Attention to information, attention to prices *

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Abstract

We show that attention to fundamental information and attention to market prices are distinct constructs that lead to differing outcomes in financial markets. Using new measures for both constructs, we find that only attention to information affects informational efficiency. Attention to information reduces post-announcement drifts, while attention to prices does not. Evidence suggests that behaviorally biased investors drive attention to prices and that momentum and lottery-like stocks attract higher attention to prices. Our results show that, in addition to the *when* and the *who*, the *what* is an important factor in determining how investor attention affects stock prices.

Keywords: investor attention, company announcements, market efficiency, behavioral biases
JEL classification: G12, G14, G40

* The Internet Appendix accompanying this study can be found at this link (https://bit.ly/3fybkkY).
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1. Introduction

Investors are not always fully attentive to new information in financial markets and price in new information with a lag when distracted (Hirshleifer and Teoh, 2003; DellaVigna and Pollet, 2009).[1] The inattention literature does well to document *when* the market pays attention and *who* within the market pays attention, but it largely ignores *what* attracts the market's attention. This is important since attention to different items can have differing effects. For example, a trader trading after observing some new fundamental information (e.g., a corporate disclosure) that affects the stock's intrinsic value might help impound this information into the stock's price, whereas a trader observing a recent price increase and purchasing the stock in the belief that prices will keep rising might make no such contribution. Both traders are paying attention to markets, however, their trading does not have the same effect on markets since they are paying attention to different items.[2]

Our paper dissects investor attention into two components—"attention to fundamental information" and "attention to price movements"—and separately examines the effects of each component on informational efficiency. The distinction between attention to information and attention to prices is important since some investors tend to ignore fundamental information and trade solely based on price movements.[3] In particular, we hypothesize that two types of traders consistently base their trades only on price movements and thus only pay attention to prices. The first type includes traders that use analytical techniques such as technical analysis that rely only on prices and trading volumes (technical traders). The second type includes traders that exhibit behavioral biases such as extrapolation bias, disposition effect, and lottery preferences that trigger trades based solely on price movements (behaviorally biased traders). Since both these traders trade without using fundamental information, we expect that the aggregate trading of these traders at best contributes to the noise in returns and at worst contributes to mispricing after information releases.[4] In either case, their trading does not improve pricing efficiency. In this paper, we argue

[1] See Barber, Lin, and Odean (2019) and Gabaix (2019) for thorough literature reviews on the role of inattention in finance.

[2] A related theoretical notion is that of news watchers and momentum traders in Hong and Stein (1999). In their model, momentum trading causes overreactions at long horizons. However, our idea of price watchers is not exactly the same as the momentum traders in Hong and Stein (1999) since, as we discuss later in the paper, price watching can entail strategies other than momentum trading too.

[3] Previous findings support the idea of attention to prices as a separate construct. For example, Grinblatt and Keloharju (2001) and Barber and Odean (2008) document that salient price events such as extreme daily returns and hitting monthly highs and lows trigger attention-induced trading.

[4] In individual cases, momentum and extrapolative traders might by chance contribute to improving efficiency if, for example, they trade immediately following an announcement. However, in aggregate, this improvement might be

that these traders' attention (attention to prices) does not improve informational efficiency after company announcements, only attention to information does.

We construct two new cross-sectional measures, one for attention to information and one for attention to prices, since the existing measures do not fit our purpose. The existing attention measures either conflate attention to information and attention to prices (Google search interest, Wikipedia page views), or only capture attention to information for a subset of investors (Bloomberg news search activity) or through limited channels (EDGAR downloads).[5] None of the existing measures specifically capture attention to prices. The new measures we construct are primarily meant to gain insights into the differing effects of attention to information and attention to prices and do not serve as substitutes for the existing attention measures.

Our attention to information measure is built on the intuition that inattentive investors do not cancel or update their pending orders (if any) after the release of new information that has a material impact on the stock's price. Our attention to information measure is the average proportion of order cancellations and amendments for a stock in overnight periods with material information events. We deliberately use overnight periods to construct our measure since they allow us to disentangle attention to information from attention to prices; during these periods, companies can release new information and investors can amend orders, but prices do not change.

Our attention to prices measure is the number of times a stock is mentioned on specific sub-forums in a popular stock market discussion forum. A unique feature of these sub-forums is that they are exclusively for day traders and short-term traders, who mainly speculate on prices (Linnainmaa, 2003; Barber et al., 2014). Throughout the day, traders gather on these forums to discuss stocks with sharp price movements. Our attention to prices measure has higher values for stocks preferred by technical and behaviorally biased traders (momentum and lottery-like stocks),

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negated by contrarian or disposition effect traders trading in the opposite direction. Even these momentum and extrapolative traders might not necessarily improve efficiency if they overshoot the true impact of the announcement as in Hong and Stein (1999), which is possible since they are not paying attention to the announcement itself.

[5] The Bloomberg news search activity measure (Ben-Rephael, Da, and Israelsen, 2017) only measures attention for institutional investors since it based on news activity on Bloomberg terminals, which are typically only used by institutional investors. Attention to information is not synonymous with institutional attention since institutions also trade based solely on price movements and retail investors are becoming more informed in recent times (Menkhoff, 2010; Farrell et al., 2022). The EDGAR downloads measure (Drake, Roulstone, and Thornock, 2015) captures both retail and institutional attention but only through one information channel, i.e., the US Securities and Exchange Commission's EDGAR platform. There exist many alternative channels, such as Bloomberg, Thomson-Reuters, Yahoo Finance etc., through which investors can obtain the same information as the EDGAR platform (corporate filings, financial statements) or view summarized financial information, and there is no evidence to suggest that the EDGAR platform is the dominant channel.

suggesting that these traders mainly populate these forums.[6] We discuss both measures in detail in Sections 3.1 (attention to information) and Section 3.2 (attention to prices).[7]

We conduct our study on Australian firms in the year 2019.[8] Australia offers a nice setting to examine market reactions to news since it imposes stringent continuous disclosure rules, with hefty costs of non-compliance (Kalfus and Golding, 2004; Brown and Shekhar, 2018). These strict rules mean that Australian firms are likely to disclose material information more frequently throughout the year, giving us a large sample of price reactions to individual pieces of material information dispersed through time instead of bundles of information released during earnings season.[9,10] Routine disclosure also dampens the incentives to accumulate private information in between earnings announcements dates, thus mitigating the effects of pre-announcement information leakage. Additionally, the dedicated discussion forums for day traders and short-term traders in Australia make it possible to measure attention to prices.[11]

We use our attention measures to test how stock-level attention affects price reactions to material (also known as "price sensitive") overnight announcements for all stocks listed on the Australian Securities Exchange (ASX). We find that the market underreacts to new information initially. There is a sharp reaction when the market opens on the first trading day after the announcement, followed by a post-announcement drift that levels off around 12 days after the announcement. Our tests reveal that the post-announcement drifts for positive announcements decrease with attention to information. However, no such relation exists for negative announcements and for the attention to prices measure. In fact, in certain specifications, post-announcement drifts increase as attention to prices increases. We conjecture that, in our sample, price reactions to negative announcements are, on average, "too efficient" or have insufficient

[6] We examine individual threads and find that traders use technical tools such as charts and that the posts are mostly related to recent price movements rather than fundamental information (see Section 3.2).
[7] Our results are robust to using various alternative methods to construct our attention measures.
[8] We calculate our attention to prices measure in 2018 to avoid endogeneity issues.
[9] Consistent with this hypothesis, Brown and Shekhar (2018) find that, unlike the US, earnings announcements in Australia do not witness significant market reactions, a result they attribute to the information contained in earnings releases being priced into the stock before the announcement.
[10] Based on the evidence in Da, Gurun, and Warachka (2014), investors are likely to be more attentive in the latter case than the former case. However, this finding does not affect our analysis directly since this reduced attention affects all Australian firms uniformly.
[11] In the US, popular stock market discussion forums either do not have dedicated sub-forums for day traders and short-term traders or these sub-forums mainly contain discussions on investment ideas shared by users rather than discussions about stocks with sharp recent price movements.

variation in efficiency for the efficiency gains from additional attention to information to play out (see Section 4.1 for details).

To assess whether the attention to information effects are economically meaningful, we examine whether the performance of long-short trading strategies that exploit the post-announcement drift improves after conditioning on attention. We compare the performance of baseline trading strategies that purchase stocks after positive announcements and sell short stocks after negative announcements with attention-based strategies that only purchase and sell short low attention stocks. Using the attention to information measure to condition on attention improves the baseline strategy's statistically significant daily alpha of 19 basis points by 18 basis points for a seven-day holding period.[12] In contrast, conditioning on the attention to prices measure leads to a statistically insignificant alpha, causing even the statistically significant alpha of the baseline strategy to disappear. By the end of the sample period, the attention-based strategy earns a 58% (90%) higher (lower) total return than the baseline strategy when using the attention to information (attention to prices) measure.

We verify that our attention to information results are not confounded by hidden price effects. To do so, we re-run our tests after excluding stocks that are cross-listed in American and European markets and momentum stocks. American and European markets are open when ASX is closed, meaning that investors can learn from price updates in these foreign markets even during overnight periods. If cross-listed stocks drive our results, our attention to information measure is actually capturing attention to prices in foreign markets. Another price-related confounder is momentum. Momentum stocks have a natural tendency to drift upwards (downwards) after positive (negative) announcements. If momentum stocks drive our results, our attention to information measure is just capturing momentum effects. Our results apply for non-cross-listed and non-momentum stocks, meaning that our measure captures attention to information rather than learning from prices in foreign markets or momentum.

Finally, we turn our focus to our attention to prices measure. We discuss previously how technical and behaviorally biased traders dominate our attention to prices measure, but which of these two sets of traders exert a greater influence on our measure? To attempt to answer this

[12] To verify that our attention to information results are not confounded by size effects, we compare the results of the attention-based strategy with size-based strategies. All our size-based strategies generate negative albeit not statistically significant alphas, suggesting that our attention to information measure is not merely capturing size effects.

question, we test whether our attention to prices measure demonstrates an effect that we would expect if technical traders dominate the measure but not if behaviorally biased traders dominate it. This effect is an improvement in weak-form efficiency. Technical traders actively search for patterns in historical prices that are not reflected in the current market price. In doing so, they help price in the information contained in historical prices into the market price, thereby improving weak-form efficiency. Behaviorally biased traders do not search for this information and thus do not make this contribution. We find that our attention to prices measure is not positive related with measures of weak-form efficiency such as variance ratios and return autocorrelations, suggesting that behaviorally biased traders exert a greater influence on our measure than technical traders.

Our paper contributes to the literature studying the effects of investor attention on informational efficiency. Numerous studies investigate the effects of attention on post-earnings announcement drifts in some manner (Chen, Jiang, and Zhu, 2018; Huang, Nekrasov, and Teoh, 2018; Hirshleifer and Sheng, 2019; Kottimukkalur, 2019; Li, Nekrasov, and Teoh, 2020; Liu, Peng, and Tang, 2020; Hansen, 2021). Although many studies document that drifts are stronger on days when investors are distracted or attention is otherwise low (Hirshleifer, Lim, and Teoh, 2009; Pantzalis and Ucar, 2014; Jiang, Li, and Wang, 2021) and the dissimilar effects of retail and institutional investor attention on efficiency (Ben-Rephael et al., 2017; Liu, Peng, and Tang, 2022), to the best of our knowledge, no previous study examines whether attention to different items in financial markets affects efficiency differently. We show that only attention to fundamental information improves market efficiency by reducing post-announcement drifts, while attention to prices has no such effect. We also find that technical and behaviorally biased traders are the main contributors to attention to prices, with behaviorally biased traders being more dominant. Overall, our results suggest that *what* attracts investors' attention is an important consideration in determining how investor attention affects financial markets.

Our paper also helps narrow the gap between the behavioral asset pricing literature and the market microstructure literature. Activity at the limit order level has been studied extensively in the microstructure literature. Studies examine order placements, revisions, executions, cancellations, non-executions, monitoring, and other order-level activity (Handa and Schwartz, 1996; Liu, 2009; Fong and Liu, 2010; Yamamoto, 2014; Khomyn and Putniņš, 2021). This order-level activity ultimately affects market efficiency through executed or forgone trades, and thus also mediates the relation between investor attention and pricing efficiency since the only mechanism through which information is impounded into prices is through trading by placing orders. Despite this, to the best of our knowledge, research has not yet examined the link between order updates and price reactions to announcements. We use highly granular order messages data to obtain information on order cancellations and amendments, which we use as a proxy for attention to information. In doing so, we examine the relation between investor attention and asset prices through a microstructure channel.

