News Sentiment and Momentum[☆]

Thanh D. Huynh[*], Daniel R. Smith[**]

This draft: December 2013

Abstract

This study tests Hong and Stein's (1999) underreaction model on weekly momentum returns by employing the dataset of over 10.1 million news items in four regions (the U.S., Europe, Japan, and Asia Pacific). We find that underreaction to news is the main driver of momentum effects everywhere. By jointly examining two features of news, namely staleness and tone, we document a highly profitable trading strategy that buys winner stocks with stale positive news in the past week and sells loser stocks with novel negative news over the same period. This 'news momentum portfolio' gives economically and statistically significant returns in all markets, including Japan where the normal momentum strategy does not work. Our findings provide strong international support for behavioral explanations of momentum. The persistent profitability of news momentum portfolios suggests that investors everywhere have similar biases in underreacting to news.

[☆]School of Economics and Finance, Queensland University of Technology, Australia. We thank Stan Hurn, Carole Comerton-Forde, Terry Walter, and seminar participants at QUT for helpful comments. We also thank SIRCA for channeling the data from Thomson Reuters. All errors are our own.

[*]E-mail: t12.huynh@qut.edu.au (T. D. Huynh, contact author)

[**]E-mail: dr.smith@qut.edu.au (D. R. Smith)

1. Introduction

The evidence of the momentum effect in stock returns has been a persistent challenge to asset pricing theories since the seminal study of Jegadeesh and Titman (1993).[1] Jegadeesh and Titman (1993) find that a trading strategy that buys the best performing stocks (winners) over the past 3 to 12 months and sells the worst performing stocks (losers) over the same period yields profitable returns in the U.S. markets. Despite the fact that the literature has not settled on the source of monthly momentum effects, Gutierrez and Kelly (2008) find that the momentum strategy that is formed using weekly data is even more persistent and stronger than the monthly momentum anomaly.

Many studies suggest a risk-based explanation (e.g., Conrad and Kaul (1998)), but are unable to find strong empirical support.[2] Fama and French (1996) document that their three-factor model cannot rationalize the momentum return.

The literature has therefore turned to behavioral explanations of momentum. Behavioral models such as Hong and Stein (1999) argue that the momentum effect is due to market's underreaction to news. Hong and Stein (1999) assume that firm-specific news diffuses gradually among news watching investors who are not fully rational.[3] Hong, Lim, and Stein (2000) test Hong and Stein's (1999) underreaction theory and show that the momentum effect is particularly strong in stocks with low analyst coverage, which they use as a proxy for the slow diffusion of news. They also find that the effect of analyst coverage is stronger in loser stocks than in winners. Consequently, they conclude that there is a continuation in stock returns mainly because "bad news travels slowly".

Rather than examining the level of analyst coverage in loser stocks as a proxy for the slow diffusion of bad news, we aim to provide a more direct test of Hong et al.'s (2000) hypothesis. We do so by employing a comprehensive news database provided by Thomson Reuters News Analytics (TRNA). With the state-of-the-art technology in textual analysis,

[1]Eugene F. Fama recently reconfirms this in an interview with Robert Litterman (Fama and Litterman, 2012)

[2]See Jegadeesh and Titman (2011) for a recent literature review on momentum effects.

[3]The behavioral theories can be divided into two camps. The first camp tries to link the momentum effect with overreaction to private news due to investors' overconfidence that causes positive correlation in returns (e.g., Daniel et al. (1998)). The other camp attributes momentum effects to underreaction in which price incorporate news slowly (e.g., Barberis et al. (1998), and Hong and Stein (1999)).

TRNA offers quantitative tone scores (positive and negative tone) for news items from more than 34,000 firms in global markets between 2003 and 2011.[4]

Different from Hong et al. (2000), we test this hypothesis on Gutierrez and Kelly's (2008) weekly momentum portfolios rather than Jegadeesh and Titman's (1993) monthly strategies. As Gutierrez and Kelly (2008, p. 417) argue, their weekly momentum portfolios "provide researchers of the momentum phenomenon a new, and arguably superior, testing ground for their theories." Indeed, using weekly returns allows me to take advantage of the high frequency of news events in TRNA, which monthly momentum portfolios cannot. With the available scores of good and bad news from TRNA, we construct a unified measure of news tone score, which can be used to rank stocks. Our tests are then simplified to comparing the profitability of momentum portfolios between a group of stocks with bad news and those with good news in the ranking period. The empirical literature (e.g., Hong et al. (2000), Chan (2003), and Tetlock (2011)) interprets negative momentum returns (or reversals) as overreaction in prices and positive momentum returns as underreaction.

We also provide the first joint examination of both news tone and the degree of news staleness in the literature on news analytics in finance. The literature has examined either of the news characteristics, but not both. Tetlock et al. (2008) examine negative words in news articles and find that those words can forecast firm earnings and stock returns. However, they do not account for the fact that news that has been repeated several times (stale news) should have different impacts on returns than news stories that are reported for the first time (new news). Recognizing this staleness effect, Tetlock (2011) investigates the similarity of words between news articles and shows that investors actually overreact to stale news. Tetlock (2011) nevertheless does not allow for the distinction between stale (new) positive news and stale (new) negative news. By simultaneously investigating both features of news, we can provide a more complete picture of the link between news and stock returns.

As existing research relies on the ability of researchers to parse the news content, and convert qualitative information into the quantitative score of news sentiment, we can provide improvements in this research area by taking advantage of Thomson Reuters's modern

[4]See The Handbook of News Analytics in Finance edited by Mitra and Mitra (2011) for a detailed discussion about TRNA's coverage.

news analytics technology. Tetlock (2007) was among the first to employ a textual analysis program, called General Inquirer, together with the Harvard IV-4 dictionary to determine if a word has a negative meaning. Tetlock (2007) then computes the fraction of negative words in the Wall St Journal (WSJ) *Abreast of the Market* column. Later finance studies generally use the technique similar to that of Tetlock (2007), which is also called the "bag of words" approach (e.g., Davis et al. (2012), Tetlock et al. (2008), Loughran and McDonald (2011), and Garcia (2013)).

Although the simplicity of the bag-of-words technique is appealing, its primary limitation is that it analyzes words without putting them into context. In textual analysis, defining a group of words to have negative meanings does not necessarily suggest that standing together in the full sentence they will also have a negative meaning. Indeed, Boudoukh et al. (2012) show that parsing news contents at the phrase or sentence level is more important, and may produce different results from the bag-of-words approach. This textual analysis accounting for grammatical contexts is exactly the method that TRNA employs.

By performing the analysis at the sentence level, TRNA can compute different scores (e.g., degree of relevance and sentiment) for different companies when an article mentions multiple firms in the content. The bag-of-words algorithm, however, cannot do this, but will assign the same score for all firms. TRNA is also able to determine which news is stale and which news is novel. Tetlock (2011) measures the staleness of news by computing the number of common unique words (or adjacent word pairings) between two news articles. Again, the advantage of this technique is its simplicity, but being applied on financial news may overestimate the degree of news staleness, because financial journalists tend to use simple common financial terminologies that are easily understandable to the public. Without looking at the news context, most news articles may, to some extent, read similar to one another.

Our study does not claim that TRNA measures are perfect because research in textual analysis is important and still developing in its own right. Rather, we aim to employ a relatively new dataset that is improved over those used in the previous finance research. In particular, we point out two examples of how TRNA analyzes news contents differently from the bag-of-words technique in terms of quantifying (1) the degree of staleness of the news, (2) the tone of the news, and (3) the degree of relevance of the news to a firm.

The first example is the development of events surrounding Microsoft's acquisition of Skype in May 2011. This example demonstrates the ability of TRNA to identify whether a news story is stale, even though the news topic is still about the acquisition. On May 10 at 1:57:16 (GMT), a Reuters's news article read (with some more details in the content being truncated) "Microsoft Corp. is to buy Internet phone company Skype...". As TRNA cannot locate similar contents in previous news articles, it classifies this news event with 100% novelty.[5] Then on the same day at 02:00:14 (GMT), there was a news brief sourced from the WSJ: "Brief – Microsoft close to buy Skype for more than $7 BLN – WSJ". This brief is classified as stale news since it conveys similar information to the first one.

Later on the same day at 02:49:40 (GMT) new details regarding the acquisition arrived, and Reuters reported another news alert: "Microsoft Corp. nears deal to buy Skype for $8.5BLN including debt", which was classified as 100% novelty. Assigning 100% novelty to the last news alert is correct because it is not just repeated news, but gives updates about the certainty of the deal as well as new details about the deal's value. In contrast, the bag-of-words approach will classify the last news alert as a repetition simply because of the high commonality of words in the text.

The second example is on how TRNA processes news mentioning two companies in the text, and computes a different score for each firm. On May 23, 2011 at 16:44:24 (GMT), Reuters reported a news alert: "IBM surpasses Microsoft's market capitalization for the first time." The news analytic metric of Thomson Reuters recognizes that there are two firms in the news, and calculate different scores for each firm. Since TRNA cannot find any linked articles over the past 7 days, this news alert has 100% novelty. For IBM, TRNA computes the relevance score of 1 (100% relevance), and the positive, neutral, and negative scores of 0.8534, 0.1170, 0.0295, respectively. The highest positive score indicates that this is positive news for IBM, and therefore TRNA assigns the sentiment score of +1 for IBM.

The relevance score of this news alert for Microsoft is 0.71 (71%, which is highly relevant), and the positive, neutral, and negative scores are 0.0556, 0.1252, and 0.8191, respectively. The negative score is the highest, indicating that this is negative news for Microsoft, and

[5] For Microsoft, the sentiment scores of positive, neutral, and negative tones are 0.8538, 0.1169, and 0.0293, respectively. The highest positive score indicates that the general tone of news is positive.

consequently TRNA gives this news the sentiment score of -1 for Microsoft. This example demonstrates the ability of TRNA to treat two firms differently and assign to them different scores. This is in contrast to the bag-of-words approach, which simply scans the text for negative words as defined by the Harvard-IV4 dictionary. If there are two firms in the news as in this case, the bag-of-words approach will assign the same score for both companies. As a result, this news alert may be falsely treated as positive news for Microsoft while it should have been negative (at least in comparison with the effect on IBM).

The above examples suggest that in examining the effect of news tone, we should also account for the novelty of news because breaking news such as a big merger or acquisition often makes the headlines for several days or weeks. This repetition in media coverage is particularly problematic when studies often source news from multiple news providers who tend to cover the same big event. Accounting for the novelty of news will therefore allow novel positive news to have different effects on stock prices from those of stale positive news. Consequently, we aim to provide a complete picture on the effect of news on stock returns by jointly investigating both features of news, namely staleness and tone.

Our results in the U.S. markets can be summarized as follows. Within stale news groups, we find that weekly momentum returns are higher among stocks with positive news in the ranking period. However, when we look at stocks with novel news in the ranking period, momentum portfolios are actually more profitable among stocks with bad news. Thus, by looking at another dimension of news namely staleness, we are able to support Hong et al.'s (2000) hypothesis that the momentum effect is mainly attributable to market's underreaction to bad news.

Nevertheless, those results no longer hold after we control for the effects of earnings and merger news. We find that it is the underreaction to positive news (regardless of whether it is stale or new news) that actually drives momentum returns.[6] Momentum strategies earn significant returns ranging from 8bps per week (t-statistic 2.09) to 18bps per week (t-statistic = 6.41) in the positive news group whereas these portfolios produce almost zero returns

[6]The results are robust to the volatility effect of Bandarchuk and Hilscher (2013). Bandarchuk and Hilscher (2013) show that strategies that sort stocks based on firm characteristics will also select those with high total risks, which in turn should command high returns. When they account for stocks' volatility in the portfolio-sorting approach, the effect of analyst coverage in Hong et al.'s (2000) disappears.

among stocks with negative news in the past week. Although these results are not consistent with Hong et al.'s (2000) empirical evidence, they actually support the original theoretical explanation of Hong and Stein (1999): the momentum effect is mainly attributable to underreaction of (positive) news in the long run.[7]

We find that, holding staleness fixed and controlling for a variety of variables suggested in the literature, markets initially overreact to positive news. Among stocks with new news, the 1-1 momentum strategy, which ranks stocks based on their returns and positive news scores in the past week and then holds the winner-minus-loser portfolio in the following week, earns an average reversal return of -1.71% per week (t-statistic = -7.98). This average return is much more negative than that of the same strategy constructed among stocks with bad news, which earns -0.92% per week (t-statistic = -7.81), suggesting that investors overreact to positive news rather than negative news in the short run.[8]

By comparing returns across different levels of staleness, we confirm the findings of Tetlock (2011) that investors overreact to stale news in the short run. Among stocks with stale news, the 1-1 momentum portfolio yields the average returns of -3.37% and -1.99% per week in the groups of positive and negative news, respectively, which are both much more negative than returns on respective portfolios in the new news group. Although bid-ask bounce effects can cause short-run negative correlations in returns, we attempt to mitigate this bias by employing mid-quote returns as in Gutierrez and Kelly (2008) and also examining strategies with a skipping week between ranking and holding periods.

Our findings on the effect of staleness are stronger than those of Tetlock (2011) who finds only weak evidence in the subsample period from 2002 to 2008, which overlaps with our sample period from 2003 to 2011. We conjecture that the reason for our stronger support is

[7]Our results may also support the model of Daniel et al. (1998) in which investors overreact to private information (and hence underreact to public news). But they are even more consistent with Hong and Stein's (1999) model because tests of Daniel et al.'s (1998) model require a good measure of psychological bias (i.e., overconfidence and bias self-attribution), a non-requisite assumption in the former model. The theoretical prediction of Hong and Stein (1999) only asserts that market's underreaction to firm-specific news drives momentum effects, but does not mention specifically whether good or bad news is in play.

[8]Throughout the study, except for the 4-52 strategy, we denote other momentum strategies as 1-H to represent one-week ranking period and H-week holding period. The Gutierrez and Kelly's (2008) 4-52 momentum strategy also has the ranking period of one week, but it waits four weeks before starting to hold the momentum portfolio in the following 52 weeks.

due to data differences. As we discuss in the Data section, our staleness data from TRNA better captures the similarity in the content of news articles. Moreover, different from Tetlock (2011), our staleness measure directly accounts for the relevance score of news, thereby allowing me to use all available news items and avoiding the need to impose unnecessary restrictions on the data.[9]

We uncover another important finding that is identifiable only by looking at both features of news. We document a new profitable trading strategy that buys winner stocks with stale positive news in the past one week and sells loser stocks with new negative news over the same period. This 'news momentum portfolio', which lasts up to 52 weeks in the holding period, earns an average return of 47bps per week in the U.S. market with an associated t-statistic of 8.48. This return is economically significant because it is much higher than the 6bps per week (t-statistic = 2.77) of Gutierrez and Kelly's (2008) 1-52 momentum portfolio. The profitability of our news strategy is robust to considerations of size, analysts, book-to-market ratio, industry, earning news, merger news, volatility effects, the use of CRSP's daily (instead of intraday) returns, and the exclusion of small, illiquid, and penny stocks. It cannot be explained by Fama and French's (1993) risk factors and downside risk.

Since our sample period is relatively short (between 2003 and 2011, with 458 weeks), we also provide an out-of-sample test for the profitability of our news momentum portfolios by using stock returns and news data from 21 developed markets. In doing so, our study is the first to examine the link between news and weekly momentum returns outside the dominant U.S. market. Griffin et al. (2011) is one of the few studies that examines the impact of financial media on price volatility in 56 markets. Griffin et al. (2011), however, do not examine the tone or staleness of news but focus on differences in volatility between news and non-news days. Our study also contains a much larger amount of news with well over 10.1 million news items in 22 developed markets (including over 5.3 million items from the U.S. – the largest of its kind in the literature) compared with Griffin et al.'s (2011) 870,000 news items in 56 markets.[10]

[9]The initial overreaction that is followed by longer run momentum is also consistent with the empirical findings of Gutierrez and Kelly (2008). Gutierrez and Kelly (2008), however, do not investigate how the mechanisms of news tone and staleness effects drive momentum returns.

