the week effects. [30,31]

30. July is the month when the majority of financial statements and accounts are finalized in Japan. I also include day of the week effects as it is plausible that these effects could occur.

31. See: Jaffe & Westerfield (1985), Kato and Schallheim (1985) for discussion about January effects and Sakakibara, Yamasaki & Okada (2013) for a review of common Japanese calendar effects.

I run this regression for the 2x3 and 5x5 portfolio sorts.[32,33] The final specification is as follows:

$$\begin{aligned} R_{pt} - R_{ft} &= \alpha_p + \beta_p (R_{mt} - R_{ft}) \\ &+ \delta_p SMB_t + \gamma_p HML_t + \kappa_p Psent_t \\ &+ j_p Jan_t + \lambda_p March_t + l_p July_t + d_p Day_t + \varepsilon_{pt} \end{aligned} \tag{12}$$

where R_{pt} is the return of the portfolio on day t; R_{ft} is the return of the risk free asset on day t; α_p is the intercept term of the portfolio p; R_{mt} is the market return on day t; *SMB* is the size factor on day t; *HML* is the B/M factor on day t; *Psent* is sentiment on day t; *Jan* is a dummy variable for January; *March* is a dummy variable for March; *July* is a dummy variable for July; *Day* are day of the week dummy variables and ε_{pt} is the error term for the portfolio.

3.3 Results

Table 13 presents statistics commonly utilized to assess different model specifications (Fama and French 2012). I begin by considering the zero-intercept rule as a selection criterion (Merton 1973). Panels A and B of Table 13 present results for the Gibbons Ross Shanken (GRS) test of the null hypothesis that the intercepts of all the portfolios examined using a model are jointly equal to zero.

Panel A of Table 13 focuses on tests for the 5x5 portfolio sorts while Panel B presents results for 2x3 portfolio sorts. The GRS test cannot reject the null that the intercepts are jointly equal to zero for models (5) and (11), which are models augmented with sentiment. In other words, models (5) and (11), where the three factors are augmented with sentiment and control variables, seem to satisfy Merton's zero intercept criterion: the three factors augmented with sentiment and control variables is the best model. In contrast, the GRS test rejects the null hypotheses in the other models.

Like Fama and French (2012), I turn to other criteria to help my considerations of the best model. These criteria suggest that the inclusion of

32. I run all regressions with robust standard errors.
33. For the sake of brevity I report only the 5x5 portfolio sorts.

sentiment improves my understanding of Japanese returns. Table 13 shows that inclusion of sentiment in three models - (3), (5), (9) and (11) (models augmented with *Psent*) - results in lower values of SR(α). SR(α) is equal to $\left(\alpha'\Sigma^{-1}\alpha\right)^{1/2}$ where α is the column vector of the 25 regression intercepts produced by a model when applied to 25 global or local Size and B/M portfolios, and Σ is the covariance matrix of regression residuals. “Lower is better” for this statistic which is interpreted by Fama and French as a “Sharpe ratio for the intercepts (unexplained average returns) of a model” (p.466). Models (3), (5), (9) and (11) also have the highest average adjusted R-squared values. The values of adjusted R-squared are consistent with the notion that including sentiment results in better models, although the incremental contribution, using this metric as a benchmark, is small.

Table 13 Model Performance Statistics

This table presents statistics commonly utilized to assess different model specifications (Fama and French 2012). I examine the average absolute alpha for each model specification and utilize a zero-intercept rule as a selection criterion (Merton 1973). Panels A and B of Table 13 presents results for a Gibbons Ross Shanken test (GRS) test of finite sample.

Panel A 5x5 Portfolio Sorts	Statistics				
Model	GRS	$\|\alpha\|$	R^2	$S(\alpha)$	$SR(\alpha)$
(1) Japan three - factor model	4.45**	0.0002	0.8812	8.77×10^{-5}	0.2035
(2) Japan orthogonalized three - factor model	5.53**	0.0002	0.8219	1.10×10^{-4}	0.2268
(3) Japan three - factor model with psent	3.03**	0.0002	0.8813	9.37×10^{-5}	0.1796
(4) Japan orthogonalized three - factor model with psent	217.90**	0.0011	0.8813	9.32×10^{-5}	1.5143
(5) Japan three-factor model with psent and control variables	1.25	0.0002	0.8814	2.06×10^{-4}	0.2537
(6) Japan three-factor model with psent and control variables with orthogonalized factors	46.37**	0.0012	0.8814	2.05×10^{-4}	1.5424

Panel B 2x3 Portfolio Sorts	Statistics				
Model	GRS	$\|\alpha\|$	R^2	$S(\alpha)$	$SR(\alpha)$
(7) Japan three - factor model	10.68**	0.0001	0.9676	4.21×10^{-5}	0.1631
(8) Japan orthogonalized three - factor model	11.73**	0.0001	0.9020	8.05×10^{-5}	0.1709
(9) Japan three - factor model with psent	6.68**	0.0001	0.9677	4.50×10^{-5}	0.1380
(10) Japan orthogonalized three - factor model with psent	715.93**	0.0012	0.9677	4.47×10^{-5}	1.4194
(11) Japan three-factor model with psent and control variables	1.77	0.0001	0.9677	9.87×10^{-5}	0.1565
(12) Japan three-factor model with psent and control variables with orthogonalized factors	143.91**	0.0013	0.9677	9.86×10^{-5}	1.4052

** denotes significance at the 1% level, * 5% level.

Noting that model (5) presented an insignificant GRS test and was amongst the best models I discussed in the preceding paragraph, I present more detailed results for this model in Table 14 to help us understand the role of sentiment in Japanese returns. Results are not presented for model (11) as they add little to the discussion. In Table 14 I report estimated coefficients and associate t-statistics for each equation estimated for the 5x5 double sorted portfolios.

The results in Table 14 show that only one α is significant in the 25 portfolios. The market premium R_m - R_f is positively and statistically significant for all the portfolios, while *SMB* is statistically significant except in the largest growth portfolio. *HML* is also significant and depicts a monotonically increasing coefficient, from strongly negative to strongly positive. These results indicate and confirm that the three-factors are useful in explaining Japanese stock returns.

In Table 14, I also see that *Psent* is significant for eight portfolios, with the majority of these significant coefficients being found in the smallest stocks and the largest growth stocks. The main contribution from sentiment would appear to be in the removal of the statistical significance for estimates of α. The identified pattern for *Psent* is consistent in six of the eight portfolios, with the most common patterns observed for sentiment effects in the literature with positive coefficients. There is a heterogeneous effect by size which is explained in the sentiment literature. Small stocks and the largest stocks are those which tend to be most affected by sentiment, as opposed to the stocks in the "middle". Small stocks tend to be more "sentiment prone" as they are more likely to be harder to value due to opaque characteristics. I also find that one, large growth stock portfolio is affected. Large growth stocks with low B/M may have characteristics, such as intangibles, which make them more easily influenced by sentiment. Another potential reason is the reaction to news. Luo et al. (2015) argue that institutional investors will react more to news in larger stocks than in smaller stocks since their holdings are concentrated in larger stocks; I observe evidence for this here. One further explanation is that the amount of news per firm, or news coverage, is most concentrated in the largest stock. In two instances however, there are two portfolios which have statistically significant negative coefficients, (-0.0013 and -0.0017), which suggests that these two particular portfolios may behave differently to what might be expected given the general literature. This issue is followed further when analysis is conducted with sentiment orthogonal to the other factors. In table 15 we see that the negative signs on these two portfolios are positive as expected.

Table 14 Time-Series Regressions 5x5 B/M and ME Portfolios Japan three-factor Model with Psent and control variables

This Table reports regression results over the period January 2003 – June 2014. This regression uses the daily three-factors constructed for Japan and sentiment *Psent*. Firms in the following portfolios are value weighted return portfolios which are formed on the 1st trading day of October each year and held for one year. For firms sorted in to these portfolios I use the book equity (BE) for each firm using the Japanese fiscal year which is April in the previous year *t-1* to the end of March in the following year t. B/M is BE divided by market equity ME on the last trading day of March year t, size, is taken as the ME of a firm on the last trading day of September year t.

The Model is specified as: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t + \kappa_p psent_t + j_p Jan_t + \lambda_p March_t + l_p July_t + d_p Day_t + \varepsilon_{pt}$

B/M	Low	2	3	4	High	Low	2	3	4	High
	α					t(α)				
Small	0.0013	-0.0002	-0.0001	-0.0001	-0.0000	1.839	-0.897	-0.297	-0.804	-0.078
2	-0.0008**	0.0001	-0.0001	-0.0001	-0.0001	-2.972	0.498	-0.493	-1.193	-0.854
3	-0.0003	-0.0002	-0.0001	-0.0002	-0.0001	-0.930	-1.407	-0.688	-1.429	-1.002
4	0.0001	0.0000	-0.0001	-0.0002	-0.0000	0.535	0.262	-0.480	-1.150	-0.109
Big	-0.0002	-0.0001	0.0000	0.0000	0.0004	-1.421	-1.299	0.000	0.088	1.181
	β					t(β)				
Small	1.1197**	0.9421**	0.8987**	0.8636**	0.7962**	24.514	59.161	43.983	46.36	55.621
2	1.1437**	0.9958**	0.9005**	0.9163**	0.9310**	68.419	67.387	107.65	76.689	122.144
3	1.1731**	1.0423**	0.9713**	0.9903**	1.0241**	62.772	86.149	100.112	91.992	53.951
4	1.0802**	1.0365**	1.0108**	1.0295**	1.1371**	63.531	103.608	104.81	88.416	52.647
Big	0.9188**	0.9417**	0.9645**	1.0533**	1.0861**	113.263	148.883	71.502	101.605	48.800
	δ					t(δ)				
Small	1.8991**	1.2209**	1.1430**	1.0935**	1.0441**	20.635	39.966	29.356	30.898	36.828
2	1.3827**	1.1341**	0.9991**	0.9815**	1.0175**	39.686	36.421	59.733	43.346	69.374
3	1.1756**	0.9012**	0.8112**	0.8523**	0.8914**	31.620	36.640	44.126	47.508	25.566
4	0.7703**	0.5665**	0.5261**	0.5322**	0.6845**	23.843	28.202	27.407	22.314	18.133
Big	-0.0408**	-0.1089**	0.0122	0.1412**	0.1978**	-2.727	-10.568	0.498	6.259	4.723

(Continued next page)

B/M	Low	2	3	4	High	Low	2	3	4	High
	γ					t(γ)				
Small	-2.3151**	0.5900**	0.6004**	0.6024**	0.6242**	-6.553	6.823	8.758	11.002	18.851
2	0.5446**	0.5041**	0.5682**	0.5803**	0.6916**	3.612	4.751	12.479	19.923	67.179
3	0.4829**	0.4505**	0.5050**	0.5782**	0.6630**	3.898	6.757	20.712	41.875	20.739
4	0.3068**	0.3402**	0.3808**	0.4638**	0.6209**	3.477	13.397	22.050	10.375	9.524
Big	-0.1534**	-0.0654**	0.1235*	0.2692**	0.3787**	-2.987	-6.988	2.546	3.657	3.377
	κ					t(κ)				
Small	-0.0014	0.0025**	0.0020**	0.0019**	0.0024**	-0.643	2.714	2.813	2.967	4.544
2	-0.0007	0.0000	0.0012*	0.0006	0.0000	-0.760	0.008	2.411	1.567	0.093
3	-0.0005	-0.0006	0.0002	0.0005	0.0002	-0.395	-0.988	0.415	0.963	0.430
4	-0.0007	-0.0003	-0.0010	-0.0013*	-0.0007	-0.796	-0.475	-1.642	-2.105	-0.757
Big	0.0017**	0.0003	-0.0005	-0.0017**	-0.0018	3.865	0.784	-0.911	-2.692	-1.465
	R-squared									
Small	0.743	0.768	0.818	0.852	0.878					
2	0.813	0.797	0.906	0.944	0.956					
3	0.758	0.902	0.928	0.938	0.930					
4	0.833	0.906	0.913	0.910	0.875					
Big	0.954	0.976	0.938	0.910	0.770					

** denotes significance at the 1% level, * 5% level.

I have noted that there are two potential pathways through which sentiment might affect returns. The first is that sentiment may have market wide effects and could influence portfolios *via* the Fama and French factors. Alternatively, and perhaps additionally, sentiment may act as a separate additional factor. The better models have not been orthogonalized to Psent. This approach means that any influence of *Psent via* these factors cannot be discerned.

