

News Sentiment and Momentum[☆]

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Abstract

This paper tests Hong and Stein's (1999) underreaction model on weekly momentum returns by employing the dataset of 19.9 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 supports for behavioral explanations of momentum. The persistent profitability of news momentum portfolios suggests that investors everywhere have similar bias of underreaction to news.

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1. Introduction

The evidence of momentum effect in stock returns has been a challenge to asset pricing theories since the seminal study of Jegadeesh and Titman (1993).¹ Jegadeesh and Titman 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 not able to find strong empirical supports.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 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 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".

In this study, instead of 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 to 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,

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

²See Jegadeesh and Titman (2011) for a review on this literature.

³The 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 instead of 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 us 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 are able to provide a complete picture on 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 news

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

analytics technology. Tetlock (2007) is 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 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 contexts. 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 the news 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 news, (2)

the tone of news, and (3) the degree of relevance of 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 metrics of Thomson Reuters recognize 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.

⁵For 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.

The negative score is the highest, indicating that this is negative news for Microsoft, and 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 investigate 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 stale or new news) that actually drives momentum returns.⁶ Momentum strategies earn significant returns ranging from 8bps per week (t -statistics= 2.09) to 18bps per week (t -statistics = 6.41)

⁶The 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.

in the positive news group whereas these portfolios produce almost zero returns 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 -statistics = -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 -statistics = -7.81), suggesting that investors overreact to positive news rather than negative news in the short run.⁸

Comparing returns across different levels of staleness, we confirm Tetlock (2011) that investors overreact to stale news in the short run. Among stocks with stale news, the 1-1 momentum portfolio yields an average return 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. We also attempt to control for the effect of bid-ask bounce that may cause the short-run negative correlation in returns.

Our findings on the effect of staleness are even stronger than those of Tetlock (2011) who finds very weak evidence in the subsample period from 2002 to 2008, which overlaps with our sample period from 2003 to 2011. The primary reason for our stronger support is perhaps due to data differences. As we will discuss in the Data section, our staleness

⁷Our 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 model because tests of Daniel et al.'s 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.

⁸Throughout the paper, 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.

data from TRNA better captures the similarity in the contents of news articles. Moreover, different from Tetlock’s study, our staleness measure directly accounts for the relevance score of news, thereby allowing us 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 of holding period, earns an average return of 47bps per week in the U.S. markets with the associated t -statistics of 8.48. This return is economically significant because it is much higher than the 6bps per week (t -statistics = 2.77) of Gutierrez and Kelly’s 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, and the exclusion of small and illiquid stocks. It cannot be explained by the Fama and French’s (1993) risk factors and downside risks, and is even stronger than Gutierrez and Kelly’s momentum strategy.

Since our sample period is relatively short (between 2003 and 2011, with 458 weeks), we also provide out-of-sample tests 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. markets. Griffin et al. (2011) is one of a few studies examining the impact of financial media on price volatility in 56 markets. Different from our paper, Griffin et al. 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 more than 19.9 million news items in 22 developed markets (including slightly over 7.2 million items from the U.S. – the largest of its kind ever studied in the literature) compared with Griffin et al.’s 870,000 news items in 56 markets.¹⁰

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

¹⁰Bhattacharya et al. (2000) hand-collected 75 news event dates in Mexico between 1994 and 1997, and find no unusual movements in stock returns, volatility or trading volume. Due to lack of news data in

The general conclusion from the out-of-sample test is that our news momentum portfolio is persistent and strong everywhere. Of particular notice 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 news momentum portfolios in the following 52 weeks, yields an average return of 50bps per week (t -statistics = 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 Gutierrez and Kelly’s weekly momentum strategy does in Japan.¹¹ The 1-1 news momentum portfolio produces an average return of 4bps per week (t -statistics = 0.33) whereas the normal 1-1 momentum portfolio yields a significant average return of -92bps per week (t -statistics = -9.45).¹²

These findings are important because they provide another rare strong international support for behavioral theories, specifically the underreaction theory of Hong and Stein (1999).¹³ The persistent profitability of news momentum portfolios in all markets indicates that investors everywhere have similar bias of underreaction to news events.

The layout of the paper is 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. Section 3 discusses our data and methodology. We report results from the portfolio-sorting

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.

¹¹TRNA’s news is predominantly 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 us to investigate what type of investors trades on news. We therefore leave this question for future research.

