Melancholia and Japanese Stock Returns – 2003 to 2012

Joyce Khuu*

Robert B. Durand

Lee A. Smales

JEL classifications: G02.

Keywords: Japan, Behavioral finance, sentiment, bear markets.

The authors are from the Department of Finance and Banking, School of Economics and Finance, Curtin University, Bentley, Western Australia, Australia.

* Corresponding author E-mail: Joyce.Khuu@curtin.edu.au

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ABSTRACT

Japan's "lost decades" challenge Finance's central tenet of a positive expected relationship of return and risk. We present evidence that Japan's dismal returns are a function of sentiment both at the aggregate market and individual firm level. Utilizing a text-based measure of news sentiment (Thomson Reuters News Analytics) to proxy for investor sentiment, we find that sentiment is predominately negative during our sample period (2003 to 2012) and is associated with negative returns. The effect of news sentiment is greatest for smaller firms.

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I. 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 we 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 paper 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".

We find that sentiment has a significant positive relationship with stock returns, and thus the prolonged downturn in Japanese markets may be attributed to the prevalent negative mood throughout the period being studied.[5] Our analysis uses a text-based measure of news sentiment (Thomson Reuters News Analytics) to proxy for investor sentiment.

We 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. Our 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 our knowledge, not been examined in Japan. Our 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

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[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] We 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.

[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 tranquillity". Our measure of market sentiment is negative for most years in our 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.

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.

Our analysis of the association between investor sentiment and Japanese returns contributes to a growing literature (outlined above and, in more detail, in Section II) linking returns to sentiment. Further, our findings, presented in Section IV, 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, our analysis provides evidence that sentiment can play an important role in understanding markets outside of the US. Section III discusses our methodology; in particular, we detail how we construct text based sentiment measures for the Japanese markets using data from Thomson Reuters News Analytics (TRNA). [6]

II. 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, a term used interchangeably with sentiment (as we will do in this paper), influences share market behavior, (Baker and Wurgler 2006; Brown and Cliff 2005; 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 we 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

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

[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).

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 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 paper 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 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,

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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 favourite 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.

11 See Chen (1991) for a seminal analysis.

growth in employment and the 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. Papers 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 we 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 we 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 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. We 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.[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 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 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;

[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).

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.

III. 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 we 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 we have highlighted, the 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 we use to construct our 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 our primary analysis we limit our sample to those news articles with a relevance score above 0.8 to ensure that the sentiment measure we construct is relevant[14] to stock prices and returns. Groß-Klußmann and Hautsch (2011) and Smales (2014b) find that relevance is highly important in identifying information and filtering "noise". Dzielinski (2011) employs an even stricter filter than we do, only considering news items with relevance equal to 1. Owing to the limited attention of investors, we focus only on relevant articles since these are most likely to influence investor behavior.

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

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 we are interested in unique news, we filter for content that is considered "novel", that is news items that are not similar to previous articles.

Table 1 illustrates the effect of our filtering process for news related to Japanese stocks in the TRNA dataset over our sample period, which runs from 1st of January 2003 – 31st of October 2012, coinciding with data availability for TRNA. Initially, we have 971,290 news items for stocks traded on the Tokyo Stock Exchange, of which 363,574 are novel. If we 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 our analysis.

<Insert Table 1>

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 our results. We are 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 we are 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.

<Insert Figure 1>

In a similar vein to Allen et al. (2015), Smales (2014a) and Uhl (2014) we 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

[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 analysed from over 15% at the start of our sample period to approximately 30% in 2014. This is reported to be steadily increasing each year (Fujikawa 2014).

found to construct that firm's daily sentiment score. We 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 we take the simple average of those scores to form a daily market wide level sentiment measure:

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

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:

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

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.

<Insert Table 2>

Figure 2 illustrates the time series of our daily market sentiment measure for the TOPIX for our sample period. We drop all non-trading days from our 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 we filter for relevant and novel news items relating to Japan. Rather than winsorize our 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 we use both sentiment measures in this analysis.

<Insert Figure 2>

Figure 3a 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. 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 of 2008 to 2009 (see Figure 3c). Note that, for Japan, market sentiment is more negative during the crisis period.

<Insert Figure 3>

Figure 3b 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.

A similar measure is constructed for each firm in our sample. Based on a firm's RIC code on any given day, we 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, we find the average of the sentiment scores attached to each unique firm news item to construct the firm level sentiment measure:

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

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, we 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:

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

We 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 4 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, we would expect to see positive returns based on Merton's (1980) relationship of risk and expected returns.

<Insert Figure 4>

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, we include trading volume to proxy for the market's limited attention. We 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, we 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, we 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, we would see a cross sectional effect of news stories in smaller stocks.

Table 3 shows the summary statistics for the main variables used in our 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 we relate negative sentiment to negative (low) returns the two different sentiment measures are also negative for the sample period. This occurs even though the standard deviation of returns is positive and is, as we have noted, contrary to what we would expect, given standard Finance's belief in a positive relationship of return and risk.

<Insert Table 3>

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. We conduct Augmented-Dickey Fuller tests and reject the null of non-stationarity at the 1% level for all our main time series variables.

[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. We 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.