Not orthogonalizing the Fama-French factors, however, may confound any effects which may be incorporated in prices though sentiment's influence on the factors. I wish to consider this aspect further and, in order to do so, I present results for model (6) which has undergone orthogonalization of the three-factors to sentiment, where the effects of *Psent* on the factors have been removed and where I utilize the residuals of equation (9). Table 15 presents the results of model (6).[34]

The estimated results in Table 15 indicate that the effect of sentiment is greatest for the largest sized portfolios. There also appears to be a growth effect, with the coefficient for *Psent* increasing for growth stocks and decreasing for value stocks. This pattern does not readily emerge in Table 14, which presents results for model (5) where the three other factors are not orthogonalized to *Psent*. *Psent* in model (6) seems to affect large stocks, more so than smaller stocks. This result is, *prima facie*, at odds with the results reported in Table 14, where smaller stocks and in particular smaller growth stocks should be the most influenced by sentiment. The literature would suggest that this is small growth stocks which tend to have "opaque" characteristics,[35] yet large stocks have the largest loadings on *Psent* once the other factors are orthogonalized. Alternatively, this may be due to the fact that institutional investors react to news (sentiment) in larger stocks than smaller stocks given their holdings in larger stocks (Luo et al. 2015).

34. I note that the orthogonalization of the model results in far more significant alphas, than what was observed in table 14. That being said, table 15 fails the GRS test. I believe that sentiment works through the factors or independently of the factors. Therefore, table 15 allows us to clearly see the effect of psent perse and allows us to focus on the two anomalous portfolios which had unexpectedly negative coefficients in table 14.

35. Characteristics such as high information asymmetry, low liquidity and high transaction costs.

Table 15 Time-Series Regressions 5x5 B/M and ME Portfolios using Orthogonalized Factors and Control Variables

This Table reports regression results over the period January 2003 – June 2014 using the daily three-factors constructed for Japan and orthogonalized to my measure of daily news sentiment Psent. Firms in the following portfolios are value weighted return portfolios which are formed on the 1st trading day of October each year and held for one year. For firms sorted in to these portfolios I use the book equity (BE) for each firm using the Japanese fiscal year which is April in the previous year t-1 to the end of March in the following year t. B/M is BE divided by market equity ME on the last trading day of March year t, size, is taken as the ME of a firm on the last trading day of September year t.

The Model is specified as: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t + \kappa_p psent_t + j_p Jan_t + \lambda_p March_t + l_p July_t + d_p Day_t + \varepsilon_{pt}$ where Day are day of the week dummies.

B/M	Low	2	3	4	High	Low	2	3	4	High
	α					t(α)				
Small	0.0021**	0.0007**	0.0009**	0.0008**	0.0008**	3.187	2.789	4.102	4.086	5.474
2	0.0004	0.0012**	0.0009**	0.0009**	0.0010**	1.714	4.795	7.231	8.181	9.807
3	0.0011**	0.0010**	0.0011**	0.0010**	0.0011**	3.411	6.330	8.170	7.698	7.747
4	0.0015**	0.0014**	0.0013**	0.0012**	0.0015**	6.239	7.884	7.689	6.540	6.652
Big	0.0013**	0.0014**	0.0015**	0.0016**	0.0020**	10.334	14.093	10.229	8.432	5.887
	β					t(β)				
Small	1.1197**	0.9421**	0.8987**	0.8636**	0.7962**	24.514	59.161	43.983	46.360	55.621
2	1.1437**	0.9958**	0.9005**	0.9163**	0.9310**	68.419	67.387	107.650	76.689	122.144
3	1.1731**	1.0423**	0.9713**	0.9903**	1.0241**	62.772	86.149	100.112	91.992	53.951
4	1.0802**	1.0365**	1.0108**	1.0295**	1.1371**	63.531	103.608	104.810	88.416	52.647
Big	0.9188**	0.9417**	0.9645**	1.0533**	1.0861**	113.263	148.883	71.502	101.605	48.800
	δ					t(δ)				
Small	1.8991**	1.2209**	1.1430**	1.0935**	1.0441**	24.514	59.161	43.983	46.36	55.621
2	1.3827**	1.1341**	0.9991**	0.9815**	1.0175**	68.419	67.387	107.65	76.689	122.144
3	1.1756**	0.9012**	0.8112**	0.8523**	0.8914**	62.772	86.149	100.112	91.992	53.951
4	0.7703**	0.5665**	0.5261**	0.5322**	0.6845**	63.531	103.608	104.810	88.416	52.647
Big	-0.0408**	-0.1089**	0.0122	0.1412**	0.1978**	113.263	148.883	71.5020	101.605	48.800

(continued next page)

B/M	Low	2	3	4	High	Low	2	3	4	High
	γ					$t(\gamma)$				
Small	-2.3151**	0.5900**	0.6004**	0.6024**	0.6242**	-6.553	6.823	8.758	11.002	18.851
2	0.5446**	0.5041**	0.5682**	0.5803**	0.6916**	3.612	4.751	12.479	19.923	67.179
3	0.4829**	0.4505**	0.5050**	0.5782**	0.6630**	3.898	6.757	20.712	41.875	20.739
4	0.3068**	0.3402**	0.3808**	0.4638**	0.6209**	3.477	13.397	22.05	10.375	9.524
Big	-0.1534**	-0.0654**	0.1235*	0.2692**	0.3787**	-2.987	-6.988	2.546	3.657	3.377
	κ					$t(\kappa)$				
Small	0.0221**	0.0200**	0.0188**	0.0181**	0.0169**	10.180	24.06	25.711	27.671	31.462
2	0.0216**	0.0199**	0.0192**	0.0192**	0.0185**	24.835	22.031	39.821	46.449	54.940
3	0.0243**	0.0224**	0.0217**	0.0221**	0.0224**	21.798	40.938	47.246	51.018	41.850
4	0.0247**	0.0252**	0.0239**	0.0240**	0.0263**	30.359	43.494	44.188	42.777	33.473
Big	0.0291**	0.0286**	0.0273**	0.0274**	0.0277**	68.137	91.542	52.868	45.377	24.300
	R-Squared									
Small	0.743	0.763	0.811	0.846	0.873					
2	0.809	0.794	0.902	0.939	0.953					
3	0.754	0.899	0.924	0.934	0.927					
4	0.829	0.903	0.910	0.907	0.872					
Big	0.951	0.975	0.936	0.907	0.768					

** denotes significance at the 1% level, * 5% level.

To further consider the role of the channel through which sentiment effects returns, I also consider the coefficient for *Psent* in all of the models I have examined. Table 16 reports *only* the coefficients of *Psent* for a variety of model specifications presented in Panel A of Table 13. It is noteworthy that the preferred model, model (5), and model (3) present the lowest number of significant coefficients of *Psent*. I find that *all* of the estimated coefficients of *Psent* are significant when the orthogonalized Fama-French factors are used. My analyses therefore present evidence that sentiment acts as a separate additional factor but that it can influence portfolios *via* the Fama and French factors. I note that incorporate sentiment as an additional factor, and not orthogonalizing the other factors, results in better models. Table 16 confirms that there is a role for sentiment in all of the models studied.

Table 16 Psent coefficients of different model specifications presented in Panel A of Table 5

This Table reports the coefficients of Psent for the different model specifications presented in Panel A of Table 5.

(3) $R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t + \kappa_p Psent_t + \varepsilon_{pt}$

(4) $R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft})^{orthog} + \delta_p SMB^{orthog}{}_t + \gamma_p HML^{orthog}{}_t + \kappa_p Psent_t + \varepsilon_{pt}$

(5) $R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t + \kappa_p Psent_t + j_p Jan_t + \lambda_p March_t + l_p July_t + d_p Day_t + \varepsilon_{pt}$

B/M	Low	2	3	4	High	Low	2	3	4	High
	(3)					t(κ)				
Small	-0.0016	0.0024**	0.0020**	0.0019**	0.0023**	-0.707	2.674	2.799	2.951	4.468
2	-0.0006	-0.0001	0.0012*	0.0007	0.0000	-0.657	-0.067	2.413	1.651	0.055
3	-0.0004	-0.0005	0.0002	0.0005	0.0003	-0.341	-0.915	0.437	1.058	0.528
4	-0.0007	-0.0003	-0.0010	-0.0012*	-0.0006	-0.877	-0.473	-1.668	-2.017	-0.709
Big	0.0017**	0.0003	-0.0005	-0.0017**	-0.0018	3.877	0.806	-0.944	-2.674	-1.490
	(4)					t(κ)				
Small	0.0220**	0.0200**	0.0188**	0.0180**	0.0168**	10.067	23.939	25.744	27.795	31.782
2	0.0217**	0.0198**	0.0192**	0.0192**	0.0185**	25.057	21.754	40.247	46.964	55.442
3	0.0244**	0.0225**	0.0217**	0.0221**	0.0224**	21.761	41.146	47.521	51.452	42.014
4	0.0246**	0.0252**	0.0239**	0.0241**	0.0264**	30.510	43.665	44.401	42.665	33.523
Big	0.0291**	0.0286**	0.0273**	0.0274**	0.0277**	68.633	91.416	53.400	45.835	24.273
	(5)					t(κ)				
Small	-0.0014	0.0025**	0.0020**	0.0019**	0.0024**	-0.643	2.714	2.813	2.967	4.544
2	-0.0007	0.0000	0.0012*	0.0006	0.0000	-0.76	0.008	2.411	1.567	0.093
3	-0.0005	-0.0006	0.0002	0.0005	0.0002	-0.395	-0.988	0.415	0.963	0.430
4	-0.0007	-0.0003	-0.001	-0.0013*	-0.0007	-0.796	-0.475	-1.642	-2.105	-0.757
Big	0.0017**	0.0003	-0.0005	-0.0017**	-0.0018	3.865	0.784	-0.911	-2.692	-1.465

** denotes significance at the 1% level, * 5% level

3.4 Conclusion

The results presented in this chapter indicate there is a role for sentiment in explaining Japanese stock returns. Using the Fama and French three-factor model as the basis for my analysis, I find that sentiment functions as an additional independent factor to the Fama and French three-factors. There is also evidence to suggest that sentiment can affect prices through its influence on the Fama-French factors. My research finds that the effects of sentiment are heterogeneous and are mostly concentrated in smaller and larger stocks. These effects of sentiment are relatively small but non-trivial and not explained by the three-factor model.

