Melancholia and Japanese Stock Returns – 2003 to 2012

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ABSTRACT

Japan's "lost decades" challenge Finance's central tenet of a positive 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. Sentiment is predominately negative during our sample period (2003 to 2012). The effect of news sentiment is greatest for smaller firms. We utilize a text-based measure of news sentiment (Thomson Reuters News Analytics) to proxy for investor sentiment.

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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. Since the crash that followed the Nikkei stock index which peaked, at 38,916, in December 1989, the Japanese share market has failed to come close to regaining pre-crash levels. The market further declined into the 2000s, and this result has translated into historically poor equity returns.

Shiratsuka (2005) describes this time period and bubble as a consequence of "euphoria" or "optimism", consistent with the "irrational exuberance" of Shiller (2000). Shiratsuka argues that this asset pricing bubble is distinct from a rational asset pricing bubble, since there is divergence from economic fundamentals. Shiratsuka's argument motivates us to explore a behavioural-based explanation of Japan's stock market stagnation. This paper examines if sentiment can be a potential explanation.

In particular, we examine the relationship between the returns on the Tokyo Stock Exchange (TOPIX)[2] and investor sentiment over the period from January 2003 to October 2012. This time period encompasses part of the "second lost decade of Japan".

Using a text-based measure of news sentiment (Thomson Reuters News Analytics) to proxy for investor sentiment, we find a positive contemporaneous relationship between market sentiment and stock returns at both an aggregate market and individual firm level. The consistently poor returns of the Japanese stock market are driven by negative sentiment that is pervasive. Our measure of market sentiment is negative for most years in our sample, 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. We also find evidence to suggest that the effect of news sentiment is greatest on stocks of smaller firms, although smaller firms generally have fewer news items.

The remainder of this paper is as follows: Section II provides a background into the literature, Section III describes research questions, Section IV explains data and methodology, Section V presents empirical results and Section VI concludes the paper.

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[1] See Müller, Durand, and Maller (2011) for a review of literature discussing the relationship of risk and expected return.

[2] 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.

II. Background

Mood has been found to have influencing or conditioning effects on human decision making, perception and behaviour (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 theorised that an individual's judgement is influenced by their current mood state, even if the subject matter they are analysing 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 influence an individual's mood or emotion, which in turn acts as a channel influencing preferences. As a result, an individual investor's behaviour 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 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 behaviour, (Brown and Cliff 2005, Baker and Wurgler 2006, Tetlock 2007, Tetlock, Saar-Tsechansky, and Macskassy 2008, Stambaugh, Yu, and Yuan 2012). Sentiment is not directly observable, only its effects are visible, and so in seeking to analyse its influence on market behaviour we must introduce a proxy. The earliest works proxy investor sentiment through weather. Psychology and behavioural economics developed the framework illustrating effects of weather on investors. In this literature, Saunders (1993) presented an early and influential 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 behaviour 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 26 countries from 1982 to 1999 and also found a significant positive relationship between sunny days and stock returns. Although the effect found is weak, it is associated with positive abnormal returns. Kamstra, Kramer, and Levi (2003) and Goetzmann et al. (2014) examined mood fluctuations due to Seasonal Affective Disorder (SAD) and the effects on stock markets. Kamstra, Kramer, and Levi (2003) found a relationship between SAD and investor risk aversion. They examined 9 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, selling (buying) stock 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 increased propensity to buy on sunnier days, but 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 has a negative sentiment effect. Ashton, Gerrard et al. (2003; 2011) documented a relationship between the performance of the English National Football team and share prices on the London stock exchange. Edmans, García, and Norli (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 theorised 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"[3] affects expected household investor returns more "intensely than expected risk". They examined the relationship between non-economic "sentiment-creating measures"[4] on investors

[3] 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).

[4] 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.

using survey data from 5,000 households in the Netherlands. These measures are comprised of mood inducing factors which have been identified in previous literature as having aggregate investor behaviour effects on share market returns. They confirmed the existence of an asymmetric effect of mood on expectations, the presence of a SAD effect 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 to intended investment behaviour. 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 popularised 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 6 candidate proxies for market sentiment.[5] The six identified 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 principle components analysis of the candidate proxies orthogonalised to a set of state variables (commonly used in empirical work in intertemporal, or consumption, Capital Asset Pricing Models[6]). These state variables are industrial production, real growth in durable, non-durable, and services consumption, 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 utilise 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, Wurgler, and Yuan (2012), Chung, Hung, and Yeh (2012) and Stambaugh, Yu, and Yuan (2012). On the other hand, the literature (Nai-Fu, Kan, and Miller 1993, Qiu and Welch 2006, Lemmon and Portniaguina 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 (Lemmon and Portniaguina 2006, Akhtar et al. 2011, 2012, Antoniou, Doukas, and Subrahmanyam 2013, Brown and Cliff 2005, Hengelbrock, Theissen, and Westheide 2013). Examples of surveys include the Conference Board Consumer Index

[5] 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 orthogonalised 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 principle components analysis.
[6] See Chen 1991 for a seminal analysis.

(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 (Tetlock, Saar-Tsechansky, and Macskassy 2008, Tetlock 2007, García 2013, Smales 2014a, Uhl 2014, Dzielinski 2011, Groß-Klußmann and Hautsch 2011, Allen, McAleer, and Singh 2015). 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 (Da et al. 2014), and social media posts (Bollen, Mao et al., 2011), in addition to more traditional dissemination 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 behaviour. The other two measures are updated at a slower rate and arguably misses this dynamic component of sentiment. Tetlock, Saar-Tsechansky, and Macskassy (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 readily simple to identify a candidate for the mechanism through which the sentiment identified from 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, or music.[7][8]

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 proportion of each word-type. This simple approach may be problematic as there is no guarantee that negative words

[7] To experience the effectives 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).

[8] For reviews on mood induction see, Gerrards-Hesse, Spies, & Hesse, 1994 and Westermann, Spies, Stahl, & Hesse, 1996.

on their own imply negative sentiment (e.g. double negatives). Contemporary methods utilise 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. Examples of market vendors of these services are Thomson Reuters News Analytics (TRNA) and Ravenpack.