IV. Empirical Analysis

We begin by examining the effects of sentiment on the Japanese stock market as a whole. We 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:

$$R_{mkt_t} = \alpha + \delta avgsentiment_{mkt_t} + \gamma \log volume_{mkt_t} + \lambda \log news_{mkt_t} + \varepsilon_t \quad (5)$$

R_{mkt_t} is the log daily market return of the TOPIX on day t and $avgsentiment_{mkt_t}$ is the contemporaneous sentiment of the TOPIX on day t. As we highlighted previously, sentiment *per se* may not be the only effect news articles may have on the market. Therefore, we include trading volume and the number of news items to proxy for the market's limited attention. $logvolume_{mkt_t,}$ is the change in trading volume by value of the TOPIX on day t and $lognews_{mkt_t,}$ is the number of news articles on the TOPIX on day t.

Sentiment in our equations (1) and (2) 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.

<Insert Table 4>

Table 4 Panel A 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 our sample period, we 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

[18] Available from the corresponding author on request.

breaks in our data set. This result is different to García (2013) who found that the effect of sentiment is greater during recessions.

We repeat the above regression using a weighted probability sentiment measure. Panel B presents the probability weighted sentiment score for equation (3). 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 paper 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. We 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 we have 5,021,095 firm-level daily return observations but only 220,784 individual news items. We sort our sample into deciles based on market capitalization on the 1st of April each year. We choose this date as the majority of firms on the Tokyo Stock Exchange have their financial year-end on the 31st of March. Figure 5 illustrates the composition of news by decile and year. News is concentrated in decile 10 which comprises the largest stocks sorted by market capitalization.

<Insert Figure 5>

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

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

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 we 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 4. The firm level data is a panel and, accordingly, we use panel estimation in our analysis. We conducted a Hausman test for model specification using 1-way fixed (i.e., firm) and random effects, with the null hypothesis of random effects. Using this test, we reject the null hypotheses at 1% and therefore use a fixed effects model.

<Insert Table 5>

We 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 5 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. We also confirm Baker and Wurgler's (2006) result that sentiment typically has a greater effect on small stocks. Baker and Wurgler's hypothesis predicts 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), we do not find evidence of differences in news sentiment effects dependent on market conditions as we did not detect any structural breaks in our 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.

We also see evidence for news and limited attention when we examine the firm news dummies, which are positively significant for all size deciles. This is something that we 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 5, we 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, we 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, we would expect to see cross sectional effects in returns based on firm size and the number of firm news items that we observe. We 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 5 is, to our minds, difficult to explain. We observe significant coefficients on the negative news firm dummies in Table 5. 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 we have adopted panel methodology for examining firm level effects, we have closely followed the approach for the market-level analysis closely. This may be problematic for the panel in that we have assumed that our 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, we repeat the analysis using firm level instruments for sentiment; we model firm sentiment with lagged values using one-way panel fixed effects. The results are presented in Table 6 and are substantively unchanged except for the negative news dummy, where we find evidence of asymmetry in the expected direction except for the middle decile.

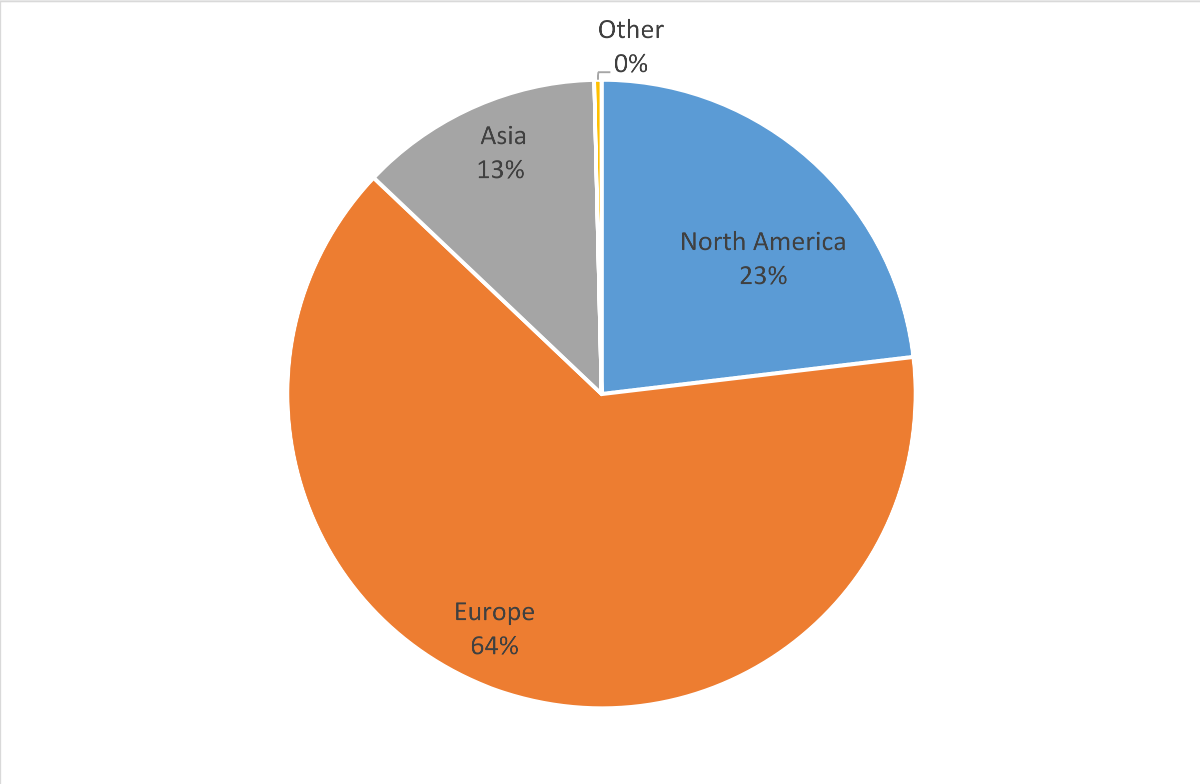
V. Conclusion

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. We use the psychological links between mood 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, we find that sentiment and, in particular, negative sentiment, can explain these returns.