[10]Bhattacharya et al. (2000) hand-collected 75 news event dates in Mexico between 1994 and 1997, and

The general conclusion from the out-of-sample test is that our news portfolio is persistent and strong everywhere. Of particular note is its strong performance in Japan where the normal momentum strategy does not work. The 1-52 news momentum strategy, which ranks stocks based on their news staleness, tone scores and returns over the past one week and then holds the portfolios in the following 52 weeks, yields an average return of 50bps per week (t-statistic = 8.77) in Japan. In contrast, Gutierrez and Kelly (2008) momentum portfolios earn almost zero return over the same period. Moreover, this news strategy does not reverse in the first week as the normal momentum strategy does in Japan.[11] The 1-1 news momentum portfolio produces an average return of 4bps per week (t-statistic = 0.33) whereas the normal 1-1 momentum portfolio yields a significant average return of -92bps per week (t-statistic = -9.45).[12]

These findings are important because they provide strong international support for behavioral theories, specifically the underreaction theory of Hong and Stein (1999), which is actually quite rare to find.[13] The persistent profitability of news momentum portfolios in all markets indicates that investors in every country display similar bias in underreacting to news.

The rest of the study proceeds as follows. We first present the findings for U.S. markets and then employ the international evidence as part of the robustness and out-of-sample tests.

find no unusual movements in stock returns, volatility or trading volume. Due to lack of news data in international markets, most studies focus on individual countries with earnings announcements rather than general firm news (e.g., DeFond et al. (2007) and Bailey et al. (2006)). As argued by Tetlock et al. (2008), we should investigate all types of news events because it can help prevent researchers from running event studies on various data to get meaningful results. It should be noted again that our results are not affected by special event news such as earnings announcements and merger and acquisitions.

[11]TRNA's news is reported in English. Consequently, if one believes that Japanese investors do not read English news (which may not be true for domestic institutions), then the Japanese findings may be driven by foreign investors. This issue however has not been resolved in the literature, and unfortunately the data is not available for me to investigate what type of investors trades on news. We therefore leave this question for future research.

[12]We find mixed international results for Hong et al.'s (2000) hypothesis. Although momentum returns in one type of news groups are higher than those of the other, the difference is not as economically significant as in the U.S. market. Moreover, all momentum portfolios conditioned on news characteristics earn higher average returns than the normal momentum strategy, re-confirming that underreaction to news is an important driver of international momentum effects. We discuss these findings in more details in the body text.

[13]Chui et al. (2010) provide international evidence for the link between investors' overconfidence (as measured by the individualism index of Hofstede (1980)) and Jegadeesh and Titman's (1993) monthly momentum effects.

Section 3 discusses our data and methodology. We report results from the portfolio-sorting approach in Section 4. Section 5 presents various robustness checks for the U.S. findings. We then provide international evidence in Section 6 and conclude in Section 7.

2. Related literature

Our study contributes to the growing literature that attemtps to explain momentum effects using firm-specific news. Employing the news headlines of 25% of all CRSP stocks between January 1980 and December 2000, Chan (2003) compares the profitability between momentum portfolios constructed using stocks that had news published about them over the ranking period and those constructed using firms that did not have news over the same period. Chan (2003) finds that momentum returns are significantly positive among stocks with news headlines whereas those portfolios constructed in the no-news group exhibits no momentum effects. In contrast, Gutierrez and Kelly (2008) test Chan's headlines data on their weekly momentum portfolios and find that both news and no-news groups generate significant returns. Fang and Peress (2009) examine the monthly cross-sectional relationship between media coverage and stock returns, and find that stocks not covered by the media earn 3% per year more than those that are covered by the media. In this study, apart from employing a larger database containing more recent data, we extend their analysis beyond the simple distinction between news coverage and no-news coverage by offering new evidence on which type of news actually drives returns.

Several studies that examine return predictability of news do not consider the staleness of news. Antweiler and Frank (2006) conduct event studies using corporate news stories from the WSJ and document short-run reversals after the news publication. Tetlock (2007) analyzes negative words (as defined by the Harvard IV4 Dictionary) in the WSJ *Abreast of the Market* and finds that pessimism in the column predicts negative returns (reversals) in the next day, but this predictability disappears within a week. Similarly, Tetlock et al. (2008) show that negative words from the Dow Jones News Service (DJNS) and the WSJ can predict earnings and returns on the S&P500 firms. Employing a similar technique to Tetlock (2007), Engelberg (2008) counts the number of negative words in the firm's earnings announcement and finds that the qualitative information in the text has stronger return predictability than quantitative financial measures such as Standardized Unexpected Earnings.

Our study examines both negative news and positive news. By doing this, we uncover that investors initially overreact to positive news in the first few weeks of holding period and then underreact to positive news over 52-week holding period. Garcia (2013) investigates the effect of positive news, and finds that news sentiment extracted from financial columns of the New York Times (which may be stale) has strong return predictability during recessions. Unlike our study, Garcia (2013) focuses U.S. market index rather than individual stock returns. Similar to Tetlock (2007) and most studies, Garcia (2013) uses the so-called “bag-of-words” approach in textual analysis. Some studies employ statistical methods for quantifying news tones based on vector distance, Naive Bayes classifications or likelihood ratios (Antweiler and Frank (2004), Das and Chen (2007) and Li (2010)), but they only examine single news events. Another limitation of those statistical approaches, as Tetlock (2007) argue, is that they are difficult to replicate and subject to researchers’ classification of news tone.

Other studies (Davies and Canes (1978), Barber and Loeffler (1993), Hand (1990), Ball and Kothari (1991), and Tetlock (2011)) consider the dimension of news staleness, but ignore the effect of sentiment, and focus on a particular event such as earnings announcement or analyst recommendation. This study is related to Tetlock (2011) who provides a direct examination of the staleness effect and finds that markets overreact (i.e., strong short-run reversals) to stale news. Our study improves this research by employing TRNA data, which is more current, larger, and covers all types of news items. In Section 3, we also point out some differences between our measures and those of current research.

3. Data and methodology

We describe our data for U.S. markets and how we control for important variables that may confound the effect of news on momentum returns. International data and results are reported as out-of-sample tests in later sections.

3.1. Data

We collect news data from Thomson Reuters News Analytics (TRNA), which is available between January 2003 and December 2011. TRNA processes and scores news from various sources including major news providers such as the Wall St Journal, PR Newswire, Business Wire, and Reuters. News items are time-stamped and the corresponding scores for each news item are computed in real time. TRNA provides the following scores that are employed in this study. The first is relevance score, which measures how relevant the news item is to a firm. The second measure is sentiment, which is the probability that the tone of the news is positive, neutral or negative (thus for each news item, positive score + neutral score + negative score = 1). The third measure is the novelty of the news, which indicates the similarity of a news item to other news items reported over the past seven days. Specifically, we employ the variable of 'total link counts' (data items: LNKD_CNTn and XLNKD_CNTn) that shows the number of news articles being linked (i.e., having similar contents) with the current news item over the past seven days.[14] [15]

We source market data (e.g., stock prices, number of shares outstanding, capitalization changes, dividends, and name changes) from Thomson Reuters Tick History (TRTH) for U.S. markets (NYSE/Amex and Nasdaq).[16] The advantage of TRTH is that it has the same firm codes (Reuters Instrument Code, RIC) as those of TRNA, which enhances the matching rate between the two databases (as evidenced by the high number of 10,198,831 news items in our dataset for four regions including well over 5.3 million items in the U.S. – the largest of its kind in the literature). TRTH also offers intraday data (similar to TAQ) with bid and ask quotes, which allow me to compute the midpoint quote. We use quote data rather than transaction prices to compute returns following Gutierrez and Kelly (2008) in part because it avoids spurious negative correlation induced by bid-ask bounce (Roll, 1984) of daily return data.

Weekly returns are computed based on the midpoint of the final bid and ask quotes from Wednesday to Wednesday between 2003 and 2011.[17] we require that firms must be covered

[14]TRNA offers various look-back windows for computing link counts such as 12 hours, 24 hours, 3 days, 5 days and 7 days. In this study, because we use weekly data we report results using seven day window, but they are not qualitatively changed by using five- and three-day windows.

[15]LNKD_CNTn compares the current news item with the number of previous items from the same feed provider whereas XLNKD_CNTn compares news items across all feed providers. We report results from XLNKD_CNTn, but again our conclusions do not change when using LNKD_CNTn.

[16]Both TRNA and TRTH are supplied by SIRCA. We thank SIRCA staff for helping with the data collection.

[17]Following Gutierrez and Kelly (2008), late quotes recorded after 4:10pm are excluded. If a price is

in the TRNA database. TRNA and TRTH have classifications for security types, which are used to select equities only. Following Ince and Porter (2006), weekly returns are set to missing if they are greater than 300% and then reversed in the following week. Specifically, if either r_t or r_{t-1} is greater than 300% and $(1+r_{t-1})(1+r_t)-1 \leq 50\%$, then both r_{t-1} and r_t are treated as missing values.[18] If a news item arrives after 3:30pm, the news is treated as tomorrow news.

We use U.S. book values of equity from Compustat. The book-to-market ratio is then computed by dividing the lagged six month book value of equity by the current market price of the stock. Following Asness et al. (2013) we lag the book equity by 6 months so that the information is available to the market. We obtain weekly analyst coverage (defined as the number of analysts who provide fiscal year one earnings estimates in the past quarter) from I/B/E/S. As a robustness check, we also employ a more conservative measure of analyst coverage by only counting the number of analysts covering the firm over the past week, but our results do not qualitatively change.

Measures of tone and staleness. In each week t, we compute the tone and staleness scores of all news items for a firm as follows:

$$tone_{j,t} = \sum_{i=1}^{N} (positive_i - negative_i) \times relevance_i \tag{1}$$

$$staleness_{j,t} = \sum_{i=1}^{N} (\#links_i \times relevance_i) \tag{2}$$

where N is the total number of news items for firm j in week t; *positive* and *negative* are respectively the probabilities of the news being positive and negative as computed by TRNA. Thus, $positive + neutral + negative = 1$. TRNA has another sentiment variable that takes values of 1, 0, and -1 to represent positive, neutral, and negative news, respectively. Using this convention, the quantity inside the brackets of formula (1) can be thought as $(1 \times positive + (-1) \times negative)$ where 1 and -1 are TRNA sentiments. We do not include neutral scores in formula (1) because they receive a sentiment score of zero, which has no

missing on Wednesday, we use Tuesday's closing price instead.

[18]Ince and Porter (2006) investigate the quality of Datastream's data.

effect on the final *tone* score. The *relevance* score measures how relevant the news item is to firm j. Thus, the higher the *tone* score, the more positive the news sentiment. Finally, $\#links$ counts the number of articles over the past seven days being linked with the current news item i. Since $\#links$ represents the staleness of news, the higher the *staleness* score, the more stale the news item.

Unlike previous research, which does not control for the relevance of news in their quantitative measures, we want to account for the fact that news with 100% relevance to the firm should have a higher impact on its stock prices than news with only, say, 1% relevance. We do so by multiplying each news item's score by its relevance score. Another advantage of controlling for the relevance score is that it enables me to use all available news items covered in TRNA without imposing unnecessary constraints on news characteristics.

We note that Tetlock (2011) imposes three filters on his news data that are not necessary for TRNA data, and therefore we are able to use all available news items. The first filter is that news stories must have maximum of three ticker codes in the contents. Since TRNA can calculate different sentiment scores and relevance scores for different firms being mentioned in the same news story, we do not need this constraint. Second, Tetlock (2011) excludes news articles with less than 50 words. As we are interested in examining the novelty effect of news, imposing this constraint on the number of words will likely exclude breaking news (e.g., news alerts), which typically contain only a few sentences but convey new information. Healy and Lo (2011) note that news alerts are short, and indeed likely to be new news. In contrast, follow-on news stories tend to appear 5 to 20 minutes later, which provide further details on the event. Consequently, excluding those short news items can bias, possibly downwards, the staleness measure because stale news is treated as new news.

The third constraint that Tetlock (2011) imposes on the news data is that the news text must have at least 5% single-word or 2% bigrams (i.e., adjacent word pairings) in common to the previous 10 news items. Again, this may filter out completely new news articles, which are the focus of our study. In this study, instead of counting the number of common words between news articles, our staleness measure counts the number of similar news articles. As mentioned in the Introduction, because financial journalists tend to use simple common financial terminologies to quickly convey the news to a wider audience, the fact that two news articles contain similar words does not indicate that they contain similar content. TRNA attempts to parse the news content by comparing synonymous words and grammar between two news stories. It then reports how many articles over the past seven days have similar content to the current news item. This method allows the context to play a role, thereby providing a more accurate measure of staleness and tone.

Several contemporaneous studies have also used the TRNA dataset. Sinha (2012) investigates the return predictability of TRNA's sentiment scores in the U.S. market. Sinha (2012) requires that news must have (1) the minimum relevance score of 0.35, (2) $\#links$ to be less than two, and (3) news alerts are dropped out from the sample. Given that Sinha (2012) does not focus on the joint examination of both the tone and staleness of news, these constraints may seem fine although they drop out many news items that may influence the final results. In contrast, we do not need to use any of these filters in this study. Rather, we attempt to cover all news items in TRNA. Dzielinski (2011) uses TRNA's U.S. data to study the difference between news and no-news stock returns as well as differences in market reactions between positive news and negative news stocks. Both studies do not control for relevance score in the news measures, nor do they control for the joint effect of staleness and tone.[19]

$<$ INSERT TABLE 1 AROUND HERE $>$

Table 1 reports summary statistics for U.S. stocks. The number of stocks in the U.S. coverage increases every year from 5,152 stocks in 2003 to 6,278 stocks in 2011. This increasing trend is also seen in the news coverage of TRNA. The number of news articles increases from 329,341 items in 2003 (or media coverage of 31.30%) to 636,877 articles in 2011 (or 38.42% coverage). With the increase in media coverage, the percentage of stale news items also rises yearly. In 2003, 53.54% of the news items were stale while this percentage in 2011 was 68.91%.

[19]Unlike this study, both Sinha (2012) and Dzielinski (2011) do not focus on explaining the weekly momentum returns. Our study is more related to Sinha (2012) who documents the profitability of portfolios that buy winner stocks with positive news and sell loser stocks with negative news in the U.S.. This news portfolio, which only has a holding period of 13 weeks and only considers one aspect of news namely sentiment, is different from our news portfolios and has much shorter return predictability than the 52-week holding period of Gutierrez and Kelly's (2008) momentum portfolios. As we will show in later section, incorporating both tone and staleness enhances momentum returns.

The first two columns of the panel B of Table 1 show summary statistics for raw tone and staleness scores. On average, U.S. stocks have positive media coverage with the average tone score of 0.201 and the standard deviation of 11%. The 5th, 25th, 50th, 75th and 95th percentiles of the raw tone score are 0.02, 0.13, 0.19, 0.27, and 0.39, respectively. The average raw staleness score is 0.43 with the 5th and the 95th percentiles are 0.19 and 0.75, respectively. After we control for size and analyst coverage effects (the methodology is discussed in the next subsection), the average excess tone scores and excess staleness score reduce to 0.05 and 0.03, respectively. The 10th, 50th, 75th and 95th percentiles for the excess tone scores are also lower at -0.39, -0.02, 0.13, and 0.56, respectively. Similarly, the 10th, 50th, 75th and 95th percentiles for excess staleness scores are -0.51, -0.04, -0.17, and 0.83, respectively.

3.2. Methodology

Our primary objective is to jointly examine the effect of the staleness and the tone of news on momentum returns. In order to isolate news effects from other firm characteristics that may confound our results, in each week of our sample we follow Hong et al. (2000) and run cross-sectional regressions of *log*(1+staleness) or *tone* on a number of firm characteristics. We employ *log*(1+staleness) rather than the raw measure of *staleness* because it allows the effect of one extra linked article on a firm's stock returns to be nonlinear.[20] The Fama and MacBeth (1973) time-series average of the coefficients is reported in Table 2. Residuals from those regressions can be interpreted as excess news tone scores and excess staleness scores, which are then used to rank stocks (along with the past week return) in the next section. This methodology allows me to simultaneously control for firm's characteristics that may confound the effect of news on momentum returns as well as to employ the portfolio-sorting approach.

$$tone_i = \beta_0 + \beta_1 \cdot log(size_i) + \beta_2 \cdot log(1 + analyst_i) + \epsilon_i \tag{3}$$

$$log(1 + staleness_i) = \beta_0 + \beta_1 \cdot log(size_i) + \beta_2 \cdot log(1 + analyst_i) + \epsilon_i \tag{4}$$

[20]We also try the raw *staleness* score (without taking log), and results do not qualitatively change.