Chapter 4 INVESTOR SENTIMENT, PIIGS AND NON-PIIGS

4.1 Introduction

Growing evidence in finance literature indicates that sentiment may influence stock markets and investor behavior (Baker and Wurgler 2006; Brown and Cliff 2005; Lawrence et al. 2007; Tetlock 2007; Tetlock et al. 2008; Stambaugh et al. 2012) and this chapter extends upon the previous work in this dissertation. In this chapter I consider the role of sentiment in explaining European stock returns in the Fama and French five-factor model. The analysis in this chapter covers 15 European countries over the period of 2003 – 2014. I split the sample based on countries which include those most severely impacted by the European Financial Crisis (EFC). [36]

I build on the results that found in previous chapters where I examined the role that sentiment had on Japanese stock returns during the latter part of Japan's lost decade. In chapter 2 I present evidence that sentiment can help explain stock returns in a period of extended recession and bear markets. The effects of sentiment have been documented in the literature, and in chapter 2.3 to be asymmetric for stock returns, not only in size but the impact of sentiment is also greater in periods of economic and market stress. The asymmetric effect due to size has been well documented in the literature,[37] and this dissertation also finds this effect in smaller Japanese stocks. I also find that sentiment helped explain Japanese stock returns in the Fama and French three-factor model. Given that sentiment appears to help explain Japanese stock returns in periods of recession and market decline, I consider whether sentiment can help explain European stock returns for 15 countries within the Fama and French framework, and in particular for countries which were most vulnerable to the EFC. Specifically, this chapter extends upon the analysis in chapter 2, as results for Japan may also be applicable for European countries under similar circumstances or conditions.

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36. The European countries I consider are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. These are the countries which are used to form Fama French European factors and portfolios.

37. See chapter 2.2 for more detail.

The EFC began in 2009, when several European member countries were unable to repay, or manage existing sovereign debt. The most impacted countries were Portugal, Ireland, Italy, Greece and Spain, (PIIGS), with Greece being the most vulnerable to sovereign default, eventually requiring multiple bailouts.[38] Therefore, I compare two different European country groups, split by their vulnerability to the EFC and subsequent recessions. The first group are PIIGS, whilst the second group of remaining countries are members of the Eurozone, or European Union, Austria, Belgium, Denmark, France, Germany, Netherlands, Norway, Sweden, Switzerland and the United Kingdom[39]. I find that sentiment can help explain returns for stock markets in the PIIGS countries. However, this effect is less pronounced for the other European countries in the sample set (Non-PIIGS). My finding contributes to the growing literature which suggests that sentiment has asymmetric size effects on stocks such as those in PIIGS. Small stocks tend to be those most affected by sentiment due to opaqueness, however large stocks may also be affected if they contain intangibles which are hard to value.

There are several reasons to consider sentiment in a European market setting. One of these reasons is the interrelated nature of trade and economies in the sample due to membership into the Eurozone or European Union, which makes separating individual country effects more difficult. Fama and French (2015a) consider the 15 countries in this data set as a regional block. In addition, countries which are members of the Eurozone must follow European Central Bank (ECB) monetary policy. And as a result, news sentiment may affect PIIGS differently, given they are unable to alter monetary policy individually to try and stave off default and recession.

Another reason to consider Europe is due to the heterogenous nature of the different European stock markets. There are vast differences in stock market capitalizations and activity. As mentioned earlier, size is linked to the effect of sentiment, and given the different market characteristics, PIIGS stocks may be influenced by sentiment more readily than other Non-PIIGS stock markets.

38. See Lane (2012) Journal of Economic Perspectives for a in depth discussion.
39. Despite holding a referendum to leave the European Union on the 23rd of June 2016, at time of this sample set the United Kingdom was still a member of the European Union.

Finally, the perceived severity of the negative impact that the EFC had on PIIGS compared to Non-PIIGS and the resulting crisis may indicate sentiment has a role in explaining stock returns. Further evidence to split the sample into PIIGS and Non-PIIGS relates to bank credit risk and credit default swap spreads during the EFC. Smales (2016) finds evidence that the relationship between news sentiment and bank credit risk ratings and finds a significant negative relationship between news and changes in credit default swaps spreads. PIIGS CDS spreads increased drastically during the EFC, especially for Greek financial institutions (Büchel 2013). Similarly, to García (2013), Smales finds that there is a stronger relationship during times of financial crisis and that negative news has a stronger effect on credit risk compared to positive news. There is also evidence of investor attention, as the number of news items related to financial institutions in the sample set increases during the EFC increases, and on average are more negative Smales (2016). García (2013) found that markets were more sensitive to sentiment during recessions in a US market setting, and analysis in chapter 2 of this dissertation confirms this result. Caporale, Spagnolo, and Spagnolo (2016) analyzed macroeconomic news announcements using a VAR-GARCH- in mean model and found that positive (negative) news have significant positive (negative) effects on European stock markets and volatility. In particular, they find stock markets are more receptive to negative news and that market reactions are larger for PIIGS countries.

Unlike for Japan (see chapter 3.1) the five-factor model framework was found to be more appropriate than the three-facto model for Europe and the inclusion of investment and profitability factors explains more of the cross-section of European returns (Cakici 2015; Fama and French 2015a;2017). The five-factor model addresses the three-factor model's inability to capture or explain variation in returns related to profitability or investment. As a result, two new factors were introduced.

The first additional factor is profitability. Research by Novy-Marx (2013) found evidence of a profitability premium that linked variation in stock returns to gross profitability. They suggest that profitable firms with high valuations tend to generate higher returns, compared to firms which are unprofitable. This finding contradicts popular explanations of value effects. Novy-Marx (2013) also finds a negative correlation between gross profitability and book-to-market. Fama and French (2015a) therefore test this in a US market setting and include a measure of profitability,[40] robust minus weak (RMW), to capture this in the five-factor model. RMW is the difference between returns on portfolios of robust and weak profitability firms. Fama and French (2015a) find that portfolios sorted by size and had high operating profitability on average, have higher expected returns and vice versa.

The second additional factor included in the five-factor model is investment., Aharoni, Grundy and Zeng (2013) find a relationship between investment and average return. Fama and French (2015a) add this factor conservative minus aggressive investment (*CMA*) to proxy for an investment premium, where *CMA* is the difference between returns on diversified portfolios of high and low investment firms. High investment firms are aggressive, low investment firms are conservative. In the five-factor model, Fama and French found that firms which were profitable, small and with high B/M had the highest expected returns (Fama and French 2015a). Testing the five-factor framework with the inclusion of RMW and *CMA* showed that *HML* is subsumed in most cases, and a four-factor model which removes *HML* appears to perform just as well as the five-factor model, indicating the potential redundancy of *HML* (Fama and French 2015a) except in Japan (Fama and French 2017). Comparing the five-factor model against the three-factor and four-factor models, Fama and French find that the five-factor model explains the cross-section of stock returns for U.S stock markets as well as other international markets more effectively than the three-factor or four-factor models (Cakici 2015; Fama and French 2017)

The five-factor model for excess returns is as follows:

$$\begin{aligned} &R_{pt} - R_{ft} = \alpha_p + \beta_p (R_{mt} - R_{ft}) \\ &+\delta_p SMB_t + \gamma_p HML_t + \eta_p RMW_t + \iota_p CMA_t + \varepsilon_{pt} \end{aligned} \tag{13}$$

40. Novy-Marx (2013) use gross profitability

The variables for the three-factor model, Rm-Rf, *SMB*, and *HML* are introduced and discussed in chapter 3.2. RMW_t is the return of a portfolio of robust minus weak profitability stocks, CMA_t is the return of a portfolio of conservative minus aggressive investment stocks, ε_{pt} is the error term. α_p represents the intercept or abnormal return of the expected return, which would be expected to be equal to zero if the factors capture all the variation in expected returns. In this chapter and consistent with chapter 3, I consider the addition of sentiment as a behavioral aspect of asset pricing in addition to the five-factors.

4.2 Data

This study uses data from the following 15 European countries: Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom. These countries are those used to form the European factor portfolios in Fama and French (2017) and are publicly available published on Kenneth French's website. As discussed earlier in this chapter, I split the countries into PIIGS and Non-PIIGS as evidence suggests that PIIGS markets may be more sensitive to negative news than Non-PIIGS (Caporale et al., 2016,2018).

My sample period is limited by the availability of TRNA sentiment data; news coverage available from TRNA starts in 2003 and ends mid – 2014.[41] Exchange rate and currency data are taken from Datastream. Stock market and accounting data are taken from Compustat Global Vantage. Stock market data is downloaded by selecting a specific country from the database and I do this for each of the 15 countries. Stock prices available from Compustat Global Vantage may include currencies which are not part of the 15 countries under analysis. Daily data is chosen to keep analysis consistent with the other chapters in this dissertation and to preserve the dynamic relationship between news sentiment and stock prices, which would be lost in aggregation to the monthly level.

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41. See chapter 2.9 for a more thorough discussion. Chapter 1 uses a time period of 2003-2012 as the updated data was used for a revise and resubmit of a published article based on the chapter.

In the downloaded dataset there are daily firm observations denominated in currencies other than the 15 countries that I focus on, I drop any observations which stocks are not denominated in EUR, the constituent currencies of the EUR prior to joining the Eurozone, and currencies of non-Eurozone countries in my sample (CHF, DKK, GBP, NOK, and SEK). Table 17 illustrates this issue and presents the number of unique European daily firm observations for the 15 countries in my sample prior to cleaning (discussed later on in the chapter). Some of these European stocks are initially denominated in different currencies and are dropped to help ensure the sample only contains stocks related to the 15 countries in our dataset.

Table 17 Number of unique European daily firm observations and denominations prior to cleaning

ISO Currency Code - Daily	Currency	N Obs
ARS	Argentine Peso	13584
AUD	Australian Dollar	29653
BRL	Brazil Real	3442
BWP	Botswana Pula	560
CAD	Canadian Dollar	1625
CHF	Swiss Franc	1160388
COP	Colombian Peso	1185
CZK	Czech Koruna	13298
DEM	Deutsche Mark	7
DKK	Danish Krone	751266
EGP	Egyptian Pound	1964
ESP	Spanish Peseta	5
EUR	Euro	14236300
FRF	French Franc	71
GBP	Pound Sterling	8760291
GRD	Greek Drachma	44651
HKD	Hong Kong Dollar	14431
HRK	Croatian Kuna	121
HUF	Hungarian Forint	514
ILS	New Israeli Sheqel	10063
INR	Indian Rupee	1819
JPY	Japanese Yen	18018
KES	Kenyan Shilling	27
MXN	Mexican Peso, Mexican Unidad de Inversion (UDI)	15370

MYR	Malaysian Ringgit	5851
NAD	Rand, Namibia Dollar	2250
NOK	Norwegian Krone	808050
NZD	New Zealand Dollar	12218
PLN	Poland Zloty	42622
RON	Romanian Leu	2405
RUB	Russian Ruble, Russian Ruble	613
SEK	Swedish Krona	1863002
SGD	Singapore Dollar	2961
TRY	Turkish Lira	1484
USD	US Dollar	170263
ZAR	South African Rand	61741
ZWD	Zimbabwe Dollar	2016
Total		28,054,129

Note: This table presents the number of unique European daily firm observations for the 15 countries in my sample prior to cleaning. The multiple Non-European currencies are subsequently removed from the data set.

Daily return data (DRT) is not available from Compustat Global Vantage for European countries and must be calculated using a formula using daily stock prices and various adjustment factors which adjust for dividends and events such as stock splits. The following formula is used as recommended by WRDS:[42]

$$DTR = \frac{((prccd / ajexdi)* trfd)[\textbf{current}]}{(prccd / ajexdi)* trfd))[\textbf{prior time period}] - 1)} \times 100 \tag{14}$$

where *PRCCD* is daily price, *AJEXDI* is a daily adjustment factor from the sec_dprc table and *TRFD* is the daily total return factor from the sec_dtrt table for international companies.