¹²We 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.

¹³Chui 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.

approach in Section 4. Section 5 presents various robustness checks for the U.S. findings. We then provide international evidence in Section 6. We conclude in Section 7.

2. Related literature

Our study contributes to the growing literature that tries to explain momentum effects using firm-specific news. Employing news headlines of 25% of CRSP stocks between January 1980 and December 2000, Chan (2003) compares the monthly profitability of momentum portfolios with news and without news. Chan 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 higher than those covered by the media. In this study, apart from employing bigger and more recent news 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 similar technique as Tetlock (2007), Engelberg (2008) counts the number of negative words in the firm's earnings announcements and finds that the qualitative information in the text has stronger return predictability than quantitative financial measures such as Standardized Unexpected Earnings.

Our paper not only examines news negativity but also news positivity, thereby uncovers 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 is most likely stale) has strong return predictability during recessions. Different from our paper, Garcia uses U.S. market index instead of individual stock returns. Similar to Tetlock (2007) and most studies, Garcia uses the so-called “bag-of-words” approach in textual analysis, which has some limitations as discussed in the Introduction. Some studies employ alternative 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 recommendations. This paper is related to Tetlock (2011) who provides direct examinations of staleness effects and finds that market overreact (i.e., strong short-run reversals) to stale news. As mentioned in the Introduction, our study offers improvements in this direction of research by employing TRNA data, which is more current, bigger, and covering all types of news items. In the Data section, we also point out some differences in 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. Specifically, 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 19.9 million news items in our dataset for four regions, and 7.2 million items in the U.S. – the largest of its kind ever studied in the literature). TRTH also offers intraday data (similar to TAQ) with bid and ask quotes, which allow us to compute the midpoint quote. Using quote data instead of transaction prices is consistent with Gutierrez and Kelly (2008), and to avoid spurious negative correlation induced by bid-ask bounce (Roll, 1984).

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 in the TRNA database. TRNA and TRTH have classifications for security types, which are

¹⁴TRNA 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 do not qualitatively change with five- and three-day windows.

¹⁵LNKD_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 we can confirm that conclusions do not change using LNKD_CNTn.

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

¹⁷Following Gutierrez and Kelly (2008), late quotes recorded after 4:10pm are excluded. If a price is missing on Wednesday, we use Tuesday’s closing price instead. If news arrives after 3:30pm, the news is treated as tomorrow news.

used to select equities only. Following Ince and Porter (2006) and Griffin et al. (2010), 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

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. 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:

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

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

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 also 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 the sentiment of zero, which has no effect

¹⁸Griffin et al. (2010) use the breakpoints of 100% and the reversed point of 20%. Our results are not changed with these returns filters. We decided to report the returns filter of 300% because we think 100% is rather strict. Indeed, our filters are similar to those of Ince and Porter (2006) who study the quality of Datastream's data, and Karolyi and Wu (2012) who study the market integration of international asset pricing.

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.

Different from 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 higher impacts on its stock returns than the news with only 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 us to use all available news items covered in TRNA without imposing unnecessary constraints on news characteristics.

We note that Tetlock (2011) imposes three filters in the news data that we do not do in this study, and therefore we are able to use all available news items. The first filter is that news stories must have the 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 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 has a few sentences in the content and convey new information. Indeed, Healy and Lo (2011) note that news alerts are short, and 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 paper. 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 we 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 convey similar contents. 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 contents to the current news item of interest. This method allows the context to play a role, thereby provides more accurate measures of staleness and tone of news.

Several contemporaneous studies have used TRNA data. Sinha (2012) investigates the return predictability of TRNA’s sentiment scores in the U.S. markets. Sinha 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’s focus is not 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 impose any of these filters in this study, but 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 effects 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 368,423 items in 2003 (or media coverage of 31.30%) to 1,105,325 articles in 2011 (or 38.42% coverage). With the increase in media coverage, the percentage of stale news also rises yearly. In 2003, 53.54% of the news items are stale while this percentage in 2011 is 68.91%.

