Tomorrow's Fish and Chip Paper? Slowly incorporated News and the Cross-section of Stock Returns

Ran Tao * Chris Brooks † Adrian Bell ‡

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Abstract

The link between news and investor decision making is widely discussed in the literature. Utilising unique U.S. firm-level news data between 1979 and 2016, we document a cross-sectional difference in the speed of the diffusion of information contained in news. We distinguish news articles as being either slowly or quickly incorporated into contemporaneous stock prices. The return spread between stocks classified according to these two types of news yields a statistically significant profit of 139 basis points per month. This abnormal return cannot be explained by other well-known risk factors and is robust when allowing for trading costs. Overall, our research refines the role of news regarding information dissemination in the financial markets.

JEL classifications: G12; G14

Keywords: News sentiment; information dissemination; stock return predictability; investor attention; anomalies

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*ICMA Centre, Henley Business School, University of Reading. E-mail: ran.tao@pgr.reading.ac.uk

†ICMA Centre, Henley Business School, University of Reading. E-mail: c.brooks@icmacentre.ac.uk

‡ICMA Centre, Henley Business School, University of Reading. E-mail: a.r.bell@icmacentre.ac.uk

1. Introduction

News articles usually have time-limited effects due to rapid information transmission. This intuition can be summed up by the well-known idiom that "today's news is tomorrow's fish and chip paper".[1] Although financial markets build on a continuous flow of news, the analogy does not appear to apply if we follow the existing body of news predictability studies. So far, the evidence has revealed that returns following news arrivals are somewhat predictable. The literature attributes such a predictable pattern to either investor underreaction or overreaction based on *ex post* measures.[2] By contrast and to the best of our knowledge, research into the *ex ante* interaction between the information embedded in news articles and the contemporaneous stock reaction has not yet been presented in the literature.

According to Calvet and Fisher (2007), stock returns are a function of news with heterogeneous degrees of persistence ranging from a few days to several months. One negative news event could impact on the stock return gradually and persistently whereas the influence of another might be quick and prominent. Consistent with this phenomenon, Da, Gurun, and Warachka (2014) find that news flowing continuously in small amounts is likely to cause strong return momentum, whereas infrequent, dramatic news announcements do not. In this paper, we take a unique perspective by studying *ex ante* instances when the news tone does not match with contemporaneous stock reactions.[3] The research question that is addressed in this paper is: what is the impact on future stock returns when contemporaneous stock price reactions mismatch the tone of news flows?

Our empirical design is inspired by previous studies. Lochstoer and Tetlock (2020) provide empirical results showing that cashflow news decomposed from well-known anomalies (e.g., value, size, profitability, investment and momentum) is the main determinant of firm-level returns. By using the Dow Jones Newswire Archive dataset, Wang, Zhang, and Zhu (2018) document a news momentum phenomenon whereby a firm's monthly aggregated news tone predicts its one-month ahead firm-level returns. This suggests that previous returns did not capture news signals in a one-month window. To measure how quickly information

[1] In the UK, fish and chips (a takeaway treat) was traditionally wrapped in newspaper in order to absorb grease. This demonstrated that a newspaper was only valuable for the news it carried on the day of publication.

[2] For example, Chan (2003) conclude that investors underreact to public information and overreact to private information by measuring long-run stock return performance; Tetlock (2007) documents an investor overreaction pattern by constructing a VAR (Vector Autoregression) model. Other related studies include Tetlock, Saar-Tsechansky, and Macskassy (2008), Garcia (2013), Ahmad, Han, Hutson, Kearney, and Liu (2016), Jiang, Li, and Wang (2017) and Kräussl and Mirgorodskaya (2017).

[3] News tone refers to the sentiment score of news content assessed using computational tools. A news article with positive news tone (or a high news sentiment score) tends to contain good news. The terms 'news tone' and 'news sentiment score' are used interchangeably hereafter.

is incorporated *ex ante* into stock prices, we design a sequential, double-sorted approach based on monthly stock returns and aggregate news sentiment scores. If there is a mismatch between the two, it is likely that the market has not yet fully priced the news flow and a persistent shock would be expected.

We classify news items in terms of whether they convey information quickly or slowly to the market. For example, a stock which has positive stock-related news stories accompanied by modest or negative returns might suggest that its price has incorporated information slowly. Thus, a central hypothesis in this paper is that future return predictability will be stronger among slowly incorporated (SI henceforth) news stocks than those for which news is quickly incorporated (QI).

We perform the following analysis: a sentiment score is assigned to each news article by employing the Loughran and McDonald (2011) dictionary method.[4] SI and QI news are defined in two ways. Specifically, we construct monthly double-sorted portfolios by arranging stocks into terciles based on their current returns and further sorting each return group into another tercile based on their aggregate news sentiment scores. Among all nine groups, the four corner portfolios are studied as our primary research question focuses on those stocks where past returns and news tone are matched and those where they are not matched. High news sentiment scores accompanying low stock returns (LRHS) and low news sentiment scores accompanying high stock returns (HRLS) are defined as SI news, whereas news sentiment scores with matching stock returns (i.e., HRHS and LRLS) are referred to as QI news.

Next, we examine the post-formation return performance of these different types of portfolios. To do so, we compute equally-weighted average portfolio returns in the following month. A long/short portfolio consisting of buying LRHS stocks and selling HRLS stocks generates abnormal future returns even after controlling for well-known risk factors. In sharp contrast, the other strategy of buying HRHS stocks and selling LRLS stocks earns negative future returns. The abnormal returns are robust to various alternative specifications. By including quintile portfolios, splitting into different sample periods, using a weekly frequency of analysis and employing a different measure of news sentiment scores, the results are quantitatively similar, suggesting that these SI news effects are unlikely to arise from data mining or biased measures.

To further understand what drives SI news effects, we propose two hypotheses. First, one explanation follows limited attention theory, suggesting that investors tend to narrow

[4] Under this method, each word in a news item is labelled as belonging to a pre-specified category, examples of which include “positive”, “negative”, “model-weak” and “litigious”. This approach provides a means of quantifying business news tone.

their focus to a few stocks instead of dispersing their selection evenly throughout the entire stock universe (see Hirshleifer, Lim, and Teoh (2009)). To be more specific, these limited-attention investors, especially retail investors, tend to concentrate on certain stocks such as large, high media coverage, high trading volume stocks and firms with a high level of analyst coverage. Presumably, these firms have a better information environment where investors face less information asymmetry and therefore it is more efficient for them to react to news. In contrast, small and less information-rich firms are less likely to be under the spotlight, causing delayed reactions to news by investors.

Second, the speed of incorporation could result from the different nature of the news item, namely, dependent on its complexity and informativeness. Prior literature has studied the relationship between textual complexity and corresponding market reactions (Loughran and McDonald, 2014; Lawrence, 2013). For example, Loughran and McDonald (2014) document that the readability of financial disclosures has a significant impact on post-filing date returns, analyst dispersion and standardised unexpected earnings (SUE). Umar (2020) finds that long news headlines lead to a 40-basis point return underreaction on the *Seeking Alpha* forum. Thus, it is likely that SI news conveys information that is challenging to interpret for less sophisticated investors. Moreover, the literature also argues that different news articles exhibit different features regarding the information they contain. You, Zhang, and Zhang (2017) show that market-oriented media tend to be more comprehensive in reporting corporate events compared to state-controlled media. A plausible explanation for the differential cross-sectional returns between SI and QI news might be that it is driven by the complexity of the news context. Investors tend to react quickly to more informative news articles but under-react to those that they find harder to interpret (see Dougal, Engelberg, Garcia, and Parsons (2012)).

To test the two hypotheses, we examine whether SI news is concentrated among firms with less attention, proxied by small size, low media coverage and low trading volume. We find consistent evidence that SI news has stronger effects among low-attention firms. Furthermore, we investigate limited attention theory by applying two direct attention proxies: the Google Search Volume Index (SVI) and Bloomberg News Reading Activity Index (Abnormal Institutional Attention, AIA). As conventional attention proxies cannot guarantee that investors are actually reading firm-specific news (albeit they have high coverage), the literature utilises these alternative measures in order to better capture investor attention (Engelberg and Gao, 2011). Our results suggest that SI news with low investor attention, particularly without retail investor attention, predicts stronger stock returns. In contrast, we find mixed evidence for cross-sectional differences between the effects of news as measured by textual complexity and by informativeness features. While SI news is not exclusively earnings-irrelevant and too hard to read (i.e. low readability), we do find that these news articles tend to be less accurate (proxied by business uncertainty tone) and less comprehensive (measured by article length). Collectively, these results do not systemically support the notion that SI news is more complex and less informative.

Our paper contributes to several aspects of the literature: First, we propose a novel *ex ante* approach to categorise news articles as to whether they are slowly incorporated or quickly incorporated into prices. Predictable return patterns are more likely to emerge when *ex ante* news sentiment scores and contemporaneous returns are mismatched. Thus, our research complements studies showing that strong return momentum exists only when news flow arrives continuously in small amounts rather than discretely in large amounts (see Da et al. (2014)). Second, the results support limited-attention theory, according to which certain stocks remain below the horizon on the investor's radar and therefore they react to stock-related news slowly (e.g., Da et al. (2014) and Fang and Peress (2009)). By using a variety of investor attention indicators, we find consistent evidence that slowly incorporated news has stronger effects among low-attention firms. Third, the paper also contributes to research on textual complexity and informativeness. The results do not, however, support the notion that SI news is more complex and less informative, based on a wide range of analysis that we conduct using readability and business uncertainty measures. Finally, the findings also have implications for practitioners. The refined predictive model based on both news and contemporaneous returns provides a potential avenue for a news-based trading strategy, which is viable even after allowing for estimated transaction costs.

The rest of the paper is organised as follows. The related literature and hypotheses development will be discussed in Section 2. Section 3 presents the news data collection process and how we define SI and QI news. Section 4 reports the empirical results and empirical designs for two potential explanations of the findings. Six appendices cover the details of the data construction and additional empirical results. In the final section, we present the conclusions and outline further directions for research.

2. Related Literature and Hypotheses Development

This paper is related to several existing strands of the literature. First, this research is relevant to the topic of investor attention. The literature argues that it is either limited-attention theory or prominence theory that determines the impact of news on stock prices. Limited-attention theory, as suggested by Fang and Peress (2009), proposes that a firm with a lack of media coverage will earn higher returns than others, indicating that no attention can lead to stock price rises. In contrast, prominence theory embodies the value of visibility –

in other words, that more media coverage leads to higher asset returns – for example, Hillert, Jacobs, and Müller (2014) find that the media makes momentum profitability. They attribute this to an overconfidence-driven overreaction where investors tend to be attracted by a news story with high coverage and therefore become excessively optimistic. Consequently, we are able to test the implication of limited-attention theory that a firm within an inferior information environment and with less attention would tend to have news that is reacted to slowly and thus achieves better stock returns.

Second, the readability literature is also relevant to our study. Accounting research documents that the complexity of corporate releases has certain impacts on post-filing stock returns (Lawrence, 2013; Dougal et al., 2012). A major measure of document complexity is the 'Fog Index' – which is defined as a linear combination of average sentence length and the percentage of complex words. Loughran and McDonald (2014) argues that the complexity of 10-Ks certainly affects investor reaction as simple and concise materials take investors and analysts much less time to digest and to determine the valuation-relevant information.[5] Naturally, news materials can exhibit similar effects (Umar, 2020). Underpinned by this strand of the literature, we investigate whether the slow information incorporation that we identify is largely attributable to document complexity.