Calculating returns using this formula gives the daily total return for each stock. However, there some issues arise when creating returns using this formula. For instance, when countries entered the Eurozone and switched currencies to the Euro. When this occurred there would be inaccurate return calculations. Table 18

42. Daily total return can be calculated using PRCCD (daily price), AJEXDI (daily adjustment factor) from the sec_dprc table and TRFD (daily total return factor) from the sec_dtrt table for international companies. TRFD includes Cash Equivalent Distributions along with reinvestment of dividends and the compounding effect of dividends paid on reinvested dividends.

illustrates these issues. Using equation (14) would result in a one off negative return of -99.95%. Therefore, I drop any observations where this occurs

Table 18 Example of data irregularities in CRSP Compustat Global due to conversion

gvkey	datadate	isin	Ajexdi	cshoc	curcdd	prccd	trfd
212820	29-Dec-00	GRS246073001	1.07226	39293100	GRD	1500	1.042046
212820	3-Jan-01	GRS246073001	1.07226	39293100	EUR	4.26	1.042046

Note: this table illustrates a data irregularity where the price of a stock was not correctly converted into Euro.

Table 19 demonstrates another issue that arose in the data was with potential changes to the number of stocks available for a firm either due to a stock split or reverse stock split. At times the adjustment factor or price of a stock is inaccurate in the data which skews the return calculation.

Table 19 is an example of one of these issues where the same stock as identified by Global company Key (gvkey) has a change in the number of common shares outstanding on the 10th of October, compared to the previous date the 9th of October. This change should be captured by the daily adjustment factor ajexdi which is used to calculate returns using equation (14). In this example however, the adjustment factor is not updated and lead to inflated daily returns. These observations are again removed when these errors occur.

Table 19 Example of data irregularities in CRSP Compustat Global due to shares outstanding

gvkey	datadate	isin	ajexdi	cshoc	curcdd	prccd	trfd
133444	9-Oct-02	NL0000262822	2	1.61E+08	EUR	0.05	1.003199
133444	10-Oct-02	NL0000262822	2	3905241	EUR	6.5	1.003199

Note: this table illustrates a data irregularity where the adjustment factor which captures number of common shares outstanding does not reflect the change in number of shares.

After filtering for currency, and the above data irregularities, there are 17,598,510 unique daily Non-PIIGS observations and 2,914,435 unique daily PIIGS observations from which I create 5x5 portfolios.

The five-factors for Europe publicly available[43] are in US dollars, where the market premium is calculated using United States Treasury bills as a proxy for the risk-free rate and the factors are created using stock returns denominated in US dollars. To keep analysis consistent, I convert prices obtained for European stocks into US dollars to calculate returns. Finally, I exclude stocks which do not have 24 months of returns before portfolio formation dates, as well as stocks with negative book equity. The majority, of European firms in my sample have fiscal years ending 31st December. I therefore follow the traditional June to December formation periods as detailed in Fama and French (2015a).

Return portfolios are held for one year from the 1st trading day of July each year to the next. For firms sorted in to these portfolios I use the book equity (BE) for each fiscal year end December year *t -1* to the following year *t*. B/M is BE divided by market equity (ME) on the last trading day of December year *t*, size, is taken as the ME of a firm on the last trading day of June year *t*. The 6-month lag between portfolio formation and fiscal year end is commonly used to ensure that accounting information is publicly available and has been disseminated. I form twenty-five (5x5) size and B/M return portfolios from the intersection of stocks sorted into quintiles by size and B/M. Stocks in my sample are first sorted into ME quintiles from small to large and then again independently sorted into B/M quintiles from low to high. The value weighted daily returns are calculated from the first trading day in July and held for one year. Table 20 and Table 21 present the average number of stocks in each 5x5 portfolio for the sample period split by Non-PIIGS and PIIGS. Non-PIIGS have more stocks on average as this group contains countries with larger stock exchanges.

Table 20 Average number of stocks in Non-PIIGS portfolios

B/M	Low	2	3	4	High
Small	49	46	99	180	261
2	80	92	133	169	172
3	125	144	145	132	108
4	164	167	149	107	70
Big	233	204	128	63	29

43. Attempts were made to replicate the five-factor model and reconcile with the publicly available data. However, attempts to replicate the profitability and investment factors were not successful, despite being able to replicate and reconcile the three-factor model.

Note: this table presents the average number of stocks for Non-PIIGS 5x5 portfolios sorted by size and B/M.

Table 21 average number of stocks in PIIGS portfolios

B/M	Low	2	3	4	High
Small	12	11	18	29	57
2	19	23	22	31	36
3	23	29	30	31	17
4	32	33	29	23	13
Big	45	33	31	15	6[44]

Note: this table presents the average number of stocks for PIIGS 5x5 portfolios sorted by size and B/M.

Table 22 presents the average excess returns and statistics for the 5x5 size and B/M portfolios using Non-PIIGS stocks. There is quite large variation in returns between portfolios where 7 out of the 25 portfolios give negative excess returns. In particular, it appears that small stock portfolios have on average negative excess returns. This effect could potentially be explained by a size discount. Dimson and Marsh (1999) found that reversals of size premiums and a “size effect” may have been related to poor dividend growth in small firms which follow positive size premiums.

Table 23 presents the average excess returns and statistics for the 5x5 size and B/M portfolios using PIIGS stocks. Compared to Non-PIIGS, there are significantly more negative excess returns in the sorted stock portfolios, in 15 out of the 25 portfolios. It appears that small stocks (like Non-PIIGS) have the most negative excess returns, except for the second smallest, low B/M portfolio (-0.0989) which is the 3rd largest, along with the smallest value portfolio. Premiums are monotonically increasing with size. The largest value portfolio also has a negative premium, this portfolio contains stocks which include financial institutions.

44. There is one portfolio formation year, 2005, where the number of stocks in this portfolio is 1.

Table 22 Average daily excess returns for 5x5 portfolios formed on B/M and ME using Non-PIIGS stocks

B/M	Low	2	3	4	High
	Excess Returns				
Small	-0.1427	-0.0934	-0.0451	-0.0123	-0.0641
2	-0.0641	-0.0181	0.0048	0.0172	0.0389
3	0.0108	0.0285	0.0384	0.0533	0.0573
4	0.0446	0.0656	0.0658	0.0566	0.0696
Big	0.0630	0.0630	0.0728	0.0474	0.0640
	Std. Dev.				
Small	1.0786	1.0271	1.1301	0.8407	1.2330
2	1.2330	1.0673	0.8029	1.0233	0.8780
3	1.2671	1.2371	0.8493	0.9734	0.9993
4	1.3484	1.2448	0.9635	1.0530	1.2967
Big	1.7258	1.7599	1.5968	1.3887	1.5439
	Min				
Small	-6.6123	-8.7376	-7.9725	-7.0726	-7.5181
2	-7.5181	-6.6620	-4.8372	-8.0398	-5.7144
3	-7.2128	-8.3270	-4.8381	-6.8124	-5.7236
4	-8.7446	-7.3023	-5.4927	-6.3027	-7.6624
Big	-10.8444	-10.5483	-9.1246	-8.1020	-9.5443
	Max				
Small	5.830	6.171	7.012	6.693	8.211
2	8.211	5.133	4.045	6.683	5.985
3	7.068	7.969	3.796	5.827	5.655
4	9.008	6.996	4.568	5.534	7.160
Big	12.872	10.137	8.637	8.760	8.824

Note: This table presents the average excess returns in each of the 5x5 portfolios in my sample. Presented in percentage.

Table 23 Average daily excess returns for 5x5 portfolios formed on B/M and ME using PIIGS stocks

B/M	Low	2	3	4	High
	Excess Returns				
Small	-0.1615	-0.0901	-0.0903	-0.1041	-0.0989
2	-0.0989	-0.0562	-0.0436	-0.0209	-0.0245
3	-0.0425	-0.0261	0.0126	0.0082	-0.0060
4	0.0136	0.0366	0.0362	0.0229	-0.0040
Big	0.0462	0.0352	0.0468	0.0094	-0.0066
	Std. Dev.				
Small	1.5218	1.3656	1.3170	1.2600	1.2109
2	1.2109	1.1790	1.1774	1.1592	1.3003
3	1.1605	1.1878	1.1030	1.1323	1.4837
4	1.1486	1.2058	1.2734	1.3770	1.8754
Big	1.3662	1.4575	1.6523	1.8191	2.1673
	Min				
Small	-15.0776	-8.6262	-8.4983	-7.4930	-6.9750
2	-6.9750	-9.8873	-7.2819	-7.2697	-7.7603
3	-7.6949	-8.6442	-6.7390	-5.9016	-9.5230
4	-7.3789	-7.3245	-9.4751	-7.7927	-32.7504
Big	-8.2845	-9.1610	-9.8376	-10.4496	-15.0778
	Max				
Small	7.029	5.807	6.302	5.641	6.478
2	6.478	7.014	6.254	5.752	5.808
3	6.093	6.684	6.390	5.808	7.068
4	7.180	5.411	7.804	6.598	8.407
Big	10.156	9.468	9.471	10.447	10.483

Note: This table presents the average excess returns in each of the 5x5 portfolios in my sample. Presented in percentage.

In the same way as in previous chapters I utilize TRNA to create my measure of news sentiment *Psent*. To create my sentiment proxy, first I aggregate all daily news items for each European country in my sample, and then aggregate news items to PIIGS and Non-PIIGS. I calculate sentiment for PIIGS and Non-PIIGS using data from TRNA which has news items covering the sample period 01 Jan 2003 -30 June 2014. This process is the same as in chapter 2.2 and chapter 3.2. A summary of the filtering process for news is presented in Table 24 presents the number of relevant news items for Europe, which is news that has a TRNA relevancy score ≥ 0.8**.**

Table 24. Summary of Filtering Process for News Items

	Number of News Items for Europe	**Number of News Items for Non-PIIGS**	**Number of News Items PIIGS**
Time Period	01 Jan 2003 -30 June 2014	01 Jan 2003 -30 June 2014	01 Jan 2003 -30 June 2014
Only Relevant News Sentiment ≥ ± 0.8	2,200,556	2,021,941	178,615

Note: this table presents the number of unique news items available via TRNA before and after the filtering process for all 15 European countries in my sample.

The total number of news items is far greater for Non-PIIGS compared to PIIGS. This is expected given the relative differences in the size of the stock markets between the two groups. Table 25 presents the distribution of unique news items available per country in the data set over the sample period used to create each sentiment index.