Tetlock (2007) was the first 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 “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 “news is linked to behaviour of individual investors, who own a disproportionate fraction of small stocks”. Tetlock also noted a relationship between sentiment and trading volume with trading volume increasing with negative sentiment.

García (2013) also analysed the text of a WSJ news column and found that the predictive power of such news-sentiment is concentrated in recession. Such news columns are overviews of market events, summarising 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 behavioural 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 utilises 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[9] 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

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

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 Thomson Reuters News Analytics (TRNA) to construct a sentiment measure to test the ability of sentiment to predict of returns of the Dow Jones Industrial Average (DJIA). Uhl (2014) found that this measure of sentiment was able to forecast returns better 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. Research Questions

The literature discussed for mood and text based analytics in the previous section provides the behavioural framework on which we base our first research question. Framing investor sentiment in our study using this transmission mechanism, sentiment is considered as an aggregate market-wide investor mood or feeling. García (2013) used a similar psychological framework and stated “human behaviour is significantly different in times of anxiety and fear versus periods of prosperity and tranquillity”. Our first research question examines whether news sentiment has market-wide effects in the Japanese stock market. We theorise that, consistent with the literature, that sentiment has a significant positive relationship with stock returns, and thus the prolonged downturn in Japanese markets may be attributed to a prevalent negative mood state. Durand, Simon, and Szimayer (2009) found evidence that “depression” (in particular, low arousal negative affective states) has been associated with Australian bear markets.[10] Another broad finding in the sentiment literature is that investors react more significantly to negativity, which might explain stock returns if news and sentiment is predominately negative for Japan (Tetlock 2007, Uhl 2014, García 2013, Smales 2014b, Dzielinski 2011, Akhtar et al. 2011, Tetlock, Saar-Tsechansky, and Macskassy 2008).

Our second research question examines the influence of sentiment on the returns at the individual firm-level. In general, the literature focusing on U.S. markets suggests that sentiment has a greater effect on small firms. Baker and Wurgler (2006; 2007) found a size effect and argued that limits to arbitrage will cause smaller stocks to be more “sentiment prone”. Berger and Turtle (2012)

[10] Durand *et al.* conducted their analysis before text based analytics were known and available an, therefore, they rely on proxies for their analysis of mood.

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 has a greater influence on small firms, although there is conflicting evidence as to whether the effect is greatest for stocks categorised as value or growth. The study of a cross-sectional effect of sentiment, has largely ignored text-based measures such as that employed here, and to our knowledge this effect not been examined in Japan.

IV. Data and Methodology

This study utilises a text-based sentiment measure to examine the effects of news on Japanese stock markets. As we have noted, text-based measures have been utilised on markets that exhibit the expected relationship between risk and expected returns[11], but have not been used in a Japanese context. The particular sentiment measure that we construct utilises data provided by Thomson Reuters News Analytics (TRNA). TRNA uses a uses a neural network to classify the sentiment associated with news stories, primarily by examining sentences, rather than individual words. This has the advantage of incorporating words in context rather than standalone meaning. The training of the neural network was undertaken by using 5,000 news items classified by three former traders. Recent studies that have utilised this data set include Hendershott et al. 2015; Smales 2014; 2015a; 2015.b. This dataset is chosen for several reasons. First, 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. Second, 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 announcement, will influence an investor's mood, impacting their judgement and subsequently influencing trading behaviour. Finally, the TRNA algorithm allows us to consider the potential impact of news that is categorised as "good", "bad" or "neutral".

As we have previously noted, the TRNA uses a linguistic algorithm to analyse 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 microsecond 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.

[11] For example, Tetlock (2007) and Saar-Tsechansky (2008) examine the U.S. stock market, while Smales (2014) considers the Australian market.

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 categorised 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 characterised 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 news articles of relevance score above 0.8 to ensure that the sentiment measure we construct is relevant[12] 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 on relevant articles only since these are most likely to influence investor behaviour.

3. *Novelty*: Measures how unique a particular news item is relevant to previous 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. After filtering for news classified as relevant we are left with 474,414 news items. Filtering for novel news items leaves us with 220,784 unique news items that are used to construct the sentiment measures used in our analysis.

<Insert Table 1>

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

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 subjected to cultural differences in interpretation by investors. Foreign investors account for a significant proportion of stock market activity in Japan; 45% by volume and 53% by value in 2014, and this has increased to a high of 70% in 2015 (Nikkei, 2015). Near the beginning of the sample period this was 22% by volume and 28% by value[13]. Figure 1 presents this breakdown by region.

<Insert Figure 1>

Furthermore, total foreign ownership of Japanese shares has grown over the sample period analysed from over 15% at the start of our sample period, and in 2014 was approximately 30%. This is reported to be steadily increasing each year (Fujikawa 2014). Additionally, 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.[14]

In a similar vein to Allen, McAleer, and Singh (2015), Smales (2014a), 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 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:

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

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

[13] Year 2005, as data provided by the Japan Exchange Group begins here.

[14] Similar arguments for proxies have been used in the literature. 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.

firm news items on a day, one is 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 categorised. 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.

<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 winsorise 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 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 period of 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. We take each unique news item based on a firm's RIC code on any given day 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:

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

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:

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

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 are the near zero equity returns and flat growth compared to other equity markets around the world, particularly contrasted with other developed markets. Figure 3 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, (positive σ), we would expect to see positive returns based on Merton's (1980) relationship of risk and expected returns.