In Model 1, we regress *tone* and log(1+staleness) on *size* and $log(1 + analyst)$ as in regressions (3) and (4), respectively. This model is mainly motivated by Hong et al. (2000). $log(size)$ is defined as the log of stock price times number of shares outstanding. The literature has shown that momentum portfolios yield different returns in different size groups. Hong et al. (2000) show that once they go beyond the bottom 10% size, the momentum effect is weaker as size gets larger. Fama and French (2008) also emphasize the importance of examining the profitability of momentum across size groups. In this vein, Fama and French (2012) further test the effect of size on momentum and value portfolios in 23 developed markets. In contrast to Hong et al. (2000), Israel and Moskowitz (2013) use a longer history of U.S. stock returns and find that momentum is actually stronger as size gets bigger. Israel and Moskowitz (2013) show that the results of Hong et al. (2000) are sample specific. Size also has an effect on news sentiment. DeLong et al. (1990) and Tetlock (2007) show that investor sentiment has a bigger effect on small stocks' returns.

Panel A of Table 2 shows that size plays an important role in driving news tone. The coefficient on $log(size)$ is 0.06, which is statistically significant at the 1% level. This positive coefficient suggests that large firms tend to have more positive news than smaller firms. Size plays a more important role in determining the staleness of news. The coefficient on $log(size)$ in the staleness regression (Panel B of Table 2) is 0.12, which is statistically significant at the 1% level – suggesting that a 1% increase in size will lead to 12% rise in *staleness*.[21] This is not overly surprising since the media tends to concentrate their coverage on large firms.

< INSERT TABLE 2 AROUND HERE >

We also control for $log(1+analyst)$ in Model 1, which is the number of analysts covering the firm over the past quarter. Hong et al. (2000) document that momentum is stronger for firms with low analyst coverage, which they use as a proxy for slow diffusion of news. News from firms with high analyst coverage is also less likely to be surprising to the market. We therefore control for analyst coverage in order to avoid the confounding effect of analysts on news effects. The coefficient on analyst coverage is positive in both tone and staleness regressions. The positive coefficient on $log(size)$ in the *tone* regression confirms the findings

[21] This interpretation of percentage increase is possible because both size and staleness are in log forms.

of Hong et al. (2000) that analyst coverage is higher among stocks with good news. The *staleness* regression in Panel B shows that news from firms with higher analyst coverage is more likely to be stale. This is intuitively appealing as analysts are more likely to cover a firm that makes more news headlines. Since news from those firms is more accessible to the public (Hong et al., 2000), it is more likely to be stale.

In Models 2, 3 and 4, we add five industry dummies (based on Ken French's classifications) and the firm's book-to-market (BM) ratio to the baseline regression. Since Fama and French (1992) show that book-to-market ratios can forecast stock returns, we want to be sure that any predicting power from news effects is not simply a manifestation of the well-known book-to-market effect. Controlling for industry and BM ratios does not increase R^2 (adjusted for degrees of freedom) in either regression and the effects of size and analysts remain significant. The coefficient on BM is -0.01 for the tone regression and 0.04 for the staleness regression, which are both statistically significant. These coefficients suggest that value firms (with high BM ratios) tend to have negative news, which is also more likely to be stale.

In Model 5, we further control for earnings-related news (*earn*). We follow Tetlock et al. (2008) and Tetlock (2011) and control for the effect of earnings news on stocks' returns. We do so by counting the number of news articles over the past week that contain the word stem "earn" in the headlines.[22] we then control for earnings-related news using log(1+total earnings news items). Tetlock et al. (2008) find that news stories that have the word stem "earn" in the content are better predictors of earnings. Adding *earn* boosts the R^2 in tone and staleness regressions to 4% and 24%, respectively. The *earn* coefficient in Panel A is 0.55, suggesting that earnings news tends to have positive sentiment. In the staleness regression of Panel B, this coefficient is 1.47, which is statistically significant. This indicates that there is an increase in media coverage during earnings announcement, thereby causing news during these periods to be stale. Adding industry dummies in Model 6 does not affect the importance of earnings news.

In Model 7, we add another control variable of merger-related news (*merger*). Ahern

[22]TRNA has a field named "BCAST_TEXT", which is either the full content of news if it is an alert or the news headlines if the item is an article/story. Consequently, this word scan is limited to headlines only due to the limitation of data. For our purposes, scanning the headlines can be sufficient because earnings news or merger news are often distinguishable by reading the headlines.

and Sosyuara (2013) show that bidders in stock mergers and acquisitions have incentives to manage media coverage so that they can manipulate stock prices during merger negotiation periods. Consequently, in order to address the concern that our results may be a confounding effect of stock price reactions due to mergers, we count the number of news articles that contain the following word stems: “merge”, “bid”, “acquire”, “acquisition”, and “takeover”.[23] After controlling for log(1+ total merger news items), R^2 increases to 9% and 31% in the tone and staleness regressions, respectively. The coefficient on *merger* is 1.23 in the tone regression and 1.31 in the staleness regression, respectively. Similar to the effect of earnings news, the higher number of merger news articles in a week leads to more positive news in the week, which is more likely to be stale. Adding industry dummies in Model 8 does not affect the R^2.

In Model 9, we add to Model 8 the lagged four weeks of returns. Lagged returns tend to have higher effects on tone than staleness. All coefficients are positive and statistically significant, suggesting that higher past returns lead to more positive news in the current week, and news is also more likely to be stale. Nevertheless, R^2 remains the same as that of Model 8.

In Models 10 and 11, we add to Model 8 the rank of stocks' total risks ($IVOL$). $IVOL$ is the stock's rank based on its total risk. In each week t, we compute the stock's total risk as the standard deviation of the past 52 weekly returns.[24] we then sort stocks into 25 volatility portfolios where portfolio 1 contains stocks with the lowest total risk, and portfolio 25 contains those with the highest risk. These rankings are then used as a control variable.[25] Bandarchuk and Hilscher (2013) show that when stocks are sorted based on firm characteristics and past returns, the strategy also picks up stocks with extreme volatility, and therefore the portfolio should command higher returns. Consequently, if $IVOL$ is the

[23] These are word stems, which also account for variations such as “merger”, “merges”, “bids”, “bidder”, and “acquirer”. This word scan also controls for news about merger rumors that may cause stock price reactions. An alternative way to control for merger news is to employ the news topic code “MRG” for mergers and acquisitions available in TRNA. We ensure that our conclusions do not change.

[24] We also computed idiosyncratic $IVOL$ by running 52-week rolling time-series regressions of stock returns on Fama and French (1993) three factors. Our results do not qualitatively change. Bandarchuk and Hilscher (2013) also document that different measures of risks do not affect their results because they are highly correlated with total risks.

[25] We confirm that our conclusions do not change if we use 10 portfolios instead of 25.

main driver of news effect on momentum, then controlling for $IVOL$ will cause the average momentum return to be insignificant. Indeed, after Bandarchuk and Hilscher (2013) control for $IVOL$ ranks, the double-sorted portfolio based on various firm characteristics (including the analyst coverage of Hong et al. (2000)) and momentum does not yield significant returns.

However, we should note the endogeneity problem in Model 11. In particular, the causation can also go the other way that news can drive volatility in returns. Griffin et al. (2011) show that volatility is much higher on news days than non-news days. Tetlock (2011) finds that news staleness is associated with lower return volatility. Hong et al. (2000) use similar methodology to this study and argue that controling for the endogeneous variable is conservative because it significantly weakens the power of portfolio tests. Similar to Hong et al. (2000), this endogeneity is not a serious problem in our study because (1) our goal is not to claim the causation between news and volatility and (2) although it is conservative to control for $IVOL$, our conclusions do not qualitatively change. The important findings on the profitability of our news momentum portfolios also remain robust to the control of $IVOL$ in international markets.

Table 2 shows that the coefficient on $IVOL$ rank is negative and statistically significant in both regressions; but the R^2 remains unchanged from Model 8. Nevertheless, the negative sign suggests that stocks with higher volatility tend to have more negative news, which is also less likely to be stale.

4. Portfolio returns

In this section, we report returns on weekly momentum portfolios that are subsequently sorted by size, Model 1's residual staleness, and finally residual tone scores.

4.1. Weekly momentum portfolios sorted by past returns

Table 3 reports returns on the raw momentum portfolio. As in Gutierrez and Kelly (2008), in each week t, stocks are ranked and sorted into three groups based their past one week returns where the first group contains the worst performing stocks (losers) and the third group contains the best performing stocks (winners). The momentum strategy then buys winner stocks and sells the loser stocks. Following Gutierrez and Kelly (2008), we examine various holding periods for this portfolio from 1 week to 52 weeks.[26]

< INSERT TABLE 3 AROUND HERE >

Panel A shows that momentum portfolios earn negative returns in the first three weeks of holding periods. The strategy incurs an average return of -3.45% per week in the first week, which is statistically significant at the 1% level. As the holding period is increased to 3 weeks, the negative average return reduces to -1.19% per week (t-statistic = -17.5). When we hold the winner-minus-loser (WML) portfolio for 52 weeks, the average return becomes positive 4bps per week with an associated t-statistic of 1.81, which is statistically significant at the 10% level. The strongest strategy is 4-52 with 4-week skipping time between ranking and holding periods, earning 11bps per week (t-statistic = 5.60), which is both economically and statistically significant.

Following Gutierrez and Kelly (2008), Jegadeesh and Titman (2001), Asness et al. (2013) and many others, we are also interested in examining the performance of momentum portfolios when microcap stocks are excluded. We define microcap stocks as those with size below the 10th percentile (computed using the universe of stocks) at the end of the ranking period. These stocks are generally illiquid and if the profitability of momentum strategies depends on returns of those stocks, then the strategy may not be investible.

Consistent with the literature, momentum profits are higher when excluding microcap stocks in the ranking period. The 1-52 strategy now earns a higher average return of 6bps per week with an associated t-statistic of 2.77, significant at the 1% level. The 4-52 strategy however is not affected by the microcap group. The average return for this strategy still remains at 11bps per week (t-statistic = 6.05), which is both economically and statistically significant.

The negative return on loser portfolios also indicates that the momentum profitability relies on the short side. When the micro cap stocks are excluded at the end of each ranking

[26] Grouping stocks into three groups is consistent with Hong et al. (2000) and Fama and French (2012). As we will also dependently sort stocks based on staleness, tone, and past returns, sorting stocks into 10 groups as in many U.S. studies will leave too few stocks in each portfolio. Moreover, the equal-weighting scheme is also consistent with Jegadeesh and Titman (1993) and Gutierrez and Kelly (2008).

period, 116.67% ($= \frac{|-0.07|}{0.06} \times 100$, not reported in Panel B of Table 3) of the average return on 1-52 momentum portfolios comes from the loser portfolio. For the 4-52 momentum portfolio, this percentage is 109.09% ($= \frac{|-0.12|}{0.11} \times 100$, not reported). In order to make a conclusion about the implementability of weekly momentum strategies, we will further explore the importance of size and short selling (i.e., the reliance on the negative return of loser portfolios) in the next subsection.

4.2. Momentum portfolios sorted by size

Fama and French (2008) suggest that it is important to examine the profitability of trading strategies in different size groups. Hong et al. (2000) show that the monthly momentum effect is stronger in the small size groups and weaker in the largest size group. However, Israel and Moskowitz (2013) show that Hong et al.'s (2000) results are sample specific. Using more current data, they show that monthly momentum portfolios are still highly profitable in the largest size group. We provide one of the first evidence of size for the weekly momentum portfolio.

Table 4 shows average WML returns among three size groups. We first sort stocks into three size groups; small, medium and large. Momentum portfolios are then formed within each size group. In panel A, we use the full sample (i.e., without dropping stocks with size below the 10th percentile). The general picture is that as size gets bigger, reversals in the first three weeks of holding periods decline (become less negative), and average returns on the 1-52 and 4-52 strategies are also higher. Going from small to large size groups, the average return on the 1-1 strategy increases from -7.13% (t-statistic = -25.1) to -0.26% per week (t-statistic = -1.16). Thus, short-term reversals are mainly attributable to small stocks.

The 1-52 strategy earns an average return of 9bps per week with an associated t-statistic of 3.03, significant at the 1% level. The average return in the medium group is only 2bps/week, which is both economically and statistically insignificant. The strategy is however highly profitable in the largest group, which earns 12bps per week (t-statistic = 2.88). Thus, beyond the smallest group, momentum effect is actually stronger as size gets bigger. Panel B drops stocks with size below the 10th percentile, and our conclusions do not change. These findings support the evidence of Israel and Moskowitz (2013) for monthly momentum returns.

< INSERT TABLE 4 AROUND HERE >

The contribution of shorting varies with firm size in such a way that is also consistent with Israel and Moskowitz (2013). Specifically, once we move beyond the smallest group, the role of short selling increases as firm size rises. Panel B of Table 4 shows that, in the medium sized group, 400% ($= 0.20/0.05 \times 100$, not reported) of the average return on 1-52 portfolios comes from the winner portfolio. This percentage decreases to only 9.09% ($= 0.01/0.11 \times 100$, not reported) in the largest group of stocks. As Israel and Moskowitz (2013) argue, the fact that shorting is less important in the smaller sized group suggests that the implementability of momentum strategies may not be a big concern (as raised by Hong et al. (2000)) because shorting small, losing stocks is harder and more expensive than shorting large stocks.

4.3. Momentum portfolios sorted by tone score or staleness

In this subsection we examine the momentum profitability in different groups of news characteristics. In each week t, stocks are first ranked and sorted into three groups based on Model 1's residual *tone* or Model 1's residual *staleness*. The first group contains stocks with the lowest *tone* score (*staleness* score), which are interpreted as negative (new) news groups whereas the third group contains stocks with the highest *tone* scores (*staleness* score), which are interpreted as positive (stale) news groups. Then, within each news group, 1-1, 1-2, 1-3, 1-52, and 4-52 momentum portfolios are formed based on stock returns over the past week. To simplify the presentation of tables, we do not report results for the 1-3 strategies because they are similar to 1-2 strategies.

Panel A of Table 5 reports average momentum returns in negative and positive news groups. Markets initially overreact to positive news as observed in the 1-1 and 1-2 momentum portfolios. The 1-1 strategy yields a negative average return of 2.69% per week (t-statistic = -19.5) in the positive news group whereas the average return in the negative news group is -1.85% per week (t-statistic = -9.80).

In the longer holding period markets also underreact to positive news. The 4-52 strategy earns an average return of 16bps per week with an associated t-statistic of 7.04, which is statistically significant at the 1% level. This average return (conditioned on positive news) is higher than the average return of 11bps per week for the full-sample momentum portfolios.

Among stocks with bad news in the ranking week, this strategy however only yields an average profit of 4bps per week (t-statistic = 2.07), which is statistically significant at the 5% level. A trading strategy that buys winner stocks with positive news and sells loser stocks with negative news will yield an average return of 31bps per week (t-statistic = 7.22), which is higher than the average return on normal momentum portfolios.

These results support the theory of Hong and Stein (1999) that momentum effects are due to investors' underreaction to news, but do not support the empirical evidence of Hong et al. (2000) that momentum is mainly attributable to underreaction to bad news. Panel A shows that the momentum profit in the positive news group is four times higher than that in the negative news group, indicating that momentum effects are mainly due to market's underreaction to positive news. Our results may also support the model of Daniel et al. (1998) in which investors overreact to private information (and hence underreact to public news). But they are even more consistent with the model of Hong and Stein (1999) because the test of Daniel et al.'s (1998) model require a good measure of psychological bias (i.e., overconfidence and bias self-attribution), an unnecessary assumption in the former model. Both models do not predict specifically which type of news actually drives momentum returns.