¹⁹Unlike this study, both Sinha (2012) and Dzielinski (2011) do not focus on explaining the weekly momentum returns. Our paper 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 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 excess tone scores are also lower to -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 effects of staleness and 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) to run cross-sectional regressions of $\log(1+\text{staleness})$ or tone on a number of firm characteristics. We employ $\log(1+\text{staleness})$ 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 are then interpreted as excess news tone scores and excess staleness scores, which are used to rank stocks (along with the past week return) in the next section. This methodology allows us 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.

$$\text{tone}_i = \beta_{0,i} + \beta_{1,i}\log(\text{size}_i) + \beta_{2,i}\log(1 + \text{analyst}_i) + \epsilon_i \quad (3)$$

$$\log(1 + \text{staleness}_i) = \beta_{0,i} + \beta_{1,i}\log(\text{size}_i) + \beta_{2,i}\log(1 + \text{analyst}_i) + \epsilon_i \quad (4)$$

In Model 1, we regress tone and $\log(1+\text{staleness})$ on size and $\log(1 + \text{analyst})$ as in

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

regressions (3) and (4), respectively. This model is mainly motivated from 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 we go beyond the bottom 10% size, the momentum effect is weaker as size gets bigger. 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 show that Hong, Lim and Stein’s results are sample specific. Size also has effects on news sentiment. DeLong et al. (1990) and Tetlock (2007) show that investor sentiment has a bigger effect on small stocks’ returns.

< INSERT TABLE 2 AROUND HERE >

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 means that the bigger the firm the more likely the firm’s news contents are positive. 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 somewhat not surprising because the media tends to cover big firms.

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 (particularly bad 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 and higher than that of size for both tone and staleness regressions. The positive coefficient on $\log(size)$ in the *tone* regression confirms Hong et al. (2000) that analysts tend to cover

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

firms 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 correct because 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 stocks’ returns, we should ascertain that any predicting power from news effects is not a manifestation of the well-known book-to-market effect. Controlling for industry and BM ratios does not increase R^2 in either regression and the effects of size and analysts remain significant. The coefficient on BM is also small with -0.01 for tone and 0.04 for staleness although they 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) to 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 $\log(1+\text{total earnings news items})$. 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 both economically and 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 and Sosyura (2013) show that bidders in stock mergers and acquisitions have incentives to

²²TRNA 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 headlines.

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 $\log(1 + \text{total merger news items})$, R^2 increases to 9% and 31% in the tone and staleness regressions, respectively. The coefficient on *merger* is both economically and statistically significant with 1.23 and 1.31 in tone and staleness regressions, 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 importance of merger news.

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 weeks’ 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 high volatility in the extreme decile, and therefore the portfolio should command higher returns. Consequently, if *IVOL* is the main driver of news effect on momentum, then controlling for *IVOL* will cause

²³These 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.

²⁴We 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.

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

the average momentum return to be insignificant. Indeed, after Bandarchuk and Hilscher control for *IVOL* ranks, the double-sorted portfolio based on various firm characteristics (including Hong et al.’s (2000) analyst coverage) and momentum does not yield significant returns.

However, we should note the endogeneity problem inherent in Model 11. In particular, the causation can also go the other way that news can drive volatility in returns. Indeed, 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 significantly weaken the power of our tests because we regress *tone* (or *staleness*) on a noisy proxy for itself.

Table 2 shows that although the coefficient on *IVOL* rank is statistically significant at the 1% level in both regressions, it is economically small with only -0.01, and the R^2 also 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), at the end of each week, 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 >

²⁶Grouping 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).

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 we lengthen the holding period to 3 weeks, the negative average return reduces to -1.19% per week (t -statistics = -17.5). When we hold the winner-minus-loser (WML) portfolio for 52 weeks, the average return becomes positive 4bps per week with the associated t -statistics of 1.81, 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 -statistics = 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 the associated t -statistics 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 11bps per week (t -statistics = 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 period, 116.67% ($= |-0.07|/0.06 * 100$, 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% ($= |-0.12|/0.11 * 100$, not reported). In order to make a conclusion about the implementability of weekly momentum strategies, we will explore further the importance of size and shorting 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 small size groups and weaker in the largest size group. However, Israel and Moskowitz (2013) show that Hong et al.'s 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.

< INSERT TABLE 4 AROUND HERE >

Table 4 shows average WML returns in 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 employ full sample 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 reduce (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 -statistics = -25.1) to -0.26% per week (t -statistics = -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 the associated t -statistics 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 -statistics = 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.