<Insert Figure 4>

Sentiment *per se* may not be the only effect news articles may have on the market. Therefore, we include trading volume to proxy for the market's limited attention. We also obtain data on trading volume and the number of news items in order to control for limited attention. Limited Attention affects investor behaviour since investors tend to buy rather than sell 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, Limkraingkrai and Fung (2015) highlight and utilise Broadbent's (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 behaviour – 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. (2015) provide evidence that both trading volume and the number of news stories are proxies for limited attention. Durand et al. (2015), however, argue that market capitalization is a proxy for investors' selective attention. Accordingly, we will form portfolios based on firm size to further analyse if sentiment is in some way associated with limited attention.[15]

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, Lamont, and Wizman 1998). da Silva Rosa and Durand (2008) found that the

[15] 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 capitalisation 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, Limkriangkrai and Fung (2015) is that the latter make the claim that firm size is associated with salience by assertion whereas the latter argue that size is related to selective attention using empirical evidence.

choice of portfolio stocks is predominantly 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 Observations represents the common observations used in the regression analyses. Panel A shows summary statistics and median 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 as expected. This occurs even though σ is positive.

<Insert Table 3>

Panel B shows summary statistics for daily data at the *firm* level. The average firm return in most years is close 0. The two sentiment measures are marginally negative and are much smaller than for the market level due to the many neutral firm sentiment scores that bias the sentiment measure downwards. The majority of our variables are not normally distributed, largely as a result of the clustering of sentiment scores around 0 due to firms with no news items on a given day. We reject the null of non-stationarity at the 1% level for all our main time series variables. We perform Augmented-Dickey Fuller tests and were able to reject the Null hypothesis of stationary in our data series.

V. Empirical Analysis

We first examine the effects of sentiment on the Japanese stock market using a wide lens to broadly confirm our hypothesis of sentiment effects before delving into cross-sectional analysis. 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:

$$R_{mkt_t} = \alpha + \delta avgsentiment_{mkt_t} + \gamma \log volume_{mkt_{t-1}} + \lambda \log news_{mkt_t} + \varepsilon_t \quad (5)$$

R_{mkt_t} is the 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. $logvolume_{mkt_{t-1}}$, is the lagged trading volume by value of the TOPIX on day t-1 and $lognews_{mkt_t}$, is the number of news articles on the TOPIX on day t.

Sentiment in our equation (1) and (2) are contemporaneous and exogenous to sentiment. Our approach differs from Tetlock (2007), Dzielinski (2011) and Uhl (2014) where returns were found to affect sentiment and, accordingly, methodologies such as Vector Autoregression (VAR) were utilised. Unreported analyses[16] showed that both contemporaneous, lagged and contemporaneous or lagged value of returns were insignificant in models of both the simple average and probability weighted sentiment. Therefore, neither a two-stage least squares analysis nor Vector VAR analysis, such as that presented in Tetlock (2007) or Uhl (2014), appears 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. This indicates that a day with negative news sentiment depresses daily stock returns by -0.0046%. This result is consistent with other results in the literature that find a positive relationship between sentiment and share market returns (Tetlock 2007, Uhl 2014, García 2013, Allen, McAleer, and Singh 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 by the number of news articles of the day. On the face of it this suggests that sentiment, rather than the alternative explanation of limited attention is the primary driver behind negative or zero returns.

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 disconnect between Merton's (1980) theory of a positive expected risk-return relationship and the returns of the Japanese share market. 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, 0.0075[17].This measure's construction is similar to the simple average sentiment measure used previously and has been used previously in the literature (Dzielinski 2011; Smales 2014a; Allen, McAleer; and Singh 2015). 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 co-efficient, however the direction of the effect is unchanged. A Quandt-Andrews Breakpoint Test was conducted which did not detect any structural breaks in our data set. This result is different to García (2013) who found that the effect of sentiment is greater during recessions.

[16] Available from the corresponding author on request.
[17] A Wald test for equality in the two co-efficient finds that they are significantly different.

The previous section highlights the potential effects that news sentiment has on investor decision making in the Japanese stock market, and provides prime 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 capitalisation 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 4 illustrates the composition of news by decile and year. News is concentrated in decile 10 which is comprised of the largest stocks sorted by market capitalisation.

<Insert Figure 5>

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

$$\begin{aligned} r_{firm_{i,t}} &= \alpha + \beta sentiment_{firm_{i,t}} + \delta \log volume_{mkt_{i,t-1}} + \gamma negativenews_{i,t} \\ &+ \varphi\, firmnews_{i,t} + \lambda lognews_{mkt,t} + \varepsilon_{i,t}\, i \end{aligned} \tag{6}$$

Where $rfirm_{i,t}$ is the daily adjusted firm return of day t, $sentiment_{firmi,t}$, is the contemporaneous sentiment of firm i on day t, $logvolumemkt_{t-1}$, is the lagged trading volume by value of the TOPIX i on day t-1, $negativenews_{i,t}$ 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 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 relatively to other deciles. Decile 1 in both Panel A and B of Table 5 have the highest positive coefficients at 0.0145 and 0.0385 respectively. This is compared to the highest decile 10, which has 0.0020 and 0.0049, 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, Wurgler, and Yuan 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 dependant on market conditions given we did not detect any structural breaks in our data set. One of the reasons could be 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, similarly to 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, but this is 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 not 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 coefficient, 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 that 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 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 simply applies in this case 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 using lagged values using one-way panel fixed effects. The results are presented in Table **7** 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.

As we have highlighted when discussing market level sentiment, we did not find evidence that sentiment was endogenous to returns at the market level. In addition, we found that there is no support for endogeneity at the firm level either.[18] However, it is worthwhile considering if our results are robust to the possibility of the endogeneity of sentiment and, therefore, we re-examine the effect that firm sentiment has on firm returns using a two stage least squares (TSLS) estimator, using predicted values of sentiment as an instrument. Table 6 presents the results for the two staged least squares regression for a market level analysis. Using the predicted values of sentiment as an instrument returns a positively significant coefficient of 0.1042. This result broadly corresponds to the results discussed in the previous section where our coefficients for sentiment were positively significant for all model specifications. Using the TSLS framework yields a general picture which is consistent with our results in the previous sections, however a clearer interpretation for the effects of firm news and negative news can be identified. In the previous sections firm news and negative news had mixed results in the firm level analysis, especially once viewed in cross section sorted by size. In this framework, both of the coefficients for firm news and negative news are significant at 0.0039 and -0.0040 respectively. We interpret these coefficients as indicating that firstly, news matters owing to limited attention and secondly, that the presence of negative firm news has a detrimental effect on contemporaneous firm returns. Table 6 and Table 7 presents these results in more detail, however they broadly agree with our previous analysis.