Table 25 Distribution of news by country for all years in sample

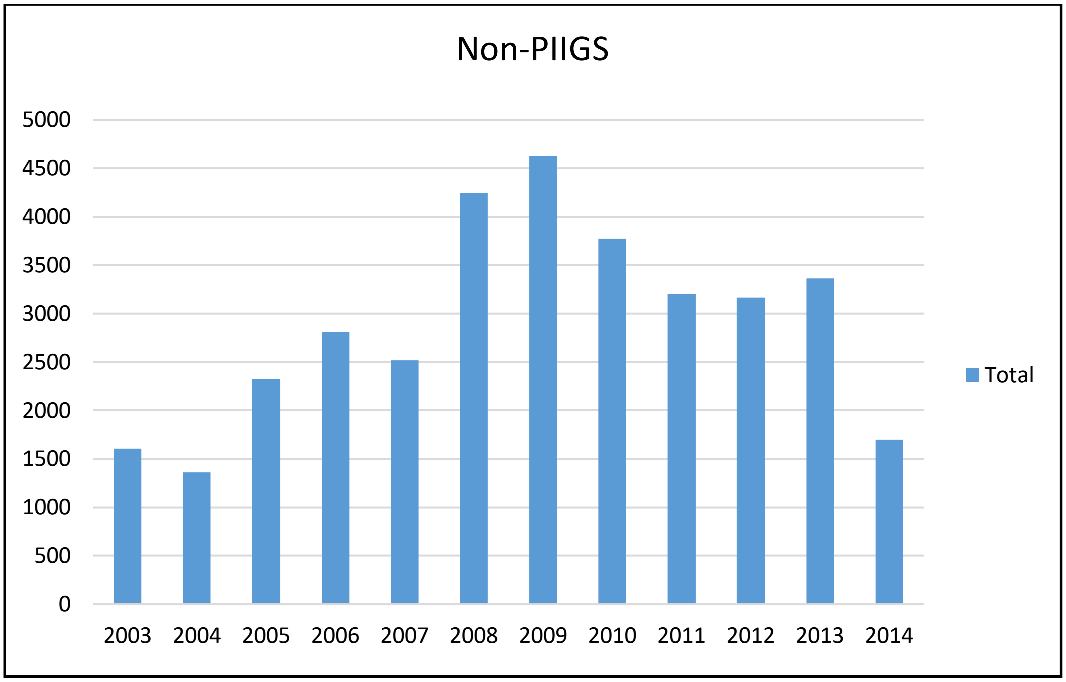
Non-PIIGS	N	PIIGS	N
Austria	146,186	Portugal	6,870
Belgium	36,960	Ireland	43,970
Denmark	17,193	Italy	66,478
France	166,380	Greece	17,633
Germany	282,555	Spain	43,664
Netherlands	50,854		
Norway	64,347		
Sweden	37,354		
Switzerland	121,846		
United Kingdom	1,098,266		
Total	2,021,941	Total	178,615

Note: this table presents the distribution of unique news items available per country in my data set over the sample period.

Figure 8 and Figure 9 illustrate the number of news items per year. Given the GFC occurred in 2008 and the following EFC in 2009, the number of unique news items is highest around this period. This is more apparent in the Non-PIIGS data set. Potentially because of the larger volume of news, as well as the potential news covering potential contagion from PIIGS due to Non-PIIGS financial institutions holding large amounts of Greek sovereign debt.

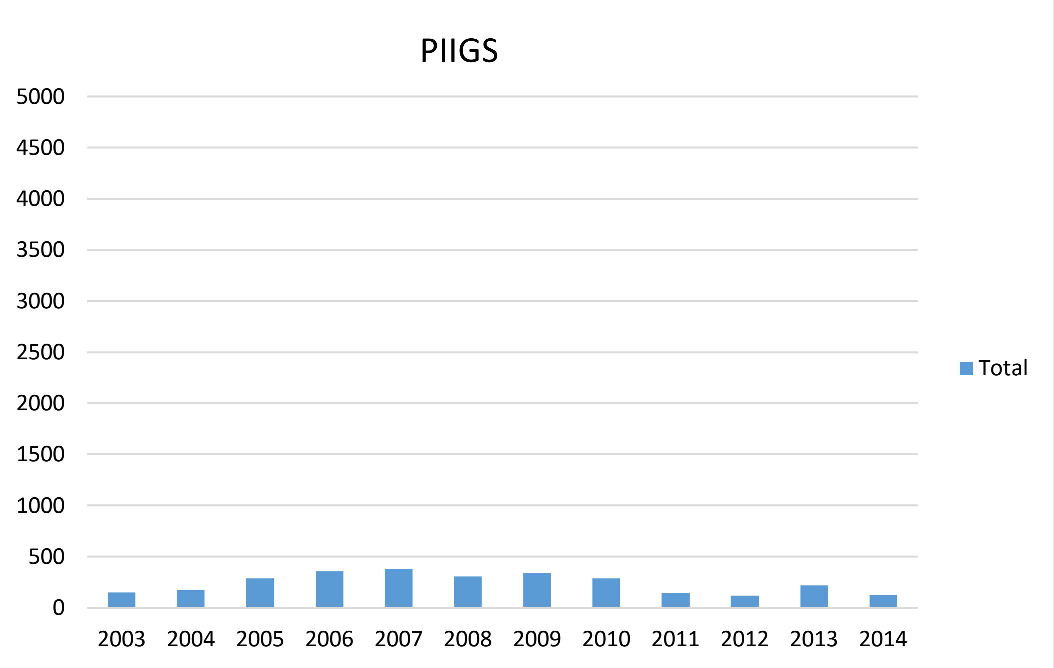
Frequency of news coverage has been linked to market volatility. Active media coverage (newspaper articles) and, increased intensity of news coverage can lead to large market volatility as investors react to the increased intensity of news coverage (Aman (2013)). I would therefore expect to see an increase of news coverage corresponding with high volatility around the GFC and EFC and potentially a correlation to sentiment during this time.

Figure 8 frequency of news items by year for Non-PIIGS



Note: this figure illustrates the frequency of news items by year for Non-PIIGS. 2014 is a half year due to portfolio holding periods and as a result has less news than the other years.

Figure 9 frequency of news items by year for PIIGS



Note: this figure illustrates the frequency of news items by year for PIIGS. 2014 is a half year due to portfolio holding periods and as a result has less news than the other years.

Table 26 illustrates the average sentiment for Non-PIIGS and PIIGS, and the combined measure for the 15 countries in the data set. As described in chapter 2.2, the sentiment measure derived from TRNA takes values between (-1) and (1) where a negative number indicates negative sentiment and a positive number indicates positive sentiment. PIIGS has a slightly lower number of observations due to the number of "news" days available in the data set. If no news is released, then that day would be given a sentiment score of 0 or neutral. PIIGS sentiment also appears to be lower on average than Non-PIIGS, however both measures are low. Table 26 depicts results with no adjustments made for no news days. [45]

45. A difference in means test finds that the two mean sentiments are different from each other.

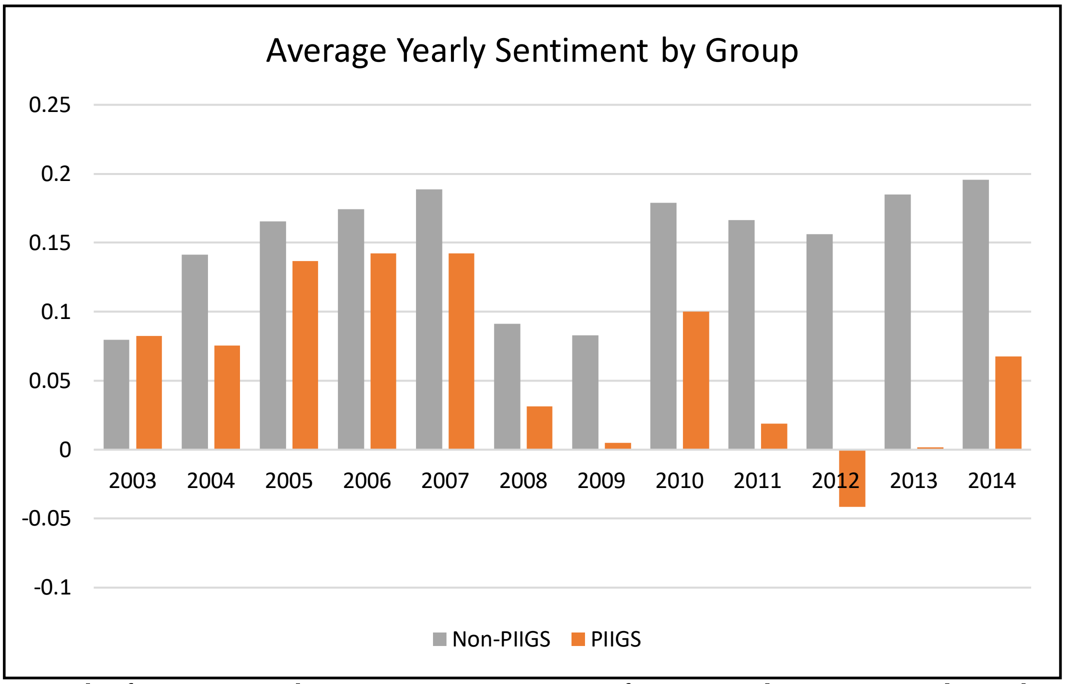
Table 26 Summary Statistics for Psent

Variable	N	Mean	Std Dev	Minimum	Maximum
Psent All	4196	0.14211	0.15087	-0.80396	0.83590
Psent Non-PIIGS	4194	0.14851	0.15827	-0.79937	0.83590
Psent PIIGS	3913	0.06359	0.27527	-0.81914	0.85511

Note: this table illustrates the average sentiment for both Non-PIIGS and PIIGS and for the combined 15 countries in the sample. 2014 is a half year due to portfolio holding periods and as a result has less news than the other years.

Figure 10 charts average sentiment by year and splits PIIGS and Non-PIIGS sentiment. Sentiment for Non-PIIGS and PIIGS appear to be following the same pattern in the years leading up to the Global financial crisis prior to 2008. However, PIIGS sentiment appears to diverge post-2008, whilst average sentiment for Non-PIIGS remains positive (similar to U.S market sentiment).[46]

Figure 10 average yearly sentiment by Non-PIIGS and PIIGS



Note: This figure presents the average sentiment per year for PIIGS and Non-PIIGS, and a combined measure.

Table 27 presents summary statistics and Pearson correlations for the five-factors and two sentiment measures for PIIGS and Non-PIIGS. Table 27 Panel A presents summary statistics of the two measures of sentiment for PIIGS and Non-PIIGS, as well as the five-factors, whilst panel B presents Pearson correlations. Panel

46. See figure 3c in chapter 2.2

B of Table 27 indicates that there are correlations between both measures of sentiment and the five-factors.

For PsentPIIGS, sentiment is positively and statistically significantly correlated with the market premium (0.0330), *SMB* (0.0164), *HML* (0.0452), and *CMA* (0.0099). It is however, negatively correlated to RMW (-0.0316). For PsentNon-PIIGS, sentiment is only positively and statistically correlated to the market premium (0.0548). Otherwise there are statistically negative correlations for *SMB* (-0.0224), RMW (-0.0175) and *CMA* (0.0279). *HML* is insignificant for PsentNon-PIIGS which may be early indication that *HML* for Non-PIIGS in the five-factor model does not contribute compared to the other four factors and sentiment.[47] The positive correlations between the two sentiment measures and the market premiums appear consistent with findings in chapter 3. In that chapter I link positive sentiment to positive market premiums. The correlation between *SMB* and PsentPIIGS is positive, compared to negative for Non-PIIGs. This may suggest that when sentiment is positive for PsentPIIGS, a size premium may also be positive, potentially due to speculation. However, for Non-PIIGS the correlation is negative. As correlation is measured as deviations from the average. The size premium would be smaller than average. Which means it could be negative but does not need to be. Baker and Wurgler (2006) and Yu and Yuan (2011) provide two potential explanations for this, where periods of high (low) sentiment can lead to future reversals in the size premium (Baker and Wurgler 2006), with exuberance and over confidence potentially being another (Yu and Yuan 2011). Whilst all sentiment measures are positively correlated and significant, the correlation between Non-PIIGS and PIIGS sentiment is weak at 0.1686 but statistically significant at the 1% level. This gives an indication that the news sentiment of Non-PIIGS and PIIGS are not as correlated as one might expect given the intertwined nature of the Eurozone and European Union. This suggests that there may be different effects of sentiment on stock returns based on the two country groupings.