Panel B of Table 5 shows average momentum profits in new and stale news groups. Consistent with Tetlock (2011), investors overreact to stale news as evidenced in the average returns on 1-1 and 1-2 momentum portfolios, which are more negative (-2.46% per week) in the stale news group than that in the new news group (-1.51% per week). We extend the literature with the evidence of staleness effects on weekly momentum returns. Returns on the 1-52 and 4-52 strategies show that investors also underreact to stale news in the long run. The 4-52 strategy yields an average return of 13bps per week (t-statistic = 6.04) but only earns 4bps per week (t-statistic = 1.78) in the new news group.

Our findings on the effect of staleness are even stronger than those of Tetlock (2011). Although Tetlock (2011) shows that investors overreact to stale news in the short run, he finds only weak evidence using the subsample period from 2002 to 2008, which overlaps with our sample period from 2003 to 2011. We conjecture that the primary reason for our stronger support is due to data differences. As mentioned in the Introduction and Section 3, our staleness data from TRNA better captures the similarity in the contents of news articles.

Moreover, in contrast to Tetlock (2011), our *staleness* measure accounts for the relevance score of news, thereby avoiding the need to impose unnecessary restrictions on the data. We also control for the bid-ask bounce effect that may cause the spurious negative correlations in returns.

< INSERT TABLE 5 AROUND HERE >

The short-run reversal and longer-run momentum effects are consistent with the mechanisms of both Tetlock (2011) and Hong and Stein (1999). For short-run reversals, Tetlock (2011) models the interaction between rational and imperfectly rational investors. Because rational investors know that irrational investors will react to stale news, they will jump in and trade on the news first, causing the particularly strong overreaction in the short run. In the longer run, the mechanism of Hong and Stein (1999) can explain the underreaction to news that causes momentum effects. Hong and Stein (1999) model the interaction between the news watcher and the momentum trader who are both not fully rational. News watchers trade on news only while momentum traders can only condition their trades on historical prices. Moreover, not all news traders receive the news at the same time (i.e., slow diffusion of news), which causes the underreaction to news among news watchers. Momentum traders observe the trend created by news traders and start trading aggressively on it. This interaction between the two groups causes momentum effects in stock prices.

The findings in this subsection are based on separate examinations of news tone and staleness. However, it makes sense to expect that negative news that has been repeated a few times in the media should have a different impact on the market than the new negative news. Given that investors overreact to stale news and that they also overreact to positive news in the short run as we showed above, we expect that they will overreact to stale positive news rather than new positive news in the first few weeks of holding periods. We will test this hypothesis in the next subsection.

4.4. Momentum portfolios sorted by staleness and tone score

In this subsection, we provide the first joint examination of staleness and tone effects. We first rank and sort stocks into three groups based on Model 1's residual *staleness*, and then within each staleness group we further sort stocks into three groups based on their Model

1's residual *tone*. Finally, we form 1-1, 1-2, 1-52 and 4-52 momentum portfolios within each of the nine news groups, and results are reported in Table 6. Stocks with size below the 10th percentile at the end of the ranking period are not ranked.

The upper half of Table 6 reports results in the new news groups. Apart from the 1-1 portfolio where there is not much difference in the overreaction between negative and positive news groups, investors generally still overreact more to positive news. The average momentum return on the 1-2 strategy is -0.69% per week (t-statistic = -6.13), which is more negative than that in the negative news group with -0.59% per week (t-statistic = -4.70).

< INSERT TABLE 6 AROUND HERE >

In contrast to the results in Table 5 but consistent with Hong et al. (2000), investors underreact to new negative news. The average return on the 4-52 portfolio is 9bps per week (t-statistic = 3.29), which is higher than 5bps per week (t-statistic 1.35, insignificant even at the 10% level) in the positive news group. Thus, by taking into account another dimension of news namely staleness, we are able to confirm the hypothesis of Hong et al. (2000) that investors underreact to bad news. We add to their results that investors underreact to new bad news only. Nevertheless, the difference in 4-52 WML returns between negative and positive news groups is 4bps per week (not tabulated) with the insignificant associated t-statistic of only 0.98. This difference for the 1-52 strategy is only 2bps per week (t-statistic = 0.42). Thus, although the magnitude of the difference is consistent with Hong et al.'s (2000) hypothesis, momentum portfolios are not significantly more profitable in the negative news group than in the positive news group.

The lower half of Table 6 shows results in the stale news group. In general, investors overreact to stale positive news in the short run and underreact to stale positive news in the long run. Within stale news groups, the 1-1 strategy earns a negative average return of 2.55% per week (t-statistic = -18.47), which is much more negative than -1.96% per week in the negative news group. In contrast to the new news group, stocks with stale positive news exhibit much higher momentum returns than those with stale negative news in the past week. The strategy yields an average profit of 15bps per week (t-statistic = 5.52) among stocks with stale positive news whereas it earns -1bp per week (t-statistic = -0.22) in the negative stale news group.

The difference in average 4-52 WML returns between negative and positive news stocks is -0.16% per week (not tabulated) with the significant t-statistic of -3.46. Therefore, the momentum strategy is significantly more profitable in the positive news group than among negative news stocks. Finally, it should also be noted again that, regardless of news tone and staleness, momentum portfolios being conditioned on news yield higher average returns than the normal Gutierrez and Kelly's momentum strategies. These findings are consistent with Chan (2003) that the momentum effect is driven by investors' underreaction to news. We attempted to reduce the bid-ask bounce that causes short-run reversals by using the midpoint of bid and ask quotes to compute returns.

New trading strategies

Two interesting observations can be seen from Table 6. Firstly, the strategy (WPos-LNeg) that buys positive news winners and sells negative news losers is not profitable in the stale news group. The 1-52 WPos-LNeg strategy earns an average return of -3bps per week (t-statistic = -0.51) in the stale news group while it yields a significant profit of 23bps per week (t-statistic = 5.43) in the new news group. This suggests that the profitability of trading strategies that sort stocks based on news tone only is not robust to the joint examination both news features.

Secondly, a new trading strategy that seems to be more persistent is the one that buys winner stocks with stale positive news in the past week and sells loser stocks with new negative news over the same period (the last row of Table 6). As with normal momentum strategies, this news strategy does not incur any look-ahead bias because all information is available at the end of each ranking period. For the 1-52 portfolio, this strategy earns an average return of 47bps per week, with the t-statistic of 8.48, which is statistically significant at the 1% level. This 1-52 news momentum strategy earns 0.36% per week higher than the respective 1-52 Gutierrez and Kelly's momentum portfolio. This difference is both economically and statistically significant at the 1% level (t-statistic of the difference = 6.52, not tabulated). Similarly, the 4-52 news momentum strategy also yields 0.32% per week higher than the normal 4-52 momentum portfolio with a significant associated t-statisitc of 6.07.

Since this news strategy produces economically and statistically significant returns and also clearly represents market's considerable underreaction to news, we will focus on examining the robustness of this news strategy for the rest of the study. We will use the term 'news momentum' and 'WPosStale-LNegNew' interchangeably to represent our new trading strategy that exploits both staleness and tone of news.

5. Sensitivities

In this section, we examine the sensitivity of our main results in Table 6 to several variations from the baseline analysis. Firstly, we test whether the average return on news momentum (WPosStale-LNegNew) portfolios is still significant after adjusting for risks using the Fama and French (1993) three-factor model. Secondly, we examine whether the news momentum effect is a manifestation of Gutierrez and Kelly (2008)'s weekly momentum effects or whether they are independent from each other. Thirdly, we provide robustness tests for the news momentum effect using residuals from different variations to Model 1. Finally, we investigate whether our findings are sensitive to the exclusion of penny stocks, the impact of size, the use CRSP data, and downside risks. More importantly, the next section shows that the profitability of news momentum strategies is robust to out-of-sample tests, thereby avoiding the critique of "data-snooping" bias of Lo and MacKinlay (1990).

5.1. Risk-adjusted returns

Table 7 shows the properties of the normal unconditional WML portfolio and WPosStale-LNegNew portfolios by regressing their weekly returns on the Fama and French (1993) three-factor model (FF3F).[27] In order to examine whether one anomaly is a capture of the other, we also regress the WML return on the WPosStale-LNegNew return and vice versa. If the news momentum portfolio (the right-hand side variable) is stronger than the unconditional momentum portfolio (the left-hand side variable), we should see the intercept from this regression to be economically and statistically equal to zero.

< INSERT TABLE 7 AROUND HERE >

[27] Fama and French's risk factors are downloaded from Ken French's website.

The upper half of Table 7 shows the intercept from the regression with WML returns on the left-hand side. We drop stocks with size below the 10th percentile at the end of each ranking period. The FF3F model cannot rationalize the weekly momentum effect as the magnitude of all risk-adjusted returns almost stays the same or even higher. The short-run reversal 1-1 and 1-2 strategies still incur the loss of -2.88% and -1.49% per week respectively, which are even more negative than the raw average return in Table 3. Risk-adjusted returns on 1-52 and 4-52 portfolios are still the same as their raw returns with 6bps (t-statistic = 2.75) and 11bps per week (t-statistic = 6.01) respectively, which are both economically and statistically significant.

Adding the news momentum (WPosStale-LNegNew) return in the right-hand side of the regression does not reduce the alpha in all strategies but the 1-52 strategy. When we regress Gutierrez and Kelly's (2008) 1-52 WML returns on the FF3F and the WPosStale-LNegNew return, the intercept reduces to 3bps per week with an associated t-statistic of 1.42, which is both economically and statistically insignificant. This low intercept indicates that our news momentum effects are stronger than the 1-52 momentum effect of Gutierrez and Kelly (2008). Nevertheless, the 4-52 WML portfolio is still strong with the intercept being 10bps per week (t-statistic = 4.63), which is statistically significant at the 1% level.

The lower half of Table 7 reports the intercept from regressions where the left-hand side variable is returns on the WPosStale-LNegNew portfolio. The FF3F model still cannot explain returns on the news momentum portfolio as all intercepts are still as high as their raw returns. When we add the return on Gutierrez and Kelly's (2008) WML portfolios on the right-hand side of the regression, the intercept in all strategies is still high and statistically significant although the magnitude is slightly reduced. The intercept of 1-52 regression is 42bps per week with an associated t-statistic of 8.71, which is economically and statistically significant. Although the alpha of 4-52 portfolio in the four-factor model is 39bps per week (t-statistic = 7.90), 4bps lower than that from the FF3F model, it is still economically and statistically high.[28]

[28] To be conservative, we use returns on Gutierrez and Kelly's 4-52 momentum portfolios, which are their strongest portfolios, in order to explain returns on our news momentum strategies.

To sum up, Table 7 shows that our news momentum portfolios and Gutierrez and Kelly's (2008) unconditional momentum are independent from each other. For the 1-52 strategy, our news momentum portfolio is even much stronger, and able to fully capture the return on Gutierrez and Kelly's (2008) momentum portfolios.

5.2. News residuals from Model 8 and Model 11

We repeat the exercise in Table 6, but use the residuals from Model 8, which includes $log(size)$, $log(1 + analyst)$, book-to-market ratios, industry dummies, log(1+earn), and log(1+merger) as controlled variables. The two important controls in this Model are earning news ($earn$) and merger news ($merger$). As noted above, it may be the case that our results are driven by the effects of earnings news (Tetlock et al., 2008) and merger news (Ahern and Sosyuara, 2013), which also have return predictability. If returns on the news momentum portfolio become insignificant and small by using residuals from Model 8, then our results are not attributable to general firm-specific news, but purely a capture of return predictability from earnings news and the well-known stock return anomaly from mergers and acquisition.

Table 8 shows that our results are still robust to earnings and merger news. In fact, the news momentum effect is even stronger. The short-run reversal (1-1) strategy disappears with the average return of -0.24% per week and an associated t-statistic of -1.33, which is statistically insignificant even at the 10% level. The WPosStale-LNegNew portfolio earns a significantly positive average return starting from week two of holding periods. The 1-2 strategy yields an average return of 29bps per week (t-statistic = 2.63). The best performing news portfolio is 1-52, which earns an average return of 48bps per week (t-statistic = 7.74). In sum, Table 8 indicates that our results are not driven by earnings and merger news.

The next robustness check is to use residuals from Model 11, which adds volatility ranks ($IVOL$) in the model 8. Controlling for $IVOL$ is motivated by Bandarchuk and Hilscher (2013), who argue that when one sorts stocks based on firm characteristics, they also pick up stocks with extreme total risks that make the newly refined portfolio to earn higher returns. In other words, it is the total risk, not the sorting characteristic employed by researchers, that drives the higher profit. Using residual analyst coverage (that controls for $IVOL$), Bandarchuk and Hilscher (2013) find that Hong et al.'s (2000) results are not due to the effect of analyst coverage but purely total risks. In similar spirits, we employ residuals from Model 11 and report results Table 9.

However, as mentioned above, Model 11 suffers from potential endogeneity problems in that news can also determine volatilty. Griffin et al. (2011) show that volatility is much higher on news days than non-news days. Tetlock (2011) finds that news staleness is associated with lower return volatility. Thus, to the extent that news can affect volatility, using Model 11 will be conservative as we significantly reduce the power of our tests by regressing *tone* (or *staleness*) on a noisy proxy for itself, thereby biasing the residuals. Although we take this conservative approach to control for $IVOL$, we can confirm that the news momentum strategy remains profitable (but weaker). The 1-52 news strategy yields the average return of 0.15% per week with the significant associated t-statistic of 2.15.

Table 9 shows that returns on the news momentum portfolios are weaker; but the average return on the 1-52 WPosStale-LNegNew strategy, the most persistent portfolio, is 0.15% per week (t=2.15) – still economically high and statistically significant at the 5% level. The 1-1 news strategy incurs a significant reversal in the first week of holding period with -0.60% per week (t=-4.57). Similar to results in the previous tables, the news strategy stops reversing in week 2: the 1-2 news strategy yields an insignificant negative return of -0.12% per week with an associated t-statistic of -1.43, insignificant even at the 10% level. Although the 4-52 WPosStale-LNegNew portfolio earns an average return of 11bps per week (t=1.65), the fact that the best performing strategy (1-52) still yields a significantly positive average return indicates that our news momentum portfolios are not just an artifact of extreme selection of stocks based on total risks.

< INSERT TABLE 8 AROUND HERE >

The final point worth noticing again is that existing trading strategies in the literature that are conditioned only on news tone (e.g., those of Sinha (2012), which we denote $WPos-LNeg$ portfolios) are not profitable among stocks with stale news. Our news momentum strategy overcomes this by conditioning the trade on both news features. As we will show in the next section, our trading strategy also works in 21 other developed markets whereas the profitablity of existing strategies is not robust to different degrees of staleness.

< INSERT TABLE 9 AROUND HERE >

In sum, we do not find evidence to support Hong et al.'s (2000) hypothesis that "bad news travels slowly" and causes momentum effects in stock returns. Using residuals from Model 8 and Model 11, we find that even after we consider the dimension of staleness, markets still underreact to positive news (the average momentum return in the positive news group is significantly higher than that in the negative news group). In other words, even though we could confirm Hong et al.'s (2000) hypothesis using Model 1, the finding is not robust to considerations of earnings, merger news, and $IVOL$. We again support the original theory of Hong and Stein (1999) that momentum returns are driven by underreaction in prices to (positive) news.

More untabulated robustness checks

Penny stocks. With the exclusion of stocks priced below $5 at the end of each ranking period, we confirm that our results do not qualitatively change. For example, using Model 8's residuals, the 1-52 news momentum portfolio still earns a significant average return of 0.24% per week with an associated t-statistic of 4.56, statistically significant at the 1% level. Thus, our findings are not driven by penny stocks.