This research is also inspired by the link between textual analysis and investor decision making – see (Tetlock, 2007; Tetlock et al., 2008; Garcia, 2013; Ahmad et al., 2016; Jiang et al., 2017; Caporale, Spagnolo, and Spagnolo, 2018; Tao, Brooks, and Bell, 2020). Tetlock et al. (2008) documents that tone can predict earnings surprises and daily stock returns. Tao et al. (2020) show that investors' gambling behaviour is attenuated when maximum daily return events are associated with public news announcements. Ahmad et al. (2016) select 20 big firms with consecutive daily news and categorises this news into being either informative or noise. They show that informative news can predict persistent future returns whereas 'noise news' forecasts a subsequent reversal. Moving to the intra-day frequency, the effects of media tone become fairly straightforward (i.e., good news predicts positive asset returns while bad news predicts negative returns) (Jiang et al., 2017). Our study adds to this literature as we show that SI news can forecast asset returns.

Based on the studies discussed above, we develop three hypotheses that are then tested in this paper. It has been widely accepted that both investor underreaction and overreaction can cause predictable return patterns following measurable news. Chan (2003) documents that investors underreact to public information (i.e., measurable DJNS news) and overreact to private information while Tetlock et al. (2008) find that stock prices will have positive drifts

[5] A 10-K is a comprehensive corporate filing by a U.S. publicly-listed company about its annual financial performance and is required by the Securities and Exchange Commission (SEC).

after good news and become negative when the news is bad. Wang et al. (2018) show that stocks in the highest news sentiment score portfolio will typically continue to have high news sentiment scores in the next month and vice versa. Their results further show that future returns will be high (low) for those stocks from the highest (lowest) news sentiment score portfolio. On the other hand, Tetlock (2007) documents an investor overreaction pattern: the tone of the *Abreast Of The Market column* predicts positive stock index price movements on the next trading day and predicts them to be negative on subsequent days, suggesting a return reversal. Applying these findings we infer that investors will underreact to these measurable news stories when contemporaneous stock reactions do not rapidly match with the news tone. As a result, one can expect a delayed reaction in the following months. On the other hand, investors might overreact to these news items when both news sentiment scores and stock returns are in the top (bottom) bins.

Collectively, the three hypotheses tested in this paper are as follows:

Hypothesis 1: SI news tends to lead to high future returns and QI news tends to produce low future returns.

Hypothesis 2: The differential cross-sectional returns between SI and QI news portfolios is driven by investor underreaction to news.

Hypothesis 3: The differential cross-sectional returns between SI and QI news portfolios is driven by the complexity of the news.

3. Data and Methodology

3.1. News Collection and Sentiment Analysis

Our primary data comprise news taken from the Dow Jones Newswire Archive.[6] It contains all of the news from the Dow Jones newswire and *Wall Street Journal* newspapers. To examine SI and QI news and their cross-sectional return patterns, we construct a sample of firm-level news released by the common U.S. stocks listed on the NYSE, AMEX and NASDAQ between 1979 and 2016. The details of the data collection procedure can be found in Appendix A.

[6]The Dow Jones Newswire is a global real-time news product and is used in many research papers – e.g., (Tetlock, 2010, 2011; Engelberg, Reed, and Ringgenberg, 2012; Engelberg, McLean, and Pontiff, 2018).

As can be seen in Panel A of Table 1, firms have a wide range of numbers of news items in each month: the lowest figure is only one whereas the highest is 1568. On average, each firm has around 13 news items every month. This suggests the distribution of the number of news items is highly skewed. We next examine this issue from both time-series and cross-sectional perspectives.

Concerning the time-series pattern of firm-level news, we first examine the ratio using the number of matched Dow Jones News firms against the total number of firms from the CRSP universe in each year. During the early period (1979 to 1995), the percentage of firms covered by measurable Dow Jones news reports is between 20% and 30%. However, this statistic increases rapidly to over 95% after 1995. As a result, it reveals that some missing firms are clustered, probably due to the underdeveloped and incomplete archive in the early years. To further allay readers' potential concerns that the baseline results might be significantly influenced by these unmatched firms in the early years, we perform a sub-sample analysis and the results remain qualitatively unaltered across the four sub-periods in Appendix E.

To gain an understanding of the cross-sectional patterns in the data, we also plot a histogram of the news observations. The distribution of the number of news items is highly skewed. As can be seen in Figure 1, the percentage of firms with larger numbers of news items is small. To be specific, there are 4492 firms with 1 to 100 news items, accounting for 32% of the total sample. This statistic declines to 15% for firms with 100-200 news items and only 8% for those with 200-300 news items. Collectively, it can be concluded that most news items belong to a small number of firms. This pattern is consistent with Tetlock et al. (2008), who find that large firms tend to have news coverage every day whereas small firms only have sparse observations. One implication of this property is that the baseline results might be driven by the small size effect. However, further robustness checks eliminate this concern as we remove stocks whose prices are below $5 per share and the results remain positive. We also incorporate the size factor into the Fama-French factor models and control for firm size in the Fama-MacBeth regression respectively.

In addition, we perform robustness checks by collecting firm-level news with more strict conditions to increase its relevance. For example, there might be a difference in terms of the likely strength of any stock price reaction between an article analysing the cell phone industry and a news article addressing iPhone products specifically. In Appendix A, we show that the use of a stricter firm-level news criterion does not qualitatively alter the results.

——————— Insert Figure 1 here ———————

To quantify the sentiment from firm-specific news, we employ the Loughran and McDonald dictionary method as this approach builds on the work of Henry (2008).[7] This sentiment analysis method is a reliable and popular technique as it is tailored specifically to finance applications (e.g., see Loughran and McDonald (2011) and Loughran and McDonald (2015)). For instance, the word "abandoned" is pre-assigned as a negative sentiment word in this dictionary. Any document which contains the word "abandoned" will be counted and increases the negative percentage. To show that the results are not sensitive to different sentiment tools, we later employ the Google Natural Language API as an alternative.[8]

The first step is to construct an article-level sentiment score. For each news story, we adapt the method proposed by Garcia (2013), constructing such a score by taking the number of positive words minus negative words divided by the total number of words. In the second step, we standardise these news sentiment scores at the stock-level by subtracting the rolling mean of the previous 12 months and dividing by the standard deviation of the same period for each firm. In the following paragraphs, NSS denotes the standardised news sentiment score. The final step is aggregation. To fit the score into our empirical setting (i.e., monthly portfolio analysis), we aggregate these NSS every month. $NSS_{i,t}$ represents the aggregate news sentiment score standardised in a time-series manner for firm i in month t:

$$nss = \frac{No.\,of\,pos - No.\,of\,neg}{total\,number\,of\,words} \tag{1}$$

$$NSS = \frac{nss - \mu_{nss}}{\sigma_{nss}} \tag{2}$$

where μ_{nss} is the rolling mean of the previous 12 months' news sentiment scores and σ_{nss} is the rolling standard deviation of NSS during the same period for each firm. As can be seen in Panel A of Table 1, NSS exhibits fairly a even distribution. The average values are close to zero with no extreme outliers, suggesting that the procedure for constructing NSS is effective in capturing unexpected components.[9]

[7] Although Henry (2008) is the first work that contributes to sentiment analysis, we do not employ the word list developed by therein for two reasons: First, Henry's list only has a very limited number of sentiment words (e.g., 85 negative words) whereas that of Loughran and McDonald (2011) includes 2329 such words. More importantly, the most frequent LM negative words based on 10-K annual reports such as *loss, losses, claims, impairment, against, adverse, restated, adversely, restructuring and litigation*, do not appear in Henry's list. This suggests that Henry's dictionary may not sufficiently capture all potential negative tone from the text.

[8] The Google Natural Language API is a newly-built natural language processing tool by Google Cloud, details of which can be found at https://cloud.google.com/natural-language/.

[9] In an unreported test, we confirm its even distribution by performing the Jarque-Bera test suggested by the Editor.

3.2. *Slowly and Quickly incorporated News*

The finding in Wang et al. (2018) suggests that previous returns did not capture news signals in a one-month window. For the data studied in this paper, the correlation between contemporaneous monthly returns and the news sentiment score is also very low (0.066) on a monthly basis. It is perhaps surprising but consistent with Wang et al. (2018) that initial market responses to the tone of news articles are insufficiently large. Otherwise, we should observe that the market responds favourably to the news tone (i.e., a highly positive correlation between the two sorting variables). Collectively, we use a sequential double-sorted approach based on monthly stock returns and news sentiment scores to measure how quickly information is incorporated. If returns cannot match news sentiment, it can be accepted that stock prices did not catch the news signal promptly and a SI news item is defined.

To ensure that the stock returns we utilise are firm-specific, we calculate DGTW-adjusted returns following Daniel, Grinblatt, Titman, and Wermers (1997) to remove the expected return components of common risk factors including SMB (Small-Minus-Big), HML (High-Minus-Low), UMD (Up-Minus-Down). Specifically, we independently sort the entire stock universe into quintile portfolios based on firm size, industry-adjusted book-to-market ratio and industry-adjusted momentum. Next, we compute these 125 (i.e. $5 \times 5 \times 5$) value-weighted benchmark returns. The cleaned return is each stock's raw return minus the corresponding portfolio benchmark return, which can be interpreted as an abnormal return.

The double-sorted portfolios are constructed as follows: in each month, all stocks are divided into tercile portfolios based on contemporaneous DGTW-adjusted returns. Low return, medium return and high return subsets are defined as LR, MR and HR, respectively. We then form another three subsets in each return group individually based on stock-level news sentiment scores (i.e., LS, MS and HS refer to low, medium and high news sentiment subsets), resulting in nine portfolios having different stock return and news sentiment characteristics. Next, we label each portfolio given its news return characteristics. For example, the $HRLS$ portfolio comprises stocks with high contemporaneous stock returns and low news sentiment scores. Similarly, we define the $LRHS$ and $HRLS$ portfolios as SI news groups and the $HRHS$ and $LRLS$ portfolios as QI news groups.

In Panel B of Table 1, we report univariate analysis for the four types of news. The $LRHS$, $HRLS$, $LRLS$ and $HRHS$ portfolios are presented in each column. Specifically, both news sentiment scores and stock returns statistics exhibit considerable differences across the groups. For example, the $LRHS$ portfolio has an average stock return of -12% per month and an average news sentiment score of 0.94, which suggests that stocks in this portfolio tend to have negative returns and positive news. In other words, $LRHS$ stocks are slowly incorporating good news. Consistent with this notion, we then find that the $HRLS$ portfolio exhibits negative news (the news sentiment score is -0.96) and positive return performance (average 15% per month), while the figures are: -1.17 (news sentiment) and -15% (monthly return) for the $LRLS$ portfolio and those of $HRHS$ are 1.02 and 15% respectively.

Moving to news volume, $LRHS$ stocks release relatively fewer news articles compared to the other three counterparts (an average of 8.68 for $LRHS$ stocks, 11.75 for $HRLS$ stocks, 10.87 for $HRHS$ stocks and 11.71 for $LRLS$ stocks). The increasing number of news items in the following month can be observed for all four types of stock. This can be interpreted as suggesting that news stocks are likely to have a continuous information flow, especially SI news stocks. Readers may be concerned that these next month news items could more heavily drive their contemporaneous stock returns than the news released in previous periods. However, in later robustness checks, we show that this is not the case by dropping all news observations in the portfolio holding periods. Lastly, the average number of stocks in each month for all four portfolios is reported in Panel B. As can be seen, each portfolio contains roughly 240 stocks per month, accounting for around 11% of all stocks. If all of these portfolios are aggregated, the total percentage of stocks covered is 44%.

Overall, we conclude that the sequential double-sorted approach separates stocks into portfolios based on different types of news effectively.