47. Fama and French (2015a, 2015b) find that HML is subsumed in most markets by *RMW* and CMA.

Table 27 Summary Statistics for Fama French Five-Factors and Sentiment Measures

Panel A: Summary Statistics	Factors						
	Rm-Rf	SMB	HML	RMW	CMA	PsentPIIGS	PsentNon-PIIGS
Mean	0.0448	0.0073	0.0112	0.0132	0.0080	0.0707	0.1973
Sd	1.3226	0.5881	0.4336	0.2888	0.2866	0.1385	0.0711
Min	-9.0200	-5.3900	-4.3500	-2.4900	-2.0700	-0.8040	-0.3280
Max	10.8300	3.2400	3.7800	4.2100	1.7000	0.8482	0.6859
Panel B: Correlation Matrix							
Rm-Rf	1						
SMB	-0.6986**	1					
HML	0.4100**	-0.2527**	1				
RMW	-0.1955**	0.1209**	-0.4911**	1			
CMA	-0.2868**	0.1384**	0.0759**	-0.2034**	1		
PsentPIIGS	0.0330**	0.0164**	0.0452**	-0.0316**	0.0099**	1	
PsentNon-PIIGS	0.0548**	-0.0224**	0.0018	-0.0175**	-0.0279**	0.1686**	1

Note: this table presents Pearson correlations for Non-PIIGS and PIIGS sentiment as well as the sentiment measure for all 15 countries. PsentPIIGS and PsentNon-PIIGS take values between ±1. **indicates significance at 1% level.

As in Chapter 3.2, to assess if sentiment is potentially useful I run several different models based on the five-factor model. Given the initial evidence for two different sentiment indices based on correlation, I run the standard five-factor model with the inclusion of sentiment for PIIGS and Non-PIIGS:

$$\begin{aligned} R_{pt} - R_{ft} &= \alpha_p + \beta_p (R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t \\ &+ \varsigma_p RMW_t + \eta_p CMA_t + \kappa_p Psent_t^{Non-PIIGS} + \lambda_p Psent_t^{PIIGS} + \varepsilon_{pt} \end{aligned} \tag{15}$$

This specification includes returns for all European stocks in my sample sorted into 5x5 portfolios. where R_{pt} is the return of the portfolio on day t, R_{ft} is the return of the risk-free asset on day t, α_p is the intercept term of the portfolio p, R_{mt} is the market return on day t, *SMB* is the size factor on day t, *HML* is the B/M factor on day t, *RMW* is the measure for profitability, *CMA* is the measure for investment, $\kappa_p Psent^{Non\text{-}PIIGS}$ is the sentiment measure for Non-PIIGS, $\lambda_p Psent^{PIIGS}$ is the sentiment measure for PIIGS and ε_{pt} is the error term for the portfolio.

The second specification focuses on Non-PIIGS stocks and Non-PIIGS sentiment:

$$\begin{aligned} R_{pt} - R_{ft} &= \alpha_p + \beta_p (R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t \\ &+ \varsigma_p RMW_t + \eta_p CMA_t + \kappa_p Psent_t^{Non-PIIGS} + \varepsilon_{pt} \end{aligned} \tag{16}$$

The final specification focuses on PIIGS. Where I form portfolios of stocks from PIIGS and utilize PIIGS specific sentiment.

$$\begin{aligned} R_{pt} - R_{ft} &= \alpha_p + \beta_p (R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t \\ &+ \varsigma_p RMW_t + \eta_p CMA_t + \lambda_p Psent_t^{PIIGS} + \varepsilon_{pt} \end{aligned} \tag{17}$$

4.3 Results

Table 28 presents the results for stocks from all 15 European countries (combination of stocks from both PIIGS and Non-PIIGS) which are sorted into 5x5 portfolios by size and B/M. When the 15 countries are pooled together, it appears that small growth stocks with low B/M have negative significant alphas, with -0.2827 for the smallest growth stock portfolio and -0.2004 for the next smallest and next lowest B/M portfolio. There appears to be a strong size effect, with *SMB* significant for all but one portfolio and showing a humped pattern of coefficients as portfolios increase in size, and from low to high B/M. Stock returns in this pooled sample also show positive significant coefficients to the market premium. *HML*, *RMW* and *CMA* are not significant for all portfolios. The results presented in this dissertation do not directly translate to the results in Fama and French (2017) for European stocks potentially due to the differences in data frequency (daily compared to monthly) and time period (2003 – 2014 compared to 1990 – 2015). However, in terms of direction from low B/M to high B/M coefficients generally follow the patterns in Fama and French (2017). One distinct difference that does occur is in small stock growth portfolios. Fama and French (2017) find negative coefficients for HML, RMW and CMA which can be interpreted as small growth stocks which behave like firms that invest, despite having low profitability. In Tables 28, 29 and 30 of this dissertation, the coefficients are mostly negative for RMW but generally positive for HML and CMA, which would indicate a conservative investment consistent with low profitability.[48]

Turning to sentiment, the focus of this chapter, small stocks in this sample also appear significant to PIIGS sentiment, with all the smallest portfolios showing a positive relationship to PIIGS sentiment. This is consistent with the small firm sentiment effect I have documented in this dissertation. There are also 4 other portfolios which are responsive to PIIGS sentiment. The largest value portfolio of Table 28 has a positively significant co-efficient of 0.2867 and this portfolio contains some of the larger European banks which were exposed to Greek debt. These include

[48] There appears to be no clear pattern in terms of significance of these results. Further research will perhaps try to solve this puzzle.

French banks BNP Paribas and Crédit Agricole.[49] The sentiment co-efficient for Non-PIIGS sentiment is however, insignificant for all stock portfolios. The weak correlation between PIIGS and Non-PIIGS in Table 27 may explain partially why this is the case. This result indicates that stocks are not impacted by sentiment of Non-PIIGS countries, even though the stock exchanges in this group are on average larger than those in PIIGS. One potential explanation these results to mean that the pooled European sample is positively correlated to only PIIGS sentiment for smallest stocks, along with some potentially idiosyncratic large size portfolios which contain banking stocks that were holding sovereign debt affected by the EFC.

To get a clearer picture of the relationship between stock returns and PIIGS and Non-PIIGS sentiment, the following analysis splits stocks into a Non-PIIGS and PIIGS sample with their respective sentiment indices. I do this as mentioned earlier due to the differences in vulnerabilities to the EFC. Table 29 presents results of 5x5 portfolios sorted by size and B/M formed from stocks in Non-PIIGS countries with corresponding news sentiment for Non-PIIGS. Only one portfolio, shows significance to sentiment. The smallest growth portfolio shows a positive sentiment co-efficient of 0.696 (t-stat 1.980) and is marginal. The small number of significant coefficients for sentiment indicates that stocks in Non-PIIGS countries are less impacted by their own sentiment with stock returns in Non-PIIGS more likely to be explained by the five-factors.

Table 30 presents results of 5x5 portfolios formed from stocks in PIIGS, which are stocks listed in countries which were heavily impacted by the EFC. Unlike stocks in Non-PIIGS, stocks in PIIGS show greater sensitivity to sentiment, with 9 portfolios showing a positive co-efficient. The positive coefficients for sentiment are concentrated in growth portfolios, as well as small portfolios which is consistent with my expectations and findings. There are mixed findings as to the effect of sentiment in growth stocks compared to value stocks for PIIGS. This may also indicate potential sensitivity to speculative investment where high growth stocks are more impacted by positive sentiment and vice versa. The largest value portfolio of Table 21 also contains

48. A report by JP Morgan stated that Crédit Agricole was said to have held 3.5 billion euros in exposure to Greece at the end of 2013 (https://www.reuters.com/article/us-eurozone-greece-banking-exposure/german-bank-exposure-to-greece-around-28-billion-banks-idUSKBN0KE16H20150106) (Accessed November 23 2017)

Greek financial institutions, which may be more affected by sentiment due to fears of default. This result indicates that sentiment may play a greater role in explaining stock returns in addition to the five-factors compared to Non-PIIGS most likely due to the opaque nature of small stocks listed on these stock exchanges as well as potential intangibles.

The results in Table 30 are concentrated in the smaller portfolios, as well as the largest growth portfolio. I observed a similar pattern for Japanese stocks in chapters 2.3 and 3.3. This result is consistent with previous findings in the literature which indicate an asymmetric effect of sentiment on stocks based on size. I expect small stocks and the largest stocks tend to have characteristics which may make them sensitive to sentiment. Small stocks may have characteristics that make them difficult to value due to information opaqueness (Baker and Wurgler 2006, 2007; Berger and Turtle 2012; Brown and Cliff 2005; Lemmon and Portniaguina 2006 and Schmeling 2009). One potential reason for the largest value portfolio in Table 30 having a positive co-efficient of 0.4688, is because a number of PIIGS financial institutions are sorted into this portfolio and these institutions are more likely to be perceived as being vulnerable to default. Another reason could be because of institutional investors are reacting to news in larger stocks (or in this case, large PIIGS financial institutions) as other Non-PIIGS have holdings (debt)[50] which are concentrated in these larger stocks. Luo et al. (2015) argue that institutional investors will react more to news in larger stocks than in smaller stocks since their holdings are concentrated in larger stocks.

4.4 Conclusion

This chapter expands on previous findings in chapters 2 and 3 and examines sentiment in the context of two groups of European countries PIIGS and Non-PIIGs. Results in this chapter find that small stocks, and in particular, small PIIGS stocks are more likely to be influenced by sentiment. A result which is consistent throughout this dissertation and within the literature. I also find that Non-PIIGS stocks are not sensitive to my measure of sentiment, and the effect is only pronounced in PIIGS. Large value stocks, or PIIGS financial institutions are positively related to sentiment, potentially

49. French bank Crédit Agricole owned Greek bank Emporiki through a merger an acquisition in 2006. Eva and Mark (2016)

due to the impact and news coverage of these institutions had on other European financial institution.

Table 28 European portfolios with Non-PIIGS and PIIGS sentiment

This Table reports regression results over the period January 2003 – June 2014. This regression uses the five-factors for Europe and sentiment Psent for PIIGS and Non-PIIGS. Firms in the following portfolios are value weighted, daily returns are calculated from the first trading day in July and held for one year. For firms sorted in to these portfolios I use the book equity (BE) for each fiscal year end December year t -1 to the following year t. B/M is BE divided by market equity (ME) on the last trading day of December year t, size, is taken as the ME of a firm on the last trading day of June year t. The 6-month lag between portfolio formation and fiscal year end is commonly used to ensure that accounting information is publicly available and has been disseminated.