This paper is structured as follows. Section 2 introduces our data and sample. Section 3 discusses our attention measures and provides some summary statistics. Section 4 presents and discusses our empirical results. Section 5 concludes.

2. Data description

Our main sample includes all announcements released outside of trading hours (overnight announcements) for all stocks listed on ASX in 2019.[13] An advantage of conducting our study in the Australian market instead of the US is the strict statutory continuous disclosure regime that Australian firms face. Australian continuous disclosure obligations require firms to disclose all relevant information (except confidential information) as they become aware of it and carry harsh penalties if they are found to be in breach of the law (Kalfus and Golding, 2004; Brown and Shekhar, 2018). This is unlike the US, where continuous disclosure rules are imposed by exchanges rather than through a statute, and the legal principles surrounding continuous disclosure are relatively uncertain (Kalfus and Golding, 2004; Brown and Shekhar, 2018).

Given the strict continuous disclosure rules, Australian firms are more likely to disclose material information in individual pieces throughout the year rather than in a combined form along with the company's financial statements. This offers a nice setting to examine market reactions to information releases since it gives us a large, nearly complete compilation of relevant firm-specific information that is also less susceptible to strategic concealment by management due to the high penalties associated with doing so. Continuous disclosure also means that more information is swiftly out in the open, reducing the benefits associated with privately acquiring and trading on

[13] Announcements released outside of trading hours offer a relatively cleaner setting to examine price reactions as investors have more time to assess the information content of the announcement. Immediate price reactions to announcements made during trading hours are likely to be noisier.

this information before the next earnings announcement. This means that the information disclosed in announcements made by Australian firms is less likely to be leaked before the announcement.

The Australian equity market is among the top ten equity markets in the world by market capitalization, with ASX being among the top 20 stock exchanges.[14] ASX lists around 2,000 stocks with a total market capitalization of approximately $2.07 trillion, or AUD 2.87 trillion, at the time of writing.

To filter out immaterial announcements, we restrict our sample to announcements classified as "price sensitive" by the ASX based on their nature and information content.[15] Further, we apply a liquidity filter that excludes all announcements for which there are no trades in the next trading day's opening auction.[16] We collect the announcement data from the Australian company announcements database provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). From this database, we collect information about the date, time, and type of the announcement.[17]

In total, there are 11,753 announcements and 1,791 stocks in our sample. Of these, 4,110 announcements can be classified as positive news and 7,643 announcements can be classified as negative news based on the return in the ten trading days following the announcement release. We use this criteria to classify announcements as positive or negative throughout the paper, except in Section 4.2.

To compute the attention to information measure, we use order messages data. Order messages data include information about order additions, amendments, cancellations, and executions. Unlike the more conventional trade and quote data and order book data, these data contain a unique identifier for each order that is sent to the market and thus enable us to trace the entire life cycle of all orders. We obtain these data from SIRCA, which in turn obtains these data on a real-time basis directly from ASX's trading platform.

To compute the attention to prices measure, we use discussion threads data from the 'ASX – Day Trading' and 'ASX – Short Term Trading' sub-forums on HotCopper, the largest stock

[14] Source: Statista.
[15] Throughout the paper, we use the terms "price sensitive" and "material" synonymously.
[16] ASX conducts opening auctions between 10:00 and 10:10. Stocks are sorted alphabetically into groups based on the first letter of their ASX code. Groups are assigned time slots, and stocks in the same group open together during their assigned time slot. The market closes with a closing auction conducted between 16:10 and 16:11.
[17] Announcement types are based on ASX's disclosure requirements (ASX Listing Rule 3.1). There are 19 announcement types in total. The list of announcement types can be accessed at this link (https://bit.ly/3uf4vJL). A given announcement can belong to multiple types depending on its information content.

market discussion forum in Australia. For each discussion thread, we download the topic of the thread, the content of each post in the thread, details of the author of the post (such as their username, number of previous posts etc.), and the date and time of the post.

Lastly, we obtain prices, trading volumes, market capitalization, and institutional ownership data from SIRCA, search interest data from the Google Trends website, and analyst estimates data from Refintiv I/B/E/S.

3. Attention measures

The investor attention literature proposes various proxies that approach the problem of measuring investor attention from different angles. Popular stock-level proxies include Google search interest, Wikipedia page views, download activity on the US Securities and Exchange Commission's (SEC) EDGAR platform, and firm-related news search and reading activity on Bloomberg Terminal (Da, Engelberg, and Gao, 2011; Drake, Roulstone, and Thornock, 2012; Drake et al., 2015; Ben-Rephael et al., 2017; Focke, Ruenzi, and Ungeheuer, 2020). However, the existing measures either confound attention to information with attention to prices or only measure attention for a particular set of investors (rather than total investor attention) or only measure information acquisition through one channel.

One of the most popular attention proxies in the literature is the Google SVI proxy introduced in Da et al. (2011) and Drake et al. (2012). deHaan, Lawrence, and Litjens (2021) report that the Google SVI proxy has been used by over 80 published papers. Essentially, the proxy uses the Google search activity for the stock as a measure of investor attention. However, this proxy is not useful for our study since it confounds attention to information and attention to prices. Two simple examples demonstrate how this is the case.

Recently, the major technology companies listed on NASDAQ released their quarterly results for the April to June 2023 quarter.[18] All of these earnings announcements were made after trading hours, meaning that investors only observe this new information and do not get any price feedback until the next day. These earnings releases caused a spike in the Google searches for each firm's ticker, with the announcement day SVIs being 96%–426% higher than the average SVI in

[18] The companies we include in the category are: Alphabet, Amazon, Apple, Meta, Microsoft, and Tesla.

the three days leading up to the announcement.[19] In this instance, Google searches capture attention to fundamental information.

Conversely, in early 2021, markets witnessed a trading frenzy for the stock of GameStop, a video game retailer, wherein a group of traders coordinated their trading on Reddit, a social media platform, and tried to short squeeze GameStop's stock. In January 2021, GameStop's stock rose from $4.75 to a high of $103.50, before ending the month at $81.25. During the month, the SVI for GameStop's ticker also rose to 100 (the maximum value) from an average value of 1 in December 2020. In this case, Google search activity largely captures attention to the large fluctuations in the GameStop's price and the Reddit short squeeze.

We find evidence of this confounding effect in our data as well; SVI is related to both our attention to information and attention to prices measures (see Section 3.3). A similar issue affects the Wikipedia page views proxy as well since the firm's Wikipedia page could be viewed by investors searching for fundamental information and those searching for recent prices, and there exists no easy method to disentangle the page views of both these categories of investors.

Other proxies proposed in the literature more recently including the EDGAR downloads proxy (Drake et al., 2015) and the Bloomberg news activity (Ben-Rephael et al., 2017) are more accurate measures of attention to information since both these proxies use the user activity at different information access points as measures for attention.

Bloomberg news activity mainly captures institutional investor attention rather than total investor attention since it only uses news search and reading activity on the Bloomberg terminal, which is a costly tool mostly used by institutional investors. Although institutional attention is likely to be correlated with overall attention to information since institutions tend to be more informed, both of these concepts are not necessarily synonymous. Institutional investors also tend to use technical analysis (Menkhoff, 2010). Conversely, recent technological innovations are leading retail traders to become more informed (Farrell et al., 2022).

EDGAR downloads uses the number of downloads of corporate filings on SEC's EDGAR platform as a proxy for attention and thus serves as a better proxy for total investor attention since it does not exclude retail investors. However, there are many agencies that offer the same

[19] Prices moved sharply on the next trading day after each announcement and not the announcement day, suggesting that investors were not paying attention to information that leaked into prices on the announcement day rather than the announcement itself.

information as the EDGAR platform (including Bloomberg, Thomson-Reuters, Capital IQ etc.) and the main financial information contained in financial statements is also summarized by websites such as Yahoo Finance and Seeking Alpha. The EDGAR downloads proxy would not capture information acquisition by investors who primarily use these alternative platforms.

We select the Australian setting since it allows us to identify both attention to information and attention to prices in a relatively clean manner. Since the existing proxies do not capture these individual constructs, we construct new cross-sectional measures for both attention to information and attention to prices.

3.1. Attention to information

We use highly granular order messages data to construct our measure for attention to fundamental information. The intuition behind our measure is simple. In essence, the attention to information measure categorizes investors who do not amend or cancel their orders in response to material overnight news as inattentive. An investor must pay attention to the market to realize that new material news about the stock has been released. Since the material nature of the information causes a change in the fair valuation of the stock, this information is likely to affect an investor's pending order, which would be based on the valuation at the time the order was made. Hence, a cancellation or an amendment to the price of the order is warranted.[20] Inattentive investors are likely to miss these events and thus are unlikely to cancel or amend their pending orders in response to these events.[21]

Although the above rationale applies for all news events, focusing on overnight news helps us disentangle attention to fundamental information from attention to prices. During trading hours, in addition to news, market prices are a source of information that investors can use to make their trading decisions. In contrast, during overnight periods, firms can release new information, but

[20] Say the closing price of a security is $10 and an investor wishes to purchase the security at a 10% discount. They submit a buy order at $9 that is unexecuted until the market close and remains in the order book overnight. Now, say there is some overnight news release that causes the fair value of the price to drop by 20%. If the investor does not cancel or update their order, it will be executed when the market opens and the investor will end up purchasing the security at a 12.5% premium rather than a 10% discount. If they wish to purchase the security at a 10% discount, they must accurately process the new information and revise the order price to $7.2.

[21] To a certain degree, our measure jointly measures attention to information and the magnitude or importance of the information since important news events are likely to be observed by more investors and thus might have more order updates. However, this is not necessarily undesirable since it arises due to the natural correlation between the magnitude of news and attention to the news. In general, important news events are likely to be covered by more news media outlets and thus receive greater public attention.

prices do not move. Restricting our focus to material overnight news events helps isolate a window in which an investor's trading actions are most likely to be a direct result of important new information about the stock, rather than other motivations for trade. During trading hours, high-frequency traders (HFTs) that engage in arbitrage and market making contribute significantly to order cancellations (Jones, 2013). These cancellations are unrelated to the information-related cancellations we aim to capture. To minimize the influence of these HFT cancellations on our measure, we begin our overnight periods at 17:00, which is well after the ASX closing time (16:10), and end our overnight periods at 9:30, which is well before the opening time (10:00).

There are two channels through which material news can be conveyed to investors. First, material news can be disclosed by the company itself in the form of a market announcement. Given the continuous disclosure requirements, this channel covers almost all relevant firm-specific information. Second, if the news item does not necessitate a disclosure, it can reach investors through financial media outlets. This channel covers all other relevant information such as macroeconomic news, industry news, expert commentary, analyst forecasts, etc. As mentioned previously, ASX requires that certain announcements to be labeled as "price sensitive" based on their information content. Hence, in our data, the first channel can be easily identified by looking at overnight releases of these price sensitive or material announcements. Some announcements might be mislabeled as price sensitive or might not contain any new information that has not already been priced into the stock. To filter out these cases, we remove announcements that generate a post-announcement ten-day absolute abnormal return lower than 3%. To capture the second channel, we look at the overnight return.[22] We classify all stock-days with an absolute overnight return exceeding 0.5% as material news event days.[23]

To calculate the attention to information measure, we first extract the limit orders that remain in the order book after the market close for each stock i on each day in our sample period. Next, we calculate the proportion of orders updated during the overnight period as the number of orders amended or canceled overnight divided by the total number of pending orders at the day's close. We then remove all stock days on which there is no overnight material announcement and

[22] Although we could directly look at firm-level and macroeconomic news coverage to capture this channel, doing so would not help us determine whether a given news item is material. Unlike announcements, there is no clean categorization of news articles into price sensitive and non-price sensitive news.
[23] We set the materiality threshold at 0.5% since an overnight return of 0.5% is a reasonably high return in our sample. The 75th percentile for overnight returns is 0.3%, while the median is 0%. Thus, the absolute overnight return is likely to exceed 0.5% only on days when important news about the stock is released overnight.

the absolute overnight return (previous day's close to next day's open) does not exceed 0.5%.[24] Our attention to information measure for stock i is the average value of the proportion of updated orders for the stock across the remaining days.

3.2. Attention to prices

We use discussion threads from online stock market discussion forums to construct our attention to prices measure. Our attention to prices measure involves isolating discussions between traders who primarily trade based on price movements (rather than using fundamental information), and counting the number of times a stock is mentioned by these traders.