We find that Japanese returns have a positive association with sentiment. The low returns we 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 our sample period. Analyzing the relationship of market sentiment to market level returns, we find that sentiment is the only significant coefficient in our model. Our 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, we 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. We 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 stocks.

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



Source: Japan Exchange Group: http://www.jpx.co.jp/english/markets/statistics-equities/investor-type/07.html.

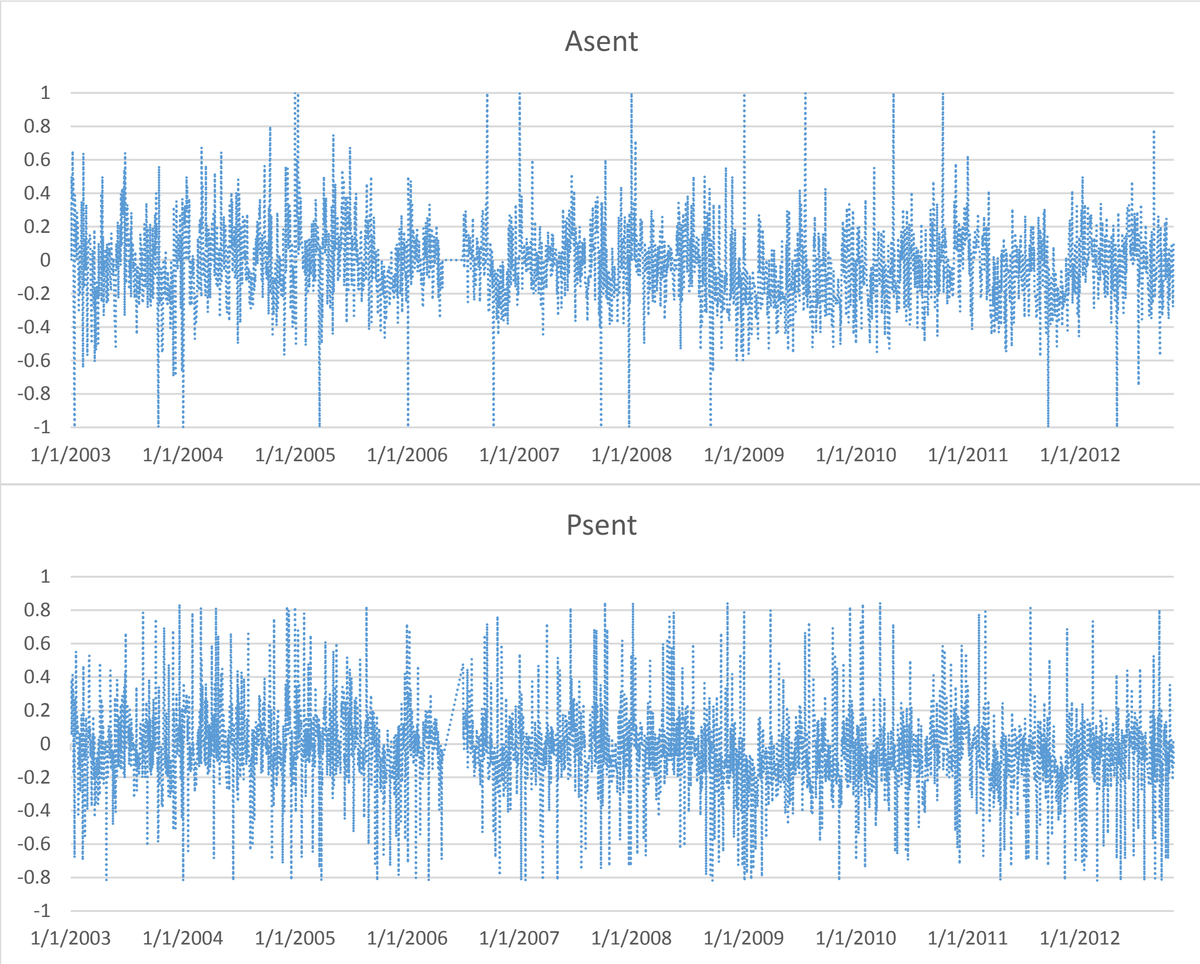
General trading participants with capital of at least 3 billion yen.

The Japanese Exchange Group Defines Foreigners as:

a. "Non-residents" as defined in Article 6, Paragraph 1, Item 6 of the Foreign Exchange Act (Foreign Exchange and Foreign Trade Act). Since the overseas branch offices and overseas subsidiaries of Japanese corporations are also classified as "Non-residents", they are included in "Foreigners", but since Japanese branch offices of foreign corporations excluding those in b. below are classified as "Residents", they will be included in (5) Other corporations or (9) Other financial institutions. Similarly, since Japanese subsidiaries of foreign corporations are classified as "Residents", they will be classified into the respective investment category.