Size. we re-examine the profitability of news momentum portfolios by dropping all stocks with size below the median at the end of each ranking period. Using Model 8, the average returns on 1-52 and 4-52 strategies are 0.27% (t-statistic = 7.20) and 0.26% (t-statistic = 7.17) per week, respectively. These results show that the profitability of news strategies is robust to the exclusion of small stocks.[29]

CRSP's daily data. In more untabulated results, we repeat the exercise in Table 6 using daily data from the Center for Research in Security Prices (CRSP) instead of midpoint returns from TRTH. We also confirm that our results do not qualitatively change. For example,

[29] Our results are stronger with Model 11's residuals in the sample of large stocks. With the residuals from Model 11, the 1-52 and 4-52 news strategies on average yield 25bps per week with an associated t-statistic above 6.97, which is economically and statistically significant at the 1% level. This finding indicates that the weaker average return on news momentum portfolios using Model 11's residuals is due to the returns (and high volatility) of small stocks.

with Model 8's residuals, the average returns on 1-52 and 4-52 news momentum (WPosStale-LNegNew) portfolios are 0.11% (t-statistic = 4.01) and 0.10% per week (t-statistic = 3.91) respectively, which are economically and statistically significant at the 1% level. We report midpoint returns to be consistent with Gutierrez and Kelly (2008) who argue that this method can alleviate the bid-ask bounce effect in calculating portfolio returns.

Downside risks:. we also test the business cycle dependence of our news momentum portfolios. Garcia (2013) shows that news sentiment has strong predictability during recessions as dated by the NBER.[30] Consequently, we are interested in whether the average profit of news momentum strategies is stronger during recessions. The disadvantage of this test is that our sample period is short (between January 2003 and December 2011), leaving me with only one recession period from December 2007 to June 2009 (or 87 weeks). Thus, because we have unequal periods of expansions and recessions, our tests are weakened and we can only interpret the magnitude of returns and the percentage of weeks having negative returns. Using residuals from Model 8, we can report that average returns on the 1-52 news momentum portfolio are 0.51% per week (t-statistic = 2.75) and 0.46% per week (t-statistic = 7.20) during contractions and expansions, respectively. These returns are both economically and statistically significant at the 1% level. The average return during contractions is only 5bps higher than that during expansionary times. Finally, the 1-52 news strategy earns negative returns in 36.78% of the (87) recession weeks whereas 33.96% of the (371) expansion weeks has negative returns. For comparison purposes, the Gutierrez and Kelly's (2008) 1-52 momentum portfolio yields negative returns in 58.62% of the recession weeks while 29.92% of the expansion weeks is negative. In other words, the news momentum strategy is less exposed to recessions (or downside risks) than the normal momentum portfolio.

6. Out-of-sample evidence: International weekly momentum returns

One disadvantage of using TRNA data is the relatively short period of time although we employ weekly data, which gives me 458 weeks of returns. One way to overcome this

[30] Grundy and Martin (2001) and Daniel and Moskowitz (2011) find that betas of monthly momentum portfolios are lower following down markets.

disadvantage is to use the TRNA's international coverage, which allows me to test the above findings with out-of-sample evidence. In fact, the results reported in previous sections, especially the profitability of news momentum strategies, are not only true in the U.S., but they also hold in 21 other developed markets. In this section, we essentially repeat the exercise in the previous section, particularly Table 9, for 21 international markets. By doing so, we also provide the first international study that links firms' news to weekly momentum returns.

6.1. Data and weekly momentum returns

We employ TRTH again to collect daily market data for 21 developed markets. Firms must be covered in TRNA to be included in the analysis. We repeat the data cleaning process as for the U.S. markets to get weekly data from Wednesday to Wednesday, except that we do not use the midpoint of bid and ask quotes to calculate returns. Rather, we compute weekly returns using closing prices from Wednesday to Wednesday. The reason why we do not use midpoints of bid and ask prices is because international markets generally do not have a specialist to facilitate transactions as in the NYSE. Consequently, returns computed using midpoints may not be tradeable.[31]

We follow Fama and French (2012) and categorize stocks into three regions: (i) Japan; (ii) Asia Pacific, including Australia, New Zealand, Hong Kong and Singapore (but not Japan); and finally (iii) Europe, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The purpose of these market combinations is parsimony as well as maintaining a certain degree of market integration. Most European countries are members of the European Union (EU), which undoubtedly enjoy the benefits of market integration in the Euro zone. As noted in Fama and French (2012), the most segmented region is Asia Pacific, which may reduce the power of our portfolio tests. Appendix A reports summary statistics for these markets.

Table 10 reports raw momentum returns in each of the regions. The left-hand side panel

[31] As TRTH also provides bid and ask prices, we are able to calculate returns with midpoint of bid and ask prices. We confirm that our conclusions in international markets still hold.

reports results using all stocks while the right-hand side panel drops stocks with size below the 10th percentile (computed using the regional breakpoint). Using the universe of stocks in each region, there is no evidence of momentum effect anywhere. The weekly momentum strategy of Gutierrez and Kelly (2008) earns negative average returns for all strategies but the 4-52; but the 4-52 strategy is also economically and statistically insignificant in all markets.

< INSERT TABLE 10 AROUND HERE >

After dropping microcap stocks at the end of each ranking period, momentum returns are higher although the 1-52 strategy is still not profitable. The 1-1 portfolio produces average returns of -1.48%, -0.92% and -1.68% per week in Europe, Japan and Asia, respectively. The average profit of the 1-52 strategy is almost zero everywhere. The best performing portfolio is the 4-52 with four week skipping period between ranking and holding periods. This strategy is profitable everywhere, earning 4bps per week (t-statistic = 2.57) in Europe, 4bps per week (t-statistic = 3.11) in Japan, and 5bps per week (t-statistic = 3.88) in Asia, which are all statistically significant at least at the 5% level. Since the momentum effect is weak in the presence of extremely small stocks and since these stocks are highly illiquid, we will focus our analysis on the more investible strategy that drops these microcap stocks at the end of each ranking period.

6.2. Momentum portfolios sorted by staleness and tone

Table 11 reports momentum returns sorted first by residual staleness and then residual tone scores. Again, we use residuals from Model 11, which avoids the critique of Bandarchuk and Hilscher (2013). This model choice is conservative not only because of the endogeneity problem that weakens our tests, but also because our U.S. results show that the profitability of news momentum portfolios is the weakest (but still profitable) under this model. Nevertheless, we find that the news momentum strategy earns significantly positive returns in all markets (even though Gutierrez and Kelly's (2008) 1-52 weekly momentum portfolio is not profitable). We also use residuals from other models, and can confirm that our results do not qualitatively change.

< INSERT TABLE 11 AROUND HERE >

Europe. The first panel of Table 11 shows average news momentum returns for different strategies in Europe (the last row). The WPosStale-LNegNew portfolio still produces negative aveage return of -0.31% per week (t-statistic = -3.69) in the first week of holding period. The average news momentum return increases to 27% per week (t-statistic = 7.76) for the 1-52 strategy, which is economically and statistically significant. Recall that the average return on Gutierrez and Kelly's (2008) 1-52 momentum portfolios is almost zero in Table 10. Thus, our news momentum portfolio is much stronger and not a confounding effect of their weekly momentum counterpart. The 4-52 news strategy (with four-week skipping period) yields the highest average return of 29bps per week with an associated t-statistic of 8.07 – statistically significant at the 1% level. This average return is also higher than the normal weekly momentum return in Table 10.

We find mixed evidence for Hong et al.'s (2000) hypothesis in Europe. Among stocks with new news, the average momentum profit in positive news groups is doubled that in negative news groups. The 4-52 momentum strategy yields an average return of 18bps per week in the positive news group, which is 11bps (untabulated t-statistic for this difference = 1.65, significant at the 10% level) higher than that in the negative news group. This finding does not support Hong et al. (2000), but is consistent with the U.S. evidence that underreaction to positive news drives momentum returns. In contrast, we find supporting evidence for Hong et al.'s (2000) hypothesis within the stale news group although the difference in returns between positive news groups and negative news groups is only 2bps per week and statistically insignificant. For example, the average momentum profit on the 4-52 portfolio in the negative news group is 11bps per week, which is 2bps higher than the average momentum return among stocks with good news, and an associated t-statistic for this difference is only 0.57 (not tabulated). Consequently, although these findings provide equivocal supports for Hong et al.'s hypothesis, underreaction to positive news seems to be a stronger driver of momentum profits in both new and stale news groups. The final point of interest is that European markets overreact to stale positive news, but not new positive news. The average profit for 1-1 strategy among stale positive news stocks is -1.15% per week (t-statistic = -10.48) while the average profit in the new positive news group is 0.18% per week (t-statistic = 0.98).

Japan. The middle panel of Table 11 reports results for Japan. Surprisingly, the news momentum strategy (reported in the last row) is highly profitable in Japan, and more importantly it does not reverse in the first week. The average return on the 1-1 WPosStale-LNegNew portfolio is 4bps per week (t-statistic = 0.33), which is not significant in both economic and statistical terms. This evidence is important because it is well known that the monthly momentum effect of Jegadeesh and Titman (1993) is not present in Japan. We have shown that Gutierrez and Kelly's weekly momentum portfolios have significant reversals in the first few weeks of holding periods. Consequently, our results shed lights on a new anomaly that is very strong and persistent in a market that the known momentum strategies do not "work". Also in contrast to the normal Gutierrez and Kelly's (2008) momentum evidence in Table 10, the 1-52 news momentum strategy earns the highest return in Japan with 50bps per week and an associated t-statistic of 8.77, statistically significant at the 1% level. The 4-52 news strategy also performs well, yielding 47bps per week (t=8.40).

In testing Hong et al.'s (2000) hypothesis, Japan's findings are consistent with the European evidence that the momentum effect is marginally stronger among stocks with stale negative news but much weaker in the new negative news group. For example, within stale news groups, the 1-52 strategy in the negative news group earns an average return 20bps per week (t-statistic = 5.68), which is only 4bps (t-statistic difference = 0.92) higher than that in the positive news group. This supports the hypothesis, though weakly, that bad stale news travels slowly. But this slow diffusion of bad news is not found in the new news group where the difference in profitability between two tone news groups is bigger. The 4-52 momentum portfolio earns 16bps per week (t-statistic = 3.72) among stocks with positive news, which is doubled that in the bad news group. The difference of 8bps has the significant associated t-statistic of 1.96. Thus, as in Europe, the underreaction to positive news is still a stronger driver of momentum returns in Japan.

Finally, in terms of short-run overreactions, Japanese markets tend to overreact to new news more than to stale news – in contrast to Tetlock (2011) – although the difference is economically small. Within the new news group of stocks, the 1-1 strategy earns -0.40% (t-statistic = -4.14) and -0.90% per week (t-statistic = -4.34) in the negative and positive news groups, respectively. These average returns are more negative than the average returns of -0.25% and -0.87% per week for stale negative and stale positive news groups, respectively.

Asia (ex. Japan). The last panel of Table 11 presents results for Asian markets. The 1-52 news momentum strategy is again the best, earning 0.66% per week with an associated t-statistic of 7.93, statistically significant at the 1% level. This news momentum effect is obviously not a manifestation of the normal momentum effect because the Gutierrez and Kelly's (2008) 1-52 momentum strategy earns only 0.01% per week (t-statistic = 0.80) in Asia. The 4-52 news portfolio yields the slightly lower return of 60bps per week (t-statistic = 7.32), which is still higher than that in other markets. Among all markets, the news momentum strategy performs the best in Asia.

We also find very weak supporting evidence for Hong et al.'s (2000) hypothesis that "bad news travels slowly" in Asia because the difference in WML returns between negative and positive news groups is not significant. Also, in contrast to Europe and Japan, this support is in the new news group only. Within new news groups, the 1-52 momentum portfolio formed using stocks with negative news earns 15bps per week (t-statistic = 3.83), compared with 7bps per week among positive news stocks. This 8bps difference is however not statistically significant (t-statistic = 1.32, not tabulated). Looking at stale news groups, although the average WML in the positive news group is higher than in the negative news group, the difference is again both economically and statisitcally insignificant.

To sum up, this subsection has shown that our news momentum strategy that buys winner stocks with stale positive news in the past one week and sells loser stocks with new negative news over the same period yields profitable returns everywhere for the holding period of up to 52 weeks. This significant profitability is only identifiable by simultaneously investigating both staleness and tone of news. Unlike the well-known monthly momentum portfolio and weekly momentum strategies, this news momentum portfolio is even highly profitable and not reversing in the first week of holding period in Japan. Finally, unlike the U.S. evidence where the rejection of Hong et al.'s (2000) hypothesis is very strong, the rejection is weak in Europe, Japan, and the rest of Asia. In most cases the difference in momentum returns between negative and positive news groups is not statistically significant and is dependent on the degree of staleness of news, not just the tone of news. Nevertheless, regardless of the tone and staleness of news, we still find strong empirical evidence for the original model of

Hong and Stein (1999) that underreaction to news is the driver of momentum returns. In all markets, momentum strategies that are conditioned on news yield higher average returns than the normal momentum portfolio of Gutierrez and Kelly (2008).

7. Conclusion

The main contribution of this study is, with a much bigger and more current news dataset, to jointly investigate the effect of tone and staleness of news on weekly momentum returns. In the U.S. markets, we do not find evidence to support Hong et al.'s (2000) hypothesis that momentum returns are driven by the slow diffusion of bad news. Instead, we find that it is the underreaction to positive news that drives the profitability of momentum portfolios. However, using international data from 21 developed markets, we find mixed supports for Hong et al.'s (2000) hypothesis and results depend on the staleness of news. Nevertheless, regardless of the tone and staleness of news, we provide strong evidence for Hong and Stein's (1999) theoretical model that momentum effects are attributable to the market's underreaction to news in general. Finally, we document a new investible trading strategy that buys winner stocks with stale positive news in the ranking period and sells losers with new negative news over the same period. This strategy is highly profitable everywhere including Japan where the normal momentum strategy does not work. These findings, which have not been documented in the literature, can only be found by jointly examining the two features of news. Our results are important because they provide strong empirical support (both in the U.S. and international markets) for behavioral theories, specifically the underreaction to news of Hong and Stein (1999), which is rare to find. The fact that our news momentum strategy is profitable in all markets suggests that investors everywhere have similar behavioral bias and underreact to news.

References

Ahern, K. R., Sosyuara, D., 2013. Who writes the news? Corporate press release during merger negotiations. The Journal of Finance forthcomming.

Antweiler, W., Frank, M. Z., 2004. Is all that talk just noise? The information content of Internet stock messages boards. The Journal of Finance 59, 1259–1293.

Antweiler, W., Frank, M. Z., 2006. Do U.S. stock markets typically overreact to corporate news stories? Working Paper, University of British Columbia.

Asness, C. S., Moskowitz, T. J., Pedersen, L. H., 2013. Value and momentum everywhere. The Journal of Finance LXVIII.

Bailey, W., Karolyi, G., Salva, C., 2006. The economic consequences of increased disclosure: Evidence from international cross-listings. Journal of Accounting and Economics 81, 175–213.

Ball, R., Kothari, S. P., 1991. Security returns around earnings annoucements. The Accounting Review 66, 718–738.

Bandarchuk, P., Hilscher, J., 2013. Sources of momentum profits: Evidence on the irrelevance of chracteristics. Review of Finance 17, 809–845.

Barber, B. M., Loeffler, D., 1993. The "dartboard" column: Second-hand information and price pressure. The Journal of Financial and Quantitative Analysis 28, 273–284.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49 (207–43).

Bhattacharya, U., Daouk, H., Jorgenson, B., Kehr, C., 2000. When an event is not an event: The curious case of an emgerging market. Journal of Financial Economics 55, 69–101.

Boudoukh, J., Feldman, R., Kogan, S., Richardson, M., 2012. Which news moves stock prices? A textual analysis. NBER Working Paper.

Chan, W. S., 2003. Stock price reaction to news and no-news: Drift and reversal after headlines. Journal of Financial Economics 70, 223–260.

Chui, A. C., Titman, S., Wei, K. C. J., 2010. Individualism and momentum around the world. The Journal of Finance 65, 361–292.

Conrad, J., Kaul, G., 1998. An anatomy of trading strategies. Review of Financial Studies 11, 489–519.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. The Journal of Finance 53, 369–403.

Daniel, K., Moskowitz, T., 2011. Momentum crashes. NBER Working Paper.

Das, S., Chen, M., 2007. Yahoo! for Amazon: Opinion extraction from small talk on the web. Management Science 53, 1375–88.