———————————— Insert Table 1 here ————————————

4. Empirical Results

4.1. Calendar-time Portfolio Analysis

We use a sequential double-sorted calendar-time portfolio approach to examine SI and QI news return predictability. In each month from July 1979 to December 2016, we divide all stocks into tercile portfolios based on their contemporaneous monthly DGTW-adjusted stock returns. The LR, MR and HR groups contain stocks with low returns, medium returns and high returns respectively. For each return portfolio, we further rank stocks into another three portfolios based on news sentiment scores. LS, MS and HS therefore collect stocks with low, medium and high new sentiment scores. Subsequently, we track the performance of each subset over the following month by computing their equally-weighted stock returns. By rolling this monthly window through the entire sample period, we obtain a time-series of return performance for all nine portfolios. In Panel A of Table 2, it can be observed that news predictability decreases across different return groups. For example, the LR and HS portfolios predict a 1.45% return per month in the post-formation period whereas the LR

and LS conjunction only achieves 1.05% every month. Similarly, it is also evident that the predictive power of return performance decreases for each news group from LR to HR.

We further study SI and QI news effects in Panel B. If investors do indeed react slowly to arriving news, we should observe that slowly incorporated news predicts stronger post-formation stock returns than quickly incorporated news.

Panel B of Table 2 supports this hypothesis: the SI news portfolio (i.e., the spread between $LRHS$ and $HRLS$) earns 101 basis points per month (t-statistic: 5.85) whereas the QI news portfolio (i.e., the spread between $HRHS$ and $LRLS$) has negative return predictability. The difference between the two, which we term SMQ (Slow Minus Quick), gains 139 bps per month, which is significant at the 1% level.

Further, we perform a Fama-French regression analysis of these results and we report the alpha for the two news groups. We include five different risk factor models: the Fama-French 3-factor model (FF3F), Fama-French-Carhart 4-factor model (FF4F), Fama-French 5-factor model (FF5F), a liquidity-augmented Fama-French-Carhart 5-factor model (FF4F + Liq) and a short-term reversal-augmented Fama-French-Carhart 5-factor model (FF4F + Rev)[10]. The reason for including liquidity and short-term reversal risk factors is to examine whether the constructed portfolio picks up these effects. However, the risk-adjusted returns of the SI news portfolios remain consistently significant across all models, even when the short-term return reversal factor is included. This result suggests that the SI news effect cannot simply be interpreted as a short-term return reversal. In contrast, the QI news portfolio return becomes insignificant after controlling for the Fama-French three- and five-factors. The alpha of the SMQ portfolio is significant across risk-adjusted models, suggesting that SI news indeed has stronger return predictability compared to QI news. Since most of the long-short portfolio returns come from SI news rather than QI news, we next focus on SI news predictability instead of SMQ in the regression analysis.

——————————— Insert Table 2 here ———————————

4.2. Fama-MacBeth Regressions

The asset pricing literature identifies that a number of stock characteristics have stock return predictability. To ensure that the results we documented are not driven by those characteristics, we use Fama and MacBeth (1973) regression models to study the predictability of SI and QI news on the following months stock returns after controlling for additional stock

[10]The Fama-French risk factors can be downloaded from Kenneth French's Data library `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary:html`. The liquidity factor we utilise is Pástor and Stambaugh (2003), which can be accessed from `https://faculty.chicagobooth.edu/lubos-pastor/data`

characteristics. The choice of this regression follows the convention of the asset pricing literature. Specifically, each month we perform an OLS regression of the dependent variable of interest. All regression coefficients are then averaged across different months and determine whether they differ from zero. The regression is as follows:

$$\begin{aligned} EXRet_{i,t+1} = \alpha + \beta_1 * NSS_{i,t} + \beta_2 * (NSS * SINws)_{i,t} + \beta_3 * (NSS * QINws)_{i,t} \\ + \beta_4 * SIGdNws_{i,t} + \beta_5 * SIBdNws_{i,t} + \beta_6 * QIGdNws_{i,t} \\ + \beta_7 * QIBdNws_{i,t} + X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $EXRet_{i,t+1}$ is the excess return of stock i at time *t+1* and $\epsilon_{i,t}$ is an error term that is assumed to be independently and identically distributed with zero mean and constant variances along the diagonal elements and zero elsewhere. NSS is the news sentiment scores of stock i at time t. $SIGdNws$, $SIBdNws$, $QIGdNws$ and $QIBdNws$ are dummy variables for whether a stock has a news article identified as slowly incorporated good news (LRHS), slowly incorporated bad news (HRLS), quickly incorporated good news (HRHS) or quickly incorporated bad news (LRLS). $NSS*SINws$ and $NSS*QINws$ are the interaction terms where news sentiment scores are multiplied by the $SINws$ or $QINws$ dummy variables. The literature and previous sections in this paper imply positive β_2 and negative β_3 coefficients on the interaction variables $NSS*SINws$ and $NSS*QINws$, respectively. In the X vector, a number of control variables are added to capture various stock characteristics. Specifically, we first include $SIZE$ and BTM to control for the Fama and French (1993) characteristics. $LRET$ is the lagged one-month stock return to control for short-term reversals. Furthermore, MOM is added in order to capture momentum effects, which is computed by taking the past twelve-month cumulative return with at least eight months' valid observations. $BETA$ is included and computed by following Scholes and Williams (1977); Dimson (1979). We include $IVOL$ (Idiosyncratic volatility) in the regression motivated by Fu (2009), who argues that idiosyncratic volatility represents how fast firm-level information is incorporated into stock prices. We also add $ILLIQ$, a firm-level illiquidity proxy by Amihud (2002), which is computed by taking the average value of daily absolute stock returns divided by the dollar trading volume over the previous year.

Table 3 reports all primary variable coefficients from the three regression specifications. First, the NSS positively predicts future returns, indicating that the news articles are indeed informative. Second, the $SIBdNws$ and $NSS*SINws$ variables are statistically significant under all regression specifications. In particular, the coefficient of $NSS*SINws$ is 0.2004 (t-statistic=2.21) whereas the $NSS*QINws$ term is insignificant in model 6. The positive

$SIBdNws$ coefficient suggests that the return continuation mainly comes from slowly incorporated bad news rather than good news occurring during the formation period. Comparing the magnitudes of NSS and $NSS * SINws$, the $NSS * SINws$ term is more than double that of NSS (0.2004 for $NSS * SINws$ vs 0.0959 for NSS). However, the coefficient of $NSS * QINws$ varies across different model specifications and we therefore cannot infer its stock return predictability. Collectively, these tests confirm that the primary news variable, $NSS * SINws$, has some stock return predictability and is robust to the incorporation of a number of control variables.

——————————— Insert Table 3 here ———————————

4.3. Performance Evaluation

We evaluate the performance of SI news over different horizons. If the news source contains genuine information about a firm's fundamentals, the return predictability of SI news should not subsequently reverse in the long run. In addition, the performance evaluation could potentially have useful implications for practitioners to develop a news-based trading strategy. To examine the long-run performance, we conduct a calendar-time portfolio approach over four different holding periods as follows: 3 months (month 2 to month 4), 6 months (month 2 to month 7), 9 months (month 2 to month 10) and 12 months (month 2 to month 13). The current month is included as a comparison. We again construct an SI news portfolio that buys stocks with low returns but high news sentiment (LRHS) and sells stocks with high returns but low news sentiment (HRLS) and a QI news portfolio comprising of buying HRHS stocks and selling LRLS stocks. These portfolios are then rebalanced monthly and their performance monitored over different holding periods. The results, reported in Table 4, show that after the first-month period, SI returns are not significantly different from zero. It is evident that the return predictability of SI news does not reverse in the long run. Similarly, we can also observe that the slow-minus-quick (SMQ) factor gains significantly during the post-formation period but these portfolio returns do not reverse in the following months.

——————————— Insert Table 4 here ———————————

Graph A of Figure 2 shows a comparison of the indexed value of the portfolio with that of the S&P500 index. Overall, the portfolio generates over \$26, assuming \$1 of initial investment. In contrast, the S&P500 index only achieves \$5.60. There are, however, two big recessions during the period covered -– namely, the Internet Bubble and the financial crisis of 2007/8. It can be seen that the long-short portfolio is riskier during times of market turbulence. Graph B of Figure 2 shows the 12-month holding period returns for the SI news portfolio and the S&P500 index. It can be observed that overall the portfolio performs well. In contrast, the S&P500 has experienced a number of negative return periods – for example, it dropped by 40% during the financial crisis. The holding period return series indicate that since 2010 profitability has declined for both the portfolio and the benchmark. Nevertheless, the results suggest that a news-based strategy may be attractive to practitioners.

In addition, we evaluate the impact of considering reasonable transaction costs on the news trading strategy's profitability. We calculate the Break-Even Trading Cost (BETC) of the strategy – the trading cost that makes the average realised returns of the strategy become zero following Han, Yang, and Zhou (2013). In other words, the higher the BETC, the more likely it is that the trading strategy will survive and remain profitable after considering actual transaction costs. Since the BETC is associated with the strategy's realised returns, we monitor the turnover of the portfolio and compute the BETC only when each stock drops out at the end of that month (i.e., the position of a stock is closed at the end of the month and is not included in the portfolio in the next month). The estimated BETC includes all necessary expenses such as commissions, exchange fees, bid/ask spreads, market impact costs and transaction taxes. Overall, the BETC of the SI news trading strategy is more than 100 bps per month, suggesting that the actual transaction costs would have to be unrealistically high to eliminate the trading profit. This estimated BETC substantially outperforms the transactions cost levels employed in prior studies that are usually set at a fixed rate or a pre-specified range (e.g., 25 bps – see Lynch and Balduzzi (2000) and 1 to 10 bps – see Tetlock et al. (2008)). Graphs C and D of Figure 2 cross-validate that the trading strategy remains profitable after considering 25 and 50 bps transaction costs respectively.

Moreover, we also compute an alternative BETC to penalise trading on small stocks that are of limited use for arbitrage due to their illiquidity and high bid/ask spreads. In each month, we sort all stocks into deciles based on their market capitalisation so that small firms will be assigned to the lowest decile whereas large firms will be in the highest group. The lowest BETC for trading on the size decile is 58 bps on average per month, which is still higher than the transactions cost values assumed in existing studies (i.e., assuming a fixed cost of 50 bps).

——————— Insert Figure 2 here ———————

Overall, this subsection confirms that SI news does contain new information and indeed this is incorporated into the market at a later stage. The performance evaluation of the news-based trading strategy confirms its profitability and its robustness even after considering transaction costs.

4.4. Limited Attention Theory

Since these news portfolios exhibit cross-sectional differences in future return performance, we ask what drives this cross-sectional difference of stock returns. One explanation for market-delayed reactions is limited-attention theory. The growing literature of this strand of research includes Engelberg and Gao (2011) on the volume of Google searches for stock names, Da et al. (2014) on continuous information and momentum effects and Fang and Peress (2009) on non-news stock returns. The theory predicts that investors underreact regarding stocks with low volumes of attention and thus the subsequent return predictability is the result of this delayed reaction. Intuitively, stocks with small size, low media coverage, low turnover and low analyst coverage are generally associated with a poor information environment. In other words, it is information asymmetry that slows investors' perceptions of arriving news. If so, we would expect that SI news effects are concentrated in low attention-grabbing stocks whereas QI news stocks would receive a relatively high volume of attention.

In this section, we employ four different investor attention proxies to study SI news effects following the previous literature (in particular (Da et al., 2014; Huang, 2018)), which includes size, media coverage, trading volume and analyst coverage. We first examine the cross-sectional difference between small and large firms. To do so, we perform a double-sort and construct calendar-time portfolios. Specifically, we rank the firm's market capitalisation values and divide these firms into small and large size groups before constructing SI and QI news portfolios. Market capitalization ($SIZE$) is in logarithmic form and rebalanced at the end of June. The next-month stock return performance is traced for each month and the results are reported in Panel A of Table 5. This shows that the returns from small firms are higher than those for large firms with the difference being significant at the 1% level, suggesting that SI news effects are concentrated in small firms, a finding consistent with limited-attention theory. There is no evidence of cross-sectional differences between small and big firms with QI news, although the SMQ factor also confirms the SI news effect.