The Model is specified as: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t + \varsigma_p RMW_t + \eta_p CMA_t + \kappa_p Psent_t^{Non-PIIGS} + \lambda_p Psent_t^{PIIGS} + \varepsilon_{pt}$

B/M	Low	2	3	4	High	Low	2	3	4	High
	Constant					t(α)				
Small	-0.2827**	-0.2004**	-0.0897	-0.0975	-0.0131	(-3.929)	(-3.124)	(-1.367)	(-1.313)	(-0.191)
2	-0.1363*	-0.1006*	-0.0578	-0.0166	0.0262	(-2.411)	(-2.004)	(-1.466)	(-0.238)	(0.400)
3	-0.0437	-0.0453	-0.0283	0.0117	0.0102	(-0.873)	(-0.864)	(-0.729)	(0.199)	(0.162)
4	0.0141	-0.0169	0.0045	0.0062	-0.0080	(0.269)	(-0.375)	(0.122)	(0.109)	(-0.130)
Big	0.0365	0.0137	0.0321	0.0476	0.0886	(0.653)	(0.257)	(0.652)	(0.670)	(1.057)
	mktrf					t(β)				
Small	0.3252*	0.3256**	0.1073**	-0.1798**	0.1527**	(10.038)	(11.404)	(3.524)	(-5.387)	(5.091)
2	0.9171**	0.8421**	0.6384**	0.0147	0.3388**	(40.293)	(40.168)	(39.404)	(0.458)	(11.703)
3	0.9890**	0.9626**	0.7907**	0.2759**	0.5402**	(48.896)	(47.019)	(48.992)	(11.272)	(21.000)
4	1.0770**	1.0278**	0.8434**	0.4319**	0.7926**	(52.446)	(53.638)	(57.354)	(18.545)	(31.457)
Big	1.2359**	1.1901**	1.1012**	0.5007**	0.6537**	(51.377)	(53.792)	(48.134)	(18.252)	(21.119)
	SMB					t(δ)				
Small	0.6091**	0.4517**	0.3278**	0.0015	0.3411**	(11.062)	(9.220)	(6.537)	(0.026)	(7.202)
2	0.9848**	0.9254**	0.7874**	0.1554**	0.4588**	(23.011)	(25.202)	(25.733)	(2.899)	(9.751)
3	1.0569**	1.0136**	0.8514**	0.2480**	0.5227**	(27.307)	(25.560)	(28.106)	(5.513)	(11.389)
4	1.0492**	1.0575**	0.8287**	0.2056**	0.5771**	(26.622)	(30.480)	(28.673)	(4.773)	(12.411)
Big	0.3490**	0.2034**	0.2315**	-0.4372**	-0.2698**	(8.274)	(4.582)	(5.546)	(-8.338)	(-4.018)

Continued Next Page

	HML					t(γ)				
Small	0.0366	-0.1002	-0.0394	0.0370	0.1295	(0.296)	(-1.082)	(-0.328)	(0.284)	(1.030)
2	-0.1083	-0.0550	-0.0411	0.0211	0.2083	(-1.646)	(-1.022)	(-0.875)	(0.162)	(1.807)
3	-0.0959*	-0.0187	0.0265	0.1244	0.2832**	(-2.046)	(-0.322)	(0.640)	(1.425)	(3.076)
4	-0.0874	-0.0117	0.0957	0.2480**	0.3953**	(-1.691)	(-0.204)	(2.212)	(3.559)	(4.471)
Big	-0.2438**	0.1500	0.4577**	0.4928**	0.2855**	(-2.763)	(1.573)	(3.998)	(4.463)	(3.333)
	RMW					t(ζ)				
Small	-0.1780	-0.1778	-0.2979*	-0.3940*	-0.2460	(-1.228)	(-1.584)	(-2.050)	(-2.564)	(-1.658)
2	-0.1891*	-0.1867**	-0.2095**	-0.4181**	-0.2581	(-2.049)	(-2.586)	(-3.321)	(-2.722)	(-1.798)
3	-0.1434*	-0.0896	-0.0958	-0.3368**	-0.2016	(-2.219)	(-1.051)	(-1.486)	(-2.887)	(-1.594)
4	-0.1049	-0.1437	-0.0960	-0.1467	-0.2281	(-1.555)	(-1.832)	(-1.341)	(-1.557)	(-1.740)
Big	-0.0517	-0.1366	-0.4210*	-0.5337**	0.1205	(-0.395)	(-0.817)	(-2.208)	(-3.382)	(0.923)
	CMA					t(η)				
Small	0.2624**	0.2264**	0.2387**	0.2613**	0.3067**	(2.813)	(2.725)	(2.687)	(2.597)	(3.441)
2	0.1552*	0.0702	0.1666**	0.1547	0.0768	(1.990)	(1.062)	(3.158)	(1.659)	(0.886)
3	0.1930**	0.1634*	0.1150*	0.0339	-0.0955	(3.021)	(2.192)	(2.260)	(0.414)	(-1.125)
4	0.0704	0.1289*	0.1640**	-0.0498	-0.1967*	(0.942)	(2.048)	(3.165)	(-0.650)	(-2.398)
Big	0.1647*	0.2216**	0.0604	0.1128	-0.2487*	(2.030)	(2.656)	(0.810)	(1.091)	(-2.431)
	psentnopig					t(κ)				
Small	0.4780	0.2130	-0.1441	0.1864	-0.1210	(1.530)	(0.759)	(-0.502)	(0.586)	(-0.419)
2	0.1097	0.1365	0.0165	0.0981	-0.1102	(0.440)	(0.604)	(0.092)	(0.327)	(-0.399)
3	-0.0353	0.0625	0.0163	0.0520	0.0353	(-0.155)	(0.270)	(0.093)	(0.204)	(0.132)
4	-0.1319	0.0679	0.0052	0.0392	0.0727	(-0.577)	(0.340)	(0.032)	(0.157)	(0.278)
Big	-0.1368	-0.0282	-0.1125	-0.1243	-0.3862	(-0.558)	(-0.119)	(-0.518)	(-0.406)	(-1.062)
	psentpig					t(λ)				
Small	0.3328**	0.3462**	0.3329**	0.2766*	0.3126**	(2.604)	(2.867)	(2.945)	(2.291)	(3.067)
2	0.1270	0.1195	0.1159	0.2302*	0.1613	(1.211)	(1.217)	(1.388)	(2.059)	(1.581)
3	0.0472	0.0663	0.1647*	0.1407	0.1055	(0.460)	(0.668)	(2.061)	(1.428)	(1.061)
4	-0.0382	0.0151	0.1038	0.2077*	0.1700	(-0.386)	(0.171)	(1.461)	(1.975)	(1.277)
Big	-0.1244	-0.0999	-0.0110	0.0713	0.2867*	(-1.219)	(-1.023)	(-0.119)	(0.619)	(2.019)

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	Adjusted R-squared				
Small	0.105	0.0921	0.0395	0.0760	0.0726
2	0.559	0.578	0.509	0.0319	0.200
3	0.633	0.631	0.657	0.167	0.407
4	0.692	0.717	0.725	0.350	0.573
Big	0.788	0.811	0.828	0.564	0.493

** denotes significance at the 1% level, * 5% level.

Table 29 European Non-PIIGS portfolios with Non-PIIGS sentiment

This Table reports regression results over the period January 2003 – June 2014. This regression uses the five-factors for Europe and sentiment *Psent* for Non-PIIGS. Firms in the following portfolios are value weighted, daily returns are calculated from the first trading day in July and held for one year. For firms sorted in to these portfolios I use the book equity (BE) for each fiscal year end December year t -1 to the following year t. B/M is BE divided by market equity (ME) on the last trading day of December year t, size, is taken as the ME of a firm on the last trading day of June year t. The 6-month lag between portfolio formation and fiscal year end is commonly used to ensure that accounting information is publicly available and has been disseminated.

The Model is specified as: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t + \varsigma_p RMW_t + \eta_p CMA_t + \kappa_p Psent_t^{Non-PIIGS} + \lambda_p Psent_t^{PIIGS} + \varepsilon_{pt}$

B/M	Low	2	3	4	High	Low	2	3	4	High
	Constant					t(α)				
Small	-0.2824**	-0.1912**	-0.0911	-0.1427*	-0.0713	(-3.812)	(-2.731)	(-1.233)	(-1.887)	(-1.053)
2	-0.1606**	-0.0960	-0.0350	-0.0300	0.0346	(-2.759)	(-1.922)	(-0.720)	(-0.392)	(0.545)
3	-0.0327	-0.0564	-0.0258	0.0227	0.0140	(-0.612)	(-1.057)	(-0.618)	(0.325)	(0.218)
4	0.0087	0.0438	0.0116	0.0341	0.0200	(0.155)	(0.896)	(0.283)	(0.487)	(0.347)
Big	0.0405	0.0079	0.0591	0.0579	0.0342	(0.674)	(0.139)	(1.191)	(0.758)	(0.448)
	mktrf					t(β)				
Small	0.2027**	0.1781**	-0.0743*	-0.2944**	0.1798**	(5.934)	(5.230)	(-2.171)	(-8.476)	(5.840)
2	0.9215**	0.7912**	0.4288**	-0.1660**	0.3568**	(37.737)	(37.322)	(19.565)	(-4.731)	(12.329)
3	1.0211**	0.9807**	0.5990**	0.0757*	0.5613**	(45.746)	(44.943)	(33.979)	(2.487)	(20.211)
4	1.1125**	1.0378**	0.7545**	0.2637**	0.8840**	(48.304)	(47.789)	(45.048)	(8.868)	(38.171)
Big	1.3151**	1.2578**	1.0872**	0.3328**	0.7790**	(48.976)	(50.595)	(48.276)	(10.500)	(26.374)
	SMB					t(δ)				
Small	0.4193**	0.3642**	0.1355*	-0.1473*	0.3914**	(7.184)	(7.096)	(2.350)	(-2.432)	(8.203)
2	0.9895**	0.9097**	0.6358**	-0.0638	0.4868**	(21.035)	(23.368)	(17.249)	(-1.080)	(10.513)
3	1.1406**	1.0625**	0.7302**	0.0326	0.6115**	(26.706)	(24.891)	(22.642)	(0.582)	(13.386)
4	1.1088**	1.1123**	0.7652**	-0.0217	0.7069**	(25.005)	(27.563)	(24.128)	(-0.401)	(15.702)
Big	0.4147**	0.2828**	0.2987**	-0.7358**	-0.0336	(8.706)	(5.682)	(6.702)	(-12.147)	(-0.519)

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	HML					t(γ)				
Small	-0.0099	-0.1211	0.0358	0.0247	0.1254	(-0.080)	(-0.925)	(0.263)	(0.203)	(0.955)
2	-0.1363*	-0.0691	0.0021	0.0639	0.1933	(-2.304)	(-1.248)	(0.025)	(0.466)	(1.633)
3	-0.0914	-0.0350	0.0361	0.1571	0.2720**	(-1.510)	(-0.595)	(0.566)	(1.453)	(2.599)
4	-0.1393*	-0.0641	0.0985	0.2430*	0.3564**	(-2.411)	(-1.081)	(1.910)	(2.468)	(4.925)
Big	-0.3420**	0.1346	0.3574**	0.3009**	0.3914**	(-3.639)	(1.280)	(4.425)	(2.714)	(4.277)
	RMW					t(ζ)				
Small	-0.2527	-0.4137**	-0.3490*	-0.3660*	-0.2245	(-1.718)	(-2.704)	(-2.121)	(-2.505)	(-1.458)
2	-0.2013*	-0.1732*	-0.3037**	-0.3682*	-0.2559	(-2.564)	(-2.161)	(-2.937)	(-2.269)	(-1.756)
3	-0.1160	-0.0899	-0.1617	-0.3685**	-0.1912	(-1.314)	(-1.045)	(-1.844)	(-2.638)	(-1.399)
4	-0.1009	-0.1019	-0.0768	-0.2134	-0.1649	(-1.325)	(-1.278)	(-0.925)	(-1.641)	(-1.494)
Big	-0.0185	-0.0910	-0.4381**	-0.4972**	0.2496	(-0.136)	(-0.501)	(-3.085)	(-3.389)	(1.730)
	CMA					t(η)				
Small	0.3815**	0.2548**	0.3156**	0.2102	0.3492**	(3.830)	(2.826)	(3.163)	(1.942)	(3.869)
2	0.1661*	0.1702*	0.2973**	0.1146	0.1041	(2.020)	(2.553)	(4.444)	(1.108)	(1.200)
3	0.1920*	0.1960*	0.2144**	-0.0862	-0.0281	(2.574)	(2.499)	(3.684)	(-0.854)	(-0.325)
4	0.1180	0.2273**	0.2362**	-0.2463*	-0.2308**	(1.467)	(3.253)	(4.212)	(-2.491)	(-2.961)
Big	0.2027*	0.3023**	0.2027*	-0.2464*	-0.2846**	(2.240)	(3.234)	(2.416)	(-2.210)	(-2.887)
	psentnopig					t(κ)				
Small	0.6496*	0.2965	0.0084	0.5831	0.2379	(1.980)	(0.957)	(0.026)	(1.737)	(0.812)
2	0.2585	0.1894	0.0890	0.2958	-0.0739	(0.989)	(0.833)	(0.415)	(0.879)	(-0.268)
3	-0.0459	0.1685	0.1625	0.1570	0.0674	(-0.188)	(0.699)	(0.867)	(0.508)	(0.240)
4	-0.1024	-0.1647	0.0640	0.0655	0.0261	(-0.409)	(-0.743)	(0.343)	(0.209)	(0.101)
Big	-0.1889	-0.0308	-0.1886	-0.0757	-0.0514	(-0.707)	(-0.120)	(-0.841)	(-0.224)	(-0.152)