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 shorting (i.e., the reliance on the negative return of loser portfolios) increases as firm size rises. Panel B of Table 4 shows that, in the medium sized group, 400% (= $0.20/0.05*100$, not reported) of the average return on 1-52 portfolios comes from the winner portfolio. This

percentage decreases to only 9.09% ($= 0.01/0.11 * 100$, 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, 1-52 and 4-52 momentum portfolios are formed using the stocks' past one week returns.

< INSERT TABLE 5 AROUND HERE >

Panel A of Table 5 reports average momentum returns in negative and positive news groups. Markets initially overreact to positive news as evidenced in the 1-1 and 1-2 momentum portfolios. The 1-1 strategy yields a negative average return of 2.69% per week (t -statistics = -19.5) in the positive news group whereas the average return in the negative news group is -1.85% per week (t -statistics = -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 the associated t -statistics of 7.04, 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 -statistics = 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 -statistics = 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 Hong and Stein's model because tests of Daniel et al.'s 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 1-52 and 4-52 portfolios 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 -statistics = 6.04) but only earns 4bps per week (t -statistics = 1.78) in the new news group.

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

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 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.

< INSERT TABLE 6 AROUND HERE >

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 -statistics = -6.13), which is more negative than that in the negative news group with -0.59% per week (t -statistics = -4.70).

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 -statistics = 3.29), which is higher than 5bps per week (t -statistics=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 Hong et al.'s hypothesis 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 -statistics of only 0.98. This difference for the 1-52 strategy is only 2bps per week (t -statistics = 0.42). Thus, although the magnitude of the difference is consistent with Hong et al.'s 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 -statistics = -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 -statistics = 5.52) among stocks with stale positive news whereas it earns -1bp per week (t -statistics = -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 -statistics 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

We can see two interesting observations 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 -statistics = -0.51) in the stale news group while it yields a significant profit of 23bps per week (t -statistics = 5.43) in the new news group. This suggests that the profitability of trading strategies that sort stocks based on only one feature of news (either tone or staleness) is not robust to the joint examination both 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 -statistics of 8.48 – 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 -statistics 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 the significant associated t -statistics 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 paper. 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 news momentum effects 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 >

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,

²⁷Fama and French’s risk factors are downloaded from Ken French’s website.

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 -statistics = 2.75) and 11bps per week (t -statistics = 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 1-52 WML returns on the FF3F and the WPosStale-LNegNew return, the intercept reduces to 3 bps per week with the associated t -statistics 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). However, the 4-52 WML portfolio is still strong with the intercept being 10bps per week (t -statistics = 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 the associated t -statistics of 8.71, which is economically and statistically significant. Although the alpha of 4-52 portfolio in the four-factor model is 39 bps per week (t -statistics = 7.90) – 4bps lower than that from the FF3F model, it is still economically and statistically high.²⁸

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 momentum portfolios.

²⁸To 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.

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 Sosyura, 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.

< INSERT TABLE 8 AROUND HERE >

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 the associated t -statistics 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 -statistics = 2.63). The best performing news portfolio is 1-52, which earns an average return of 48bps per week (t -statistics = 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 which news can also drive volatility. 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).

< INSERT TABLE 9 AROUND HERE >

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 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 the associated t -statistics 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 the news momentum effect is not just an artifact of extreme selection of stocks based on total risks.

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 profitability of existing strategies is not robust to different degrees of staleness.

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 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 market's underreaction 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 and the 1-52 news momentum portfolio still earns a significant average return of 0.33% per week with the associated *t*-statistics of 6.92, 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. Our results are surprisingly stronger even with Model 11's residuals. With the residuals from Model 11, the 1-52 and 4-52 news strategies on average yield 25bps per week with the associated *t*-statistics 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. It also shows that the profitability of news strategies is robust to the exclusion of small stocks.

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. The average return on the news momentum (WPosStale-LNegNew) portfolio is still economically and statistically significant at the 1% level, and more importantly they are robust to the use of Model 11's residuals. 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.²⁹ 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 us 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 -statistics = 2.75) and 0.46% per week (t -statistics = 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 us 458 weeks of returns. One way to overcome this disadvantage is to use the TRNA's international coverage, which allows us 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

²⁹Grundy and Martin (2001) and Daniel and Moskowitz (2011) find that betas of monthly momentum portfolios are lower following down markets.

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 midpoint of bid and ask quotes to calculate returns. Instead, 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 NYSE. Consequently, returns computed using midpoints may not be tradeable.³⁰

We follow Fama and French (2012) to 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.