VI. Conclusion

Japan's historically poor stock returns challenges a central idea in Finance of a positive relationship between returns and risk. We use the psychological links between mood and investor

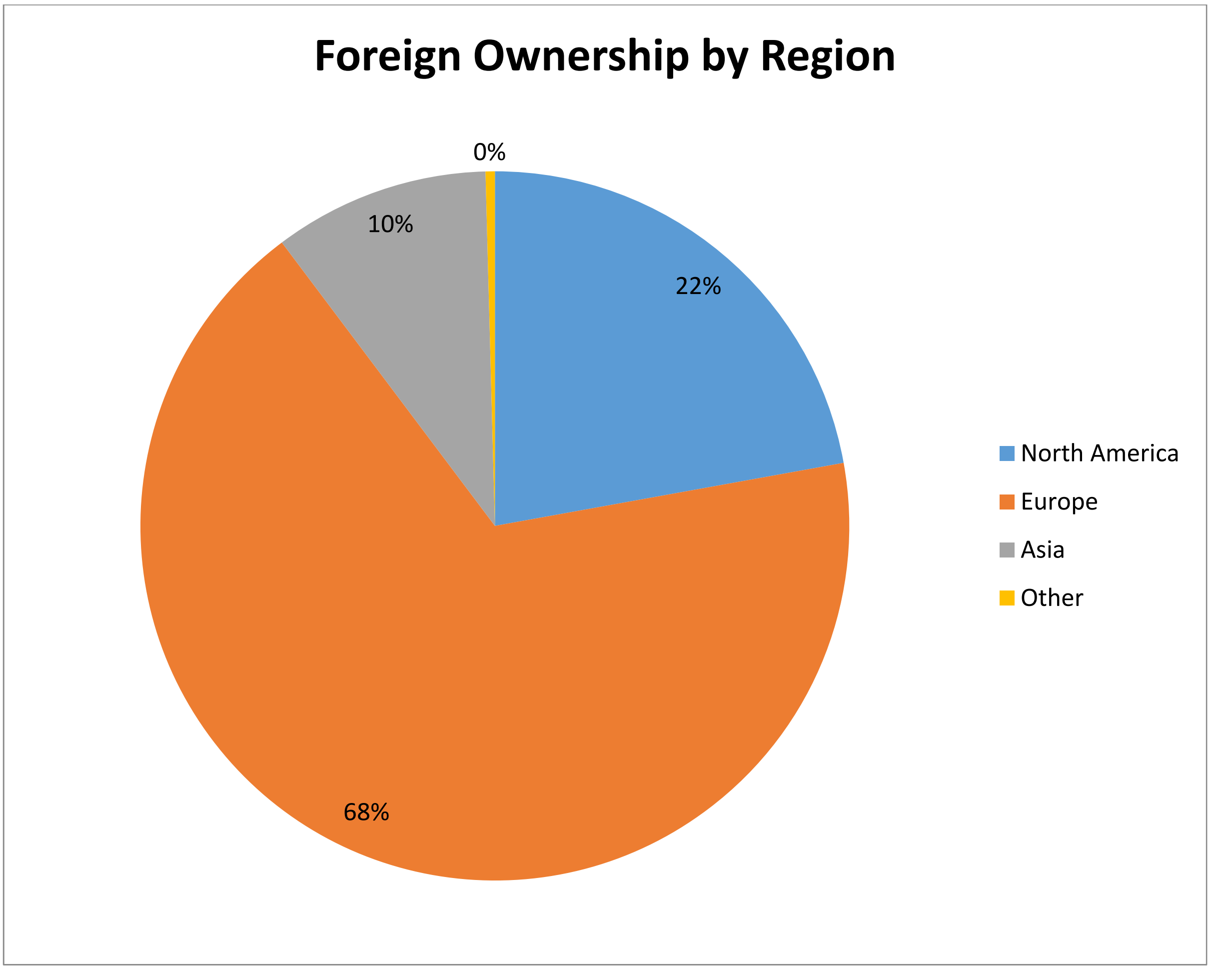
[18] We conducted a vector autoregressive analysis using returns, sentiment, news and trading volume and initially found evidence suggestive that lagged relationships might be statistically significant. Consideration of the variance decomposition associated with this vector autoregression, however, indicated that these initial inferences were not robust. Variance decomposition using impulse functions show that less than 0.01% of the variation in returns was explained by sentiment and vice versa. Variance decomposition can be utilised as a check on inferences made using impulse response functions. If a factor's variance is fully explained by its own variance, none of the lagged observations of the other variables have a role in explaining the variable.

decision making to examine if there is any relationship between sentiment and Japanese stock returns. Taking advantage of sentiment classified news to proxy for our measure, we find that sentiment, and in particular negative sentiment can explain of these returns.

We find that Japanese returns have a positive association with sentiment. The low returns we observe in Japan are a function of negative sentiment. Sentiment derived from newswire messages for Japan is on average negative during our sample period. Analysing 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 size, 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 limited attention and news when examining sentiment and the cross section of firms. The presences 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)