We collect the discussion threads data from HotCopper, a popular stock market discussion forum in Australia. HotCopper claims to be the largest stock trading discussion forum in Australia and has over 250,000 registered users and 21 million monthly page impressions. Crucially, HotCopper offers two dedicated discussion sub-forums for short-term traders and day traders. These are the 'ASX – Short Term Trading' forum and the 'ASX – Day Trading' forum. Previous research shows that day traders typically engage in price speculation (Barber et al., 2014; Barber et al., 2017) and tend to use technical trading strategies such as intraday momentum strategies that involve trading primarily based on recent price movements (Linnainmaa, 2003).

The unique nature of discussions on these channels provides a nice setting to calculate our attention to prices measure. Traders on these forums tend to identify stocks that have had sharp price movements recently or stocks whose prices they expect to move sharply in the near future, and try to bring their fellow traders' attention to these stocks by posting about them. For example, in the set of messages on the left-hand side of Figure 1, traders mention specific stocks and their recent price increases or price targets. Interestingly, on some occasions, traders mention only the name of a stock (without its price or any other details) to draw the attention of their fellow traders to the stock's price movements. For example, in the messages on the right-hand side of Figure 1, traders mention the names of many individual stocks without providing much additional detail. A deeper look into these stocks reveals that each of these stocks experienced a price increase of 5–30% during the market open on the day these messages were posted (these messages were posted soon after the market opened for the day). These traders also use technical analysis to analyze price

[24] Our results are robust to only using overnight periods with material announcements to calculate the measure.

movements and share insights they gain from technical charts with their fellow traders (see Figure 2).

< Figure 1 here >

< Figure 2 here >

Traders converse about stocks with the sharpest price movements on a daily or weekly basis on daily threads labeled “morning trading” and “afternoon trading” and weekly threads labeled “short term trading week”. We examine in detail 50 randomly selected threads from each of the two sub-forums. Out of the 2,725 posts on these threads that mention at least one stock, around 77% of the posts only mention the stock due to a recent price movement and do not make any reference to new or existing fundamental information. Given that the discussions on these forums are mainly concentrated on stock price movements, they provide us a relatively clean setting to measure attention to prices since the more times a stock is mentioned on these forums, the more attention its prices garner.

Broadly, we hypothesize that two types of traders frequent these forums: technical traders and behaviorally biased traders. Both sets of traders have differing trading styles and different reasons to pay attention to prices. Technical traders watch prices to infer information contained in historical price patterns that is not reflected in the current market price.

At least three behavioral biases can drive traders to watch prices. The first one is extrapolation or recency bias. Traders who exhibit extrapolation bias overweight recent price movements in forming their beliefs about future prices; they expect recent price movements to continue in the near future (Greenwood and Shleifer, 2014; Barberis et al., 2015). Naturally, since these traders mainly rely on recent prices to form beliefs about future price movements, they need to watch prices.

The next bias is the disposition effect. The disposition effect is the tendency to sell winning stocks prematurely and hold on to losing stocks for too long (Shefrin and Statman, 1985). Disposition effect traders also pay attention to prices and sell stocks following gains, independent of the stock’s fundamentals.[25]

[25] Interestingly, extrapolative traders and disposition effect traders might trade in opposite direction in certain cases. For example, say there is a recent price increase in a given stock. Extrapolative traders observing this stock might

The last behavioral bias is a preference for stocks with lottery-like payoffs or skewness preference. Numerous studies show that some investors prefer stocks that have positively skewed returns since they value the low probability scenario of earning a high return (Barberis and Huang, 2008; Kumar, 2009). These investors need to watch prices to gauge the returns distribution of different stocks and select lottery-like stocks. In Section 4.5, we confirm in our data that both these set of traders dominate HotCopper discussions, and, more specifically, behaviorally biased traders have a greater influence on our attention to prices measure.

There might be rational reasons to pay attention to HotCopper discussions too. Hedge funds or other rational investors that wish to trade against technical or behaviorally biased traders can use these discussion forums to gauge and/or predict order flow from these traders. In this case, another set of actors (hedge funds or other rational traders) would be paying attention to HotCopper discussions but our measure will not be able to capture their attention since they are unlikely to post messages on these forums.[26]

There exist equally popular online stock market forums in the US, such as Stocktwits and Seeking Alpha, but they either do not have dedicated discussion forums for short-term traders or, even if they do, the discussions tend to revolve around investment theses shared by individual traders rather than around stocks with the sharpest price moves in the day or week. Hence, the Australian stock market discussion forums offer a better setting to measure "attention to prices" than the US forums.

To calculate the attention to prices measure, we begin by downloading all discussion threads on the 'ASX – Short Term Trading' and 'ASX – Day Trading' sub-forums on HotCopper for the year 2018.[27] We then count the number of times each ASX stock is mentioned on either forum during the year. Finally, we divide the total number of mentions for each stock by 365 and use the daily average stock mentions as the attention to prices proxy. Since some of our tests involve using stock returns in 2019 as the dependent variable, we construct this proxy using 2018 data to avoid reverse causality issues.

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expect prices to keep rising and thus would purchase the stock. In contrast, some disposition effect traders that hold the stock might experience a gain on their holding as a result of the price increase and thus might be tempted to sell the stock.

[26] They could post messages to deliberately mislead or manipulate the users of the forum. However, there is no way for us to verify this in our data.

[27] Our results are robust to constructing the proxy using either sub-forum individually and using data from 2017 and 2018 (see Section 4.1).

3.3. Google search interest and our attention proxies

We begin by examining the relation between our attention proxies and one of the most popular attention proxies in the literature, Google search interest or Google SVI. We use a more refined version of the Google SVI proxy that only includes Google searches related to investing, i.e., the ISVI metric suggested by deHaan et al. (2021). ISVI does not naturally serve as a cross-sectional proxy. We adopt a unique method of downloading the Google ISVI to ensure that it can be used as a cross-sectional proxy. We describe the problems related to using ISVI as a cross-sectional proxy and our download method in detail in Section IA2 of the Internet Appendix.

As discussed previously, we conjecture that Google search interest confounds attention to information and attention to prices; thus, we expect ISVI to be correlated with both our attention measures. Table 1 reports the results of regressions of the 2018, 2019, and 2020 ISVIs on our attention measures. Across all three models, both our measures have a positive coefficient that is statistically significant at the 1% level. As conjectured, we find some evidence to suggest that Google search interest confounds attention to information and attention to prices. Interestingly, the attention to information (attention to prices) measure is constructed in 2019 (2018) but is related to ISVIs in 2018, 2019, and 2020. This result suggests that our measures capture cross-sectional variation in attention well, and that this cross-sectional variation is persistent through time.

< Table 1 here >

3.4. Summary statistics

We examine how our attention measures vary with various stock characteristics. Table 2 reports average values for our attention measures for quartiles of attention level, number of announcements, price level, momentum, size, liquidity, volatility, analyst attention, and institutional ownership.

Stocks with more announcements do not attract more attention to information but do attract more attention to prices, potentially suggesting that beyond a certain level, additional announcements might not be incrementally informative but might be contributing to noisier prices. Interestingly, the stock's price level affects our attention measures in opposite directions. Attention to information (attention to prices) increases (decreases) as the price level increases. This is consistent with low-priced stocks attracting the attention of investors with lottery preferences (Kumar, 2009) and, hence, having a higher attention to prices value. A similar pattern also exists for our price momentum measure, which is the number of months a stock appears in the top or bottom decile for lagged six-month cumulative returns. Attention to information (attention to prices) is inversely (positively) related to momentum, indicating that momentum stocks attract attention to prices but do not attract attention to information.

As expected, attention to information increases with size and liquidity. However, this result does not apply to attention to prices, which peaks in the second (third) lowest quartile for size (liquidity). The largest and most liquid stocks witness higher attention to information but not higher attention to prices. Volatility also affects our attention measures in opposite directions. The attention to information measure has a U-shaped relation with volatility, while the attention to prices has an inverse U-shaped relation. Stocks with high volatility could have more information uncertainty or be more complex and harder to value and, hence, require more attention to information.

Finally, stocks that attract high analyst attention and those that have high institutional ownership tend to have high attention to information. This is unsurprising since analysts and institutional investors play an important role in helping incorporate information into prices. Interestingly, stocks in the top quartile for analyst attention also witness slightly higher attention to prices, suggesting some correlation between analyst attention and attention to prices.

< Table 2 here >

4. Empirical results

In this section, we discuss the results of our empirical tests. Section 4.1 examines whether our attention proxies explain price reactions to announcements. Section 4.2 assesses the performance of attention-based trading strategies that exploit post-announcement drifts. Section 4.3 examines whether price effects confound our attention to information measure. Section 4.4 considers some other factors that affect our attention to information measure. Finally, Section 4.5 asks which set of traders (technical traders or behaviorally biased traders) dominates our attention to prices measure.

4.1. Price reactions to announcements

In this sub-section, we examine how our attention proxies affect price reactions to price sensitive announcements. Numerous previous studies show that price reactions are slower when earnings announcements are released at times when investors are inattentive, such as on Fridays (DellaVigna and Pollet, 2009), on days when there are more announcements released by other firms (Hirshleifer et al., 2009), and after trading hours (Francis, Pagach, and Stephan, 1992), among other times. Since high attention results in faster reactions and weaker drifts, we expect investor attention to be negatively related to the post-announcement drift.

We conjecture that the above effect only exists for attention to information and not for attention to prices. As discussed previously, irrespective of their type (institutional or retail), investors that pay more attention to information are more likely to aid in incorporating this information into prices. It should be noted, however, that an individual investor paying attention to prices could still contribute to incorporating information into prices if they trade in the same direction as the information, for instance, if they follow an intraday momentum strategy immediately after an earnings announcement. However, in aggregate, the contribution of these momentum traders could be canceled out by contrarian traders that trade in the opposite direction. Since these traders use a variety of strategies and certain strategies trade in opposite directions after the same price movement (e.g., momentum and contrarian strategies), we expect traders paying attention to prices to behave like noise traders in Kyle (1985) and trade randomly in expectation. Overall, we expect stocks with a larger mass of traders paying attention to information to have more efficient price reactions to announcements and weaker drifts than other stocks but do not expect this effect to apply for attention to prices. Stocks with a larger mass of traders paying attention to prices might be more inefficient if these traders somehow impede the incorporation of information into prices.

We include both earnings and non-earnings announcements in our tests and figures, and thus are unable to classify announcements as positive or negative based on the earnings surprise or using any other *ex-ante* benchmark. Hence, we segregate announcements into positive and negative announcements based on the return in the ten trading days following the announcement. Additionally, in our tests, we isolate the post-announcement drift by excluding the price reaction at the market open ("opening price reaction") while calculating the cumulative abnormal returns.

Throughout the paper, we calculate cumulative abnormal returns using the method in Hirshleifer and Sheng (2019).

Figure 3 plots price reactions to announcements for low attention (bottom decile) and high attention (top decile) stocks. Panel A plots price reactions for our attention to information measure. This graph shows sharp reactions at the market open and some preliminary evidence that, in some cases, this initial price reaction is an underreaction and is followed by a price drift. Visually, the drifts appear to be stronger for low attention stocks as compared to high attention stocks at least for positive announcements. For positive announcements, the abnormal return from one day after the announcement to 20 days after the announcement is almost 8% higher for low attention stocks than high attention stocks. The drift gap is much lower for negative announcements, with low attention stocks having a 2% lower absolute abnormal return than high attention stocks. In all cases, price reactions appear to be complete and prices level off around 12 days after the announcement. Panel B plots the same graph for the attention to prices measure. Visually, there appears to be no discernable gap in the price drifts for low and high attention stocks here. In fact, high attention stocks have stronger drifts; high attention stocks earn around a 1% higher (7% lower) post-announcement abnormal return after positive (negative) announcements. Based on the initial graphical evidence, low attention stocks have stronger post-announcement drifts only for the attention to information measure and not for the attention to prices measure.

< Figure 3 here >

The differences between attention to information and attention to prices become much more evident visually when we isolate the post-announcement drifts. Figure 4 plots the drift (excluding the opening price reaction) for the extreme announcement return quintiles separately for low and high attention stocks.[28] We first split announcements into low and high attention buckets based on the stock's attention level. Then, within each bucket, we plot the drifts for announcements in the extreme return quintiles separately. Panel A displays the plots for the attention to information measure. The return spread, i.e., the difference between the cumulative returns for the highest return quintile and the lowest return quintile after 20 days, is much wider

[28] Here, announcement return is the same as the return used to classify announcements as positive or negative, i.e., return in the ten trading days following the announcement.

for low attention stocks than high attention stocks, driven primarily by the stronger drifts for low attention stocks after positive announcements. In contrast, the return spreads for both low attention and high attention stocks seem similar for the attention to prices measure (Panel B). Overall, the graphical evidence suggests that low attention stocks have stronger price drifts only for our attention to information measure, and mainly after positive announcements.