Changes of media coverage (Δ media coverage hereafter) are often applied as the representation of investors' attention. Stocks with higher Δ media coverage can naturally diffuse information much quicker than lower Δ media coverage stocks. Thus, SI news is more likely to be observed among low-attention stocks and QI news concentrated in high-attention stocks. Empirically, Panel A supports this limited-attention theory with the monthly Δ media coverage shifting from low to high, SI news predicts next-month returns from 144 basis points per month to only 9 bps. The difference between the two coverage groups is significant at the 1% level. The SMQ factor also suggests that information diffusion is likely to be slower within the low media volume portfolio (2.21% with a t-statistic of 7.56 for the cross-sectional difference between low and high media coverage groups), which is consistent with limited attention theory.

Panel B also tests the hypothesis regarding whether stocks with lower trading volume predict higher SI news profitability. The literature documents that trading volume is a proxy for investor attention (Barber and Odean, 2007). We again construct a double-sorted calendar-time portfolio by employing stock-level trading volume. The variable is calculated as the natural log of average share volume divided by the number of shares outstanding over each month using daily data. We then trace the portfolio performance by a rolling one-month window to observe SI news effects within either high or low trading volume groups. In Table 5, we report all coefficients with t-statistics for each subset of stocks, finding that SI news stocks earn 1.36% per month (t-statistic=8.94). The difference in profitability between low and high turnover SI news portfolios is statistically significant at the 1% level. This is consistent with our theory that stocks without active trading activity are more likely to be under the investor's attention radar. Overall, comparing low and high turnover profits, we can conclude that low trading volume stocks are associated with higher SI news profitability.

Finally, we examine how analyst coverage is associated with cross-sectional differences in SI news predictability. The literature uses analyst coverage as a proxy for investor attention (Hirshleifer and Teoh, 2003). If investor inattention slows information incorporation from news articles, the predictability should be concentrated among firms with low analyst coverage. The analyst coverage data is retrieved from Datastream for one-year forward earnings per share forecasts for each firm. The sample is then divided into two groups based on the median number of analysts covering the stock, for each of the SI and QI news stock portfolios that have been constructed in each month. In Panel A, the performance of each portfolio is reported. Stocks with low analyst coverage have higher levels of SI news compared to those with high coverage – 1.03% and 0.57% per month respectively. The t-statistic of the low-minus-high spread portfolio is 1.19, which is significant at the 5% level. In contrast, there is no evidence of QI news effects in either the low or high coverage sub-samples.

To summarise, four different investor attention proxies consistently support limited-attention theory, which indicates that SI news predictability is positively associated with low investor attention.

——————————— Insert Table 5 here ———————————

4.5. Complexity and Informativeness

SI news effects can also potentially be explained by news characteristics. The literature identifies that variation in news content does affect market reaction (Dougal et al., 2012;

Umar, 2020). For instance, (especially retail) investors might find a complex news article challenging, in the sense that they might be uncertain about how to interpret the news content. Likewise, an ambiguous news tone could also fail to give investors a clear trading signal, which therefore discourages them form quickly responding. On the other hand, investors might under-react to a short news article because it means a less comprehensive report about a corporate event. They are also more likely to be interested in earnings-related news since these news items contain more valuable information (Tetlock et al., 2008; Chen, De, Hu, and Hwang, 2014). If SI and QI news is driven by the nature of the news in this setting, we would expect that easily-understandable and more informative news predicts lower future stock returns. In other words, investors will react quickly to news stories with fewer ambiguous words, fewer complex sentences, more comprehensive content and more earnings-related topics.

To capture the textual complexity of our news documents, we apply the fog index and weak modal words measures. The fog index is one of the most commonly applied readability measures for a firm's financial disclosures (Dougal et al., 2012; Lawrence, 2013; Loughran and McDonald, 2014). It captures document readability by computing the average sentence length and the percentage of complex vocabularies. Thus, the higher the fog index value, the more complex the material is. Weak modal words were first introduced by Loughran and McDonald (2011) in their financial dictionary to gauge uncertain business tone. Words such as "maybe", "appears", "might" frequently shown in the news suggest that these stories are less likely to attract investors. For example, Ahern and Sosyura (2015) uses this word category to gauge merger and acquisition rumours. These proxies are commonly used in the literature and should be effective to measure complexity in this paper.

To measure the news informativeness features, we first utilise article length as a proxy for comprehensiveness, as suggested by You et al. (2017). A long news article tends to convey more useful information and helps (especially retail) investors better understand underlying events. Next, we assess news informativeness by categorising the news topic as earnings-related or non-earnings-related. Specifically, we detect keywords from each news article using the word stem "earn". We identify the topic of a news article related to earnings if at least one word stem "earn" is found. The rationale behind this is that an article mentioning the word stem "earn" contains more information about a firm's fundamentals and is more likely to be value-relevant (Tetlock et al., 2008). Overall, it can be argued that a news story with long length and more "earn" word stems represents greater informativeness.

To test the hypothesis, we examine the cross-sectional difference of news characteristics individually. We first calculate the median level of weak tone at each time point, and divide the stocks with news having weaker tone into an *Ambiguous* group and the others into an

Accurate group. Similarly, we divide more readable news stocks into a *Concise* group and less readable stocks into a *Complex* group based on the median fog index in each month. For article length, we divide all stocks into *Short* and *Long* groups based on the median word count in each month. Lastly, we split the sample into two groups: *EarningsEx*, where stocks without any news articles containing earnings topics are collected and *EarningsIn*, where stocks with only earnings-related news articles are included. To examine the statistical difference between each group, we construct $Ambiguous - Accurate$, $Complex - Concise$, $Short - Long$ and $EarningsEx - EarningsIn$, respectively. If complexity and informativeness of news do affect investor trading behaviour, we expect that these four cross-sectional differences would be positive and significant for the SI news portfolio. The equally-weighted portfolio return is then computed for each subset sample to trace its post-formation performance.

Panel A of Table 6 reports the cross-sectional differences by textual complexity. The evidence is mixed: although the cross-sectional difference between ambiguous and accurate news stocks is positively and statistically significant (t-statistic=2.29 for SI news), there is no clear evidence showing a significant difference between complex and concise news. This indicates that SI news predictability is not likely to come from hard-to-read news articles. Moving to Panel B, it is evident that the cross-sectional difference between short news statements (less comprehensive) and long news statements (more comprehensive) is significant (t-statistic of 2.70) for SI news stocks. Interestingly, when we split the sample into earnings-related and non-earnings-related topics, the cross-sectional difference between these two is insignificantly different from zero. This suggests that SI news is not exclusively earnings irrelevant and contains at least some valuable information.

Collectively, it can be concluded that SI news tends to use ambiguous tone and reports less comprehensively but such stories are not too complex to read and are not completely earnings-irrelevant. Hence the empirical results do not systemically support complexity and informativeness theory.

5. Discussion and Concluding Remarks

In this paper, we first distinguish firm-level news as slowly incorporated, whereby stock returns do not promptly respond to corresponding news content, or quickly incorporated, where the stock return performance matches the news sentiment score. The feature of SI news, specifically, is having a good (bad) sentiment score but with bad (good) stock returns. A long/short portfolio is then constructed to capture the SI news effect by buying stocks with low returns but a high news sentiment score and selling stocks with high returns but a low news sentiment score. As a result, we find that this news-induced anomaly can achieve average returns of 139 basis points per month (equivalent to 16.68% per year).

The SI news effect can be explained by limited-attention theory. According to this theory, investors tend to focus on a few stocks instead of evenly dispersing their attention throughout the entire stock universe. This then leads to the phenomenon where a group of firm-related news items drop under an investor's radar. The stock returns thus react very slowly. In empirical tests, we proxy less investor attention by small size, low media coverage, low trading volume, low analyst coverage, low Google SVI and low Bloomberg AIA. The results, strikingly, show stronger stock return predictability for less attention-grabbing stocks.

The empirical results, however, do not strongly support complexity and informativeness theory in which the nature of news might cause investors' slow reaction. Generally, the textual complexity of news content should influence investors' trading behaviour, particularly for retail investors, whereby they might have no idea how to interpret complex news items or how to respond to ambiguous news articles. In addition, a short news article tends to be less comprehensive in reporting underlying events and therefore discourages investors from responding quickly. An article that does not contain value-relevant information could also fail to make investors take interest. Yet the evidence does not align with this theory.

In addition, other behavioural finance theories are consistent with the findings. Anchoring bias predicts that investors depend too heavily on initial information, making subsequent adjustments very hard. Consistent with the theory, investors may initially interpret good or bad news from stock returns since it is the easiest and most accessible approach. Contemporaneous news articles released from professional newswire archives may contain additional information over and beyond observed stock returns. The aggregated news tone associated with monthly returns, if mismatched, is less likely to be quickly accepted by investors to adjust their prior biased beliefs. As a result, this will lead to an underreaction. Nevertheless, this paper provides an interesting avenue for future research in assessing whether the news articles tested in this paper contain long-term forward-looking content, and as a result, incorporate value-relevant information into stock prices conditional upon the underlying firm's near-term events. It would also be worthwhile to conduct a more detailed topics analysis of the news articles we examine in this study.

References

Ahern, Kenneth R, and Denis Sosyura, 2015, "Rumor has it: Sensationalism in financial media," *Review of Financial Studies* 28, 2050–2093.

Ahmad, Khurshid, JingGuang Han, Elaine Hutson, Colm Kearney, and Sha Liu, 2016, "Media-expressed negative tone and firm-level stock returns," *Journal of Corporate Finance* 37, 152–172.

Amihud, Yakov, 2002, "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets* 5, 31–56.

Barber, Brad M, and Terrance Odean, 2007, "All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors," *Review of Financial Studies* 21, 785–818.

Ben-Rephael, Azi, Zhi Da, and Ryan D Israelsen, 2017, "It depends on where you search: institutional investor attention and underreaction to news," *Review of Financial Studies* 30, 3009–3047.

Calvet, Laurent E, and Adlai J Fisher, 2007, "Multifrequency news and stock returns," *Journal of Financial Economics* 86, 178–212.

Caporale, Guglielmo Maria, Fabio Spagnolo, and Nicola Spagnolo, 2018, "Macro news and bond yield spreads in the euro area," *European Journal of Finance* 24, 114–134.

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

Chen, Hailiang, Prabuddha De, Yu Jeffrey Hu, and Byoung-Hyoun Hwang, 2014, "Wisdom of crowds: The value of stock opinions transmitted through social media," *Review of Financial Studies* 27, 1367–1403.

Da, Zhi, Umit G Gurun, and Mitch Warachka, 2014, "Frog in the pan: Continuous information and momentum," *Review of Financial Studies* 27, 2171–2218.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, "Measuring mutual fund performance with characteristic-based benchmarks," *Journal of Finance* 52, 1035–1058.

Dimson, Elroy, 1979, "Risk measurement when shares are subject to infrequent trading," *Journal of Financial Economics* 7, 197–226.

Dougal, Casey, Joseph Engelberg, Diego Garcia, and Christopher A Parsons, 2012, "Journalists and the stock market," *Review of Financial Studies* 25, 639–679.

Engelberg, Joseph, and Pengjie Gao, 2011, "In search of attention," *Journal of Finance* 66, 1461–1499.

Engelberg, Joseph, R David McLean, and Jeffrey Pontiff, 2018, "Anomalies and news," *Journal of Finance* 73, 1971–2001.

Engelberg, Joseph E, Adam V Reed, and Matthew C Ringgenberg, 2012, "How are shorts informed?: Short sellers, news, and information processing," *Journal of Financial Economics* 105, 260–278.

Fama, Eugene F, and Kenneth R French, 1993, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2017, "International tests of a five-factor asset pricing model," *Journal of Financial Economics* 123, 441–463.

Fama, Eugene F, and James D MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy* 81, 607–636.

Fang, Lily, and Joel Peress, 2009, "Media coverage and the cross-section of stock returns," *Journal of Finance* 64, 2023–2052.

Frazzini, Andrea, and Lasse Heje Pedersen, 2014, "Betting against beta," *Journal of Financial Economics* 111, 1–25.