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

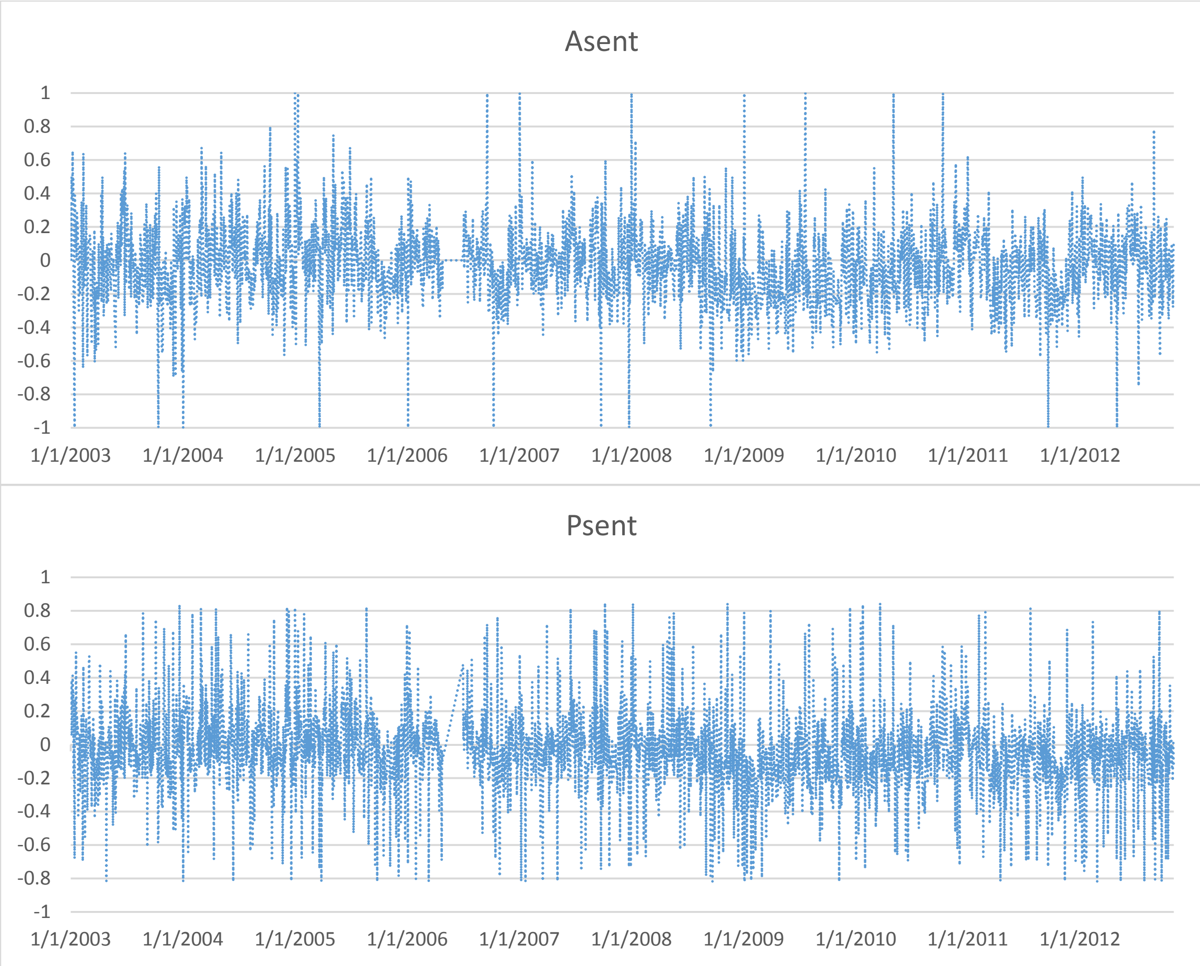
General trading participants with capital of at least 3 billion yen.

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.

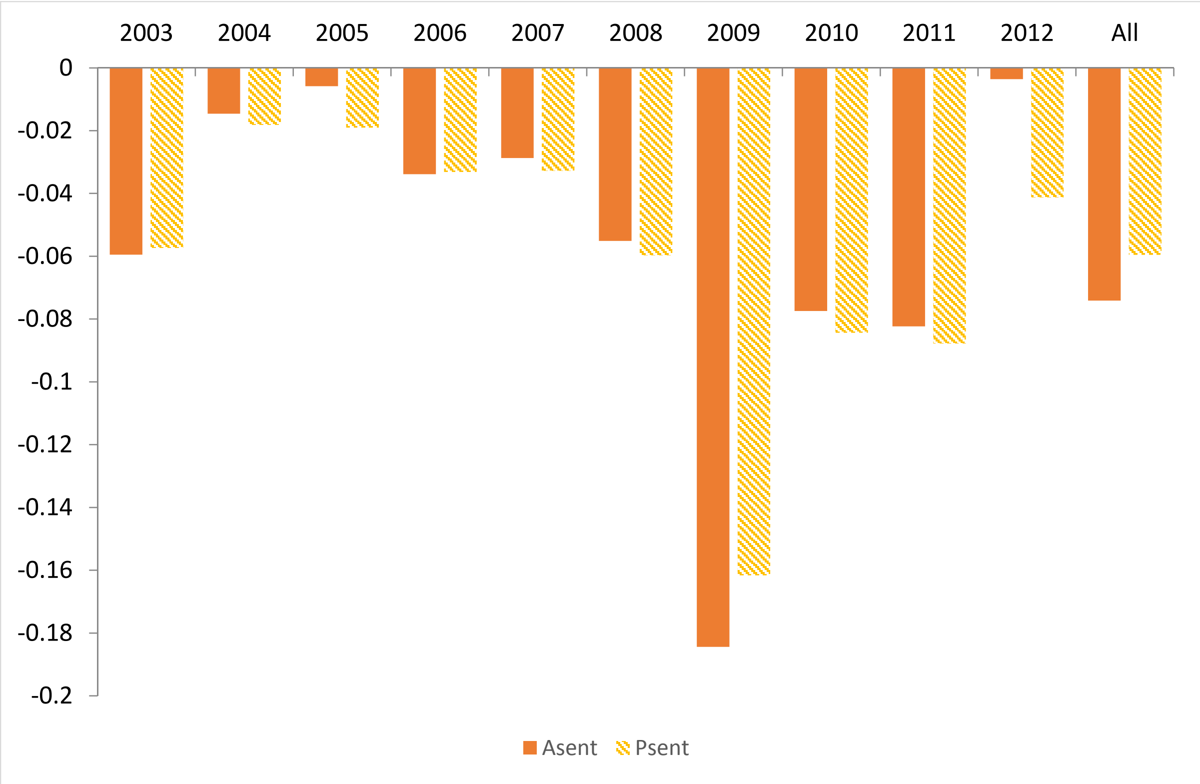
b. Japanese branch offices of foreign securities companies which are not trading participants on TSE.