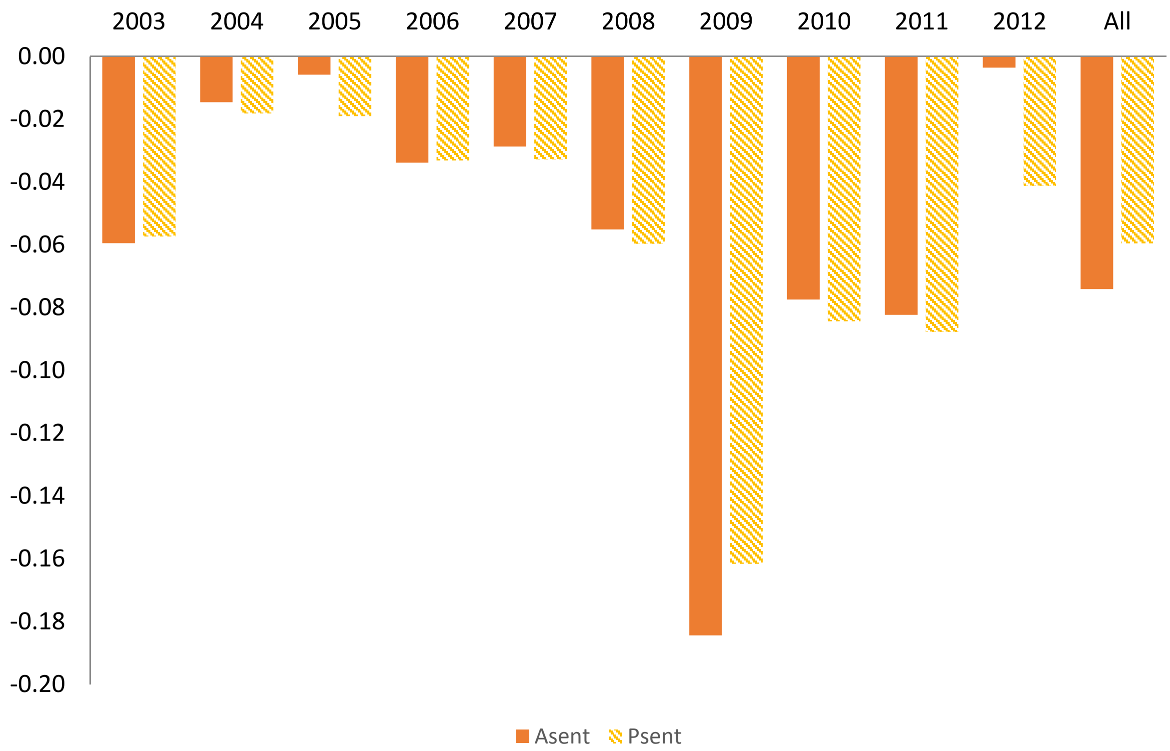
b. Japanese branch offices of foreign securities companies which are not trading participants on TSE.

Figure 2. Daily Market Sentiment for the TOPIX 2003 - 2012



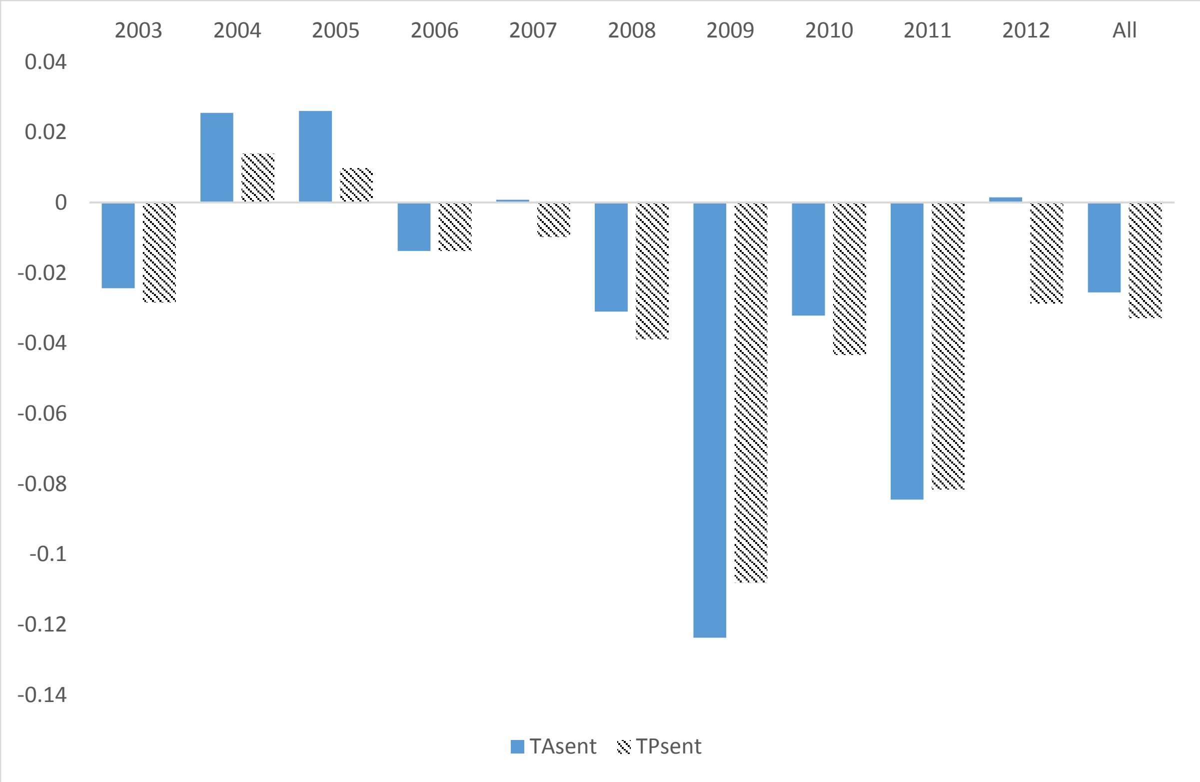
This figure presents a time series plot of constructed sentiment measures.