Fu, Fangjian, 2009, "Idiosyncratic risk and the cross-section of expected stock returns," *Journal of Financial Economics* 91, 24–37.

Garcia, Diego, 2013, "Sentiment during recessions," *Journal of Finance* 68, 1267–1300.

Han, Yufeng, Ke Yang, and Guofu Zhou, 2013, "A new anomaly: The cross-sectional profitability of technical analysis," *Journal of Financial and Quantitative Analysis* 1433–1461.

Henry, Elaine, 2008, "Are investors influenced by how earnings press releases are written?," *Journal of Business Communication* 45, 363–407.

Hillert, Alexander, Heiko Jacobs, and Sebastian Müller, 2014, "Media makes momentum," *Review of Financial Studies* 27, 3467–3501.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2009, "Driven to distraction: Extraneous events and underreaction to earnings news," *Journal of Finance* 64, 2289–2325.

Hirshleifer, David, and Siew Hong Teoh, 2003, "Limited attention, information disclosure, and financial reporting," *Journal of Accounting and Economics* 36, 337–386.

Huang, Jiekun, 2018, "The customer knows best: The investment value of consumer opinions," *Journal of Financial Economics* 128, 164–182.

Jiang, Hao, Sophia Zhengzi Li, and Hao Wang, 2017, "News momentum," Michigan State University Working Paper.

Kräussl, Roman, and Elizaveta Mirgorodskaya, 2017, "Media, sentiment and market performance in the long run," *European Journal of Finance* 23, 1059–1082.

Lawrence, Alastair, 2013, "Individual investors and financial disclosure," *Journal of Accounting and Economics* 56, 130–147.

Lochstoer, Lars A, and Paul C Tetlock, 2020, "What drives anomaly returns?," *Journal of Finance* 75, 1417–1455.

Loughran, Tim, and Bill McDonald, 2011, "When is a liability not a liability? textual analysis, dictionaries, and 10-ks," *Journal of Finance* 66, 35–65.

Loughran, Tim, and Bill McDonald, 2014, "Measuring readability in financial disclosures," *Journal of Finance* 69, 1643–1671.

Loughran, Tim, and Bill McDonald, 2015, "The use of word lists in textual analysis," *Journal of Behavioral Finance* 16, 1–11.

Lynch, Anthony W, and Pierluigi Balduzzi, 2000, "Predictability and transaction costs: The impact on rebalancing rules and behavior," *Journal of Finance* 55, 2285–2309.

Pástor, L'uboš, and Robert F Stambaugh, 2003, "Liquidity risk and expected stock returns," *Journal of Political Economy* 111, 642–685.

Scholes, Myron, and Joseph Williams, 1977, "Estimating betas from nonsynchronous data," *Journal of Financial Economics* 5, 309–327.

Tao, Ran, Chris Brooks, and Adrian R Bell, 2020, "When is a max not the max? how news resolves information uncertainty," *Journal of Empirical Finance* .

Tetlock, Paul C, 2007, "Giving content to investor sentiment: The role of media in the stock market," *Journal of Finance* 62, 1139–1168.

Tetlock, Paul C, 2010, "Does public financial news resolve asymmetric information?," *Review of Financial Studies* 23, 3520–3557.

Tetlock, Paul C, 2011, "All the news that's fit to reprint: Do investors react to stale information?," *Review of Financial Studies* 24, 1481–1512.

Tetlock, Paul C, Maytal Saar-Tsechansky, and Sofus Macskassy, 2008, "More than words: Quantifying language to measure firms' fundamentals," *Journal of Finance* 63, 1437–1467.

Umar, Tarik, 2020, "Complexity aversion when seeking alpha," Rice University Working Paper.

Wang, Ying, Bohui Zhang, and Xiaoneng Zhu, 2018, "The momentum of news," Working Paper, Central University of Finance and Economics.

You, Jiaxing, Bohui Zhang, and Le Zhang, 2017, "Who captures the power of the pen?," *Review of Financial Studies* 31, 43–96.

Appendix A. Name-ticker News collection

Our primary data comprise news items taken from the Dow Jones Newswire Archive. All news articles are stored in an XML format with tags including headlines, dates, stock tickers and subject codes. We examine the influence of firm-level news in the U.S. equity market and the detailed procedures used to extract and quantify the news are given below.

1. Extract all news items with attached stock tickers in the Dow Jones Newswire Archive.

2. Download a list of company names and tickers from CRSP's historical name change file for all common stocks (i.e., where share code is 10 or 11) traded on the NYSE, AMEX and NASDAQ between 1979 and 2016.

3. Merge each stock ticker PERMCO (CRSP permanent company identifier) with the company news items within the relevant period.

We now provide firm-level news summary statistics for replication purposes. In total, the procedure collects 10.6 million news observations and involves 14,079 unique firms between July 1979 and December 2016. The Archive on average produces 279,528 news items each year, with the lowest and highest numbers reported as 6,112 and 666,321, respectively. There is a large variation over the years in the number of firms mentioned in the Archive, with a minimum of 860 and a maximum of 7,746. There are, on average, 763 news articles for each firm during the entire lifespan.

To further examine the validity of the PERMCO-ticker linking table, we impose additional matching criteria roughly following Tetlock et al. (2008). Briefly, the procedure is as follows:

1. The firm name string must appear in the first 25 words of a news article including the headline.

2. The firm name must be detected at least twice in the main body of the news story.

3. News reports with fewer than 50 words are excluded.

We 'tweaked' the firms' names depending on the search quality we had. This is because CRSP provides very unique and different name strings in comparison to the common names applied in the Dow Jones Newswire Database. In detail, the modifications are:

1. CRSP puts spaces between the letters in abbreviations – e.g., F D X CORP. We delete the spaces in such cases.

2. If the firm name ends with Inc, Ltd, Corp, Co. then the suffix will be removed. Note that we apply this rule to all sample firms including, for example, Apple Inc. This is

necessary, but note that the keyword ‘Apple’ will not match irrelevant news reports related to apple (the fruit) since we are conditioning on company tickers.

3. We replaced the abbreviated words INTL, MFG, CHEM with International, Manufacturing and Chemical, respectively.

4. A name string ending with NEW or OLD to specify the company’s status was tweaked to keep only the name before these words.

Overall, after imposing more strict matching criteria, our sample of news items halves to 4,530,243 non-repeated firm-level news stories and the number of sample stocks decreases to 12,072.

Appendix B. Google Search Volume Index collection

Unlike Engelberg and Gao (2011), which uses a sample of Russell 3000 stocks, our sample extends to all U.S. common stocks and we also acknowledge the fact that not all stocks have a non-zero SVI. We therefore carefully deal with the potential biases and errors when retrieving the Google SVI from the Google Trends web page. The procedure is as follows:

1. Instead of using firm legal names from the CRSP historical name file as Google censor keywords, we utilise these firm names as search inputs but look into the Google auto-suggestion menu. The optimal keyword would be chosen if the category of a keyword is "company" or "corporation". The rationale behind this is to convert firm legal names to the names commonly searched by users or mentioned in the financial press.

2. The SVI data has been scaled by Google based on the sample range. In this paper, we set a 90-day period for each data request and Google censors therefore return daily data.

3. To get rid of "noise" attention, the underlying search source is restricted to business news only. Given that investors could come from the outside of the U.S., geographical location is worldwide when downloading.

4. We improve the data quality by manually validating the firm name sought with the original one. If there is a significant difference that can be visualised, the data will be excluded from our sample.

In total, we finally obtain a 4,545-firm sample out of 7,864 targets.

Appendix C. Alternative Information Incorporation Measure

Another measure of news incorporation would be to examine the beta coefficients between contemporaneous stock returns and news sentiment scores. Inspired by the calculation of market beta in the CAPM model as in (Frazzini and Pedersen, 2014), we regress the daily news sentiment score on the corresponding stock return in a monthly rolling OLS regression model to obtain the coefficient. As such, it should improve measurement accuracy when the data are of daily frequency. The regression equation is:

$$Ret_{i,t} = \alpha + \beta * NSS_{i,t} + \epsilon_{i,t} \tag{4}$$

where $Ret_{i,t}$ is the daily return of stock i on date t and $NSS_{i,t}$ is the daily pessimism value of stock-level news for stock i on date t. This regression is then performed using a rolling monthly window. As a result, we obtain time-varying beta parameters between the stock return and news sentiment for each stock and calendar month. To address the concern of overnight news or weekend news, which may have lagged return impacts and therefore might not be captured by the regression model, we allow a lagged three-trading-day window to capture market lagged reactions. For example, Monday night news will not have return impacts until Tuesday morning. Friday night news will also not influence stock returns until the following Monday when the market opens. It is then believed that our time-varying beta should capture all these delayed news reactions. Moreover, we only include a stock in the sample when it has at least five different news stories on five different trading days to preclude the regression having sparse observations. As a result, a steep sloping coefficient β indicates news that is quickly incorporated, whereas a gentle slope implies slow information incorporation.

To trace the performance of different coefficients between the daily news sentiment score and daily contemporaneous stock returns, we employ a single-sort calendar-time portfolio approach with a one-month rolling window. Specifically, in each month, we divide stocks into three terciles based on the β coefficients (i.e., $LoBETA$, $MeBETA$ and $HiBETA$ portfolios). Naturally, the higher is the coefficient, the quicker the stock return responses. The top portfolio $HiBETA$ then contains high beta coefficients, suggesting that news is incorporated quickly into stock prices. The bottom group, $LoBETA$, comprises those stocks with low beta coefficients, which indicates slow information incorporation. Finally, equally-weighted portfolio returns are computed during the post-formation period for the three portfolios separately.

The result of this alternative definition is reported in the Panel A of Table A1. The coefficient of the top portfolio (SINws group) is 1.28, which is significant at the 1% level, whereas the QINws portfolio achieves 80 bps per month (t-statistic: 2.27). The Slow-Minus-Quick (SMQ) portfolio reports an average 49 bps return in each month, which is significant at 1%. Compared to the SMQ portfolio constructed in the first way (94 bps per month), the overall profitability of SMQ created by news betas is halved. Presumably, the sample size is significantly reduced with a number of small stocks excluded due to the fact that all stocks included in the calculation must have at least five news stories published on five different days in a month. It is unlikely that small firms have more than five different news releases in any five day period in a month. Although this implies that the SI news effect is partially contributed by the size effect, the SI news theory, on the other hand, seems to be more convincing under these two different designs.

Appendix D. Further Robustness Checks

We examine the robustness of the primary SI and QI news definitions. The sequential double-sorting of SI and QI news leads to a potential issue: since news sentiment scores and stock returns are positively correlated, the second sort on returns may create further variation in the next month's stock performance. As such, we perform an independent double-sort on news sentiment and stock returns in the first robustness test. The SI and QI news defined by the independent double-sort displays the same pattern as those in Table 2, with return predictability achieving 100 bps (t-statistic=5.80) for SI news and -40 bps for QI news.

A further potential concern regarding the findings is that the effect is largely driven by penny stocks. To avoid the bid-ask bounce effect and illiquidity, we exclude stocks whose prices are below $ 5 per share at the end of each particular formation month. As panel B of Table A1 shows, the SI news effect still holds, albeit with reduced magnitudes.

One could argue that the predictability of SI news is due to a number of news articles arriving in the subsequent months. This might be true given that news volume increases over time (see Table 1). The SI news effect could be driven by news released in the holding period rather than caused by the news in the previous formation period. To address this concern, we eliminate all news observations occurring within the holding periods. As can be seen in Panel C, the SI news effects remain statistically significant.