< INSERT TABLE 10 AROUND HERE >

Table 10 reports raw momentum returns in each of the regions. The left-hand side panel 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. Gutierrez and Kelly's weekly momentum strategy produces negative average returns for all strategies but the 4-52, which is also economically and statistically insignificant everywhere.

³⁰As 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.

By dropping stocks with size in the bottom 10%, 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 4% per week (t -statistics = 2.57) in Europe, 4% per week (t -statistics = 3.11) in Japan, and 5% per week (t -statistics = 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 those stocks are highly illiquid, we will focus our analysis on portfolios that drop those micro-cap 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 under this model. Nevertheless, we find that the news momentum strategy is still profitable everywhere (even though Gutierrez and Kelly's 1-52 weekly momentum portfolio is not). We also use residuals from other models, and can confirm that 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 average return of -0.31% per week (t -statistics = -3.69) in the first week of holding period. The average news momentum return increases to 27% per week (t -statistics = 7.76) for the 1-52 strategy, which is economically and statistically significant. Recall that the average return on Gutierrez and Kelly's 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 the associated t -statistics 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 -statistics 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 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 the associated t -statistics 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 -statistics = -10.48) while the average profit in the new positive news group is 0.18% per week (t -statistics = 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 -statistics = 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 momentum evidence in Table 10, the 1-52 news momentum strategy earns the highest return in Japan with 50bps per week and the associated t -statistics of 8.77, statistically significant at the 1% level. The 4-52 news strategy also performs well, yielding 47% per week ($t=8.40$).

In testing Hong et al.’s 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 -statistics = 5.68), which is only 4bps (t -statistics 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 -statistics = 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 -statistics 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 overreaction, 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 -statistics = -4.14) and -0.90% per week (t -statistics = -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 the associated t -statistics 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 1-52 momentum strategy earns only 0.01% per week (t -statistics = 0.80) in Asia. The 4-52 news portfolio yields slightly lower return of 60bps per week (t -statistics = 7.32), which is higher than that in most 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 of "bad news travels slowly" in Asia because the difference in WML returns between negative and positive news groups is not statistically 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 -statistics = 3.83), compared with 7bps per week among positive news stocks. This 8bps difference is however not statistically significant (t -statistics = 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 statistically 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 normal Gutierrez and Kelly's portfolios.

7. Conclusion

The main contribution of this paper 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 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. Our results are important because they provide the first and rare empirical supports (both in the U.S. and international markets) for behavioral theories, specifically the underreaction to news of Hong and Stein (1999). The fact that our news momentum strategy is profitable everywhere suggests strongly that investors have similar behavioral bias and underreact to news in all markets.

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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. “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 7,240,050 news items for 9,971 firms over the sample period.

Panel A: yearly summary statistics					
Year	Firms	Size (\$mil.)	Articles	% Stale	% Coverage
2003	5152	6045.08	368423.0	53.54	31.30
2004	5562	5418.63	463419.0	56.61	30.35
2005	6085	5554.65	634391.0	61.26	33.68
2006	6665	5010.68	841364.0	64.57	35.12
2007	6985	4717.21	949222.0	65.05	36.72
2008	7276	3623.38	1163312.0	68.90	36.53
2009	5585	3395.36	931143.0	70.49	34.81
2010	5209	3774.50	783451.0	67.44	36.99
2011	6278	4602.95	1105325.0	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 and number of observations per week, respectively. Newey-West standard errors with one lag are used. *, ** and *** denote the statistical significance at the 10%, 5% and 1% levels, respectively.

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

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

This table reports average returns on Gutierrez 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 (-6.25)***	-0.38 (-2.80)***	-0.20 (-1.48)	0.04 (0.28)	0.04 (0.32)
L	2.55 (15.00)***	1.45 (9.41)***	1.00 (6.63)***	-0.00 (-0.01)	-0.07 (-0.49)
WML	-3.45 (-21.8)***	-1.82 (-20.0)***	-1.19 (-17.5)***	0.04 (1.81)*	0.11 (5.60)***
Panel B: Excluding Microcaps					
W	-0.98 (-6.70)***	-0.47 (-3.42)***	-0.29 (-2.17)**	-0.02 (-0.12)	-0.01 (-0.05)
L	1.91 (11.27)***	1.03 (6.63)***	0.67 (4.37)***	-0.07 (-0.52)	-0.12 (-0.86)
WML	-2.89 (-18.3)***	-1.50 (-16.4)***	-0.96 (-13.6)***	0.06 (2.77)***	0.11 (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 Panel 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. This table shows that, beyond the group of smallest stocks, momentum profits are higher when size gets larger.