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



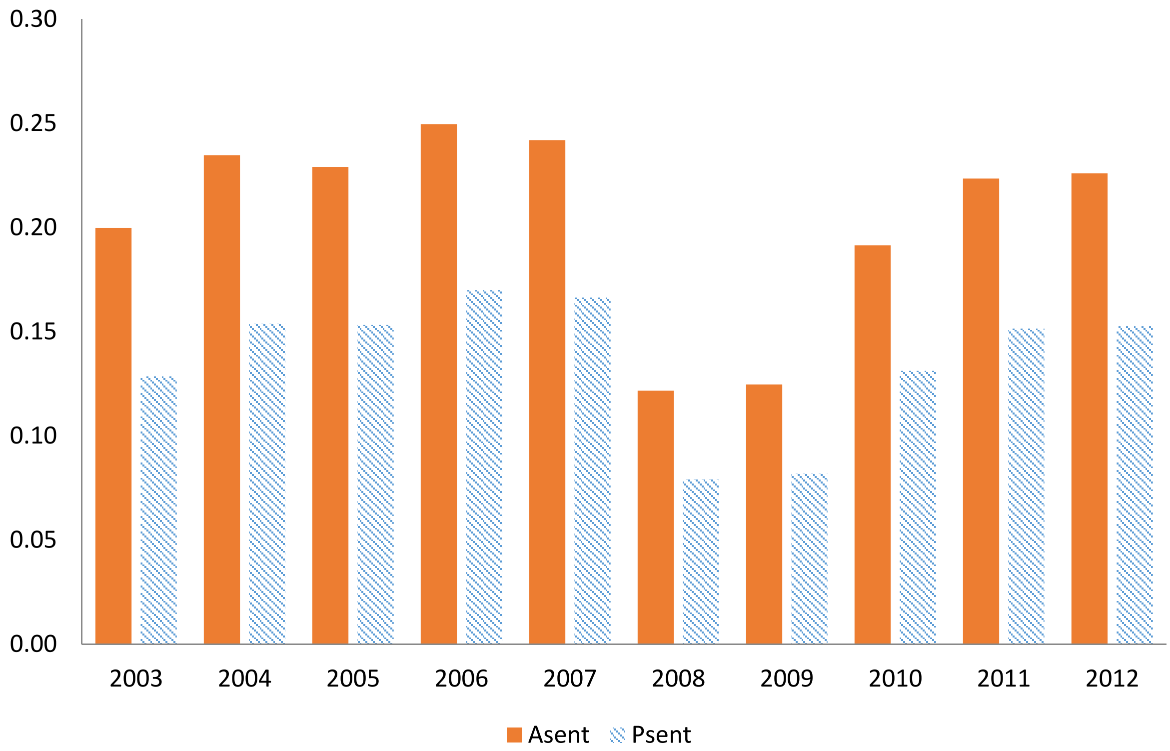
This figure shows the average yearly sentiment for the TOPIX using the same method we use to calculate our sentiment measures for Japan.