In addition, we attempt to quantify news sentiment uaing different sentiment indicators, or even different techniques. To mitigate the concern that some news items contain high volumes of both positive and negative sentiment words and lead to low levels of pessimism (i.e. Neg - Pos), we also report the results measured by only employing either Neg or Pos indicators by the Loughran and McDonald (2011) dictionary method. Furthermore, we apply a different sentiment analysis tool. Earlier methodologies have been criticised in three main ways: First, the underlying bag-of-words model only detects single words as the leading judgment of sentiment analysis. It fails to take into account that some sentences contain "negating words" such as doesn't, don't, can't, etc., which can change the sentiment of the entire sentence. Second, this model fails to consider "modifier words" such as really, too much, etc., as these words or phrases sometimes enhance the positive and negative tone. Third, without analysing grammatical structures, the Loughran and McDonald (2011) dictionary method finds it difficult to deal with part-of-speech tagging.[11] For example, the firm-specific news of company "Best buy" will be more positive than others given its firm name contains a positive sentiment word "Best". To address these pitfalls and

[11] Part-of-speech tagging is a computational linguistic method to label the category of words as noun, adverb, adjective, etc.

the potential bias caused by them, we employ the Google Natural Language API as an alternative sentiment analysis. Overall, the results remain quantitatively similar.

As for any definition, the measures of SI and QI news are somewhat subjective. For instance, we could examine the SI news effect with a one-week time interval instead of a one-month window with or without matching returns. In our sample, SI news predicts a 53 bps return on a weekly basis (equivalent to 2.21% per month), compared to 1.01% using monthly windows. QI news exhibits similar patterns (-0.79% per month). The rationale behind this finding is that the relevance of news is time-limited and its effects will fade away over longer horizons.

Finally, we compute the standardised unexpected earnings (SUE) and cumulative abnormal returns in a [t-1, t+1] window around each quarterly earnings announcement (CAR[-1,1]). The rationale for doing this is that the CAR effectively reflects the actual market reactions to the corresponding firm-level news (i.e., earnings announcements). As such, a stock with a positive SUE and a positive CAR means that the news tone and stock return are matched and vice versa. For each month, we first sort firms into high CAR and low CAR bins. Within each CAR bin, we classify all firms' quarterly earnings into positive and negative SUE bins. A stock with positive SUE and low CAR (or negative SUE and high CAR), if generating a low future return, could be interpreted as a slowly incorporated (SI) news stock. In contrast, a stock with positive SUE and CAR (or negative SUE and CAR), if followed by a high future return, is likely to be a quickly incorporated (QI) news stock. We repeat the baseline analysis reported in Table 2. For those stocks with a positive SUE and a low CAR (or negative SUE and high CAR), we again categorise nine groups and take four corner portfolios to construct the SI and QI portfolios. To evaluate their performance, we report the average excess returns. As can be seen, a 1.59% monthly average return is reported for the SI news portfolio whereas that of the QI news portfolio is close to zero. The combined portfolio of buying SI stocks and selling QI stocks also generates 1.58% per month, with a t-statistic of 2.20. In contrast, stocks with positive SUE and CAR (or negative SUE and CAR) fail to observe any predictable return pattern as expected. All such portfolios' return performances are insignificantly different from zero. Taken together, the results clearly show that the original definition of SI news is robust and can survive in an alternative setting.

Collectively, the above robustness checks of the SI news effect should eliminate concerns of data mining or biased measures. In the next subsection, we study the time-variation of SI news effects within the sample.

——————————— Insert Table A1 here ———————————

Appendix E. Subsample Analysis

Technical advances have facilitated information dissemination, therefore reducing the gap between the times when information released and when it is received by investors. If SI news is caused by information that travels slowly, we should observe that the predictive power of SI news has gradually diminished over time. To test this conjecture, we evenly split the full sample into four different periods, the first two of which might be termed pre-Internet and the later two are post-Internet. Within each period, we perform the same analysis as previously discussed above. In Table A2, SI news significantly predicts the next month's stock returns during all sub-sample periods (93 bps during 1979 to 1987, 108 bps between 1988 and 1997, 132 bps from 1998 to 2007 and 62 bps between 2008 and 2016, which are all significant). Interestingly, the largest magnitude of SI news portfolio returns emerges during the 1998-2007 period where the number of news items dramatically increases. During the crisis period (i.e., 2008 - 2016), we observe a reduced SI news effect.

Given the relatively stable performance of SI news portfolios across each sub-sample, it seems implausible to conclude that SI news is caused by the slow information diffusion, at least not for the post-Internet period.

—————————— Insert Table A2 here ——————————

Appendix F. Google SVI and Bloomberg AIA attention proxies

Although the empirical results confirm limited attention theory, we have had to assume that investors would have paid attention to the news if a company's name is mentioned. To address this issue, we further study limited-attention theory by utilising two direct attention proxies: Google Search Volume Index (SVI) and Bloomberg news reading activity (AIA, i.e., abnormal Institutional investor Attention). These direct attention proxies have been proposed and studied in the literature and have provided compelling evidence involving certain financial variables (Engelberg and Gao, 2011; Ben-Rephael, Da, and Israelsen, 2017). The Google SVI measures investor attention by using the aggregate web user search frequency based on the Google search engine. Google counts the number of visits for a particular key word during a specific time period. As exemplified in Figure A1 below, the SVI index of the keyword *Apple Technology company* rises to a peak of 100 on September 12, 2018 when a major launch event was held by Apple. Thus the SVI index brings a direct linkage between the interest of the general public and firm-level news events.

——————————— Insert Figure A1 here ———————————

Each Bloomberg terminal provides a function where the news reading activity of each firm is monitored on daily basis. Due to the financial cost and expertise required to use Bloomberg, most terminal users are from the financial services sector. In other words, Bloomberg news reading activity is highly likely to represent institutional investor attention compared to the Google search engine which tends to represent retail investor attention.

To download the Google SVI data, we use a Python web crawler to automatically send keywords (firm legal names) and retrieve the data for each firm following certain procedures detailed in Appendix B, leading to a total of 7,864 U.S. firms, for which we have evidence for 4,545 firms. As for the Bloomberg AIA data, we follow the procedure by Ben-Rephael et al. (2017), in which they download the Russel 3000 stocks from the year 2010 forwards.[12] We then move to data pre-processing. Specifically, Bloomberg news reading activity data is a time-series measure of the rolling prior 30-days terminal user reading on an hourly basis. The value is 0, 1, 2, 3 or 4 if the rolling average is below 80%, between 80% and 90%, between 90% and 94%, between 94% and 96% and above 96%, respectively. Following the method in Ben-Rephael et al. (2017), the AIA measure is a dummy variable which takes a value of zero when the score is 0, 1, or 2 and a value of one otherwise. To be consistent with the Bloomberg AIA, we also assign the score for the Google SVI data based on the same method

[12] Bloomberg AIA data is missing for the periods 12/6/2010 - 1/7/2011 and 8/17/2011 - 11/2/2011.

so the Google ASVI (Abnormal SVI) value will be one if the corresponding score is 3 or 4 and zero otherwise.

Using these two attention proxies, we ask whether low attention could explain stronger news predictability, particularly for SI news. To examine this, we conduct a calendar-time portfolio approach with a one trading day formation period and use the following ten trading days as a holding period for either the high or the low attention sub-sample. We change the research setting in this case for two reasons: first, both Google ASVI and Bloomberg AIA are reported on a daily basis and have been scaled in a proprietary manner prior to downloading. We are cautious to keep the natural data frequency in order to capture investor attention precisely. Second, due to the sample range, the period examined covers recent years where both the SI and QI effects become weaker, as discussed in Section E. The weaker effects might be partially attributed to advanced newswire transmissions such as Twitter, which speed up information dissemination. Overall, daily-basis settings can better capture the SI news effects.

In Table A3, it can be observed that Google ASVI predicts a stronger SI news effect. The difference between the low and high Google ASVI is even significant at the 1% level (with t-statistic 4.44). The coefficients for the QI news subgroup are nearly zero (all statistically insignificant). Unfortunately, we do not observe any significant evidence for the Bloomberg AIA (the proxy for institutional investor attention). The results, therefore, suggest that it is retail investors rather than institutional investors for whom genuine news slips under their radar.

——————————— Insert Table A3 here ———————————

Fig. 1. Distribution of Firm-level News Observations

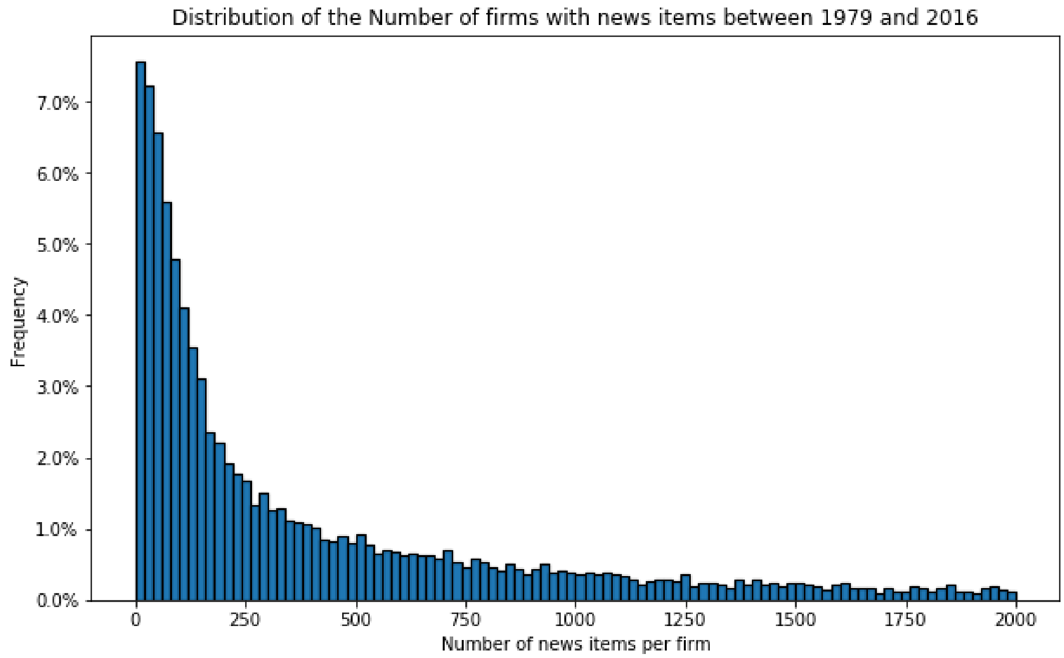

Figure 1 reports the frequency of news observations. The X-axis shows the number of news items for each firm while the Y-axis displays the percentage of firms among total sample. Sample period is 1979 to 2016.

Fig. 2. Portfolio Performance

Figure 2 plots the portfolio performance compared with the S&P500 during 1979 to 2016. Graph A is the portfolio performance index assuming a $ 1 initial investment and Graph B is the portfolio's 12-month holding period return. Graph C and D are portfolio performance after considering 25 and 50 bps transaction costs.