Davies, P. L., Canes, M., 1978. Stock prices and the publication of second-hand information. The Journal of Business 51, 43–56.

Davis, A. K., Piger, J., Sedor, L. M., 2012. Beyond the numbers: an analysis of optimistic and pessimistic language in earnings press releases. Contemporary Accounting Research 29, 845–68.

DeFond, M., Hung, M., Trezevant, R., 2007. Investor protection and the information content of annual earnings annoucements: International evidence. Journal of Accounting and Economics 43, 37–67.

DeLong, J. B., Shleifer, A., Summers, L., Waldmann, R. J., 1990. Noise trader risk in financial markets. Journal of Political Economy 98, 703–738.

Dzielinski, M., 2011. News sensitivity and the cross section of stock returns. Working Paper, University of Zurich.

Engelberg, J., 2008. Costly information processing: Evidence from earnings annoucements. Working Paper, University of North Carolina.

Fama, E., French, K. R., 1992. The cross section of expected stock returns. Journal of Financial Economics 47, 427–465.

Fama, E., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. The Journal of Finance 51, 55–84.

Fama, E. F., French, K. R., 2008. Dissecting anomalies. The Journal of Finance LXIII, 1653–79.

Fama, E. F., French, K. R., 2012. Size, value, and momentum in international stock returns. Journal of Financial Economics 105, 457–72.

Fama, E. F., Litterman, R., 2012. An experienced view on markets and investing. Financial Analysts Journal 68, 1–5.

Fama, E. F., MacBeth, J. D., 1973. Risk, return and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. The Journal of Finance 64, 2023–52.

Garcia, D., 2013. Sentiment during recessions. The Journal of Finance 68, 1267–1300.

Griffin, J. M., Hirschey, N. H., Kelly, P. J., 2011. How important is the financial media in global makets. Review of Financial Studies 24, 3941–93.

Grundy, B. D., Martin, J. S., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. The Review of Financial Studies 14, 29–78.

Gutierrez, R., Kelly, E. K., 2008. The long-lasting momentum in stock returns. The Journal of Finance LXIII (1), 415–448.

Hand, J. R. M., 1990. A test of the extended functional fixation hypothesis. The Accounting Review 65, 740–763.

Healy, A. D., Lo, A. W., 2011. Managing real-time risks and returns: The Thomson Reuters NewsScope event indicies. Handbook of News Analytics in Finance, John Wiley & Sons, 73–108.

Hofstede, G., 1980. Culture's consequences: International differences in work-related values. Sage Publication, Beverly Hills, CA.

Hong, H., Lim, T., Stein, J. C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. The Journal of Finance LV, 265–295.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance 54, 2143–84.

Ince, O. S., Porter, R. B., 2006. individual equity return data from thomson datastream: Handle with care! Journal of Financial Research 29, 463–79.

Israel, R., Moskowitz, T. J., 2013. The role of shorting, firm size, and time on market anomalies. Journal of Financial Economics 108, 275–301.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. The Journal of Finance 48, 65–91.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. The Journal of Finance 56, 699–720.

Jegadeesh, N., Titman, S., 2011. Momentum. The Annual Review of Financial Economics 3, 493–509.

Li, F., 2010. The determinants and information content of the forward-looking statements in corporate filings – a Naive Bayesian machine learning approach. Journal of Accounting Research 48, 1049–1102.

Lo, W. A., MacKinlay, A. C., 1990. Data-snooping biases in tests of financial asset pricing models. The Review of Financial Studies 3, 431–67.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. The Journal of Finance LXVI (1), 35–65.

Mitra, G., Mitra, L. (Eds.), 2011. The Handbook of News Analytics in Finance. John Wiley & Sons Ltd.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. The Journal of Finance 39, 1127–39.

Sinha, N. R., 2012. Underreaction to news in the US stock market. Working Paper, University of Illinois at Chicago.

Tetlock, P., 2007. Giving content to investor sentiment: The role of media in the stock market. The Journal of Finance LXII, 1139–69.

Tetlock, P., 2011. All the news that's fit to reprint: Do investors react to stale information? Review of Financial Studies 24, 1481–1513.

Tetlock, P., Saar-Tsechansky, M., Macskassy, S., 2008. More than words: Quantifying language to measure firms' fundamentals. The Journal of Finance LXIII, 1437–69.

Table 1: Summary statistics for U.S. markets between 19 February 2003 and 28 December 2011 (458 weeks)

This table reports summary statistics for U.S. markets "Firms" is the total number of firms. Size (in \$million) is the average market capitalization. "Firm-News" is the number of firm-news observations in a year (i.e., a news article may mention multiple firms in the content). "Articles" is the total number of news articles in a year. "% Stale" is the average percentage of stale news out of the total news articles. "% Coverage" is the average percentage of firms having at least one news article in a year. "Raw Tone" is the average tone score measured as $(positive - negative) \times relevance$, where "relevance" is the relevance score measuring how relevant the news is for a firm. "Raw Stale" is the average raw staleness measured as $log(1 + \#links) \times relevance$ where $\#links$ counts the number of articles over the past seven days having similar contents with the current news item of interest. "Res. Tone" is the average residual from the cross-section regression of raw tone score on Model 1. Similarly, "Res. Stale" is the average residual from the cross-section regression of *staleness* on Model 1. We follow the literature to examine equities only. Also, firms must be covered at least once in the TRNA database. Our final sample contains 5,373,134 news items (with unique news IDs and thus avoid overcounting news that mentions multiple firms) for 9,971 firms over the sample period.

Panel A: yearly summary statistics						
Year	Firms	Size ($mil.)	Firm-News	Articles	% Stale	% Coverage
2003	5152	6045.08	368423.0	329341.0	53.54	31.30
2004	5562	5418.63	463419.0	371083.0	56.61	30.35
2005	6085	5554.65	634391.0	505063.0	61.26	33.68
2006	6665	5010.68	841364.0	523200.0	64.57	35.12
2007	6985	4717.21	949222.0	718722.0	65.05	36.72
2008	7276	3623.38	1163312.0	800114.0	68.90	36.53
2009	5585	3395.36	931143.0	780592.0	70.49	34.81
2010	5209	3774.50	783451.0	708142.0	67.44	36.99
2011	6278	4602.95	1105325.0	636877.0	68.91	38.42

Panel B: Distributions of raw and residual news measures				
	Raw Tone	Raw Stale	Res. Tone	Res. Stale
Mean	0.201	0.430	0.045	0.027
Standard Deviation	0.110	0.172	0.793	0.517
5th percentile	0.025	0.185	−0.390	−0.510
10th percentile	0.072	0.229	−0.300	−0.440
25th percentile	0.126	0.299	−0.170	−0.240
50th percentile	0.194	0.405	−0.020	−0.040
75th percentile	0.272	0.530	0.125	0.172
90th percentile	0.344	0.676	0.364	0.407
95th percentile	0.391	0.750	0.562	0.826

Table 2: Determinants of tone and staleness of news in the U.S.

This table reports the time-series average coefficients of the Fama and MacBeth (1973) cross-sectional regressions in which either *tone* score (Panel A) or *staleness* score (Panel B) is regressed on various control variables by each week. *size* is the log of firm market capitalization (price times number of shares outstanding). *analyst* is the log of one plus analyst coverage. *earn* is the log of one plus a firm's weekly total number of news articles containing the word stem "earn". *merger* is the log of one plus a firm's weekly total number of news articles containing the following word stems: "merge", "merger", "merges", "bid", "acquire", "acquisition", and "takeover". $R1$, $R2$, $R3$ and $R4$ are the lagged one week, two weeks, three weeks and four weeks of returns, respectively. $IVOL$ is 25 portfolio ranks based on firms' total risks. IND is the industry dummies. R^2 and n are the average R^2 (adjusted for degrees of freedom) and number of observations per week, respectively. Newey and West (1987) standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

Model	*size*	*analyst*	BM	*earn*	*merger*	R1	R2	R3	R4	*IVOL*	IND	R^2	n
Panel A: Tone score as dependent variable													
1	0.06	0.08									*No*	0.02	5601
	(22.58)***	(21.96)***											
2	0.06	0.06									*Yes*	0.02	5601
	(23.57)***	(10.52)***											
3	0.09	0.06	−0.01								*No*	0.02	3665
	(21.52)***	(19.28)***	(−1.87)*										
4	0.09	0.04	−0.01								*Yes*	0.03	3665
	(22.92)***	(8.11)***	(−2.46)**										
5	0.08	0.06	−0.01	0.55							*No*	0.04	3665
	(23.78)***	(19.98)***	(−2.97)***	(7.98)***									
6	0.08	0.03	−0.01	0.55							*Yes*	0.05	3660
	(25.13)***	(7.69)***	(−3.40)***	(8.04)***									
7	0.06	0.05	−0.02	0.40	1.23						*No*	0.09	3664
	(21.30)***	(18.02)***	(−4.88)***	(6.57)***	(20.62)***								
8	0.06	0.02	−0.02	0.40	1.23						*Yes*	0.09	3664
	(22.73)***	(5.63)***	(−5.27)***	(6.61)***	(20.74)***								
9	0.06	0.02	−0.02	0.40	1.23	0.10	0.09	0.09	0.07		*Yes*	0.09	3671
	(22.82)***	(5.67)***	(−5.46)***	(6.63)***	(20.80)***	(10.83)***	(11.02)***	(9.96)***	(9.34)***				
10	0.05	0.05	−0.02	0.40	1.22					−0.01	*No*	0.09	3661
	(17.05)***	(18.05)***	(−5.67)***	(6.55)***	(20.64)***					(−10.0)***			
11	0.05	0.02	−0.02	0.40	1.23					−0.01	*Yes*	0.09	3661
	(18.33)***	(5.41)***	(−6.02)***	(6.59)***	(20.75)***					(−10.2)***			
Panel B: Staleness as dependent variable													
1	0.12	0.15									*No*	0.14	5601
	(51.74)***	(39.15)***											
2	0.12	0.19									*Yes*	0.15	5601
	(52.85)***	(33.64)***											
3	0.17	0.12	0.04								*No*	0.14	3665
	(46.56)***	(40.36)***	(12.48)***										
4	0.17	0.14	0.04								*Yes*	0.14	3665
	(49.00)***	(31.54)***	(12.17)***										
5	0.15	0.10	0.03	1.47							*No*	0.23	3665
	(46.37)***	(38.25)***	(11.53)***	(76.91)***									
6	0.15	0.12	0.03	1.47							*Yes*	0.24	3660
	(48.71)***	(30.31)***	(11.37)***	(76.84)***									
7	0.13	0.10	0.02	1.30	1.31						*No*	0.31	3664
	(43.97)***	(36.14)***	(10.64)***	(76.24)***	(172.0)***								
8	0.13	0.11	0.02	1.30	1.30						*Yes*	0.31	3664
	(46.43)***	(27.26)***	(10.66)***	(76.26)***	(174.2)***								
9	0.13	0.10	0.02	1.30	1.30	0.03	0.03	0.02	0.03		*Yes*	0.31	3671
	(46.93)***	(26.72)***	(10.44)***	(76.47)***	(172.0)***	(3.93)***	(3.30)***	(2.52)**	(3.41)***				
10	0.12	0.10	0.02	1.30	1.30					−0.01	*No*	0.31	3661
	(40.49)***	(35.74)***	(9.58)***	(75.31)***	(171.6)***					(−6.35)***			
11	0.12	0.10	0.02	1.29	1.30					−0.01	*Yes*	0.31	3661
	(43.10)***	(26.03)***	(9.79)***	(75.36)***	(174.0)***					(−6.86)***			

Table 3: Summary statistics for U.S. weekly momentum portfolios between 19 February 2003 and 28 December 2011

This table reports average returns on Gutierrz and Kelly's (2008) weekly momentum portfolios in U.S. markets. In each week t, stocks are ranked and sorted into three groups based on their past one week returns where group one contains the best performing stocks (winners) and group three contains the worst performing stocks (losers). The momentum strategy will then buy winner stocks and sell loser stocks. This portfolio is held for various holding periods of 1, 2, 3, 1-52, and 4-52 (with four weeks skipping time between holding and ranking periods) weeks. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. Panel A reports results using all stocks while Panel B shows average returns on portfolios that do not rank stocks with size below the 10th percentile at the end of ranking periods. Microcaps are defined as stocks with market capitalization in the bottom 10% of the sample each week. "WML" is the average return on Gutierrez and Kelly's (2008) winner-minus-loser portfolios. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively. On average, winner and loser portfolios equally contain 1746 stocks per week.

	1	2	3	1-52	4-52
Panel A: All Stocks					
W	−0.90	−0.38	−0.20	0.04	0.04
	(−6.25)***	(−2.80)***	(−1.48)	(0.28)	(0.32)
L	2.55	1.45	1.00	−0.00	−0.07
	(15.00)***	(9.41)***	(6.63)***	(−0.01)	(−0.49)
WML	−3.45	−1.82	−1.19	0.04	0.11
	(−21.8)***	(−20.0)***	(−17.5)***	(1.81)*	(5.60)***
Panel B: Excluding Microcaps					
W	−0.98	−0.47	−0.29	−0.02	−0.01
	(−6.70)***	(−3.42)***	(−2.17)**	(−0.12)	(−0.05)
L	1.91	1.03	0.67	−0.07	−0.12
	(11.27)***	(6.63)***	(4.37)***	(−0.52)	(−0.86)
WML	−2.89	−1.50	−0.96	0.06	0.11
	(−18.3)***	(−16.4)***	(−13.6)***	(2.77)***	(6.05)***

Table 4: Momentum returns in different size groups in U.S. markets from 19 February 2003 to 28 December 2011

This table presents average momentum returns in three size groups (small, medium and large). In each week t, stocks are ranked and sorted into three groups based on size (price times the number of shares outstanding). Within each size group, stocks are further sorted into three groups based on their one week returns where group one contains the best performing stocks (winners) and group three contains the worst performing stocks (losers). The momentum strategy will then buy winner stocks and sell loser stocks. This portfolio is held for various holding periods of 1, 2, 1-52, and 4-52 (with four weeks skipping time between holding and ranking periods) weeks. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. Panel A reports results using all stocks while Panle B drops stocks with size below the 10th percentile at the end of ranking periods. "WML" is the average return on Gutierrez and Kelly's (2008) winner-minus-loser portfolios. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

	Holding period											
	1			2			1-52			4-52		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Panel A: All Stocks												
W	−1.16	−0.87	−0.80	−0.39	−0.37	−0.43	0.06	0.12	−0.06	0.05	0.13	−0.03
	(−7.21)***	(−5.64)***	(−4.63)***	(−2.76)***	(−2.57)**	(−2.77)***	(0.46)	(0.81)	(−0.41)	(0.37)	(0.89)	(−0.22)
L	5.97	2.03	−0.53	3.43	1.14	−0.40	−0.02	0.09	−0.18	−0.19	0.05	−0.16
	(23.52)***	(10.33)***	(−2.37)**	(17.32)***	(6.65)***	(−2.22)**	(−0.15)	(0.61)	(−1.23)	(−1.25)	(0.31)	(−1.10)
WML	−7.13	−2.90	−0.26	−3.81	−1.51	−0.03	0.09	0.02	0.12	0.24	0.08	0.13
	(−25.1)***	(−15.3)***	(−1.16)	(−24.4)***	(−14.9)***	(−0.22)	(3.03)***	(1.23)	(2.88)***	(6.48)***	(4.10)***	(3.94)***
Panel B: Ex. Microcaps												
W	−0.74	−0.73	−0.70	−0.11	−0.25	−0.37	0.29	0.19	−0.02	0.27	0.20	0.01
	(−5.13)***	(−4.73)***	(−4.39)***	(−0.82)	(−1.73)*	(−2.48)**	(2.04)**	(1.34)	(−0.11)	(1.89)*	(1.42)	(0.07)
L	4.88	1.71	−0.48	2.81	1.02	−0.35	0.20	0.18	−0.13	0.07	0.15	−0.10
	(22.02)***	(8.82)***	(−2.20)**	(15.48)***	(5.94)***	(−2.03)**	(1.32)	(1.20)	(−0.86)	(0.44)	(1.00)	(−0.71)
WML	−5.62	−2.44	−0.22	−2.92	−1.27	−0.02	0.09	0.01	0.11	0.20	0.05	0.11
	(−24.3)***	(−14.0)***	(−1.06)	(−23.4)***	(−13.7)***	(−0.13)	(3.58)***	(0.69)	(3.13)***	(7.21)***	(3.12)***	(3.98)***