Figure 3b. Yearly Market Sentiment for the TOPIX - Trading Days Only 2003 – 2012



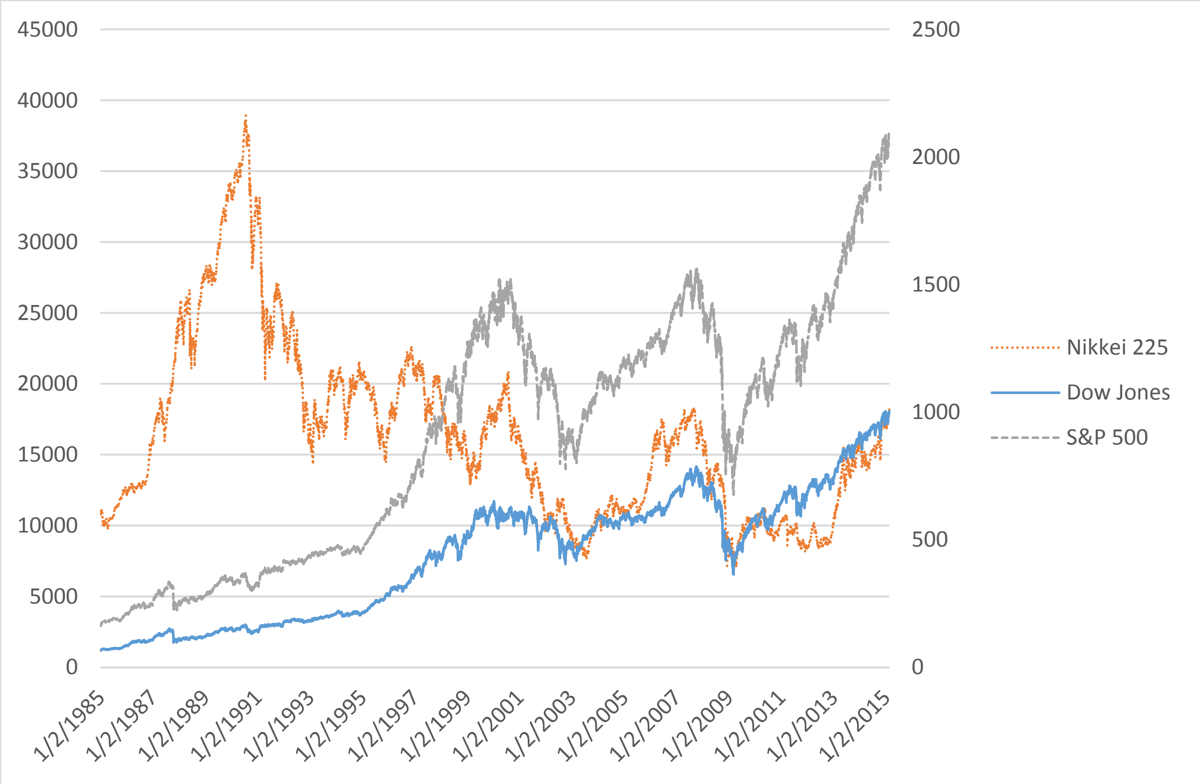
This figure shows the average yearly sentiment for trading days for the TOPIX using the same method we use to calculate our sentiment measures for Japan.

Figure 3c. Average Yearly Sentiment for the New York Stock Exchange 2003 – 2012



This figure shows the average yearly sentiment for the NYSE using the same method we use to calculate our sentiment measures for Japan.

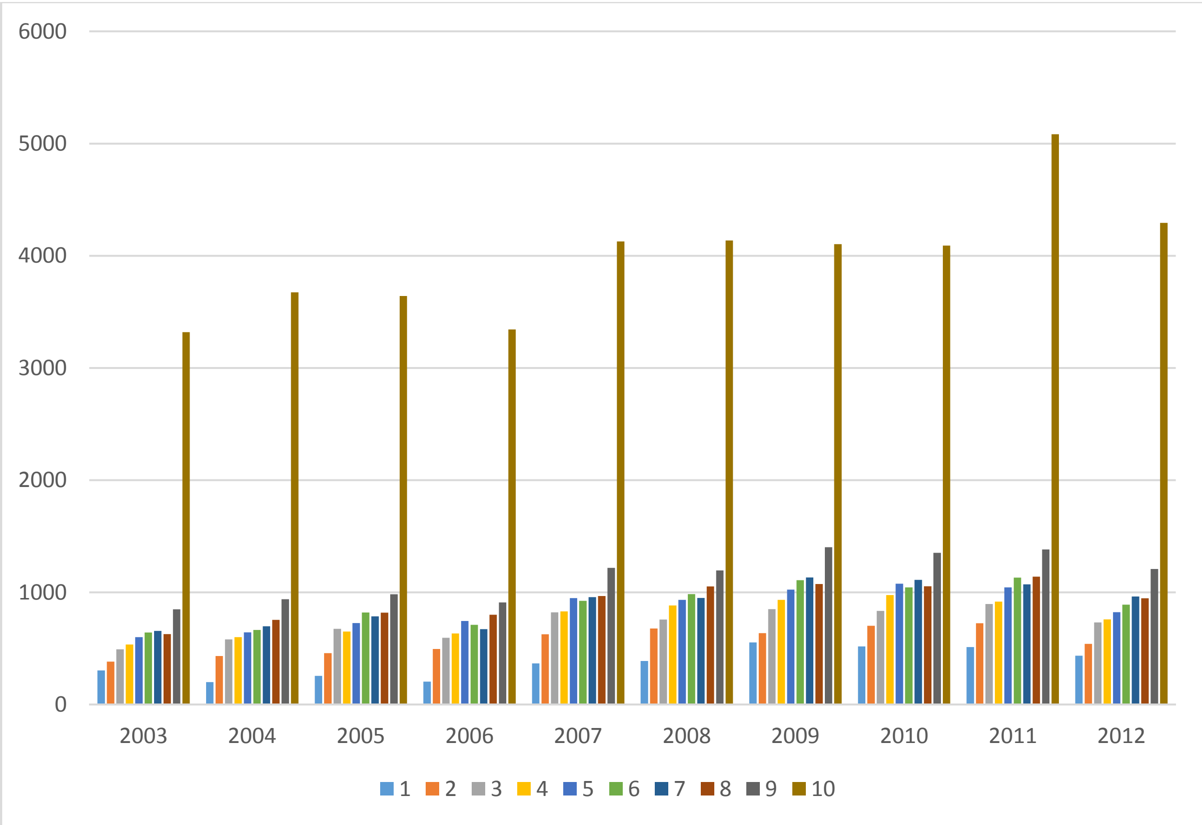
Figure 4. Historical Adjusted Price Chart for the Nikkei 225, Dow Jones and S&P 500 1985 - 2015



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.