< Figure 4 here >

We formally test the effects of our attention proxies on post-announcement drifts by regressing the post-announcement return on our attention measures. $InfoAttention_i$ is our attention to information measure for stock i, and $PriceAttention_i$ is our attention to prices measure for stock i. The dependent variable is $CAR[0,20]$, i.e., the cumulative abnormal return from the time of the announcement until 20 days after the announcement (excluding the opening price reaction on the trading day following the announcement). We control for the stock's trading volume, volatility, and market capitalization, the pre-announcement five-day return (information leakage), the market return, and the number of announcements on the day of the announcement. We also include day of the week and month fixed effects.

Table 3 reports the results. For positive announcements (Models 1–4), our attention to information measure has a negative coefficient that is statistically significant at the 1% level, while the coefficient for the attention to prices measure is not statistically significant under any specification. This result implies that drifts after positive announcements reduce as attention to information increases, while the attention to prices measure does not affect drifts after positive announcements. The effect of attention to information on post-announcement drifts is also economically meaningful. The coefficient for $InfoAttention_i$ in Model 4 suggests that, on average, stocks with an attention to information value of 20% generate a 3.3% higher 20-day abnormal return after positive announcements relative to stocks with an attention to information value of 50%.

For negative announcements, our attention to information measure does not affect the post-announcement drift in a statistically significant manner, while the attention to prices measure has a statistically significant negative coefficient without controls. Although the coefficient for attention to prices is statistically significant in some specifications, it is not in the expected direction. A negative coefficient for negative announcements implies that an increase in attention to prices *increases* the post-announcement drift rather than reduces it. This is in contrast to our expectation based on the investor attention literature that high attention attenuates post-announcement drifts. Overall, these results align with our previous observations from the price plots; only high attention to information is associated with weaker drifts, and only for positive announcements.[29,30]

Positive announcements appear to be harder to price than negative announcements in our sample, and this could explain why the attention to information effects only play out after positive announcements. The standard deviations of the two-day, five-day, and ten-day post-announcement returns as a percentage of the 20-day post-announcement return are 198.83%, 279.78%, and 254.86%, respectively, for negative announcements, while the same figures are 336.97%, 365.18%, and 349.35%, respectively, for positive announcements. The higher standard deviations for positive announcements indicate a greater variability in the extent to which the information contained in the 20-day return is reflected in prices at the two-day, five-day, and ten-day horizons. This result suggests a higher variability in efficiency across announcements for positive announcements relative to negative announcements. Negative announcements might, on average, be "too efficient" or not have sufficient variation in post-announcement efficiency for the effects of efficiency losses caused by inattention to play out, whereas positive announcements might be less efficient or have sufficient variation in efficiency for us to observe these effects.[31] This could explain why we only observe the attention to information effects after positive announcements.

To ensure that our results are not mechanically driven by how our proxies are constructed, we construct both our proxies using alternative methods and re-run these tests. We construct our attention to information measure using only overnight periods with material announcements, excluding overnight periods with absolute returns above 0.5%. These announcements are a cleaner sample of material overnight information releases than periods with extreme overnight returns. Table IA3 in the Internet Appendix reports the results for this version of the attention to

[29] These results hold even if we regress our attention measures separately (see Table IA1 in the Internet Appendix).

[30] These results hold after controlling for Google search interest, analyst attention, institutional ownership, and relative tick size (see Table IA2 in the Internet Appendix). We exclude these control variables from the main analysis since they significantly reduce the number of observations due to missing data.

[31] Negative announcements also tend to be more efficient, on average, than positive announcements in our sample. The medians for the two-day, five-day, and ten-day post-announcement returns as a percentage of the 20-day return are 33.33%, 52.17%, and 80%, respectively, for negative announcements and 20%, 39.13%, and 57.14%, respectively, for positive announcements.

information measure. Additionally, we construct our attention to prices proxy using HotCopper discussion threads data from the years 2017 and 2018 (instead of only 2018) and separately for the 'ASX – Short Term Trading' and 'ASX – Day Trading' sub-forums. Table IA4 (IA5) in the Internet Appendix reports the results for the 2017 & 2018 version (individual sub-forum version) of the attention to prices measure. Our results are robust to using these alternative methods of constructing our attention proxies.

< Table 3 here >

4.2. Trading strategy

Another way to test whether our attention proxies affect post-announcement drifts is to examine whether the performance of trading strategies that exploit post-announcement drifts improves when our attention proxies are added to the mix. In this section, we compare the performance of vanilla trading strategies that do not condition on attention with attention-based strategies that condition their trading on the stock's attention level by only trading low attention stocks.[32] If the market reaction to announcements for low attention stocks is not more inefficient than high attention stocks, attention-based trading strategies would not outperform baseline vanilla strategies. Given the results and arguments presented in the previous sections, we only expect attention-based strategies that use the attention to information measure (and not the attention to prices measure) to outperform the baseline strategy.

To avoid look-ahead bias, we ensure that our strategies only use attention-related information available at the time of each announcement. Our attention to prices measure is calculated in 2018 and is thus known for the entirety of our 2019 sample period. On the other hand, our attention to information measure is calculated in 2019 and is thus not known before every announcement in 2019 and must be calculated on-the-fly during the year. For a given announcement on day t, we calculate the attention to information measure using an expanding window that starts on the first day of 2019 and ends on day $t - 1$. Like before, we first calculate the attention to information measure for all overnight periods in this expanding window that either have a material announcement or an absolute overnight return exceeding 0.5%. Then, we take the

[32] Low attention stocks are expected to be more inefficient and can thus be exploited more profitably.

average value for the measure in this window as the stock-level attention to information proxy. We set the condition $t \geq 45$ to allow for a meaningful number of observations to build up initially.

Our attention-based strategies purchase low attention stocks (below median attention to information or attention to prices) after a positive announcement and sell short low attention stocks after a negative announcement. We benchmark the performance of these strategies against a baseline strategy that purchases stocks after positive announcements, irrespective of the stocks' attention level, and sells short stocks after negative announcements. Attention-based strategies that use the attention to information measure do not trade for the first 45 days in our sample period as we build the initial attention to information distribution. Aside from that, each strategy trades on each day of our sample period. We ignore transaction costs throughout. Although we expect the long leg of our portfolio to perform better given the stronger drifts after positive announcements that we document in the previous sub-section, we still construct long-short strategies to mitigate concerns about market risk.

We report the performance of our strategies for two holding periods: a seven-day holding period and a 14-day holding period. In both cases, the first two trading days are spent observing the post-announcement return to classify announcements as positive or negative. Each strategy establishes initial positions at the beginning of the third trading day.

Table 4 reports the excess daily returns for value-weighted portfolios constructed based on the above strategies. To capture the excess return for each strategy, we regress the strategy's returns on the factors in the Fama-French three-factor model (Fama and French, 1992). The baseline strategy earns a statistically significant daily alpha of 19 (14) basis points under the seven-day (14-day) holding period. When using the attention to information measure, the attention-based strategy outperforms the baseline strategy by 95% (36%) or 18 (5) basis points for the seven-day (14-day) holding period; however, the daily alpha for the attention to information strategy is not statistically significant for the 14-day holding period. The outperformance of the attention-based strategy dissipates through time as the market converges towards efficiency. In contrast, when using the attention to prices measure, not only does the attention-based strategy fail to outperform the baseline strategy, it even erodes the statistically significant alpha earned by the baseline strategy. Interestingly, even the outperformance of the attention to information measure disappears when constructing equal-weighted portfolios (see Table IA6 in the Internet Appendix), suggesting that the outperformance is primarily driven by larger low attention stocks.

< Table 4 here >

To further test whether the attention to information effect we document is actually a size effect rather than an attention effect, we construct similar trading strategies that condition on market capitalization instead of attention levels. Table IA7 in the Internet Appendix reports the results for these size-based strategies using various cut-offs for small capitalization stocks. Under no specification does a size-based strategy match the performance of our attention to information strategy, suggesting that our attention to information measure contains incremental information that is not captured in the market capitalization but which is relevant for explaining a stock's post-announcement returns.

The dominance of the attention to information-based strategy becomes more evident when we plot the cumulative daily returns of all strategies. Figure 5 displays these plots. Similar to the results in Table 4, the attention-based strategy outperforms the baseline strategy only when using the attention to information measure (Panel A). The final differences between the aggregate returns of the attention to information measure and the attention to prices measure are large. For the seven-day holding period, at the end of the sample period, the attention to information measure earns a 58% higher total return than the baseline strategy, while the attention to prices measure earns a 90% lower return than the baseline strategy. Overall, results for the trading strategies further corroborate our hypothesis that only attention to information and not attention to prices explains price reactions to announcements.

< Figure 5 here >

4.3. Is attention to information just attention to prices in disguise?

It is possible that the attention to information results we document are driven or confounded by price effects. For example, some of the stocks in our sample are dual listed on ASX and some foreign markets that are open when ASX is closed. Investors in these stocks could be updating their pending overnight orders after learning from price updates in the foreign markets rather than from observing information updates provided by the company or by financial news outlets. In this case, our attention to information measure would really be capturing attention to prices, albeit prices of the same stock in foreign markets. Additionally, we observe in Section 3.4 that our attention to information measure is inversely related to price momentum. Consequently, the stronger post-announcement drifts for low attention stocks could purely be a momentum effect that is unrelated to attention to information. In this section, we address both of these alternative explanations.

First, we conduct our previous tests separately for cross-listed and non-cross-listed stocks. We only consider stocks that are cross listed on American and European exchanges since, unlike most Asia-Pacific exchanges, these exchanges are open when the Australian market is closed. If our attention to information results are driven by learning from prices in foreign markets rather than learning from information releases, our previous results should only exist for cross-listed stocks and not for non-cross-listed stocks. Table 5 reports the results. Our attention to information measure is related to post-announcement drifts only for non-cross-listed stocks (Panel B), suggesting that the measure is only capturing learning from information releases rather than learning from price movements in foreign markets or learning from both information releases and price movements in foreign markets.

< Table 5 here >

Next, we conduct the previous tests separately for momentum and non-momentum stocks. Table 6 reports the results. We classify a stock as a momentum stock if it is in the top or bottom decile for lagged six-month cumulative returns in the announcement month. If the attention to information effect is merely a momentum effect, then it should largely be concentrated in momentum stocks. However, we do not find this to be the case. The coefficient for our attention to information measure is statistically and economically significant for non-momentum stocks (Panel B), suggesting that the previous results we document are not purely a momentum effect. Overall, these results suggest that the relation between post-announcement drifts and attention to information is not driven by price effects.

< Table 6 here >

4.4. Other issues affecting attention to information

Two additional factors could affect our attention to information measure: intraday announcements before overnight periods and information leakage. The starting point for our attention to information measure are the leftover pending orders at the beginning of overnight periods. The quantity of these pending orders could depend on the events that occur prior to the overnight period. For example, if an announcement is made during the trading day, the number of pending orders lying overnight might reduce if orders made by inattentive investors are adversely selected without replacement before the trading day ends. In this case, our overnight measure might not be representative of the true attention to information level on the day, which might be more accurately measured at the time of the intraday announcement.

A similar issue exists when the overnight announcements that we rely on to calculate our measure have high levels of information leakage. In such cases, pending orders belonging to inattentive investors could be adversely selected in the days leading up to the announcement. As a result, our measure, which is calculated in the overnight period in which the announcement is released, will not be representative of the true attention to information level at the time of the announcement.

To examine both these issues, we conduct additional tests that alter the method in which we calculate our attention to information measure. First, we calculate our attention to information measure in two separate ways: using only overnight periods that have at least one intraday announcement in the preceding trading day and using all overnight periods except ones that have at least one preceding intraday announcement.[33] Table 7 reports the results for both these versions. The results are qualitatively similar (statistically and economically significant) irrespective of whether our attention to information measure is calculated using only overnight periods with preceding intraday announcements (Panel A) or excluding overnight periods with preceding announcements (Panel B). The coefficient for the measure is slightly lower when calculated using only overnight periods with preceding intraday announcements, suggesting that at best these announcements have a mild negative effect on our attention to information measure.

< Table 7 here >

[33] The measure still only uses overnight periods with material information events.