		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 (-4.91)***	-0.21 (-1.47)	-0.36 (-2.39)**	0.13 (0.95)	0.03 (0.23)	0.34 (2.44)**	0.05 (0.34)	0.31 (2.27)**	
L	1.06 (4.96)***	2.47 (14.00)***	0.54 (3.01)***	1.46 (9.29)***	0.03 (0.18)	0.21 (1.51)	0.01 (0.04)	0.15 (1.11)	
WML	-1.85 (-9.80)***	-2.69 (-19.5)***	-0.90 (-8.34)***	-1.33 (-16.7)***	0.01 (0.21)	0.13 (6.13)***	0.04 (2.07)**	0.16 (7.04)***	
WPos-LNeg		-1.28 (-6.44)***		-0.40 (-3.40)***		0.31 (6.98)***		0.31 (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 (-5.81)***	-0.09 (-0.60)	-0.48 (-3.20)***	0.23 (1.57)	-0.06 (-0.40)	0.40 (2.83)***	-0.03 (-0.23)	0.36 (2.60)***	
L	0.55 (2.56)**	2.37 (12.73)***	0.22 (1.26)	1.43 (8.42)***	-0.07 (-0.49)	0.28 (1.93)*	-0.08 (-0.50)	0.23 (1.61)	
WML	-1.51 (-7.06)***	-2.46 (-19.0)***	-0.71 (-5.86)***	-1.20 (-14.9)***	0.02 (0.58)	0.11 (5.34)***	0.04 (1.78)*	0.13 (6.04)***	
WStale-LNew		-0.64 (-3.07)***		0.01 (0.02)		0.47 (8.91)***		0.44 (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 (-5.72)***	-0.62 (-3.69)***	-0.49 (-3.15)***	-0.31 (-1.94)*	-0.03 (-0.20)	0.14 (0.93)	-0.00 (-0.02)	0.15 (0.96)
	L	0.43 (1.97)**	0.71 (3.51)***	0.10 (0.55)	0.39 (2.25)**	-0.09 (-0.61)	0.10 (0.65)	-0.09 (-0.60)	0.09 (0.64)
	WML	-1.38 (-6.48)***	-1.32 (-6.93)***	-0.59 (-4.70)***	-0.69 (-6.13)***	0.06 (1.97)**	0.05 (1.17)	0.09 (3.29)***	0.05 (1.35)
	WPos-LNeg	-1.05 (-4.86)***		-0.40 (-3.05)***		0.23 (5.43)***		0.24 (5.73)***	
	W	-0.25 (-1.46)	-0.07 (-0.46)	0.11 (0.68)	0.28 (1.92)*	0.39 (2.59)***	0.38 (2.80)***	0.38 (2.52)**	0.34 (2.53)**
Stale	L	1.72 (8.14)***	2.48 (13.52)***	1.05 (5.42)***	1.47 (9.13)***	0.41 (2.54)**	0.26 (1.86)*	0.39 (2.45)**	0.20 (1.43)
	WML	-1.96 (-12.09)***	-2.55 (-18.47)***	-0.94 (-8.86)***	-1.19 (-13.69)***	-0.01 (-0.43)	0.12 (5.23)***	-0.01 (-0.22)	0.15 (5.52)***
	WPos-LNeg	-1.78 (-10.79)***		-0.77 (-6.51)***		-0.03 (-0.51)		-0.04 (-0.83)	
	WPosStale-LNegNew	-0.50 (-2.32)**		0.18 (1.36)		0.47 (8.48)***		0.43 (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. We can see that the normal momentum portfolio and news momentum portfolios are two separate effects. However, the news momentum effect tends to be stronger because it can significantly reduce the intercept (alpha) of Gutierrez and Kelly’s 1-52 WML portfolios whose returns cannot be explained by the three-factor model of Fama and French (1993).