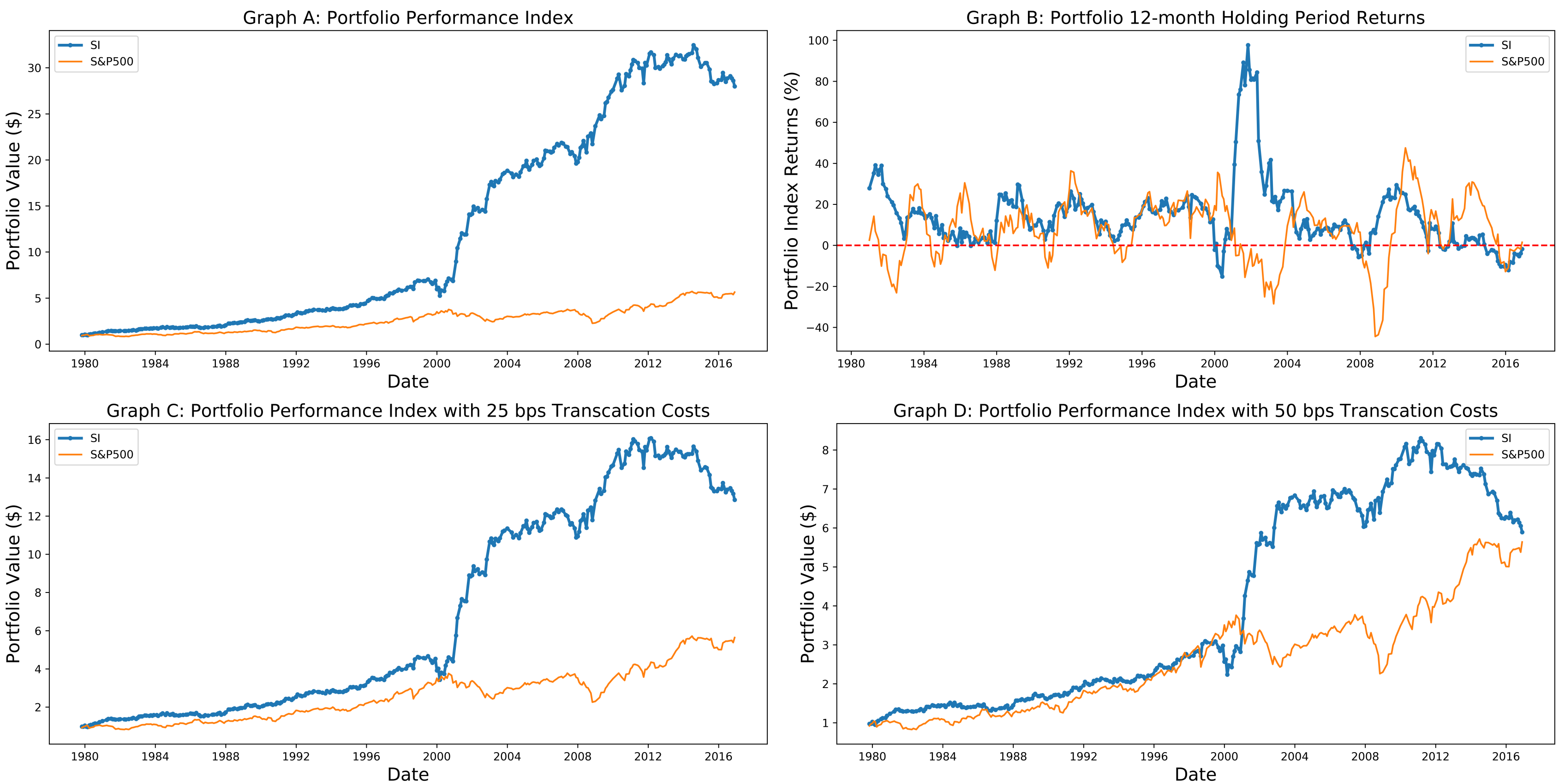

Table 1: Summary Statistics

Panel A of Table 1 presents the summary statistics. CVG is the number of news articles. RET is the DGTW-adjusted return computed by following Daniel et al. (1997). NSS is the aggregated monthly news sentiment score. $SIZE$ is computed by taking the natural logarithm of the stock market capitalisation at the end of each June. BTM is computed by taking the natural logarithm of the stock market value divided by the firm's book value, adjusted at each end of June. MOM is the stock's most recent 12-month cumulative returns. $ILLIQ$ is a proxy for stock liquidity based on Amihud (2002). $BETA$ is calculated following Scholes and Williams (1977); Dimson (1979). $IVOL$ is the idiosyncratic risk computed by the standard deviation of residuals from the Fama-French-Carhart four-factor model over the month using daily returns. Panel B reports the summary statistics across all four types of news portfolios. The monthly sequential double-sorted approach is used. In each month, firms are sorted into three groups based on their past abnormal returns and then within each group stocks are further ranked into three groups based on their news sentiment scores. $SIGoodNews$ is defined as those with low current stock returns but good positive news; $SIBadNews$ are those with high current stock returns but bad negative news; $QIGoodNews$ refers to news portfolios with high current stock returns and good positive news. $QIBadNews$ are low stock return and bad news stocks. $Avg\,\#\,of\ Stocks$ is the average number of stocks in each portfolio in each month.

Panel A	Mean	Std	Min	0.25	0.5	0.75	Max
CVG	12.81	29.12	1.00	2.00	6.00	13.00	1568.00
RET (%)	-0.28	11.83	-37.36	-6.60	-0.58	5.47	49.90
NSS	0.00	0.89	-2.33	-0.61	0.04	0.63	2.19
SIZE (Ln)	5.90	1.98	1.50	4.41	5.85	7.31	10.97
BTM	-0.67	0.79	-3.16	-1.16	-0.60	-0.12	1.33
MOM (%)	-0.74	37.73	-80.16	-22.79	-2.45	14.29	194.50
ILLIQ	0.22	0.81	0.00	0.00	0.01	0.07	9.76
BETA	0.96	1.51	-4.47	0.13	0.88	1.73	6.75
IVOL (%)	2.62	1.93	0.47	1.28	2.02	3.32	12.28

Panel B	LRHS SI Good News	HRLS SI Bad News	HRHS QI Good News	LRLS QI Bad News
NSS_t	0.94	-0.96	1.02	-1.17
RET_t	-0.12	0.15	0.15	-0.14
CVG_t	8.68	11.75	10.87	11.71
CVG_{t+1}	10.70	12.84	13.21	12.37
Avg # of $Stocks_t$	240	239	240	240

Table 2: SI and QI News

Table 2 Panel A reports the return and news predictability across terciles. The formation period and estimation period are both one month. In each month, firms are sorted into three groups based on their past abnormal returns and then within each group stocks are further ranked into three groups based on their news sentiment scores. Abnormal return is the DGTW-adjusted return computed by following (Daniel et al., 1997). All returns are reported as monthly averages denoted in percentages. The sample period ranges from 1979 to 2016. Panel B reports time-series portfolio returns with risk-adjusted alphas including the Fama and French (1993) three-factor model (FF3F), the Fama-French-Carhart four-factor model (FF4F), the Fama and French (2017) five-factor model (FF5F), a liquidity-augmented Fama-French-Carhart four-factor model (FF4F Liq) and short-term augmented Fama-French-Carhart four-factor model (FF4F Rev). The alpha estimates are obtained by regressing monthly portfolio excess returns on the monthly returns from the risk factors. The definition of SI and QI presents as follows:

$$SI = LRHS - HRLS$$

$$QI = LRLS - HRHS$$

where SI news is a long/short portfolio of buying slowly incorporated good news (LRHS) and selling slowly incorporated bad news (HRLS). QI news is a long/short portfolio made by buying quickly incorporated good news (HRHS) stocks and selling quickly incorporated bad news (LRLS) stocks. t-statistics are reported in parentheses and **, *** refers to 5% and 1% significance levels respectively.

Panel A	HS	Mid	LS
LR	1.45%	1.22%	1.05%
Mid	0.94%	0.77%	0.84%
HR	0.67%	0.53%	0.45%

Panel B	TS Ret	FF3F	FF4F	FF5F	FF4F Liq	FF4F Rev
SI News	1.01%***	0.92%***	1.09%***	0.85%***	1.09%***	0.82%***
t-stat	(5.85)	(3.66)	(3.68)	(3.00)	(4.00)	(4.11)
QI News	-0.39%**	-0.27%	-0.64%***	-0.29%	-0.61%***	-0.38%**
t-stat	(-2.09)	(-1.14)	(-2.70)	(-0.94)	(-2.55)	(-2.42)
Slow-Minus-Quick	1.39%***	1.19%***	1.73%***	1.14%**	1.69%***	1.20%***
t-stat	(4.26)	(2.59)	(3.40)	(2.01)	(3.70)	(3.75)

Table 3: Predicting Stock Returns by SI News and QI News

Table 3 reports the stock return predictability of slowly incorporated news and quickly incorporated news based on various regression specifications. $SINws$ and $QINws$ are dummy variables if news is slowly incorporated or quickly incorporated, respectively. $NSS * SINws$ and $NSS * QINws$ are the interaction terms where NSS is a news sentiment score. $CONTROLS$ is a battery of control variables including $LRET$, $SIZE$, BTM, $BETA$, $IVOL$, MOM, $ILLIQ$. $SIZE$ is computed by taking the natural logarithm of stock market values in each previous month. $LRET$ is the lagged one-month stock return. BTM is computed by taking the natural logarithm of stock market values divided by firm book values adjusted at each end of June. $BETA$ is calculated following Scholes and Williams (1977); Dimson (1979). MOM is the stock's most recent 12-month cumulative returns. $IVOL$ is the idiosyncratic risk computed by the standard deviation of residuals from the Fama-French-Carhart four-factor model over the month using daily returns. $ILLIQ$ is a proxy for stock liquidity based on (Amihud, 2002). The sample period ranges from 1979 to 2016. t-statistics are reported in parentheses and **, *** refers to the 5% and 1% significance levels respectively.

	Dep = EXRet					
	1	2	3	4	5	6
CONST	0.8823***	0.8602***	0.8841***	2.0814***	2.0905***	2.0721***
	(3.38)	(3.36)	(3.45)	(6.22)	(6.24)	(6.22)
NSS	0.1029***	-0.0445	0.2489***	0.0868***	0.1249***	0.0959***
	(3.64)	(-0.97)	(7.05)	(3.09)	(4.44)	(3.11)
NSS*SINws		0.3110***		0.2080**		0.2004**
		(3.24)		(2.30)		(2.21)
NSS*QINws			-0.2764***		-0.1651	-0.1351
			(-2.89)		(-1.63)	(-1.30)
SIGdNws		0.3508**		-0.0555		-0.0488
		(2.54)		(-0.52)		(-0.45)
SIBdNws		-0.1276		0.2653**		0.2768**
		(-1.04)		(2.36)		(2.44)
QIGdNws			-0.2443		0.1339	0.1581
			(-1.81)		(1.10)	(1.28)
QIBdNws			0.1705		-0.1609	-0.1262
			(1.10)		(-1.13)	(-0.87)
LRET				-0.0261***	-0.0265***	-0.0265***
				(-5.96)	(-6.02)	(-5.76)
SIZE				-0.1198***	-0.1195***	-0.1197***
				(-3.12)	(-3.11)	(-3.12)
BTM				0.1635**	0.1625**	0.1622**
				(2.31)	(2.30)	(2.30)
BETA				-0.0671	-0.0658	-0.0661
				(-1.41)	(-1.39)	(-1.39)
IVOL				-0.2075***	-0.2040***	-0.2078***
				(-4.44)	(-4.36)	(-4.45)
MOM				0.0043***	0.0044***	0.0043***
				(3.22)	(3.33)	(3.25)
ILLIQ				0.0982**	0.0994***	0.1021***
				(2.53)	(2.57)	(2.64)
Nobs	965505	965505	965505	794317	794317	794317
Adj_R^2	0.05%	0.36%	0.34%	6.12%	6.14%	6.19%

Table 4: The Long-run Performance of SI and QI News over Different Horizons

Table 4 reports the performance of slowly incorporated news and quickly incorporated news over different holding periods. The portfolio is constructed by sorting stocks into tercile portfolios over five different holding periods: one month, three months, six months nine months and twelve months. In each month, firms are sorted into three groups based on their past abnormal returns and then within each group, stocks are further ranked into three groups based on their news sentiment scores. Abnormal return is the DGTW-adjusted return computed by following (Daniel et al., 1997). The definition of SI and QI is presented as follows:

$$SI = LRHS - HRLS$$

$$QI = LRLS - HRHS$$

where SI news is a long/short portfolio made by buying slowly incorporated good news (LRHS) stocks and selling slowly incorporated bad news (HRLS) stocks. QI news is a long/short portfolio constructed by buying quickly incorporated good news (HRHS) stocks and selling quickly incorporated bad news (LRLS) stocks. The sample period ranges from 1979 to 2016. t-statistics are reported in parentheses and **, *** refers to the 5% and 1% significance levels respectively.