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	Adjusted R-squared				
Small	0.047	0.0413	0.0459	0.0971	0.079
2	0.523	0.51	0.273	0.043	0.206
3	0.602	0.596	0.473	0.0406	0.396
4	0.658	0.653	0.628	0.184	0.635
Big	0.763	0.786	0.786	0.438	0.542

** denotes significance at the 1% level, * 5% level.

Table 30 PIIGS portfolios with PIIGS sentiment

This Table reports regression results over the period January 2003 – June 2014. This regression uses the five-factors for Europe and sentiment *Psent* for PIIGS. Firms in the following portfolios are value weighted, daily returns are calculated from the first trading day in July and held for one year. For firms sorted in to these portfolios I use the book equity (BE) for each fiscal year end December year t -1 to the following year t. B/M is BE divided by market equity (ME) on the last trading day of December year t, size, is taken as the ME of a firm on the last trading day of June year t. The 6-month lag between portfolio formation and fiscal year end is commonly used to ensure that accounting information is publicly available and has been disseminated.

The Model is specified as: $R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \delta_p SMB_t + \gamma_p HML_t + \varsigma_p RMW_t + \eta_p CMA_t + \lambda_p Psent_t^{PIIGS} + \varepsilon_{pt}$

B/M	Low	2	3	4	High	Low	2	3	4	High
	Constant					t(α)				
Small	-0.2078**	-0.1623**	-0.1463**	-0.1568**	-0.1714**	(-7.839)	(-6.651)	(-6.369)	(-7.602)	(-8.692)
2	-0.1455**	-0.1179**	-0.1070**	-0.0800**	-0.0927**	(-7.691)	(-6.265)	(-6.192)	(-4.735)	(-4.564)
3	-0.0970**	-0.0960**	-0.0419**	-0.0565**	-0.0885**	(-5.997)	(-5.392)	(-2.898)	(-3.704)	(-4.064)
4	-0.0339*	-0.0117	-0.0216	-0.0425*	-0.0840*	(-2.498)	(-0.857)	(-1.489)	(-2.426)	(-2.066)
Big	0.0040	-0.0086	0.0084	-0.0549*	-0.0905**	(0.288)	(-0.552)	(0.489)	(-2.555)	(-2.987)
	mktrf					t(β)				
Small	0.7290**	0.7583**	0.8017**	0.8418**	0.7788**	(22.733)	(27.510)	(30.195)	(30.659)	(30.356)
2	0.7997**	0.7684**	0.8419**	0.8289**	0.8583**	(34.862)	(32.727)	(40.790)	(39.617)	(37.062)
3	0.8407**	0.8674**	0.8318**	0.8413**	0.9975**	(42.362)	(42.378)	(48.981)	(48.995)	(38.639)
4	0.9012**	0.9243**	0.9639**	0.9852**	1.0350**	(55.058)	(56.795)	(46.973)	(50.681)	(39.046)
Big	0.9155**	0.9114**	0.9239**	0.9984**	1.0712**	(57.525)	(48.052)	(40.521)	(35.747)	(26.854)
	SMB					t(δ)				
Small	0.7273**	0.7616**	0.7811**	0.8301**	0.8607**	(10.491)	(14.286)	(15.189)	(16.357)	(16.843)
2	0.7714**	0.7086**	0.8366**	0.8263**	0.8984**	(17.344)	(16.363)	(22.515)	(22.455)	(19.003)
3	0.7484**	0.8015**	0.8109**	0.8387**	0.9432**	(19.436)	(20.966)	(24.919)	(24.035)	(20.417)
4	0.7423**	0.7774**	0.7557**	0.8562**	0.7408**	(24.336)	(23.917)	(22.696)	(22.922)	(12.208)
Big	0.0300	-0.0517	-0.0971*	0.0939	0.2557**	(0.928)	(-1.402)	(-2.076)	(1.592)	(3.805)

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	HML					t(γ)				
Small	0.0603	-0.0024	0.0781	0.0995	0.0402	(0.727)	(-0.039)	(1.066)	(1.575)	(0.595)
2	0.0700	0.1381*	0.2043**	0.1589*	0.2013**	(1.600)	(2.176)	(4.297)	(2.213)	(3.397)
3	0.0718	0.1531*	0.2699**	0.2887**	0.3802**	(1.304)	(2.381)	(4.028)	(5.715)	(3.830)
4	0.1255*	0.3460**	0.3072**	0.5429**	0.5072**	(2.562)	(6.358)	(3.859)	(7.119)	(5.872)
Big	0.0984	0.3460**	0.7992**	0.9047**	1.1818**	(1.420)	(3.732)	(6.044)	(5.587)	(8.306)
	RMW					t(ζ)				
Small	-0.1908	-0.2315**	-0.1854*	-0.1680*	-0.3961**	(-1.557)	(-2.814)	(-1.860)	(-2.092)	(-3.654)
2	-0.1340*	-0.1312	-0.0837	-0.1508	-0.3272**	(-2.170)	(-1.467)	(-1.249)	(-1.478)	(-3.930)
3	-0.1616*	-0.2480**	-0.0844	-0.1143	-0.3303*	(-2.220)	(-3.108)	(-0.786)	(-1.705)	(-2.248)
4	-0.0776	-0.1907*	-0.1705	-0.2320	-0.7525**	(-1.220)	(-2.060)	(-1.796)	(-1.873)	(-6.566)
Big	-0.2468*	-0.1073	-0.2750	-0.8116**	-1.0600**	(-2.059)	(-0.688)	(-1.224)	(-3.018)	(-5.888)
	CMA					t(η)				
Small	0.0451	-0.1433	-0.1093	-0.0332	-0.2164**	(0.441)	(-1.633)	(-1.321)	(-0.406)	(-2.769)
2	0.1193	-0.0961	0.0414	-0.0099	0.0560	(1.642)	(-1.216)	(0.640)	(-0.151)	(0.732)
3	-0.1179	-0.1643**	0.0151	0.1153	-0.0952	(-1.834)	(-2.737)	(0.256)	(1.945)	(-1.164)
4	-0.1235*	-0.0110	-0.1623**	0.0034	0.1903*	(-2.355)	(-0.183)	(-2.624)	(0.053)	(2.007)
Big	0.1825**	0.0443	-0.2173**	0.1030	0.1551	(3.056)	(0.675)	(-2.877)	(1.274)	(1.300)
	psentpig					t(λ)				
Small	0.1240	0.2082	0.2430	0.3451**	0.4575**	(0.731)	(1.340)	(1.598)	(2.725)	(3.573)
2	0.0673	0.3286**	0.2505*	0.2285*	0.3546**	(0.527)	(2.943)	(2.335)	(2.178)	(2.831)
3	0.1886	0.3896**	0.1307	0.2564**	0.4412**	(1.841)	(3.065)	(1.522)	(2.756)	(3.230)
4	0.0407	0.0002	0.1281	0.1579	0.4341	(0.497)	(0.002)	(1.519)	(1.477)	(1.573)
Big	0.0150	0.0086	-0.0882	0.2580*	0.4688**	(0.176)	(0.089)	(-0.844)	(2.024)	(2.590)

Adjusted R-squared

Small	0.246	0.345	0.387	0.451	0.431
2	0.464	0.499	0.576	0.575	0.500
3	0.605	0.643	0.664	0.640	0.582
4	0.730	0.755	0.754	0.706	0.472
Big	0.803	0.800	0.804	0.748	0.632

** denotes significance at the 1% level, * 5% level.

Chapter 5 CONCLUSION

5.1 Summary of findings

This dissertation presents three essays which explore the relationship between sentiment and stock returns and finds that in most cases there is a positive relationship to sentiment. This dissertation uses a more sophisticated text-based proxy for sentiment (TRNA) linked to investor behavior influenced by mood (sentiment) which can also be influenced by news. This dissertation adds to the strand of sentiment literature that focuses on the impact of sentiment over multiple countries and markets using text-based sentiment measures.

One of the key findings and themes in this dissertation is that size is a large determinant in how influential sentiment is on returns. This is consistently the case for all the analyses conducted across different markets and aligns closely with existing literature. This finding is likely due to the characteristics of small firms which are likely to be "opaque", that is they possess characteristics which make them difficult to value. These reasons might be low liquidity, high information asymmetry, high transaction costs or intangibles that might not have clear market values. There is however, not a clear picture as to which of these features influences the sensitivity of size to sentiment, as in this dissertation we find sensitivity to sentiment in both small B/M and high B/M stocks. The overriding finding for my results is that all the smallest sorted portfolios are both statistically and economically sensitive to sentiment. Why these effects apply to both low and high book to market firms in the smallest sized portfolios is unclear.

Another finding in this dissertation is the link between sentiment and poor stock returns in periods of negative sentiment across markets in Japan and Europe. Chapter 2 presents evidence that Japan's poor stock returns can be partially attributed to sentiment at both the aggregate market and individual firm level. When augmented into a widely accepted empirical asset pricing model in chapter 3, I find that sentiment helps explain the cross-section of stock returns, however the impact is concentrated in small and large stocks. Chapter 4 finds a similar result to chapters 2 and 3, in that firms in PIIGS which are perceived to have more vulnerability to the EFC have sensitivity to sentiment. This is especially true for small stock portfolios and large portfolios which contain financial institutions which have either exposure to PIIGS debt or are PIIGS financial institutions. The sentiment findings for large stocks are not consistent across markets and could reflect distinctive features unique to certain markets or investors. For Japan, large low B/M stocks are influenced, whilst for PIIGS and Non-PIIGS it appears to be large high B/M stocks. One potential explanation is where large stocks are likely to have greater levels of media and investor attention which makes them more sensitive to sentiment, particularly sentiment which is derived from news and not necessarily based on fundamental information.

In conclusion, the analysis presented in this dissertation reveals that sentiment is related to stock returns and supports a behavioral aspect of asset pricing. However, it is the augmentation of traditional models with sentiment that reveals heterogenous sensitivity of firms to sentiment. This sensitivity is largely determined based on size, where the smallest sorted portfolios for both Japan and PIIGS are positively related to sentiment. However, we also find that this effect is also present across the lowest and highest B/M firms in the smallest sorted portfolios. Additionally, there is some evidence that large firms are also sensitive to sentiment, with opposite findings based on B/M for Japanese and European firms. This warrants future research to investigate the precise channels through which sentiment is working, as to my knowledge this has not been resolved in the literature.

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