We conduct the same set of tests for announcements with high information leakage. We re-calculate our attention to information measure in two separate ways: using only overnight periods with material announcements that have high information leakage (top or bottom quartile for the five-day return immediately preceding the announcement) and using overnight periods that do not include announcements with high information leakage.[34] Table 8 reports the results. We find that the coefficients for the attention to information measure have similar statistical significance and economic magnitude when the measure is calculated using only announcements with high information leakage (Panel A) and when it is calculated after excluding these announcements (Panel B). Overall, these results suggest that our attention to information measure largely remains unaffected by intraday announcements before overnight periods and information leakage.

< Table 8 here >

4.5. Who pays attention to prices?

In Section 3.2, we discuss how technical analysts and behaviorally biased investors drive attention to prices. In this section, we examine which of these two actors dominate our measure of attention to prices. We begin by verifying our assumption of technical and behaviorally biased traders driving attention to prices in our data. To do so, we examine whether our attention to prices measure increases after a stock displays characteristics that would typically attract the attention of technical and behaviorally biased traders.

We identify two such characteristics: price momentum and lottery-like payoffs. Momentum stocks are likely to attract the attention of both technical and behaviorally biased traders. Momentum trading is widely known as being one of the most popular technical trading strategies; thus, it is natural to expect technical traders to pay attention to momentum stocks.

Behaviorally biased traders who exhibit extrapolation bias and the disposition effect also pay attention to momentum stocks. Extrapolation bias implies that investors form beliefs about future stock prices using recent price movements, expecting these movements to continue in the

[34] Only the classification of overnight periods with material announcements differs across both these cases. Overnight periods with an absolute overnight return exceeding 0.5% are still classified as overnight periods with material information events.

future. The stocks that are the most likely to attract these investors' attention are the ones that have the highest recent price increases or decreases, i.e., momentum stocks, since they would expect these stocks to rise or fall the most in the future. In addition, investors exhibiting the disposition effect would also pay more attention to momentum stocks, in particular positive momentum stocks. Among all stocks held by these investors, those with positive momentum are the most likely to be trading at a gain and thus are also the most likely to be sold by these investors to realize the gain.[35]

Stock with lottery-like payoffs also attract the attention of investors with behavioral biases, in particular those with a preference for such stocks. A rich literature in behavioral finance documents that investors have a preference for stocks that have positively skewed returns distributions, or lottery-like payoffs (Kumar, 2009; Bali, Cakici, and Whitelaw, 2011; Green and Hwang, 2011). If the HotCopper discussions are dominated by technical and behaviorally biased traders, momentum and lottery-like stocks would be discussed more often than other stocks and thus our attention to prices measure would have higher values for such stocks.

We aggregate our data at the stock-month level to examine whether momentum and lottery-like stocks have higher attention levels than other stocks. In this set of regressions, the dependent variables are stock-month versions of our attention proxies, while the main independent variables are indicator variables that equal one if a stock is a momentum or lottery-like stock. We follow the same classification for momentum stocks as in the previous tests. $Momentum_{i,t}$ equals one if a stock i is in the top or bottom decile for lagged six-month cumulative returns in month t. For lottery-like stocks, we construct two proxies based on the two most popular measures in the literature. $Lottery\ (Kumar)_{i,t}$ is based on the Kumar (2009) method and classifies a stock i as a lottery-like stock in month t if it has a below median price, above median idiosyncratic volatility, and above median idiosyncratic skewness in the six-month period preceding month t. $Lottery\ (Bali)_{i,t}$ is based on the Bali et al. (2011) method and classifies a stock i as a lottery-like stock in month t if it is in the top quartile for maximum daily returns in the six-month period preceding month t. We take the average of the top 15 daily returns in the six-month period as a proxy for maximum daily returns. We control for liquidity, volatility, size, and month fixed effects in all regressions.

[35] Consistent with our expectation, previous research has found that stocks that are the top gainers or losers for the day and stocks that have recently hit 52-week highs or lows receive disproportionately high attention from behaviorally biased individual investors (Barber and Odean, 2008; Driessen et al., 2013; Kumar, Ruenzi, and Ungeheuer, 2021).

Table 9 reports the results.[36] As conjectured, the proxy for momentum stocks and both proxies for lottery-like stocks have positive coefficients when regressed on our attention to prices measure. Since these stocks attract the attention of technical and behaviorally biased traders, this result is consistent with these traders dominating HotCopper discussions and having a significant influence on our attention to prices measure. Interestingly, both momentum and lottery-like stocks also have lower levels of attention to information. The result for momentum stocks is consistent with our previous descriptive statistics (Table 2) that show an inverse relation between momentum and attention to information. The current set of results suggests that attention to information also has an inverse relation with skewness of returns.

< Table 9 here >

Next, we examine which of the two sets of actors (technical traders or behaviorally biased investors) has a greater influence on our attention to prices measure. To do so, we perform a simple test that exploits the variation in the effects of the aggregate trading of both these sets of actors. We test the effects of our attention measures on weak-form efficiency. Technical traders try to search for and gainfully exploit information contained in historical price patterns that has not already been incorporated in market prices. In doing so, they help incorporate the information contained in past prices into the current market price (Alexeev and Tapon, 2011). Thus, stocks that have a larger mass of technical traders actively trying to search for and exploit patterns in historical prices would be more weak-form efficient than stocks with fewer such traders. The same prediction does not apply for behaviorally biased traders. These traders do not search for any information (current or historical) and thus, in aggregate, are not expected to contribute to any form of market efficiency. Consequently, if our attention to prices measure captures the attention of technical traders, it should be positively related to weak-form efficiency. If it is not related or negatively related to weak-form efficiency, it is more likely to be capturing the attention of behaviorally biased investors.

[36] Since the endogeneity issue arising from using 2019 returns as dependent variables does not exist for this set of tests, we use 2019 HotCopper data to calculate our attention to prices measure in this table. The results remain the same even if we use 2018 HotCopper data to calculate the attention to prices measure (see Table IA8 in the Internet Appendix).

We regress our attention proxies on various measures of weak-form efficiency. Following Lo and MacKinlay (1988), Griffin, Kelly, and Nardari (2010), Rösch, Subrahmanyam, and van Dijk (2017), among others, we use variance ratios and return autocorrelations as measures of weak-form efficiency. Variance ratio, $VR(x, y)$, is the ratio of the x-day return variance divided by x and the y-day return variance divided by y. In efficient markets, variance ratios for short-term and long-term returns equal to one. Similarly, in efficient markets, returns are not autocorrelated and, hence, autocorrelations for returns equal zero. We transform both variance ratios and return autocorrelations such that they are inefficiency metrics, i.e., higher values indicate higher price inefficiency. Following Boehmer and Kelley (2009), we use the absolute value of one minus the variance ratio ($|1 - VR(x, y)|$) and the absolute value of the return autocorrelation ($|AR|$) as dependent variables.

Table 10 reports the results. Our attention to prices measure does not have a statistically significant coefficient under most of the regression specifications. When it has a statistically significant coefficient, the sign is positive, meaning that attention to prices increases weak-form inefficiency. This result suggests that behaviorally biased traders, whose trading does not help improve weak-form efficiency, dominate our attention to prices measure.

Our attention to information measure is positively related to weak-form efficiency in all regressions. Previous evidence in the investor attention literature shows that higher investor attention improves efficiency in general, including the pricing of information contained in past returns (Vozlyublennaia, 2014). These results suggest that, like post-announcement drifts, the previously documented effects of investor attention on weak-form efficiency only apply for attention to information and not for attention to prices.

< Table 10 here >

5. Conclusion

In this study, we introduce the idea that attention to different items in financial markets can lead to differing outcomes. Crucially, we show that the previous finding that investor inattention harms pricing efficiency only applies for attention to fundamental information and not for attention to market prices. Stocks with low attention to information have stronger drifts following positive announcements relative to other stocks, while stocks with low attention to prices either have similar or weaker post-announcement drifts. Trading strategies that exploit these drifts earn a daily alpha up to 37 basis points when only buying low attention to information stocks and a statistically insignificant alpha when only buying low attention to prices stocks.

Technical and behaviorally biased traders are the main actors that drive attention to prices as the stocks that they prefer (momentum and lottery-like stocks) receive more attention to prices than other stocks. Among these two sets of traders, behaviorally biased traders seem to have a greater influence since attention to prices does not improve weak-form efficiency, an effect we would observe if attention to prices was driven by technical traders.

Collectively, our findings suggest that an important consideration in determining whether investor attention improves the speed at which information is incorporated into prices is whether investors are paying attention to that information in the first place. A general increase in investor attention to markets is unlikely to improve efficiency if that attention is devoted to price movements rather than fundamental information.

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Table 1
Google search interest

This table reports results of regressions of Google search interest on our attention measures. The unit of observation is a stock i. Google search interest is measured using $ISVI_i\ t$, which is the Google SVI metric for the stock for the 'Finance – Investing' category in year t. $InfoAttention_i$ is our attention to information measure. $PriceAttention_i$ is our attention to prices measure. The sample includes all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable =		
Variable	$ISVI_i$ 2018	$ISVI_i$ 2019	$ISVI_i$ 2020
$InfoAttention_i$	129.31***	178.04***	110.05***
	(3.57)	(4.49)	(5.3)
$PriceAttention_i$	63.38***	75.16***	40.86***
	(7.29)	(7.91)	(8.21)
R^2	3.75%	4.64%	5.32%
Observations	1,649	1,649	1,649

Table 2
Summary statistics

This table reports the attention values across quartiles based on various stock characteristics. The statistic reported is the mean attention value in the stock characteristic quartile. Attention level is calculated using the measure being reported (attention to information or attention to prices). Price momentum measures the number of months the stock appears in the top or bottom decile for lagged six-month cumulative returns. Liquidity is measured using dollar trading volume. Volatility is measured as the standard deviation of daily returns. Analyst attention is the number of analysts covering the stock. Institutional ownership is the proportion of shares held by institutional investors. The sample includes all stocks listed on the Australian Securities Exchange in the year 2019.

	Attention to information				Attention to prices			
Variable	Q1 (Bottom)	Q2	Q3	Q4 (Top)	Q1 (Bottom)	Q2	Q3	Q4 (Top)
Attention level	2.95%	5.72%	9.3%	29.22%	1.17%	4.8%	12.12%	65.91%
Number of announcements	12.4%	13.58%	12.22%	10.13%	16.93%	15.59%	25.11%	36.3%
Price level	4.23%	6.73%	10.34%	27.64%	34.16%	29.49%	16.9%	17.06%
Price momentum	16.16%	9.5%	9.13%	8.89%	13.52%	23.35%	28.42%	34.89%
Market capitalization	4.74%	6.73%	8.57%	25.88%	19.54%	30.4%	21.31%	22.39%
Liquidity	5.33%	6.06%	8.26%	29.36%	9.12%	23.22%	34.8%	29.56%
Volatility	12.7%	8.8%	8.65%	18.97%	12.12%	24.9%	37.34%	22.67%
Analyst attention	9.59%	12.64%	25.58%	31.69%	18.94%	18.95%	18.91%	23.82%
Institutional ownership	9.22%	9.54%	15.01%	30.92%	28.31%	22.37%	19.36%	21.14%

Table 3
Post-announcement drifts

This table reports regression results testing how attention to information and attention to prices affect post-announcement returns. The unit of observation is an announcement j for stock i. $CAR[0,20]$ is the cumulative abnormal return from the first trading day after the announcement (excluding the opening return) to 20 trading days after the announcement. Announcements are split into positive or negative announcements based on the return in the ten trading days after the announcement. $InfoAttention_i$ is our attention to information measure. $PriceAttention_i$ is our attention to prices measure. Control variables include the stock's average trading volume, volatility, and market capitalization, the pre-announcement five-day return, the market return, and the number of announcements on the day. Time fixed effects include day of the week fixed effects and month fixed effects. The sample includes all overnight price sensitive announcements for all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = $CAR[0,20]$							
	Positive announcements				Negative announcements			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InfoAttention_i$	–12.41***	–12.22***	–11.25***	–10.86***	1.63	1.02	0.92	0.53
	(–4.93)	(–4.84)	(–4.3)	(–4.14)	(0.65)	(0.4)	(0.99)	(0.2)
$PriceAttention_i$	0.6	0.85	–0.21	0.06	–1.88***	–1.91***	–0.84	–0.86
	(0.82)	(1.15)	(–0.27)	(0.08)	(–3.34)	(–3.39)	(–1.43)	(–1.47)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.71%	1.67%	2.15%	3.12%	0.33%	1.02%	2.55%	3.23%
Observations	3,684	3,684	3,639	3,639	3,780	3,780	3,757	3,757