Figure 2. Daily Market Sentiment for the TOPIX



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

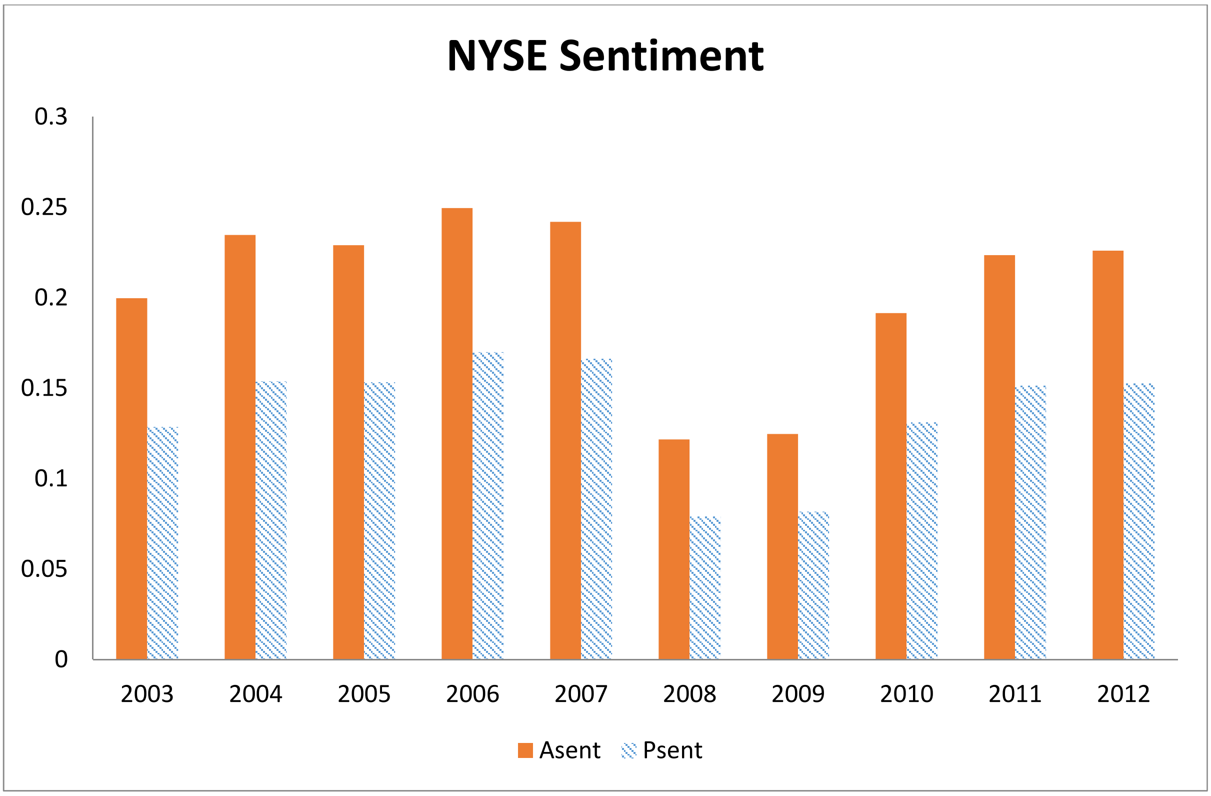


This figure shows the average yearly sentiment for the TOPIX using the same method we use to calculate our sentiment measures for Japan.

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

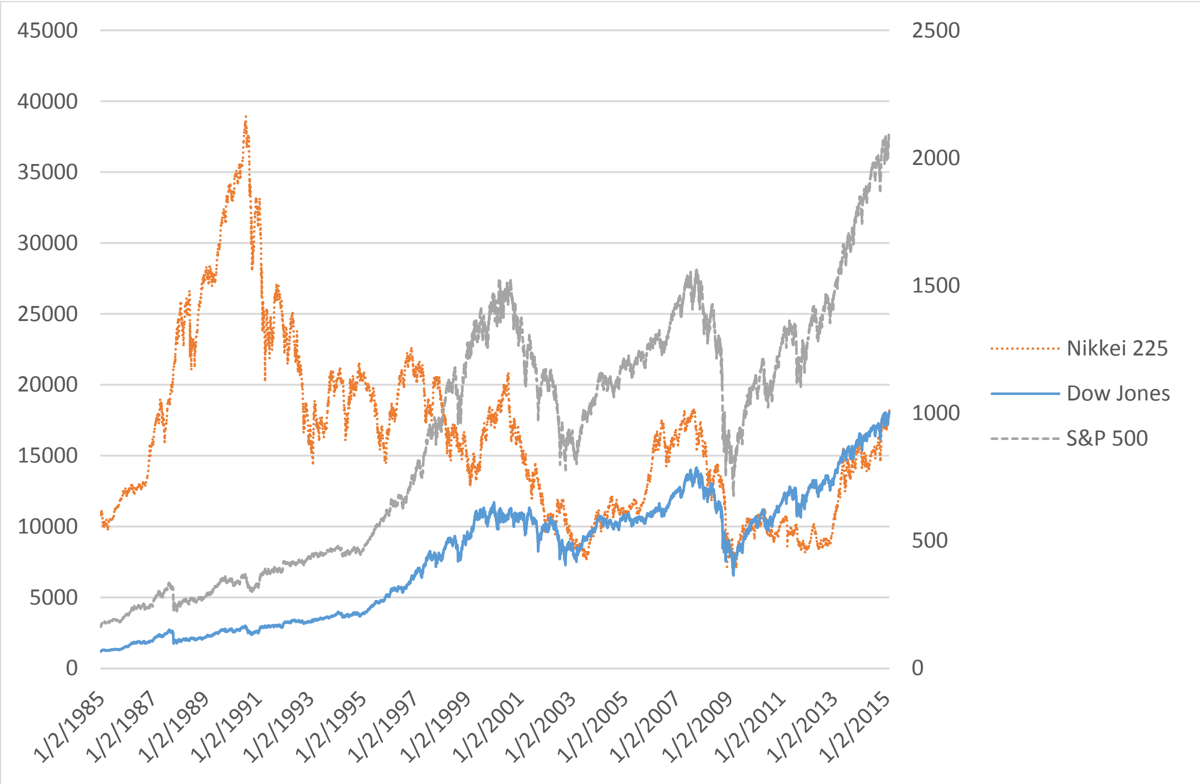
This figure shows the average yearly sentiment for trading days for the TOPIX using the same method we use to calculate our sentiment measures for Japan.