Months	SI News	t-stat	QI News	t-stat	Slow-Minus-Quick	t-stat
[1,2]	1.01%***	(5.85)	-0.39%**	(-2.09)	1.39%**	(2.43)
[2,4]	-0.03%	(-0.24)	0.20%	(1.54)	-0.22%	(-1.01)
[2,7]	-0.07%	(-0.83)	0.20%	(1.93)	-0.28%	(-1.64)
[2,10]	-0.06%	(-0.83)	0.17%	(1.79)	-0.23%	(-1.53)
[2,13]	-0.09%	(-1.30)	0.14%	(1.76)	-0.22%	(-1.90)

Table 5: SI and QI News under Different Information Environment

Table 5 reports the performance of slowly incorporated news and quickly incorporated news portfolios in different information environments. We independently sort all stocks into two portfolios based on their most recent market capitalisation (Size), current monthly change of media coverage, turnover ratio and analyst coverage. We report the "Small-Large" SIZE, "Low-High" Δ MEDIA, "Low-High" TURN, "Low-High" AstCvg spread profitability in the post-formation period. t-statistics are reported in parentheses and **, *** refers to the 5% and 1% significance levels respectively.

Panel A	Size Subsamples			MEDIA Subsamples		
	SmallSIZE	BigSIZE	Small-Big	LowMEDIA	HighMEDIA	Low-High
SI News	1.61%***	0.50%***	1.11%***	1.44%***	0.09%	1.35%***
	(6.58)	(3.04)	(4.54)	(7.52)	(0.54)	(7.10)
QI News	-0.61%	-0.18%	-0.43%	-0.64%***	0.22%	-0.86%***
	(-1.92)	(-1.07)	(-1.50)	(-3.18)	(1.41)	(-4.55)
Slow-Minus-Quick	2.22%***	0.67%**	1.55%***	2.08%***	-0.13%***	2.21%***
	(4.67)	(2.28)	(3.65)	(6.00)	(-0.48)	(7.56)

Panel B	TURN Subsamples			AstCvg Subsamples		
	LowTURN	HighTURN	Low-High	LowAstCvg	HighAstCvg	Low-High
SI News	1.36%***	0.56%**	0.80%***	1.03%***	0.57%***	0.46%**
	(8.94)	(2.03)	(2.95)	(4.53)	(3.06)	(1.99)
QI News	-0.34%**	-0.29%	-0.04%	-0.08%	-0.20%	0.12%
	(-2.12)	(-1.01)	(-0.16)	(-0.33)	(-1.04)	(0.50)
Slow-Minus-Quick	1.70%***	0.85%	0.85%	1.11%***	0.77%**	0.34%
	(6.79)	(1.71)	(1.87)	(2.76)	(2.33)	(0.94)

Table 6: SI and QI News in Different Nature of News

Table 6 reports the performance of slowly incorporated news and quickly incorporated news for different news characteristics. In Panel A, we independently sort all stocks into two portfolios based on textual complexity. In Panel B, we again sort all stocks into two portfolios based on news informativeness. We report the "Ambiguous-Accurate" Tone, "Complex-Concise" Readability, "Short-Long" Length and "EarningsEx-EarningsIn" Topic spread profitability in the post-formation period. t-statistics are reported in parentheses and **, *** refers to the 5%, 1% significance levels respectively.

Panel A	SI and QI News across Accuracy Subsamples			SI and QI News across Readability Subsamples		
	Ambiguous	Accurate	Ambiguous - Accurate	Complex	Concise	Complex - Concise
SI News	1.05%***	0.42%	0.63%**	1.10%***	0.81%***	0.30%
	(3.95)	(1.61)	(2.29)	(5.34)	(3.97)	(1.30)
QI News	-0.51%**	0.02%	-0.53%	-0.67%***	-0.32%	-0.34%
	(-2.08)	(0.07)	(-1.91)	(-2.93)	(-1.54)	(-1.68)
Slow-Minus-Quick	1.55%***	0.40%	1.15%***	1.77%***	1.13%***	0.64%**
	(3.37)	(0.83)	(2.55)	(4.77)	(3.29)	(2.11)

Panel B	SI and QI News across Length Subsamples			SI and QI News across Earnings Subsamples		
	Short	Long	Short - Long	EarningsEx	EarningsIn	EarningsEx - EarningsIn
SI News	1.29%***	0.70%***	0.58%***	0.92%***	0.77%***	0.16%
	(5.78)	(3.62)	(2.70)	(5.33)	(3.61)	(1.04)
QI News	-0.79%***	-0.19%	-0.60%***	-0.45%**	-0.27%	-0.18%
	(-3.53)	(-0.81)	(-2.60)	(-2.35)	(-1.36)	(-1.09)
Slow-Minus-Quick	2.08%***	0.90%**	1.18%***	1.38%***	1.04%***	0.34%
	(5.40)	(2.45)	(3.74)	(4.10)	(2.90)	(1.65)

Fig. A1. Google Search Volume Index for Apple Technology

Figure A1 plots the search volume index of Apple Technology by the Google search engine between 4 July and 30 September, 2018. The raw search volumes have been scaled and displayed as time-series values between 0 and 100.

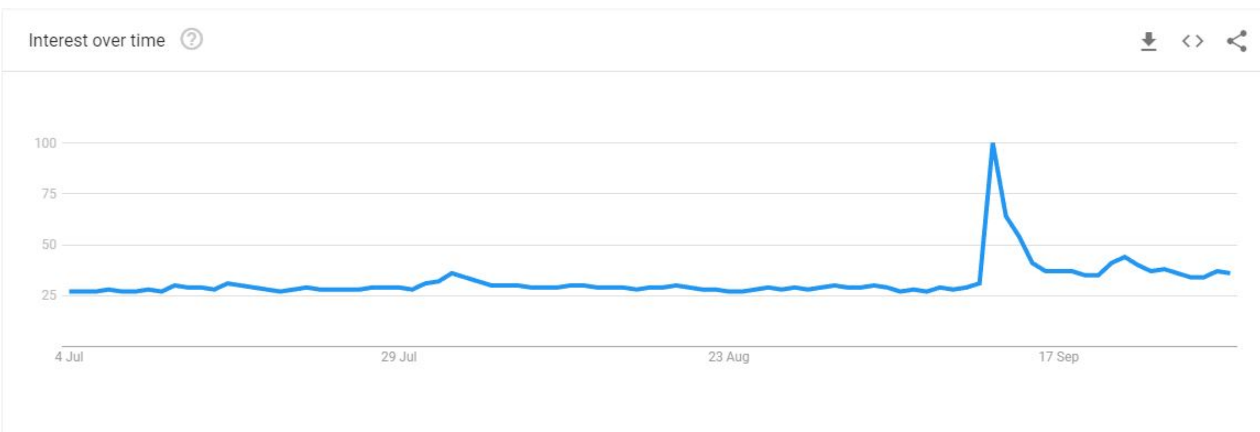

Table A1: Robustness Checks

Table A1 reports robustness checks of calendar-time portfolio tests. Panel A reports an alternative method of portfolio construction for returns and news sentiment scores. Panel B excludes stocks with prices below than \$ 5 per share. Panel C eliminates stocks with news observations in the holding period. Panel D measures news tone using different sentiment tools including Loughran and McDonald (2011) negative words and positive words and the Google Natural Language Sentiment scores. Panel E reports portfolio performance on a weekly basis. Panel F reports portfolio performance using alternative definition of slowly incorporated news. *t*-statistics are reported in parentheses and **, *** refers to the 5%, 1% significance levels respectively.

Panel A	SI News	t-stat	QI News	t-stat	SMQ	t-stat
News Beta	1.28%***	(5.16)	0.80%**	(2.27)	0.49%**	(2.36)
Independent double-sorted	1.00%***	(5.80)	-0.40%**	(-2.22)	1.41%***	(4.33)

Panel B	SI News	t-stat	QI News	t-stat	SMQ	t-stat
Price>= \$5	0.71%***	(4.81)	-0.16%	(-1.08)	0.87%***	(3.22)

Panel C	SI News	t-stat	QI News	t-stat	SMQ	t-stat
Excluded subsequent news	1.45%***	(4.59)	-0.98%***	(-3.07)	2.43%***	(5.07)

Panel D	SI News	t-stat	QI News	t-stat	SMQ	t-stat
LM negative score	0.99%***	(5.47)	-0.49%***	(-2.68)	1.47%***	(4.43)
LM positive score	0.74%***	(4.22)	-0.69%***	(-3.65)	1.43%***	(4.23)
Google NL score	0.78%***	(4.53)	-0.63%***	(-3.32)	1.41%***	(4.30)

Panel E	SI News	t-stat	QI News	t-stat	SMQ	t-stat
Weekly frequency	2.09%***	(12.32)	-0.79%***	(-4.47)	2.88%***	(9.71)

Panel F	SI News	t-stat	QI News	t-stat	SMQ	t-stat
Alternative SI new	1.59%***	(3.63)	0.01%	(0.02)	1.58%**	(2.20)
Alternative QI news	-0.07%	(-0.15)	0.01%	(0.01)	-0.08%	(-0.10)

Table A2: Slowly Incorporated and Quickly Incorporated News over Time

Table A2 reports the subsample analysis. The sample is split into four different periods: 1979 - 1987, 1988 - 1997, 1998 - 2007 and 2008 - 2016 respectively. All returns are converted into monthly averages in percent. Panel A reports the SI and QI news portfolio returns monthly. The definition of SI and QI are presented as follows:

$$SI = LRHS - HRLS$$

$$QI = LRLS - HRHS$$

where SI news is a long/short portfolio comprising of buying slowly incorporated good news (LRHS) stocks and selling slowly incorporated bad news (HRLS) stocks. QI news is a long/short portfolio of buying quickly incorporated good news (HRHS) stocks and selling quickly incorporated bad news (LRLS) stocks. t-statistics are reported in parentheses and **, *** refers to the 5% and 1% significance levels respectively.

	1979 - 1987	1988 - 1997	1998 - 2007	2008 - 2016
SI News	0.93%***	1.08%***	1.32%***	0.62%**
t-stat	(3.06)	(4.75)	(2.77)	(2.20)
QI News	0.14%	-0.53%**	-0.51%	-0.58%
t-stat	(0.47)	(-1.97)	(-1.03)	(-1.65)
Slow-Minus-Quick	0.79%	1.61%***	1.83%**	1.20%**
t-stat	(1.61)	(3.96)	(1.97)	(2.06)

Table A3: SI and QI News under Different Investor Attention

Table A3 reports the performance of slowly incorporated news and quickly incorporated news portfolios in different information environments. We independently sort all stocks into two portfolios based on their current investor attention index. We report the "Low-High"Google ASVI ATTN, "Low-High"Bloomberg AIA ATTN spread profitability in the following ten trading days. The Google ASVI is the Google Search Volume Index, which is a proxy for retail investor attention and Bloomberg AIA measures Bloomberg users' news reading activity, which represents institutional investor attention. Coefficients are ten-trading-day cumulative returns in percentages. *t*-statistics are reported in parentheses and **, *** refers to the 5% and 1% significance levels respectively.

	Google ASVI ATTN Subsamples			Bloomberg AIA ATTN Subsamples		
	LowATTN	HighATTN	Low - High	LowATTN	HighATTN	Low - High
SINws	0.05%***	0.01%**	0.04%***	0.02%**	0.00%	0.01%
	(6.23)	(2.22)	(4.44)	(2.24)	(0.28)	(0.85)
QINws	0.00%	0.01%	-0.01%	0.00%	-0.01%	0.00%
	(-0.15)	(1.22)	(-1.12)	(-0.17)	(-0.83)	(0.35)
Slow-Minus-Quick	0.05%***	0.00%	0.05%***	0.02%	0.01%	0.01%
	(4.22)	(0.42)	(3.92)	(1.72)	(0.74)	(0.40)