Figure 5. Count of Firm News Items by Decile



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.

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 ≥ ± 0.8	474,414	220,784

This table presents the results of filtering the data as described in section IV.

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

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

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

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 (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. 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:

$$R_{mkt_t} = \alpha + \delta avgsentiment_{mkt_t} + \gamma \log volume_{mkt_t} + \lambda \log news_{mkt_t} + \varepsilon_t$$

R_{mkt_t} is the daily log market return of the TOPIX on day t, $avgsentiment_{mkt,t}$ is the contemporaneous sentiment of the TOPIX on day t. We include trading volume, and the number of news items to capture the market's limited attention. $logvolume_{mkt_t,}$ is the change in trading volume by value of the TOPIX on day t and $lognews_{mkt_t,}$ 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)
Market 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 parenthesis ( ).

Table 5. 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:

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

Where $rfirm_{i,t}$ is the daily adjusted log firm return of day t, $sentiment_{firmi,t}$ is the contemporaneous 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 presents results based on an average sentiment measure (3), whilst Panel B presents results based on a probability weighted sentiment measure (4).

Panel A		Smallest									Largest
Decile	All	1	2	3	4	5	6	7	8	9	10
$Sentiment_{firm_{i,t}}$	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)
$Log volume_{mkt,t}$	-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	-.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 R2	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											
$Sentiment_{firm_{i,t}}$	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)
$\log volume_{mkt,t}$	-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
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 parenthesis ( ).

Table 6. 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:

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

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
$Sentiment_{instrume}$	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)
$\log volume_{mkt_t}$	-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)
$Firmnews_{i,t}$	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)
$Lognews_{mkt_t}$	-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–	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-	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 parenthesis ( ).

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References

Akhtar, S., Faff, R., Oliver, B., Subrahmanyam, A., 2011. The power of bad: The negativity bias in Australian consumer sentiment announcements on stock returns. Journal of Banking & Finance 35, 1239-1249.

Akhtar, S., Faff, R., Oliver, B., Subrahmanyam, A., 2012. Stock salience and the asymmetric market effect of consumer sentiment news. Journal of Banking & Finance 36, 3289-3301.

Allen, D.E., McAleer, M.J., Singh, A.K., 2015. Chapter 19 - Machine News and Volatility: The Dow Jones Industrial Average and the TRNA Real-Time High-Frequency Sentiment Series, in: Gregoriou, G.N. (Ed.), The Handbook of High Frequency Trading. Academic Press, San Diego, pp. 327-344.

Allen, E.D., McAleer, M., Singh, A.K., 2014. Machine news and volatility: The Dow Jones Industrial Average and the TRNA sentiment series.

Antoniou, C., Doukas, J.A., Subrahmanyam, A., 2013. Cognitive Dissonance, Sentiment, and Momentum. Journal of Financial and Quantitative Analysis 48, 245-275.

Antweiler, W., Frank, M.Z., 2004. Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. Journal of Finance 59, 1259-1294.

Ashton, J.K., Gerrard, B., Hudson, R., 2003. Economic impact of national sporting success: evidence from the London stock exchange. Applied Economics Letters 10, 783-785.

Ashton, J.K., Gerrard, B., Hudson, R., 2011. Do national soccer results really impact on the stock market? Applied Economics 43, 3709-3717.

Baker, M., Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. Journal of Finance 61, 1645-1680.

Baker, M., Wurgler, J., 2007. Investor Sentiment in the Stock Market. Journal of Economic Perspectives 21, 129-151.

Baker, M., Wurgler, J., Yuan, Y., 2012. Global, local, and contagious investor sentiment. Journal of Financial Economics 104, 272-287.

Barber, B.M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21, 785-818.

Berger, D., Turtle, H.J., 2012. Cross-sectional performance and investor sentiment in a multiple risk factor model. Journal of Banking & Finance 36, 1107-1121.

Boisen, M., Durand, R.B., Gould, J., 2015. From anticipation to anxiety in a market for lottery-like stocks. Review of Behavioural Finance 7, 42-59.

Bollen, J., Mao, H., Zeng, X., 2011. Twitter mood predicts the stock market. Journal of Computational Science 2, 1-8.

Broadbent, D.E., 1957. A mechanical model for human attention and immediate memory. Psychological Review 64, 205-215.

Broadbent, D.E., 1958. Perception and communication. New York : Pergamon Press, New York.

Chen, N.-F., 1991. Financial Investment Opportunities and the Macroeconomy. The Journal of Finance 46, 529-554.

Chen, N.f., Kan, R., Miller, M.H., 1993. Are the Discounts on Closed-End Funds a Sentiment Index? Journal of Finance 48, 795-800.

Chung, S.-L., Hung, C.-H., Yeh, C.-Y., 2012. When does investor sentiment predict stock returns? Journal of Empirical Finance 19, 217-240.

da Silva Rosa, R., Durand, R.B., 2008. The role of salience in portfolio formation. Pacific-Basin Finance Journal 16, 78-94.

Durand, R.B., Limkriangkrai, M., Fung, L., 2014. The behavioral basis of sell-side analysts' herding. Journal of Contemporary Accounting & Economics 10, 176-190.

Dzielinski, M., 2011. News sensitivity and the cross-section of stock returns. NCCR Finrisk Working Paper no. 719.