Table 5: Momentum returns based on sorts of Model 1 residuals and past returns in U.S. markets

This table reports average returns on portfolios sorted by excess *tone* (*staleness*) and momentum. In each week t, stocks are ranked and sorted into three groups based on Model 1's residuals (either *tone* or *staleness*). Within each residual news group, stocks are further sorted into three groups based on their one week returns where group one contains the best performing stocks (winners) and group three contains the worst performing stocks (losers). The momentum strategy will then buy winner stocks and sell loser stocks. This portfolio is held for various holding periods of 1, 2, 1-52, and 4-52 (with four weeks skipping time between holding and ranking periods) weeks. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. Panel A shows average returns from residual *tone* scores while Panel B reports those for residual *staleness*. Stocks must have size above the 10th percentile to be eligible for ranking. "WML" is the average return on Gutierrez and Kelly's (2008) winner-minus-loser portfolios. "WPos-LNeg" is the average return on portfolios that are formed by buying winner stocks with positive news and selling loser stocks with negative news. "WStale-LNew" is the average return on portfolios that are formed by buying winner stocks with stale news and selling loser stocks with new news. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: portfolios sorted based on residual tone scores of model 1 and past returns								
	Holding period							
	1		2		1-52		4-52	
	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive
W	−0.78	−0.21	−0.36	0.13	0.03	0.34	0.05	0.31
	(−4.91)***	(−1.47)	(−2.39)**	(0.95)	(0.23)	(2.44)**	(0.34)	(2.27)**
L	1.06	2.47	0.54	1.46	0.03	0.21	0.01	0.15
	(4.96)***	(14.00)***	(3.01)***	(9.29)***	(0.18)	(1.51)	(0.04)	(1.11)
WML	−1.85	−2.69	−0.90	−1.33	0.01	0.13	0.04	0.16
	(−9.80)***	(−19.5)***	(−8.34)***	(−16.7)***	(0.21)	(6.13)***	(2.07)**	(7.04)***
WPos-LNeg	-1.28		-0.40		0.31		0.31	
	(−6.44)***		(−3.40)***		(6.98)***		(7.22)***	
Panel B: portfolios sorted based on residual staleness of model 1 and past returns								
	Holding period							
	1		2		1-52		4-52	
	New	Stale	New	Stale	New	Stale	New	Stale
W	−0.96	−0.09	−0.48	0.23	−0.06	0.40	−0.03	0.36
	(−5.81)***	(−0.60)	(−3.20)***	(1.57)	(−0.40)	(2.83)***	(−0.23)	(2.60)***
L	0.55	2.37	0.22	1.43	−0.07	0.28	−0.08	0.23
	(2.56)**	(12.73)***	(1.26)	(8.42)***	(−0.49)	(1.93)*	(−0.50)	(1.61)
WML	−1.51	−2.46	−0.71	−1.20	0.02	0.11	0.04	0.13
	(−7.06)***	(−19.0)***	(−5.86)***	(−14.9)***	(0.58)	(5.34)***	(1.78)*	(6.04)***
WStale-LNew	-0.64		0.01		0.47		0.44	
	(−3.07)***		(0.02)		(8.91)***		(8.80)***	

Table 6: Momentum returns sorted based on Model 1 residual staleness, residual tone scores, and past returns in U.S. markets

This table reports average returns on portfolios sorted by excess *staleness*, *tone* and momentum. In each week t, stocks are ranked and sorted into three groups based on Model 1's residual *staleness*. Within each residual *staleness* group, stocks are further sorted into three groups based on their Model 1's residual *tone*. Finally, within each residual *tone* group, 1-1, 1-2, 1-52 and 4-52 momentum portfolios are formed. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. The 4-52 strategy skips four weeks between ranking and holding periods. Stocks must have size above the 10th percentile to be eligible for ranking. "WML" is the average return on Gutierrez and Kelly's (2008) winner-minus-loser portfolios. "WPos-LNeg" is the average return on portfolios that are formed by buying winner stocks with positive news and selling loser stocks with negative news. "WPosStale-LNegNew" is the average return on portfolios that are formed by buying winner stocks with stale positive news and selling loser stocks with new negative news. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

		Holding period							
		1		2		1-52		4-52	
		Negative	Postive	Negative	Postive	Negative	Postive	Negative	Postive
New	W	−0.95	−0.62	−0.49	−0.31	−0.03	0.14	−0.00	0.15
		(−5.72)***	(−3.69)***	(−3.15)***	(−1.94)*	(−0.20)	(0.93)	(−0.02)	(0.96)
	L	0.43	0.71	0.10	0.39	−0.09	0.10	−0.09	0.09
		(1.97)**	(3.51)***	(0.55)	(2.25)**	(−0.61)	(0.65)	(−0.60)	(0.64)
	WML	−1.38	−1.32	−0.59	−0.69	0.06	0.05	0.09	0.05
		(−6.48)***	(−6.93)***	(−4.70)***	(−6.13)***	(1.97)**	(1.17)	(3.29)***	(1.35)
	WPos-LNeg	−1.05		−0.40		0.23		0.24	
		(−4.86)***		(−3.05)***		(5.43)***		(5.73)***	
Stale	W	−0.25	−0.07	0.11	0.28	0.39	0.38	0.38	0.34
		(−1.46)	(−0.46)	(0.68)	(1.92)*	(2.59)***	(2.80)***	(2.52)**	(2.53)**
	L	1.72	2.48	1.05	1.47	0.41	0.26	0.39	0.20
		(8.14)***	(13.52)***	(5.42)***	(9.13)***	(2.54)**	(1.86)*	(2.45)**	(1.43)
	WML	−1.96	−2.55	−0.94	−1.19	−0.01	0.12	−0.01	0.15
		(−12.09)***	(−18.47)***	(−8.86)***	(−13.69)***	(−0.43)	(5.23)***	(−0.22)	(5.52)***
	WPos-LNeg	-1.78		-0.77		-0.03		-0.04	
		(−10.79)***		(−6.51)***		(−0.51)		(−0.83)	
	WPosStale-LNegNew	-0.50		0.18		0.47		0.43	
		(−2.32)**		(1.36)		(8.48)***		(7.98)***	

Table 7: Risk-adjusted returns on news momentum portfolios in U.S. markets

This table reports average risk-adjusted returns for unconditional momentum portfolios (which are formed purely based on past returns as in Table 3) and news momentum portfolios (which are average returns on portfolios of Stale Positive Winners minus New Negative Losers as in Table 6). "FF3F" are returns on the Fama and French three factors, which are obtained from Ken French's website. "WML" is the weekly return on the raw Gutierrez and Kelly's (2008) winner-minus-loser portfolio (sorted based on past returns only). "WPosStale-LNegNew" is the average return on portfolios that are formed by buying winner stocks with stale positive news and selling loser stocks with new negative news. If the LHS is WML then the RHS variable is the 4-52 News Momentum portfolio return. Alternatively, if the LHS is News WML then the RHS variable is the return on the 4-52 unconditional WML portfolio. Stocks with size below the 10th percentile at the end of the ranking period are not ranked. Newey-West standard errors with 1 lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

		Holding period			
LHS	RHS	1	2	1-52	4-52
WML	FF3F	−2.88	−1.49	0.06	0.11
		(−18.5)***	(−16.6)***	(2.75)***	(6.01)***
	FF3F & WPosStale-LNegNew	−2.97	−1.58	0.03	0.10
		(−16.3)***	(−14.6)***	(1.42)	(4.63)***
WPosStale-LNegNew	FF3F	−0.49	0.17	0.47	0.43
		(−2.32)**	(1.31)	(8.45)***	(7.92)***
	FF3F & WML	−0.66	0.07	0.42	0.39
		(−3.66)***	(0.62)	(8.71)***	(7.90)***

Table 8: Momentum returns sorted based on Model 8 residual staleness, residual tone scores, and past returns in U.S. markets

This table reports average returns on portfolios sorted by excess *staleness*, *tone* and momentum. In each week t, stocks are ranked and sorted into three groups based on Model 8's residual *staleness*. Within each residual *staleness* group, stocks are further sorted into three groups based on their Model 8's residual *tone*. Finally, within each residual *tone* group, 1-1, 1-2, 1-52 and 4-52 momentum portfolios are formed. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. The 4-52 strategy skips four weeks between ranking and holding periods. Stocks must have size above the 10th percentile to be eligible for ranking. "WML" is the average return on winner-minus-loser portfolios. "WPos-LNeg" is the average return on portfolios that are formed by buying winner stocks with positive news and selling loser stocks with negative news. "WPosStale-LNegNew" is the average return on portfolios that are formed by buying winner stocks with stale positive news and selling loser stocks with new negative news. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

		Holding period							
		1		2		1-52		4-52	
		Negative	Postive	Negative	Postive	Negative	Postive	Negative	Postive
New	W	−0.87	−0.50	−0.50	−0.14	−0.03	0.21	0.00	0.19
		(−5.14)***	(−3.07)***	(−3.21)***	(−0.84)	(−0.17)	(1.34)	(0.01)	(1.24)
	L	0.09	0.96	−0.06	0.53	−0.04	0.03	−0.03	0.02
		(0.46)	(4.51)***	(−0.38)	(3.02)***	(−0.26)	(0.21)	(−0.19)	(0.13)
	WML	−0.97	−1.45	−0.43	−0.66	0.01	0.18	0.03	0.17
		(−5.10)***	(−7.43)***	(−3.90)***	(−5.31)***	(0.38)	(3.78)***	(1.06)	(3.74)***
	WPos-LNeg	−0.59		−0.07		0.24		0.22	
		(−3.19)***		(−0.57)		(5.63)***		(5.09)***	
Stale	W	−0.22	−0.15	0.08	0.23	0.47	0.44	0.47	0.41
		(−1.35)	(−1.00)	(0.50)	(1.50)	(3.03)***	(2.99)***	(2.98)***	(2.77)***
	L	1.78	2.95	1.06	1.75	0.45	0.31	0.44	0.22
		(8.15)***	(14.27)***	(5.54)***	(10.11)***	(2.77)***	(2.07)**	(2.73)***	(1.52)
	WML	−2.01	−3.10	−0.98	−1.53	0.03	0.14	0.03	0.19
		(−11.91)***	(−18.83)***	(−9.27)***	(−15.97)***	(0.71)	(5.07)***	(0.68)	(6.59)***
	WPos-LNeg	-1.93		-0.84		-0.01		-0.03	
		(−11.23)***		(−7.31)***		(−0.07)		(−0.44)	
	WPosStale-LNegNew	-0.24		0.29		0.48		0.44	
		(−1.33)		(2.63)***		(7.74)***		(7.25)***	

Table 9: Momentum returns sorted based on Model 11 residual staleness, residual tone scores, and past returns in U.S. markets

This table reports average returns on portfolios sorted by excess *staleness*, *tone* and momentum. In each week t, stocks are ranked and sorted into three groups based on Model 11's residual *staleness*. Within each residual *staleness* group, stocks are further sorted into three groups based on their Model 11's residual *tone*. Finally, within each residual *tone* group, 1-1, 1-2, 1-52 and 4-52 momentum portfolios are formed. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. The 4-52 strategy skips four weeks between ranking and holding periods. Stocks must have size above the 10th percentile to be eligible for ranking. "WML" is the average return on winner-minus-loser portfolios. "WPos-LNeg" is the average return on portfolios that are formed by buying winner stocks with positive news and selling loser stocks with negative news. "WPosStale-LNegNew" is the average return on portfolios that are formed by buying winner stocks with stale positive news and selling loser stocks with new negative news. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

		Holding period							
		1		2		1-52		4-52	
		Negative	Postive	Negative	Postive	Negative	Postive	Negative	Postive
New	W	−0.51	−0.52	−0.23	−0.14	0.13	0.29	0.14	0.26
		(−3.47)***	(−3.09)***	(−1.57)	(−0.87)	(0.87)	(1.88)*	(0.98)	(1.68)*
	L	0.41	1.18	0.24	0.71	0.13	0.21	0.13	0.21
		(2.50)**	(5.42)***	(1.55)	(4.14)***	(0.88)	(1.45)	(0.91)	(1.44)
	WML	−0.92	−1.71	−0.47	−0.85	−0.00	0.08	0.01	0.05
		(−7.81)***	(−7.98)***	(−6.31)***	(−6.81)***	(−0.00)	(2.09)**	(0.56)	(1.34)
	WPos-LNeg	−0.93		−0.38		0.16		0.13	
		(−6.45)***		(−3.59)***		(3.83)***		(3.07)***	
Stale	W	−0.24	−0.19	0.07	0.12	0.42	0.28	0.42	0.24
		(−1.41)	(−1.26)	(0.47)	(0.81)	(2.70)***	(1.80)*	(2.62)***	(1.59)
	L	1.76	3.18	1.05	1.79	0.43	0.10	0.41	−0.00
		(8.17)***	(15.20)***	(5.52)***	(10.28)***	(2.66)***	(0.64)	(2.56)**	(−0.02)
	WML	−1.99	−3.37	−0.97	−1.67	−0.01	0.18	0.01	0.25
		(−12.23)***	(−19.87)***	(−9.34)***	(−17.15)***	(−0.08)	(6.41)***	(0.10)	(8.30)***
	WPos-LNeg	-1.95		-0.93		-0.15		-0.17	
		(−11.58)***		(−8.35)***		(−2.36)**		(−2.55)**	
	WPosStale-LNegNew	-0.60		-0.12		0.15		0.11	
		(−4.57)***		(−1.43)		(2.15)**		(1.65)	

Table 10: Summary statistics for weekly momentum portfolios between 19 February 2003 to 28 December 2011

This table reports average returns on Gutierrz and Kelly's (2008) weekly momentum portfolios in international markets. In each week t, stocks are ranked and sorted into three groups based on their past one week returns where group one contains the best performing stocks (winners) and group three contains the worst performing stocks (losers). The momentum strategy will then buy winner stocks and sell loser stocks. This portfolio is held for various holding periods of 1, 2, 3, 1-52, and 4-52 (with four weeks skipping time between holding and ranking periods) weeks. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. Panel A reports results using all stocks while Panel B shows average returns on portfolios that do not rank stocks with size below the 10th percentile at the end of ranking periods. Microcaps are defined as stocks with market capitalization in the bottom 10% of the sample each week. "WML" is the average return on winner-minus-loser portfolios. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively. The number of weeks in each sample is 463 weeks for Europe, 461 for Japan, and 463 weeks for Asia. On average, the numbers of stocks in each winner or loser portfolio in Europe, Japan, and Asia are 1079, 690, and 619 stocks per week, respectively.