Table 4

Trading strategies exploiting the drift

This table reports results for trading strategies exploiting the post-announcement drift. Portfolios are constructed using the stock's attention level and the observed return from the time of the announcement to the market open two trading days later. The attention-based strategies (for both attention to information and attention to prices) purchase low attention (below median) stocks when their announcements have a positive return and sell short low attention stocks when their announcements have a negative return. The baseline strategy purchases stocks when their announcements have a positive return, and sells short stocks when their announcements have a negative return. Results are reported for two holding periods (seven days and 14 days). All portfolios are value-weighted. The dependent variable is the daily return from the trading strategy (Rtn_t). $MarketRtn_t$, HML_t, and SMB_t are the market, value, and size factors, respectively, from the Fama-French three-factor model. The sample includes all overnight price sensitive announcements for all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = Rtn_t					
	Baseline		Attention to information		Attention to prices	
Variable	Seven-day holding period	14-day holding period	Seven-day holding period	14-day holding period	Seven-day holding period	14-day holding period
$Intercept$	0.19*** (3.06)	0.14*** (2.82)	0.37** (2.05)	0.19 (1.27)	0.06 (0.34)	0.16 (1.16)
$MarketRtn_t$	3.3 (0.39)	4.36 (0.65)	–8.4 (–0.35)	–14.39 (–0.73)	49.34 (1.94)	26.06 (1.41)
HML_t	–9.38*** (–3.17)	–8.68*** (–3.74)	–9.65 (–1.08)	–8.99 (–1.22)	0.34 (0.04)	–4.2 (–0.66)
SMB_t	–17.12*** (–3.13)	–15.89*** (–3.7)	–21.19 (–1.27)	–15.21 (–1.1)	–4.32 (–0.27)	–12.1 (–1.02)
R^2	4.53%	6.41%	0.83%	0.81%	1.8%	1.62%
Observations	250	250	206	206	250	250

Table 5
Cross-listed stocks

This table performs the tests in Table 3 separately for stocks cross-listed in American and European markets and non-cross-listed stocks. The unit of observation is an announcement j for stock i. $CAR[0,20]$ is the cumulative abnormal return from the first trading day after the announcement (excluding the opening return) to 20 trading days after the announcement. Announcements are split into positive or negative announcements based on the return in the ten trading days after the announcement. $InfoAttention_i$ is our attention to information measure. $PriceAttention_i$ is our attention to prices measure. Panel A reports the results for cross-listed stocks. Panel B reports the results for non-cross-listed stocks. Control variables include the stock's average trading volume, volatility, and market capitalization, the pre-announcement five-day return, the market return, and the number of announcements on the day. Time fixed effects include day of the week fixed effects and month fixed effects. The sample includes all overnight price sensitive announcements for all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = $CAR[0,20]$							
	Positive announcements				Negative announcements			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Cross-listed stocks								
$InfoAttention_i$	–11.01	–11.59	–4.85	–5.76	1.7	–0.89	2.37	1.36
	(–1.38)	(–1.4)	(–0.53)	(–0.6)	(0.22)	(–0.12)	(0.31)	(0.17)
$PriceAttention_i$	–2.39	–1.83	–5.57**	–4.32	–3.32**	–3.45**	–1.89	–1.87
	(–1.02)	(–0.76)	(–2.18)	(–1.63)	(–2.04)	(–2.11)	(–1.15)	(–1.12)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.74%	6.65%	5.05%	10.33%	1.28%	7.53%	12.11%	16.63%
Observations	339	339	327	327	362	362	358	358
Panel B: Non-cross-listed stocks								
$InfoAttention_i$	–12.61***	–12.35***	–11.7***	–11.28***	1.55	0.76	0.99	0.39
	(–4.76)	(–4.64)	(–4.26)	(–4.09)	(0.58)	(0.28)	(0.36)	(0.14)
$PriceAttention_i$	0.88	1.1	0.12	0.35	–1.71***	–1.76***	–0.79	–0.84
	(1.13)	(1.41)	(0.15)	(0.43)	(–2.85)	(–2.93)	(–1.26)	(–1.34)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.76%	1.77%	2.27%	3.27%	0.26%	1.07%	2.27%	3.03%
Observations	3,345	3,345	3,312	3,312	3,418	3,418	3,399	3,399

Table 6
Momentum stocks

This table performs the tests in Table 3 separately for momentum stocks and non-momentum stocks. A stock is labeled as a momentum stock if it is in the top or bottom decile for lagged six-month cumulative returns in the month of the announcement. The unit of observation is an announcement j for stock i. $CAR[0,20]$ is the cumulative abnormal return from the first trading day after the announcement (excluding the opening return) to 20 trading days after the announcement. Announcements are split into positive or negative announcements based on the return in the ten trading days after the announcement. $InfoAttention_i$ is our attention to information measure. $PriceAttention_i$ is our attention to prices measure. Panel A reports the results for momentum stocks. Panel B reports the results for non-momentum stocks. Control variables include the stock's average trading volume, volatility, and market capitalization, the pre-announcement five-day return, the market return, and the number of announcements on the day. Time fixed effects include day of the week fixed effects and month fixed effects. The sample includes all overnight price sensitive announcements for all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = $CAR[0,20]$							
	Positive announcements				Negative announcements			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Momentum stocks								
$InfoAttention_i$	–12.06	–17.1*	–11.36	–15.99	–6	–10.19	2.19	–2.14
	(–1.27)	(–1.77)	(–1)	(–1.4)	(–0.53)	(–0.88)	(0.17)	(–0.17)
$PriceAttention_i$	–0.32	–0.13	–0.15	0.13	–0.31	0.2	1.22	1.09
	(–0.2)	(–0.08)	(–0.09)	(0.08)	(–0.2)	(0.13)	(0.77)	(0.68)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.19%	3.89%	0.38%	4.51%	0.04%	1.81%	1.94%	3.39%
Observations	833	833	825	825	984	984	980	980
Panel B: Non-momentum stocks								
$InfoAttention_i$	–11.17***	–10.35***	–10.15***	–9.25***	1.33	1.25	0.66	0.71
	(–4.5)	(–4.16)	(–3.95)	(–3.58)	(0.62)	(0.58)	(0.3)	(0.32)
$PriceAttention_i$	0.77	1.11	–0.21	0.12	–2.63***	–2.68***	–1.72***	–1.76***
	(0.93)	(1.33)	(–0.24)	(0.14)	(–5.03)	(–5.12)	(–3.15)	(–3.22)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.78%	2.06%	1.73%	3.04%	0.96%	1.99%	3.62%	4.59%
Observations	2,851	2,851	2,815	2,815	2,795	2,795	2,776	2,776

Table 7
Attention to information and intraday announcements

This table reports results examining whether the attention to information measure is influenced by intraday announcements preceding the overnight period. The unit of observation is an announcement j for stock i. $CAR[0,20]$ is the cumulative abnormal return from the first trading day after the announcement (excluding the opening return) to 20 trading days after the announcement. Announcements are split into positive or negative announcements based on the return in the ten trading days after the announcement. $InfoAttention_i$ is our attention to information measure. $PriceAttention_i$ is our attention to prices measure. In Panel A, the attention to information measure is calculated using overnight periods with material news and at least one intraday announcement in the preceding trading day. In Panel B, the attention to information measure is calculated using overnight periods with material news and without any intraday announcements in the preceding trading day. Control variables include the stock's average trading volume, volatility, and market capitalization, the pre-announcement five-day return, the market return, and the number of announcements on the day. Time fixed effects include day of the week fixed effects and month fixed effects. The sample includes all overnight price sensitive announcements for all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = $CAR[0,20]$							
	Positive announcements				Negative announcements			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overnight periods with preceding intraday announcements								
$InfoAttention_i$	–9.28***	–9.09***	–8.56***	–8.21***	2.64	2.55	1.96	1.9
	(–3.16)	(–3.1)	(–2.88)	(–2.76)	(1.05)	(1.01)	(0.76)	(0.74)
$PriceAttention_i$	1.68**	1.93**	0.25	0.44	–2.27***	–2.28***	–1.18**	–1.18**
	(2.01)	(2.31)	(0.28)	(0.49)	(–4.2)	(–4.22)	(–2.09)	(–2.08)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.58%	1.84%	2.22%	3.49%	0.68%	1.9%	2.99%	4.27%
Observations	2,691	2,691	2,674	2,674	2,925	2,925	2,912	2,912
Panel B: Overnight periods without preceding intraday announcements								
$InfoAttention_i$	–12.41***	–12.22***	–11.26***	–10.87***	1.67	1.05	0.96	0.57
	(–4.94)	(–4.84)	(–4.31)	(–4.14)	(0.66)	(0.41)	(0.37)	(0.22)
$PriceAttention_i$	0.6	0.85	–0.21	0.06	–1.88***	–1.91***	–0.83	–0.86
	(0.81)	(1.15)	(–0.27)	(0.08)	(–3.34)	(–3.39)	(–1.43)	(–1.47)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.72%	1.67%	2.15%	3.12%	0.33%	1.02%	2.55%	3.23%
Observations	3,684	3,684	3,639	3,639	3,780	3,780	3,757	3,757

Table 8
Attention to information and information leakage

This table reports results examining whether the attention to information measure is influenced by information leakage. The unit of observation is an announcement j for stock i. $CAR[0,20]$ is the cumulative abnormal return from the first trading day after the announcement (excluding the opening return) to 20 trading days after the announcement. Announcements are split into positive or negative announcements based on the return in the ten trading days after the announcement. $InfoAttention_i$ is our attention to information measure. $PriceAttention_i$ is our attention to prices measure. In Panel A, the attention to information measure is calculated using material announcements with potentially high information leakage, i.e., announcements in the top or bottom quartile for pre-announcement five-day return. In Panel B, the attention to information measure is calculated without using material announcements with potentially high information leakage. Control variables include the stock's average trading volume, volatility, and market capitalization, the pre-announcement five-day return, the market return, and the number of announcements on the day. Time fixed effects include day of the week fixed effects and month fixed effects. The sample includes all overnight price sensitive announcements for all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable = $CAR[0,20]$							
	Positive announcements				Negative announcements			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Only high information leakage announcements								
$InfoAttention_i$	–11.76***	–11.67***	–11.83**	–11.5**	0.51	0.1	4.24	3.75
	(–2.64)	(–2.61)	(–2.51)	(–2.44)	(0.12)	(0.02)	(0.9)	(0.79)
$PriceAttention_i$	0.58	0.86	–0.44	–0.14	–1.79**	–1.78**	–0.77	–0.74
	(0.63)	(0.93)	(–0.45)	(–0.15)	(–2.48)	(–2.47)	(–1.01)	(–0.98)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.28%	1.78%	1.75%	3.19%	0.22%	1.07%	2.25%	3.12%
Observations	2,729	2,729	2,711	2,711	2,904	2,904	2,894	2,894
Panel B: No high information leakage announcements								
$InfoAttention_i$	–14.83***	–14.7***	–13.23***	–12.88***	1.86	1.17	3.09	2.59
	(–5.5)	(–5.43)	(–4.7)	(–4.56)	(0.7)	(0.44)	(1.12)	(0.94)
$PriceAttention_i$	0.46	0.68	–0.26	–0.02	–1.93***	–1.98***	–0.91	–0.96
	(0.58)	(0.84)	(–0.3)	(–0.02)	(–3.28)	(–3.35)	(–1.5)	(–1.57)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.92%	1.8%	2.13%	3%	0.34%	1.05%	3.83%	4.51%
Observations	3,465	3,465	3,430	3,430	3,588	3,588	3,568	3,568

Table 9
Attention to momentum and lottery-like stocks

This table reports regression results testing whether momentum stocks and lottery-like stocks receive high attention in subsequent periods. The unit of observation is a stock i and month t. $Momentum_{i,t}$ is an indicator variable that equals one if a stock i is in the top or bottom decile for lagged six-month cumulative returns in month t and zero otherwise. $Lottery\ (Kumar)_{i,t}$ is an indicator variable that equals one if a stock i is classified as a lottery-like stock based on the Kumar (2009) measure in month t and zero otherwise. Based on the Kumar (2009) measure, a stock is classified as a lottery-like stock if it has a below median price, above median idiosyncratic volatility, and above median idiosyncratic skewness based on prices and returns in the six-month period preceding month t. $Lottery\ (Bali)_{i,t}$ is an indicator variable that equals one if a stock i is classified as a lottery-like stock based on the Bali et al. (2011) MAX measure in month t and zero otherwise. Based on the Bali et al. (2011) measure, a stock is classified as a lottery-like stock if it is the top quartile for maximum daily returns in the six-month period preceding month t. $InfoAttention_{i,t}$ is our attention to information measure for stock i in month t. $PriceAttention_{i,t}$ is our attention to prices measure for stock i in month t. In these set of tests, the attention to prices measure is calculated using HotCopper data from 2019. Control variables include the stock's average trading volume, volatility, and market capitalization. The sample includes all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable =					
	$InfoAttention_{i,t}$			$PriceAttention_{i,t}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Momentum_{i,t}$	–0.02*** (–10.53)			0.02*** (9.76)		
$Lottery\ (Kumar)_{i,t}$		–0.08*** (–36.79)			0.01*** (7.62)	
$Lottery\ (Bali)_{i,t}$			–0.07*** (–32.98)			0.01*** (7.2)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	10.03%	15.45%	14.35%	1.03%	0.84%	0.81%
Observations	19,279	19,279	19,279	19,610	19,610	19,610