Edmans, A., García, D., Norli, Ø., 2007. Sports Sentiment and Stock Returns. Journal of Finance 62, 1967-1998.

Fujikawa, M., 2014. Foreign Ownership of Japan Shares Hits All-Time High, The Wall Street Journal. The Wall Street Journal.
García, D., 2013. Sentiment during Recessions. Journal of Finance 68, 1267-1300.
Gerrards-Hesse, A., Spies, K., Hesse, F.W., 1994. Experimental inductions of emotional states and their effectiveness: A review. British Journal of Psychology 85, 55-78.
Goetzmann, W.N., Kim, D., Kumar, A., Wang, Q., 2014. Weather-Induced Mood, Institutional Investors, and Stock Returns. Review of Financial Studies.
Groß-Klußmann, A., Hautsch, N., 2011. When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. Journal of Empirical Finance 18, 321-340.
Hendershott, T., Livdan, D., Schürhoff, N., 2015. Are institutions informed about news? Journal of Financial Economics 117, 249-287.
Hengelbrock, J., Theissen, E., Westheide, C., 2013. Market Response to Investor Sentiment. Journal of Business Finance & Accounting 40, 901-917.
Hirshleifer, D., Shumway, T., 2003. Good Day Sunshine: Stock Returns and the Weather. Journal of Finance 58, 1009-1032.
Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36, 337-386.
Johnson, E.J., Tversky, A., 1983. Affect, generalization, and the perception of risk. Journal of Personality and Social Psychology 45, 20-31.
Kahneman, D., Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica 47, 263-291.
Kamstra, M.J., Kramer, L.A., Levi, M.D., 2003. Winter Blues: A SAD Stock Market Cycle. American Economic Review 93, 324-343.
Kaplanski, G., Levy, H., 2010. Exploitable Predictable Irrationality: The FIFA World Cup Effect on the U.S. Stock Market. Journal of Financial and Quantitative Analysis 45, 535-553.
Kaplanski, G., Levy, H., Veld, C., Veld-Merkoulova, Y., 2014. Do Happy People Make Optimistic Investors? Journal of Financial and Quantitative Analysis FirstView, 1-42.
Klibanoff, P., Lamont, O., Wizman, T.A., 1998. Investor Reaction to Salient News in Closed-End Country Funds. Journal of Finance 53, 673-699.
Lemmon, M., Portniaguina, E., 2006. Consumer Confidence and Asset Prices: Some Empirical Evidence. Review of Financial Studies 19, 1499-1529.
Loewenstein, G., 2000. Emotions in Economic Theory and Economic Behavior. The American Economic Review 90, 426-432.
Lucey, B.M., Dowling, M., 2005. The Role of Feelings in Investor Decision-Making. Journal of Economic Surveys 19, 211-237.
Merton, R.C., 1973. An Intertemporal Capital Asset Pricing Model. Econometrica 41, 867-887.
Merton, R.C., 1980. On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics 8, 323-361.
Müller, G., Durand, R.B., Maller, R.A., 2011. The risk–return tradeoff: A COGARCH analysis of Merton's hypothesis. Journal of Empirical Finance 18, 306-320.
Qiu, L., Welch, I., 2006. Investor Sentiment Measures. SSRN Working Paper Series.
Saunders, E.M., Jr., 1993. Stock Prices and Wall Street Weather. The American Economic Review 83, 1337-1345.
Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. Journal of Empirical Finance 16, 394-408.
Schwarz, N., Clore, G.L., 1983. Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. Journal of Personality & Social Psychology 45, 513-523.
Shiller, R.J., 2000. Irrational exuberance / Robert J. Shiller. Princeton, NJ : Princeton University Press, Princeton, NJ.

Shiratsuka, S., 2005. The asset price bubble in Japan in the 1980s: lessons for financial and macroeconomic stability, BIS Papers No 21. Bank for International Settlements Basel, Switzerland.
Smales, L.A., 2014a. News sentiment in the gold futures market. Journal of Banking & Finance 49, 275-286.
Smales, L.A., 2014b. Non-scheduled news arrival and high-frequency stock market dynamics: Evidence from the Australian Securities Exchange. Research in International Business and Finance 32, 122-138.
Smales, L.A., 2015a. Asymmetric volatility response to news sentiment in gold futures. Journal of International Financial Markets, Institutions and Money 34, 161-172.
Smales, L.A., 2015b. Time-variation in the impact of news sentiment. International Review of Financial Analysis 37, 40-50.
Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104, 288-302.
Tetlock, P.C., 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. Journal of Finance 62, 1139-1168.
Tetlock, P.C., Saar-Tsechansky, M., Macskassy, S., 2008. More Than Words: Quantifying Language to Measure Firms' Fundamentals. The Journal of Finance 63, 1437-1467.
Thomson Reuters. 2013. Thomson Reuters News Analytics: Sentiment analysis, relevance, novelty. White paper, Thomson Reuters, New York.
Tsuji, C., 2006. Does investors' sentiment predict stock price changes? With analyses of naive extrapolation and the salience hypothesis in Japan. Applied Financial Economics Letters 2, 353-359.
Uhl, M.W., 2014. Reuters Sentiment and Stock Returns. Journal of Behavioral Finance 15, 287-298.
Yu, J., Yuan, Y., 2011. Investor sentiment and the mean–variance relation. Journal of Financial Economics 100, 367-381.