Panel A: All Stocks						Panel B: Excluding Microcaps				
	Holding period									
	1	2	3	1-52	4-52	1	2	3	1-52	4-52
Europe										
W	−0.05	0.29	0.42	0.70	0.72	0.00	0.28	0.39	0.63	0.65
	(−0.34)	(2.00)**	(2.96)***	(4.87)***	(5.01)***	(0.02)	(1.93)*	(2.77)***	(4.40)***	(4.52)***
L	1.92	1.36	1.15	0.72	0.70	1.49	1.08	0.93	0.63	0.61
	(11.83)***	(8.67)***	(7.35)***	(4.87)***	(4.70)***	(9.20)***	(6.95)***	(5.98)***	(4.24)***	(4.11)***
WML	−1.97	−1.07	−0.72	−0.03	0.02	−1.48	−0.80	−0.54	0.00	0.04
	(−24.1)***	(−19.1)***	(−16.7)***	(−1.69)*	(1.48)	(−19.3)***	(−15.1)***	(−12.8)***	(0.02)	(2.57)**
Japan										
W	−0.08	0.21	0.36	0.62	0.64	−0.09	0.15	0.28	0.50	0.52
	(−0.57)	(1.53)	(2.57)**	(4.24)***	(4.35)***	(−0.66)	(1.12)	(2.06)**	(3.57)***	(3.66)***
L	1.56	1.15	0.98	0.66	0.65	0.83	0.69	0.61	0.48	0.47
	(8.43)***	(6.74)***	(5.90)***	(4.33)***	(4.20)***	(5.03)***	(4.40)***	(3.98)***	(3.31)***	(3.27)***
WML	−1.63	−0.94	−0.62	−0.04	−0.01	−0.92	−0.54	−0.34	0.02	0.04
	(−13.8)***	(−12.0)***	(−10.9)***	(−2.70)***	(−0.06)	(−9.45)***	(−8.25)***	(−7.13)***	(1.41)	(3.11)***
Asia (ex. Japan)										
W	−0.19	0.29	0.50	0.83	0.85	−0.23	0.20	0.40	0.71	0.73
	(−1.02)	(1.58)	(2.75)***	(4.63)***	(4.73)***	(−1.26)	(1.15)	(2.23)**	(4.04)***	(4.16)***
L	2.29	1.69	1.43	0.90	0.86	1.45	1.12	0.97	0.70	0.68
	(10.87)***	(8.38)***	(7.17)***	(4.78)***	(4.61)***	(7.36)***	(5.77)***	(5.02)***	(3.84)***	(3.77)***
WML	−2.48	−1.41	−0.93	−0.06	−0.01	−1.68	−0.91	−0.57	0.01	0.05
	(−20.1)***	(−17.1)***	(−14.7)***	(−3.93)***	(−0.17)	(−16.5)***	(−12.7)***	(−10.1)***	(0.80)	(3.88)***

Table 11: Momentum returns sorted based on Model 11 residual staleness, residual tone scores, and past returns

This table reports average returns on portfolios sorted by excess *staleness*, *tone* and momentum in international markets. In each week t, stocks are ranked and sorted into three groups based on Model 11's residual *staleness*. Within each residual *staleness* group, stocks are further sorted into three groups based on their Model 11's residual *tone*. Finally, within each residual *tone* group, 1-1, 1-2, 1-52 and 4-52 momentum portfolios are formed. We denote the strategy as 1-H where H is the number of weeks in the holding period and 1 is the one-week ranking period. The 4-52 strategy skips four weeks between ranking and holding periods. Stocks must have size above the 10th percentile to be eligible for ranking. "WML" is the average return on winner-minus-loser portfolios. "WPos-LNeg" is the average return on portfolios that are formed by buying winner stocks with positive news and selling loser stocks with negative news. "WPosStale-LNegNew" is the average return on portfolios that are formed by buying winner stocks with stale positive news and selling loser stocks with new negative news. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

		Holding period							
		1		2		1-52		4-52	
		Negative	Postive	Negative	Postive	Negative	Postive	Negative	Postive
Europe									
New	W	0.14	0.42	0.25	0.28	0.45	0.45	0.46	0.48
		(0.93)	(2.14)**	(1.66)*	(1.61)	(3.07)***	(2.81)***	(3.10)***	(2.95)***
	L	0.63	0.24	0.55	0.31	0.40	0.32	0.39	0.30
		(3.95)***	(1.30)	(3.51)***	(1.90)*	(2.67)***	(2.20)**	(2.59)***	(2.06)**
	WML	−0.49	0.18	−0.30	−0.03	0.06	0.13	0.07	0.18
		(−5.62)***	(0.98)	(−5.21)***	(−0.23)	(2.88)***	(2.32)**	(3.77)***	(2.96)***
	WPos-LNeg	−0.21		−0.27		0.06		0.09	
		(−1.35)		(−2.77)***		(1.09)		(1.79)*	
Stale	W	0.09	0.32	0.22	0.43	0.42	0.67	0.43	0.67
		(0.52)	(2.11)**	(1.37)	(2.88)***	(2.68)***	(4.68)***	(2.79)***	(4.72)***
	L	0.55	1.47	0.35	1.05	0.33	0.61	0.32	0.59
		(2.94)***	(7.98)***	(2.07)**	(6.44)***	(2.08)**	(4.25)***	(2.04)**	(4.13)***
	WML	−0.46	−1.15	−0.13	−0.61	0.09	0.07	0.11	0.09
		(−3.61)***	(−10.48)***	(−1.43)	(−8.61)***	(2.41)**	(2.57)**	(3.00)***	(3.23)***
	WPos-LNeg	-0.23		0.08		0.34		0.35	
		(−1.89)*		(0.89)		(7.84)***		(8.52)***	
	WPosStale-LNegNew	-0.31		-0.12		0.27		0.29	
		(−3.69)***		(−1.85)*		(7.76)***		(8.07)***	

Table 11 continued.

		Holding period							
		1		2		1-52		4-52	
		Negative	Postive	Negative	Postive	Negative	Postive	Negative	Postive
Japan									
New	W	−0.01	−0.08	0.14	0.16	0.40	0.53	0.40	0.53
		(−0.08)	(−0.42)	(1.01)	(0.98)	(2.74)***	(3.47)***	(2.71)***	(3.52)***
	L	0.39	0.82	0.41	0.63	0.31	0.36	0.31	0.38
		(2.58)***	(3.64)***	(2.88)***	(3.39)***	(2.30)**	(2.59)***	(2.35)**	(2.69)***
	WML	−0.40	−0.90	−0.27	−0.47	0.09	0.17	0.08	0.16
		(−4.14)***	(−4.34)***	(−3.75)***	(−3.52)***	(3.58)***	(3.97)***	(3.20)***	(3.72)***
	WPos-LNeg	−0.47		−0.26		0.22		0.22	
		(−3.19)***		(−2.33)**		(5.45)***		(5.51)***	
Stale	W	0.30	0.43	0.52	0.51	0.67	0.81	0.65	0.79
		(2.03)**	(3.17)***	(3.58)***	(3.60)***	(4.65)***	(5.84)***	(4.47)***	(5.71)***
	L	0.55	1.30	0.59	1.00	0.47	0.65	0.47	0.62
		(3.27)***	(7.57)***	(3.90)***	(6.25)***	(3.52)***	(5.23)***	(3.50)***	(5.01)***
	WML	−0.25	−0.87	−0.07	−0.49	0.20	0.16	0.18	0.17
		(−2.08)**	(−6.94)***	(−0.71)	(−5.26)***	(5.68)***	(5.01)***	(4.95)***	(5.50)***
	WPos-LNeg	-0.12		-0.07		0.34		0.32	
		(−1.01)		(−0.84)		(8.88)***		(8.09)***	
	WPosStale-LNegNew	0.04		0.10		0.50		0.47	
		(0.33)		(1.16)		(8.77)***		(8.40)***	
Asia (ex. Japan)									
New	W	0.01	0.28	0.25	0.30	0.59	0.55	0.58	0.57
		(0.07)	(1.01)	(1.25)	(1.38)	(3.13)***	(2.79)***	(3.10)***	(2.87)***
	L	0.86	1.04	0.78	0.94	0.44	0.47	0.46	0.46
		(3.52)***	(4.00)***	(3.47)***	(3.90)***	(2.37)**	(2.54)**	(2.49)**	(2.51)**
	WML	−0.84	−0.76	−0.53	−0.63	0.15	0.07	0.12	0.10
		(−5.35)***	(−3.06)***	(−4.43)***	(−3.81)***	(3.83)***	(1.40)	(3.18)***	(1.81)*
	WPos-LNeg	−0.58		−0.48		0.11		0.10	
		(−2.45)**		(−2.88)***		(1.95)*		(1.74)*	
Stale	W	0.35	0.40	0.40	0.66	0.90	1.10	0.89	1.06
		(1.52)	(1.84)*	(1.92)*	(3.28)***	(5.04)***	(6.19)***	(4.99)***	(5.96)***
	L	1.29	1.31	0.74	1.05	0.77	0.91	0.75	0.92
		(5.08)***	(5.87)***	(3.75)***	(4.98)***	(4.54)***	(5.22)***	(4.45)***	(5.23)***
	WML	−0.94	−0.91	−0.34	−0.39	0.13	0.19	0.14	0.15
		(−3.67)***	(−5.22)***	(−2.09)**	(−2.80)***	(2.05)**	(3.01)***	(2.09)**	(2.23)**
	WPos-LNeg	-0.90		-0.08		0.34		0.31	
		(−3.66)***		(−0.49)		(4.33)***		(4.00)***	
	WPosStale-LNegNew	-0.46		-0.12		0.66		0.60	
		(−2.62)***		(−0.80)		(7.93)***		(7.32)***	

Appendices

A. Summary Statistics for Europe, Japan and Asia

As mentioned in the body text, we source international market data from TRTH's daily database. This database is fully compatible with TRNA via the Reuters Identification Code (RIC), which is used to match stocks' market data with news between the two databases. Following Griffin et al. (2011), Fama and French (2012) and the vast majority of international studies, all returns are calculated in U.S. dollar terms and weekly returns are set to missing if they are greater than 300% and reversed in the following week. Specifically, if either r_t or r_{t-1} is greater than 300% and $(1+r_{t-1})(1+r_t)-1 \leq 50\%$, then both r_{t-1} and r_t are treated as missing values. We use international book values of equity from WorldScope (data item: WC05476). The book-to-market ratio is then computed by dividing book value of equity by the market price of the stock. Exchange rates are provided by TRTH. Similar to the U.S. study, we obtain weekly analyst coverage (defined as the number of analysts who provide fiscal year one earnings estimates in the past quarter) from I/B/E/S.

Table A.1 reports summary statistics for each region. Consistent with previous international studies (e.g., Fama and French (2012)) Europe has the highest number of stocks in three regions. The lowest numbers of stocks for Europe, Japan, and Asia (ex. Japan) are 2,633, 1920, and 1420 stocks, respectively in 2003. The largest numbers of stocks are 4,556 stocks for Europe in 2009, 2,734 stocks for Japan in 2011, and 2,508 stocks for Asia in 2010. Due to its market size, Europe also has the highest total number of news articles with over 3,477,704 news items. Japan has 477,261 news items, and this number for Asia is 870,732. Japan has the lowest media coverage rate with the average of approximately 15% of total number of stocks in a year while Europe has the highest media coverage with the average of approximately 32% of yearly total stocks. On average, 71.88% of the news in Europe is stale; 64.65% of the news in Japan is stale; and finally this percentage for Asia is 65.62%.

Panel B of Table A.1 shows summary statistics for tone and staleness scores. The average raw tone scores for Europe and Asia are 0.73 and 0.05, respectively. These positive scores indicate that on average, news from these markets has positive tone. On the other hand, Japan's average raw tone score is -0.02, suggesting its news coverage on average has a negative tone. However, after controlling for variables in Model 11, average excess tone scores become negative with Europe having the most negative score of -0.05. Similar to the U.S. evidence, controlling for Model 11's variables reduces the effect of news.

Table A.1: Summary Statistics for Europe, Japan and Asia between 15 February 2003 and 28 December 2011

This table reports summary statistics in each region. "Firms" is the total number of firms. Size (in $million) is the average market capitalization. "Firm-News" is the number of firm-news observations in a year (i.e., a news article may mention multiple firms in the content). "Articles" is the total number of unique news articles in a year. "% Stale" is the average percentage of stale news out of the total news articles. "% Coverage" is the average percentage of firms having at least one news article in a year. "Raw Tone" is the average tone score measured as $(positive - negative) \times relevance$, where "relevance" is the relevance score measuring how relevant the news is for a firm. "Raw Stale" is the average raw staleness measured as $log(1+\#links)\times relevance$ where $\#links$ counts the number of articles over the past seven days having similar contents with the current news item of interest. "Res. Tone" is the average residual from the cross-section regression of raw tone score on Model 11. Similarly, "Res. Stale" is the average residual from the cross-section regression of *staleness* on Model 11. We follow the literature to examine equities only. Also, firms must be covered at least once in the TRNA database. The number of weeks in each sample is 463 weeks for Europe, 461 for Japan, and 463 weeks for Asia. The total numbers of stocks in Europe, Japan and Asia (ex. Japan) are 5242, 2824 and 2763 stocks, respectively. Europe also has the highest total number of news articles with over 3,477,704 news items (with unique news IDs). Japan has 477,261 news items, and this number for Asia is 870,732 news items.

Panel A: yearly summary statistics

Year	Firms	Size ($mil.)	Firm-News	Articles	% Stale	% Coverage
Europe						
2003	2633	9882.12	671680.0	241905.0	69.33	29.20
2004	2892	11210.14	792528.0	265269.0	68.32	29.33
2005	3167	11813.17	969222.0	308351.0	72.30	29.91
2006	3495	12855.05	1162933.0	300392.0	73.37	31.75
2007	3956	12473.94	1371247.0	452942.0	75.44	33.72
2008	4414	8236.86	2237379.0	540783.0	80.49	34.34
2009	4556	5702.01	1622598.0	491579.0	71.33	33.23
2010	4554	7060.29	986181.0	446857.0	66.25	32.38
2011	4386	7982.92	993449.0	429626.0	69.56	33.07
Japan						
2003	1920	6006.15	81179.0	45392.0	68.65	15.71
2004	2081	7455.32	88259.0	47025.0	64.68	14.12
2005	2180	7367.37	94227.0	48541.0	66.93	14.95
2006	2264	6872.42	107606.0	44817.0	67.55	16.04
2007	2351	1961.40	112118.0	56915.0	68.90	15.90
2008	2352	1729.82	91614.0	55863.0	63.23	15.42
2009	2429	1331.26	95799.0	60165.0	63.34	14.67
2010	2466	1457.67	76396.0	56523.0	59.43	13.56
2011	2734	1415.91	90940.0	62020.0	59.15	13.48
Asia (ex. Japan)						
2003	1420	1033.67	44910.0	29205.0	57.92	12.66
2004	1588	1200.71	50735.0	30559.0	55.51	11.92
2005	1792	1278.74	68206.0	36694.0	60.22	12.28
2006	1999	1485.58	77798.0	34405.0	62.65	11.89
2007	2247	2028.99	158782.0	130630.0	74.52	20.36
2008	2416	1564.00	139946.0	123129.0	72.19	19.74
2009	2456	1300.83	153970.0	150503.0	70.57	24.60
2010	2508	1719.43	173089.0	169287.0	69.76	26.60
2011	2460	1916.82	172523.0	166320.0	67.31	28.14

Panel B: Distributions of raw and residual news measures

	Raw Tone	Raw Stale	Res. Tone	Res. Stale
Europe				
Mean	0.726	0.615	−0.05	−0.00
Standard Deviation	0.249	0.114	1.318	0.780
5th percentile	0.307	0.440	−1.53	−0.94
10th percentile	0.440	0.495	−1.20	−0.75
25th percentile	0.560	0.546	−0.67	−0.44
50th percentile	0.704	0.612	−0.08	−0.13
75th percentile	0.858	0.691	0.337	0.283
90th percentile	1.041	0.761	0.836	0.780
95th percentile	1.167	0.808	1.652	1.358
Japan				
Mean	−0.020	0.135	−0.00	−0.00
Standard Deviation	0.104	0.109	0.152	0.176
5th percentile	−0.130	0.058	−0.09	−0.20
10th percentile	−0.090	0.066	−0.07	−0.16
25th percentile	−0.030	0.082	−0.03	−0.09
50th percentile	−0.001	0.103	0.002	−0.02
75th percentile	0.014	0.149	0.030	0.041
90th percentile	0.032	0.252	0.057	0.106
95th percentile	0.041	0.322	0.088	0.229
Asia (ex. Japan)				
Mean	0.052	0.239	−0.01	−0.05
Standard Deviation	0.036	0.150	0.098	0.189
5th percentile	−0.001	0.074	−0.09	−0.28
10th percentile	0.012	0.086	−0.05	−0.22
25th percentile	0.030	0.106	−0.03	−0.13
50th percentile	0.050	0.220	−0.01	−0.06
75th percentile	0.070	0.338	0.003	−0.01
90th percentile	0.093	0.447	0.051	0.046
95th percentile	0.115	0.535	0.119	0.114