Table 10
Weak-form efficiency

This table reports regression results testing the effects of our attention measures on measures of weak-form efficiency. The unit of observation is a stock i. $VR(x, y)$ is the variance ratio of the x-day variance per unit time and the y-day variance per unit time. AR is the daily return autocorrelation. All dependent variables are modified to be inefficiency metrics, i.e., higher values of the dependent variables indicate higher price inefficiency. $InfoAttention_i$ is our attention to information measure. $PriceAttention_i$ is our attention to prices measure. Control variables include the stock's average trading volume, volatility, and market capitalization. The sample includes all stocks listed on the Australian Securities Exchange in the year 2019. t-statistics are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Dependent variable =							
	$\|1-VR(1,5)\|$		$\|1-VR(1,10)\|$		$\|1-VR(1,20)\|$		$\|AR\|$	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InfoAttention_i$	–0.87***	–0.92***	–1.64***	–1.66***	–2.79***	–2.66***	–0.15***	–0.13***
	(–11.07)	(–10.73)	(–10.11)	(–10.03)	(–9.46)	(–9.27)	(–9)	(–5.03)
$PriceAttention_i$	0.04**	0.03	0.05	0.03	0.07	0.06	0.01**	0.00
	(2.14)	(1.3)	(1.08)	(0.6)	(0.93)	(0.84)	(2.4)	(1.09)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	7.6%	10.78%	6.24%	9.46%	5.49%	8.41%	5.33%	9.21%
Observations	1,568	1,193	1,568	1,193	1,568	1,193	1,568	1,193

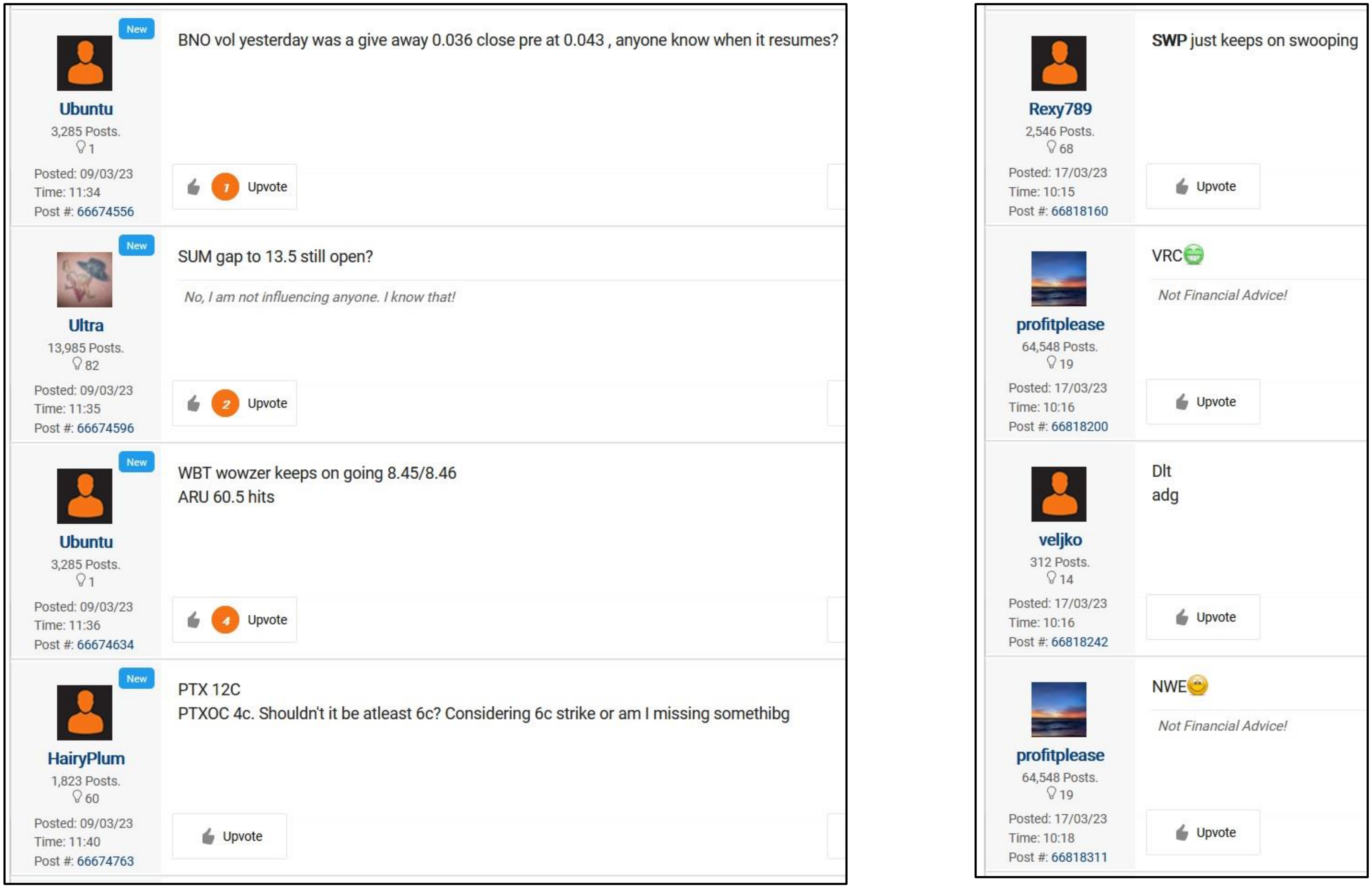


Figure 1. Sample discussions on HotCopper.
This figure shows excerpts of discussions on the ‘ASX – Short Term Trading’ and ‘ASX – Day Trading’ forums on HotCopper, a popular stock market discussion forum in Australia.

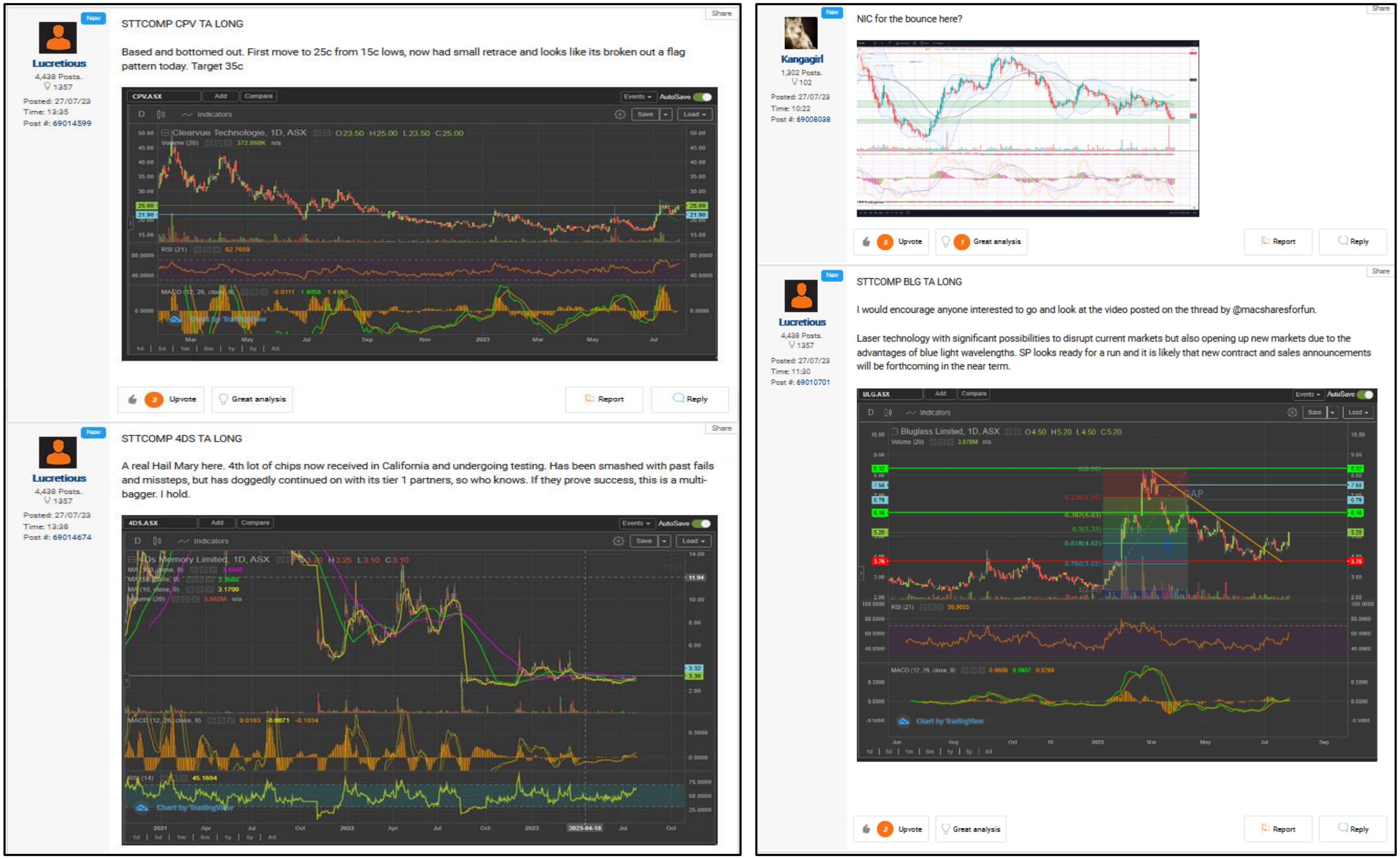
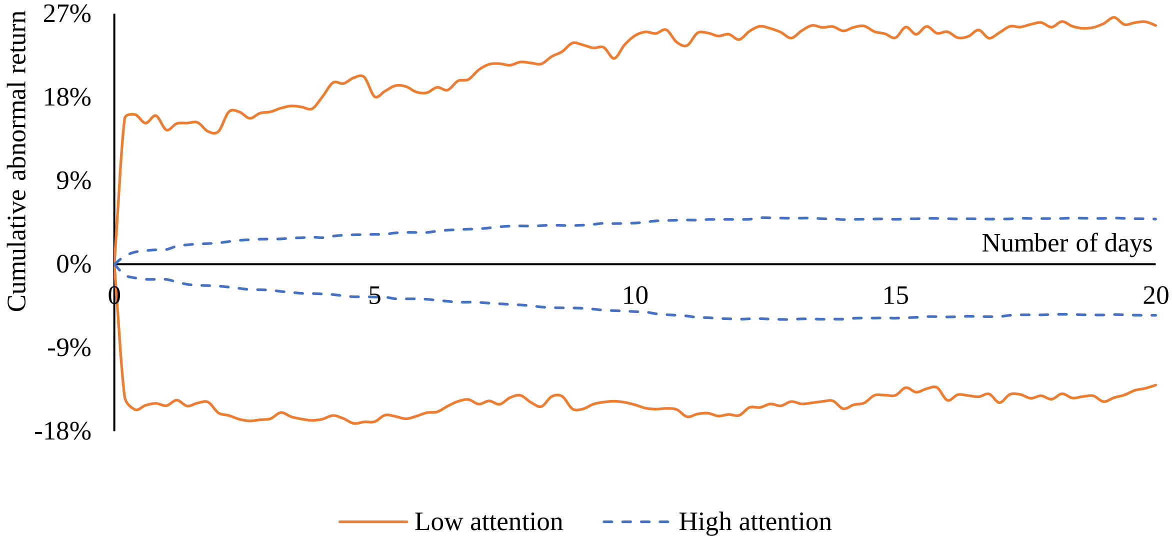


Figure 2. Technical analysis on HotCopper.
This figure shows examples of participants in the 'ASX – Short Term Trading' and 'ASX – Day Trading' forums on HotCopper using technical analysis.