LHS	RHS	Holding period			
		1	2	1-52	4-52
WML	FF3F	-2.88 (-18.5)***	-1.49 (-16.6)***	0.06 (2.75)***	0.11 (6.01)***
	FF3F & WPosStale-LNegNew	-2.97 (-16.3)***	-1.58 (-14.6)***	0.03 (1.42)	0.10 (4.63)***
WPosStale-LNegNew	FF3F	-0.49 (-2.32)**	0.17 (1.31)	0.47 (8.45)***	0.43 (7.92)***
	FF3F & WML	-0.66 (-3.66)***	0.07 (0.62)	0.42 (8.71)***	0.39 (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. The purpose of this table is to show that the profitability of "WPosStale-LNegNew" portfolios is not a capture of earnings and merger news effects.

		Holding period							
		1		2		1-52		4-52	
		Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive
New	W	-0.87 (-5.14)***	-0.50 (-3.07)***	-0.50 (-3.21)***	-0.14 (-0.84)	-0.03 (-0.17)	0.21 (1.34)	0.00 (0.01)	0.19 (1.24)
	L	0.09 (0.46)	0.96 (4.51)***	-0.06 (-0.38)	0.53 (3.02)***	-0.04 (-0.26)	0.03 (0.21)	-0.03 (-0.19)	0.02 (0.13)
	WML	-0.97 (-5.10)***	-1.45 (-7.43)***	-0.43 (-3.90)***	-0.66 (-5.31)***	0.01 (0.38)	0.18 (3.78)***	0.03 (1.06)	0.17 (3.74)***
	WPos-LNeg	-0.59 (-3.19)***		-0.07 (-0.57)		0.24 (5.63)***		0.22 (5.09)***	
	W	-0.22 (-1.35)	-0.15 (-1.00)	0.08 (0.50)	0.23 (1.50)	0.47 (3.03)***	0.44 (2.99)***	0.47 (2.98)***	0.41 (2.77)***
Stale	L	1.78 (8.15)***	2.95 (14.27)***	1.06 (5.54)***	1.75 (10.11)***	0.45 (2.77)***	0.31 (2.07)**	0.44 (2.73)***	0.22 (1.52)
	WML	-2.01 (-11.91)***	-3.10 (-18.83)***	-0.98 (-9.27)***	-1.53 (-15.97)***	0.03 (0.71)	0.14 (5.07)***	0.03 (0.68)	0.19 (6.59)***
	WPos-LNeg	-1.93 (-11.23)***		-0.84 (-7.31)***		-0.01 (-0.07)		-0.03 (-0.44)	
	WPosStale-LNegNew	-0.24 (-1.33)		0.29 (2.63)***		0.48 (7.74)***		0.44 (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. The purpose of this table is to show that the profitability of "WPosStale-LNegNew" portfolios is not a capture of earnings, merger news, and volatility effects.

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

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

This table reports average returns on Gutierrez 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.

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Panel A: All Stocks						Panel B: Excluding Microcaps				
						Holding period				
						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. The purpose of this table is to show that the profitability of "WPosStale-LNegNew" portfolios is not a capture of earnings, merger news, and volatility effects, and more importantly it is strong everywhere including Japan.