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.

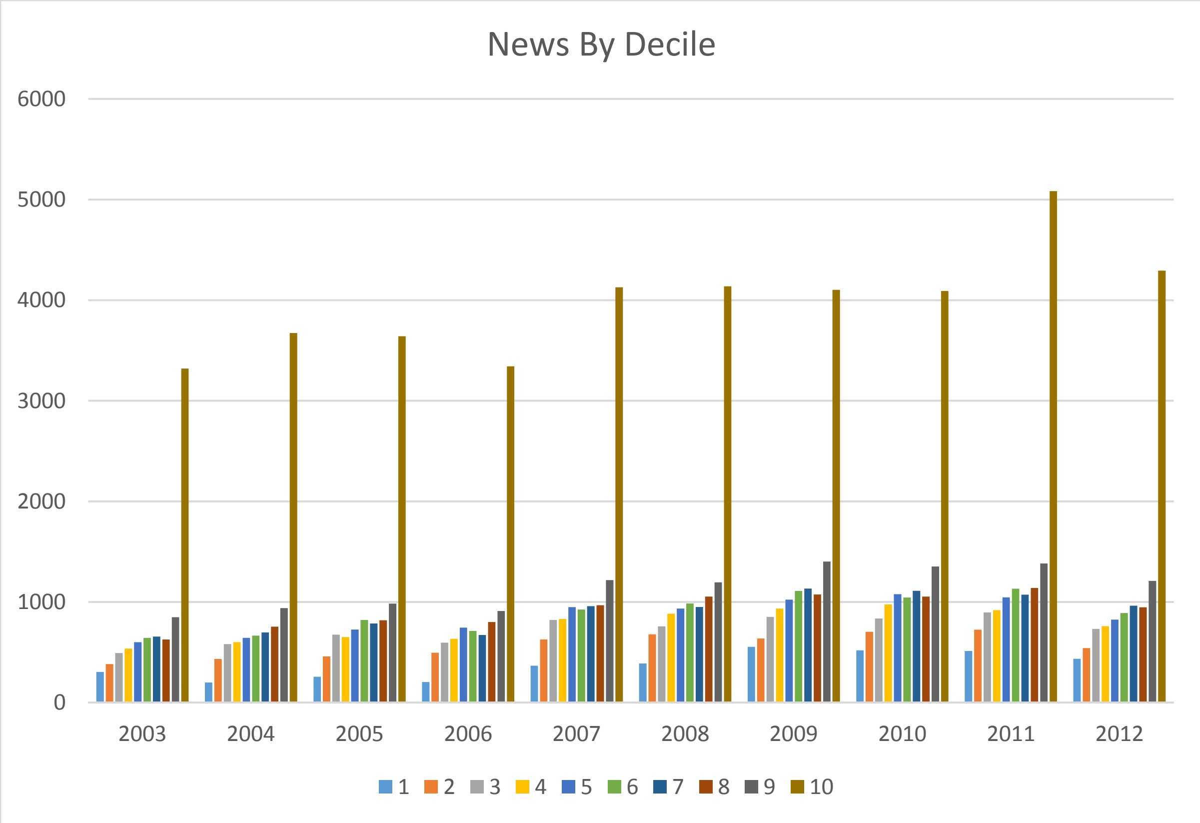
Figure 4. Historical Adjusted Price Chart for the Nikkei 225, Dow Jones and S&P 500 1985 - 2015



This figure presents a comparison of the adjusted historical prices of the Nikkei 225, Dow Jones and S&P 500.

Source: DataStream

Figure 5. Count of Firm News Items by Decile



This figure presents the split of news by decile. Decile 1 are counts of news items associated with small 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	-0.0595	-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	-0.0287	-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	2248
Average Market Sentiment	-0.0272	-0.0294	0.2030	0.06	3.38	2248
Probability Weighted Sentiment	-0.0343	-0.0357	0.1425	0.03	3.39	2248
Log(Volume)	0.0010	-0.0008	0.6421	0.00	10.16	2248
Log(Number_Of_News)	4.0654	3.9512	0.8131	0.39	3.84	2248

Panel B	Mean	Median	SD	Skewness	Kurtosis	N
Firm Return	0.0000	0.0000	0.0276	-2.70	801.73	5021095
Average Firm Sentiment	-0.0028	0.0000	0.1109	-2.10	79.05	5021095
Probability Weighted Sentiment	-0.0024	0.0000	0.0750	-3.70	91.89	5021095
Log(Volume)	0.0009	-0.0009	0.6463	0.01	10.06	5021095
Negative News Dummy	0.0081	0.0000	0.0898	10.96	121.06	5021095
Firm News Dummy	0.0208	0.0000	0.1426	6.72	46.21	5021095
Log(Number_Of_News)	4.0908	3.9890	0.8155	0.40	3.78	5021095

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 return of the TOPIX. Log(Volume) is the lagged daily 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). The negative and firm news dummies are presented here to show the sample percentage.