Panel A: Attention to information



Panel B: Attention to prices

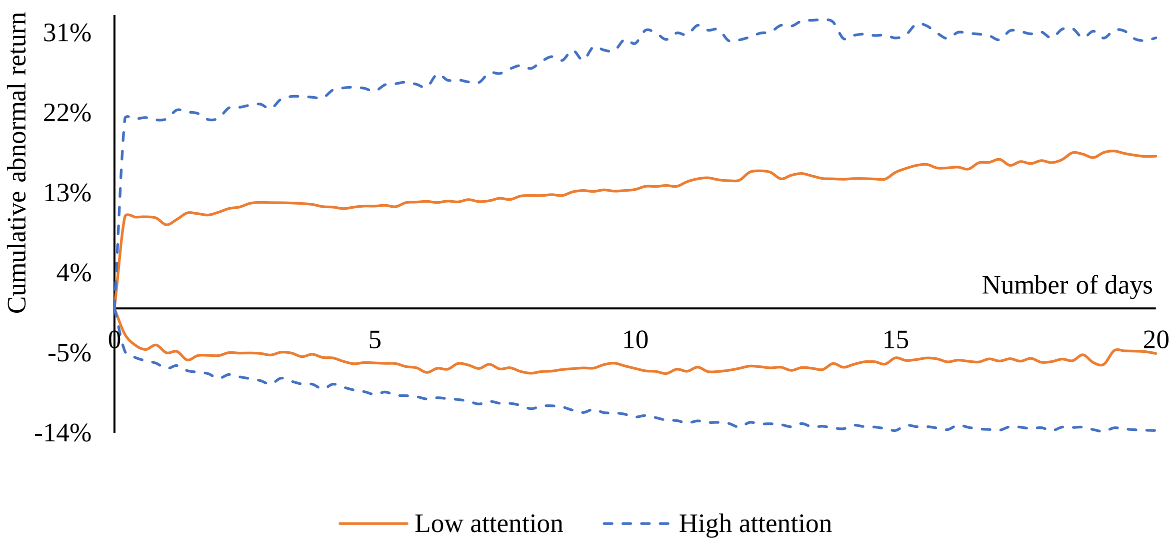
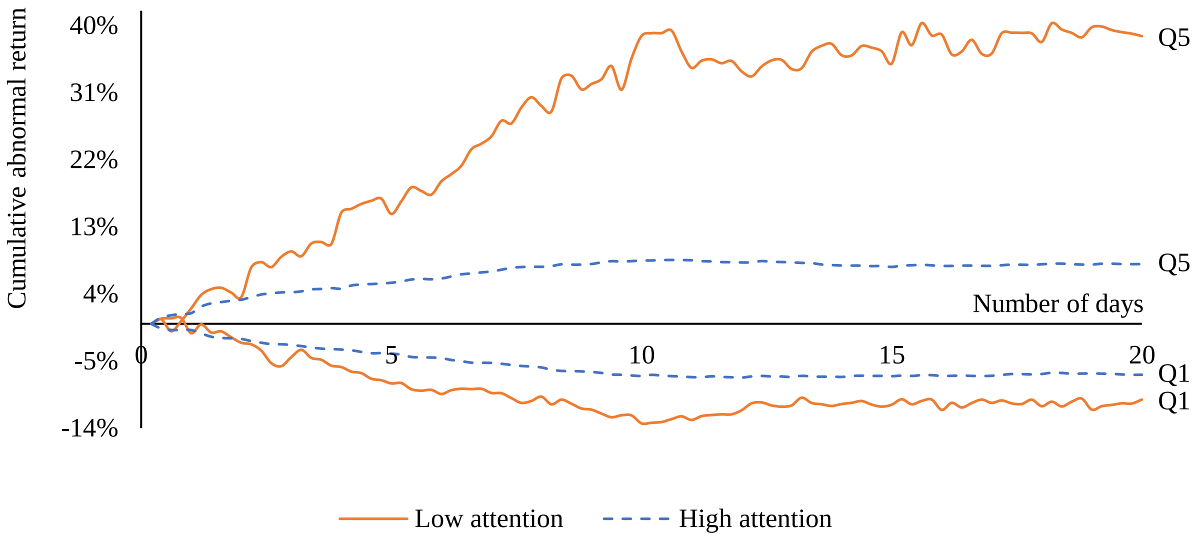


Figure 3. Price reactions split by attention level.
This figure plots price reactions to announcements split into buckets based on the stock's attention level. Low (high) attention stocks are in the bottom (top) decile for attention level. In Panel A, the attention level is calculated using the attention to information measure. In Panel B, the attention level is calculated using the attention to prices measure. The figure plots positive and negative announcements separately. Announcements are classified as positive or negative based on the return in the ten trading days after the announcement. Both panels plot cumulative abnormal returns in one-and-a-half-hour intervals from the day of an announcement ($t = 0$) to 20 trading days later.

Panel A: Attention to information



Panel B: Attention to prices

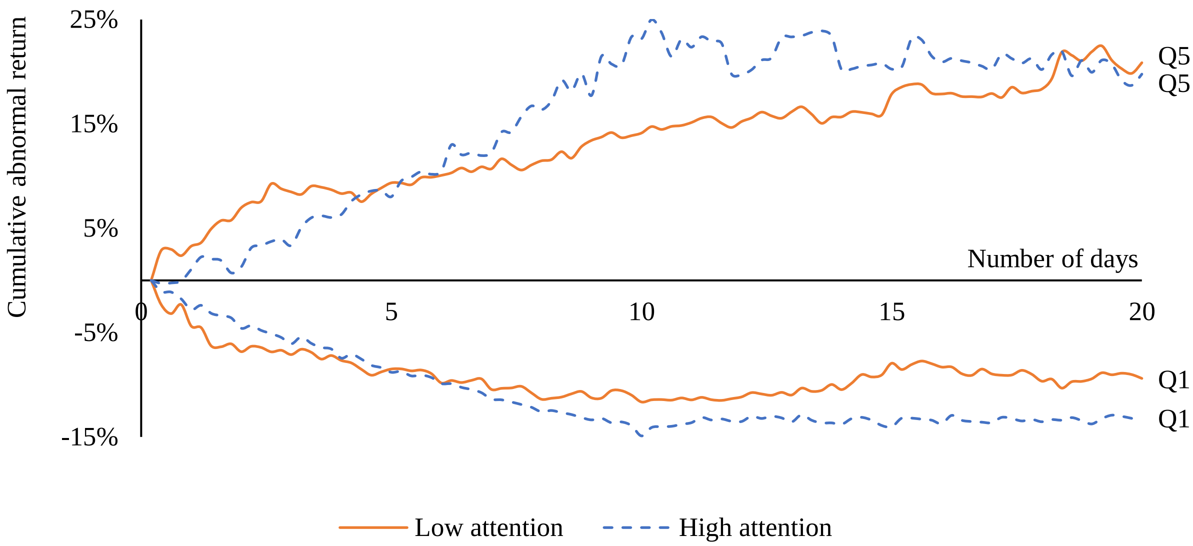
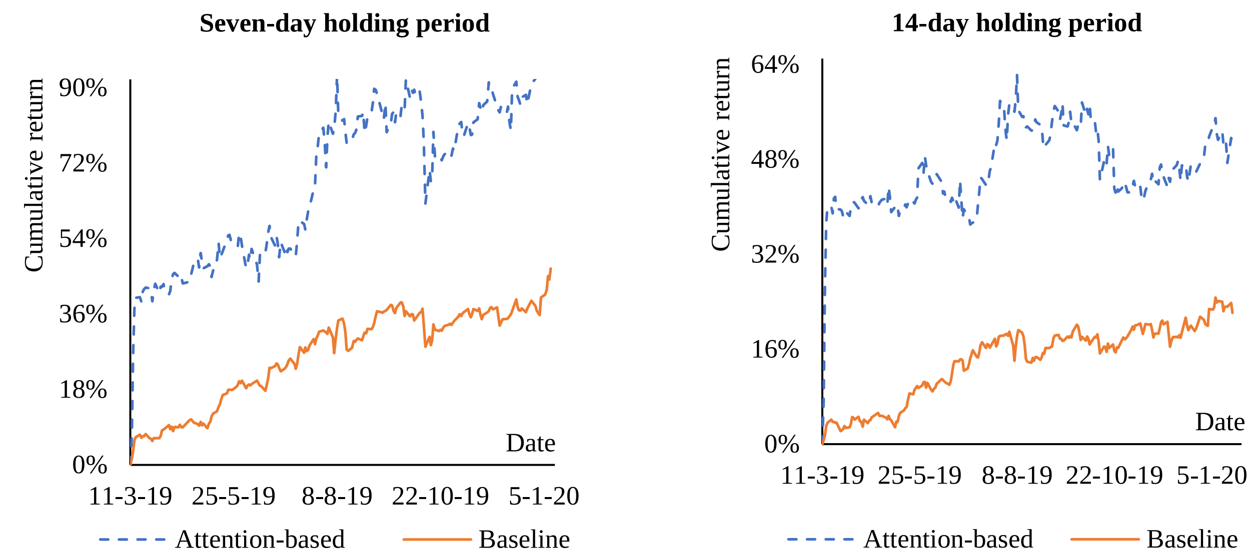


Figure 4. Return spread between announcements with extreme returns.
This figure plots the post-announcement return spread separately for low attention (bottom decile) and high attention (top decile) stocks. Announcements are first split into low and high attention buckets based on the stock's attention level. Within each attention bucket, only the returns for announcements in the top and bottom return quintiles are plotted. Announcement return quintiles are based on the return from the time of the announcement to ten trading days later. The return spread is the difference between the return in the two extreme return quintiles. In Panel A, the stock's attention level is calculated using the attention to information measure. In Panel B, the stock's attention level is calculated using the attention to prices measure. Both panels plot cumulative abnormal returns in one-and-a-half-hour intervals until 20 trading days after the announcement but exclude the initial price reaction to the announcement, i.e., the return from the time of the announcement to the next trading day's open.

Panel A: Attention to information



Panel B: Attention to prices

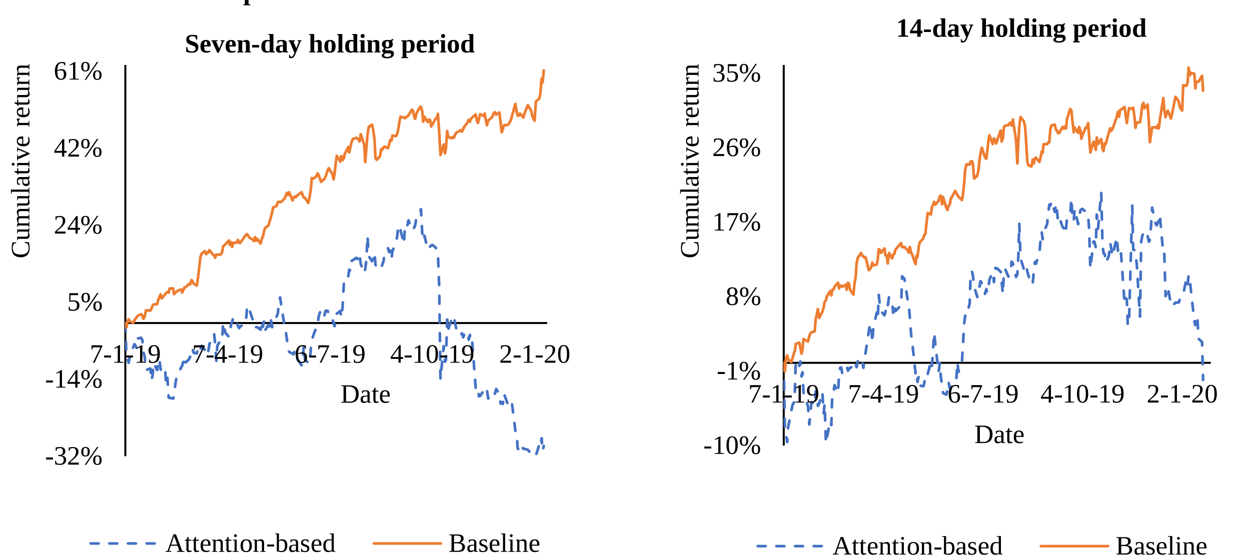


Figure 5. Cumulative returns across trading strategies.
This figure provides a side-by-side comparison of the cumulative returns for attention-based trading strategies and the baseline strategies across different time horizons. In Panel A, the attention proxy used is the attention to information measure. In Panel B, the attention proxy used is the attention to prices measure. All portfolios are value-weighted.