		Holding period							
		1		2		1-52		4-52	
		Negative	Postive	Negative	Postive	Negative	Postive	Negative	Postive
Europe									
New	W	0.14 (0.93)	0.42 (2.14)**	0.25 (1.66)*	0.28 (1.61)	0.45 (3.07)***	0.45 (2.81)***	0.46 (3.10)***	0.48 (2.95)***
	L	0.63 (3.95)***	0.24 (1.30)	0.55 (3.51)***	0.31 (1.90)*	0.40 (2.67)***	0.32 (2.20)**	0.39 (2.59)***	0.30 (2.06)**
	WML	-0.49 (-5.62)***	0.18 (0.98)	-0.30 (-5.21)***	-0.03 (-0.23)	0.06 (2.88)***	0.13 (2.32)**	0.07 (3.77)***	0.18 (2.96)***
	WPos-LNeg	-0.21 (-1.35)		-0.27 (-2.77)***		0.06 (1.09)		0.09 (1.79)*	
	W	0.09 (0.52)	0.32 (2.11)**	0.22 (1.37)	0.43 (2.88)***	0.42 (2.68)***	0.67 (4.68)***	0.43 (2.79)***	0.67 (4.72)***
Stale	L	0.55 (2.94)***	1.47 (7.98)***	0.35 (2.07)**	1.05 (6.44)***	0.33 (2.08)**	0.61 (4.25)***	0.32 (2.04)**	0.59 (4.13)***
	WML	-0.46 (-3.61)***	-1.15 (-10.48)***	-0.13 (-1.43)	-0.61 (-8.61)***	0.09 (2.41)**	0.07 (2.57)**	0.11 (3.00)***	0.09 (3.23)***
	WPos-LNeg	-0.23 (-1.89)*		0.08 (0.89)		0.34 (7.84)***		0.35 (8.52)***	
	WPosStale-LNegNew	-0.31 (-3.69)***		-0.12 (-1.85)*		0.27 (7.76)***		0.29 (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)	-0.08 (-0.42)	0.14 (1.01)	0.16 (0.98)	0.40 (2.74)***	0.53 (3.47)***	0.40 (2.71)***	0.53 (3.52)***
	L	0.39 (2.58)***	0.82 (3.64)***	0.41 (2.88)***	0.63 (3.39)***	0.31 (2.30)**	0.36 (2.59)***	0.31 (2.35)**	0.38 (2.69)***
	WML	-0.40 (-4.14)***	-0.90 (-4.34)***	-0.27 (-3.75)***	-0.47 (-3.52)***	0.09 (3.58)***	0.17 (3.97)***	0.08 (3.20)***	0.16 (3.72)***
	WPos-LNeg	-0.47 (-3.19)***		-0.26 (-2.33)**		0.22 (5.45)***		0.22 (5.51)***	
Stale	W	0.30 (2.03)**	0.43 (3.17)***	0.52 (3.58)***	0.51 (3.60)***	0.67 (4.65)***	0.81 (5.84)***	0.65 (4.47)***	0.79 (5.71)***
	L	0.55 (3.27)***	1.30 (7.57)***	0.59 (3.90)***	1.00 (6.25)***	0.47 (3.52)***	0.65 (5.23)***	0.47 (3.50)***	0.62 (5.01)***
	WML	-0.25 (-2.08)**	-0.87 (-6.94)***	-0.07 (-0.71)	-0.49 (-5.26)***	0.20 (5.68)***	0.16 (5.01)***	0.18 (4.95)***	0.17 (5.50)***
	WPos-LNeg	-0.12 (-1.01)		-0.07 (-0.84)		0.34 (8.88)***		0.32 (8.09)***	
WPosStale-LNegNew		0.04 (0.33)		0.10 (1.16)		0.50 (8.77)***		0.47 (8.40)***	
Asia (ex. Japan)									
New	W	0.01 (0.07)	0.28 (1.01)	0.25 (1.25)	0.30 (1.38)	0.59 (3.13)***	0.55 (2.79)***	0.58 (3.10)***	0.57 (2.87)***
	L	0.86 (3.52)***	1.04 (4.00)***	0.78 (3.47)***	0.94 (3.90)***	0.44 (2.37)**	0.47 (2.54)**	0.46 (2.49)**	0.46 (2.51)**
	WML	-0.84 (-5.35)***	-0.76 (-3.06)***	-0.53 (-4.43)***	-0.63 (-3.81)***	0.15 (3.83)***	0.07 (1.40)	0.12 (3.18)***	0.10 (1.81)*
	WPos-LNeg	-0.58 (-2.45)**		-0.48 (-2.88)***		0.11 (1.95)*		0.10 (1.74)*	
Stale	W	0.35 (1.52)	0.40 (1.84)*	0.40 (1.92)*	0.66 (3.28)***	0.90 (5.04)***	1.10 (6.19)***	0.89 (4.99)***	1.06 (5.96)***
	L	1.29 (5.08)***	1.31 (5.87)***	0.74 (3.75)***	1.05 (4.98)***	0.77 (4.54)***	0.91 (5.22)***	0.75 (4.45)***	0.92 (5.23)***
	WML	-0.94 (-3.67)***	-0.91 (-5.22)***	-0.34 (-2.09)**	-0.39 (-2.80)***	0.13 (2.05)**	0.19 (3.01)***	0.14 (2.09)**	0.15 (2.23)**
	WPos-LNeg	-0.90 (-3.66)***		-0.08 (-0.49)		0.34 (4.33)***		0.31 (4.00)***	
WPosStale-LNegNew		-0.46 (-2.62)***		-0.12 (-0.80)		0.66 (7.93)***		0.60 (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 1.08 million news items. Japan has 640,285 news items, and this number for Asia is 321,478. 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. “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 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 10,807,217 news items. Japan has 838,138 news items, and this number for Asia is 1,039,959.

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