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:

$$R_{mkt_t} = \alpha + \delta avgsentiment_{mkt_t} + \gamma \log volume_{mkt_{t-1}} + \lambda \log news_{mkt_t} + \varepsilon_t$$

R_{mkt_t} is the daily 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. $logvolume_{mkt_{t-1}}$, is the lagged trading volume by value of the TOPIX on day t-1 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. Panel A presents results based on an average sentiment measure (1), whilst Panel B presents results based on a probability weighted sentiment measure (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	
	(-1.38)	
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

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

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:

$$r_{firm_{i,t}} = \alpha + \beta sentiment_{firm_{i,t}} + \delta \log volume_{mkt_{i,t-1}} + \gamma negativenews_{i,t} + \varphi\, firmnews_{i,t} + \lambda lognews_{mkt,t} + \varepsilon_{i,t}\, i$$

Where $rfirm_{i,t}$ is the daily adjusted firm return of day t, $sentiment_{firmi,t}$ is the contemporaneous sentiment of firm i on day t, $logvolume_{mkt,t-1}$, ,is the lagged trading volume by value of the TOPIX i on day t-1, $negativenews_{i,t}$ 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 heteroskedasticity. 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
$Sentiment_{firm_{i,t}}$	.0031***	.0145***	.0119***	.0089***	.0090***	.0050***	.0068***	.0066***	.0050***	.0054***	.0020*
	(7.81)	(2.86)	(4.24)	(4.27)	(4.79)	(3.42)	(5.01)	(5.07)	(4.10)	(5.91)	(4.87)
$Log volume_{mkt,t}$	-.0003	.0000	-.0002	-.0002	-.0002	-.0003	-.0004	-.0004	-.0004	-.0004	-.0005
	(-1.25)	(-0.09)	(-1.01)	(-0.76)	(-1.03)	(-1.34)	(-1.48)	(-1.34)	(-1.50)	(-1.24)	(-1.55)
$Negativenews_{i,t}$	.0000	.0052	.0087***	.0067***	.0080***	.0055***	.0049***	.0050***	.0017	.0012	-
	(0.07)	(0.84)	(2.63)	(2.64)	(3.45)	(2.90)	(2.58)	(2.67)	(0.97)	(0.80)	(-4.08)
$Firmnews_{i,t}$	.0025***	.0095***	.0052***	.0040***	.0036***	.0020***	.0022***	.0022***	.0021***	.0017***	.0014*
	(7.33)	(4.93)	(5.47)	(5.11)	(5.10)	(2.72)	(3.00)	(3.15)	(2.86)	(2.66)	(4.25)
$Lognews_{mkt,t}$	-.0009***	-.0011***	-.0011***	-.0011***	-.0011***	-.0010***	-.0009***	-.0009***	-.0008**	-.0007	-.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	All	1	2	3	4	5	6	7	8	9	10
$Sentiment_{firm_{i,t}}$	.0074***	.0385***	.0309***	.0235***	.0204***	.0147***	.0174***	.0194***	.0143***	.0142***	.0049***
	(11.93)	(4.40)	(6.08)	(6.04)	(5.63)	(5.56)	(6.76)	(7.70)	(6.48)	(9.82)	(8.37)
$\mathrm{Log}\,volume_{mkt}$	-.0003	.0000	-.0002	-.0002	-.0002	-.0003	-.0004	-.0004	-.0004	-.0004	-.0005
	(-1.25)	(-0.09)	(-1.01)	(-0.75)	(-1.03)	(-1.34)	(-1.48)	(-1.33)	(-1.49)	(-1.24)	(-1.55)
$Negativenews_{i,t}$	.0026***	.0207***	.0200***	.0152***	.0137***	.0112***	.0105***	.0125***	.0072***	.0063***	-.0014
	(4.04)	(2.81)	(4.83)	(4.87)	(4.72)	(5.07)	(4.75)	(5.67)	(3.58)	(4.24)	(-1.83)
$Firmnews_{i,t}$	.0019***	.0086***	.0047***	.0035***	.0034***	.0014**	.0017**	.0012	.0012	.0006	.0008**
	(5.81)	(4.69)	(5.02)	(4.62)	(4.87)	(1.96)	(2.37)	(1.74)	(1.70)	(0.92)	(2.34)
$Lognews_{mkt,t}$	-.0009***	-.0011***	-.0011***	-.0011***	-.0011***	-.0010***	-.0009***	-.0009***	-.0008**	-.0007	-.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 in ( ).

Table 6. Two Stage Least Squares Using Sentiment as an Instrument

This table reports a two staged least squares analysis which examines the relationship between predicted values of sentiment used as an instrument at time t on the TOPIX. The regression model is as follows:

$$r_{firm_{i,t}} = \alpha + \beta sentiment_{instrument_{i,t}} + \delta \log volume_{mkt_{i,t-1}} + \gamma negativenews_{i,t} + \varphi firmnews_{i,t} + \lambda lognews_{mkt,t} + \varepsilon_{i,t}\ i$$

Where $rfirm_{i,t}$ is the daily adjusted firm return of day t, $sentiment_{instrumenti,t}$ is the predicted value of sentiment of firm i on day t, $logvolume_{mkt,t-1}$, ,is the lagged trading volume by value of the TOPIX i on day t-1, $negativenews_{i,t}$ 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 heteroskedasticity.

	(1)
Sentiment	0.1043***
	(8.38)
Log Volume	-0.0003
	(-1.24)
LogNews	-0.0009***
	(-3.37)
FirmNews	0.0039***
	(14.64)
NegativeNews	-0.0040***
	(-12.69)
α	0.0039***
	(3.45)
Adjusted R2	0.001
AIC	-4.340
Durbin-Watson	2.02
F-statistic	2.752***
Prob(F-statistic)	0.000

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

Table 7. 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 looking at the relationship between firm sentiment using predicted values of sentiment and firm returns. The regression model is as follows:

$$r_{firm_{i,t}} = \alpha + \beta sentiment_{instrument_{i,t}} + \delta \log volume_{mkt_{i,t-1}} + \gamma negativenews_{i,t} + \varphi\, firmnews_{i,t} + \lambda lognews_{mkt,t} + \varepsilon_{i,t}\, i$$

Where $rfirm_{i,t}$ is the daily adjusted firm return of day t, $sentiment_{instrumenti,t}$ is the contemporaneous sentiment of firm i on day t, $logvolume_{mkt,t-1}$, ,is the lagged trading volume by value of the TOPIX i on day t-1, $negativenews_{i,t}$ 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 heteroskedasticity. Panel A presents results using predicted values of sentiment as an instrument.

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

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