ESSAYS ON INVESTOR ATTENTION

by
Milica Matović

This thesis is submitted for the degree of
Doctor of Philosophy in Finance

Essex Business School
University of Essex
October 2019

Abstract

This thesis investigates retail and institutional investor attention and their effects on the dynamics of asset pricing. First, it examines the attention implications on the liquidity of cross-section of stocks, as well as seasonal patterns of investor attention. It documents that increased attention leads to improved liquidity, which is particularly prominent for stocks of smaller firms while large firms benefit far less from higher investor attention, as suggested by models of investor recognition. The findings also provide evidence of attention seasonality, demonstrating significantly higher levels of investor attention during the month of July, in line with the pre-holiday effect.

Second, it examines investor attention on a recent sample of S&P 500 index additions in the context of anticipatory trading effects. It finds that risk arbitrageurs anticipate the outcome of the index review and purchase stocks that have a high likelihood of becoming new index members, exploiting the mean price increase that comes with the addition announcement. These findings are referred to as the pre-announcement index effect. Moreover, it documents that the observed effect is largely driven by low-beta stocks, consistent with the betting-against-beta investment style approach. Persistent volume and stock price changes following the index addition confirm investor attention hypothesis.

Third, it studies inventor attention within the framework of M&A announcements, investigating whether market anticipation may be the cause of well documented pre-bid price run-up in target firms. It finds that investor attention to target firms significantly increases two weeks ahead of the M&A announcement. Given that surge in attention must be supported by a large population and is unlikely to be triggered by a few corporate insiders, the results suggest that the observed run-up is likely to be caused by investors' anticipation of the impending deals. Analysis of abnormal return and trading volume dynamics provide further evidence in support of this view.

It was a rocky road, but it was well worth the trip...

To my mom

For her advice, her patience, and her faith.
Because she always understood.

Acknowledgements

Pursuing a PhD has been a life changing experience. However, this was not a lonely journey. I would like to thank everyone who accompanied me and provided me with their guidance and encouragement.

I would like to express my profound gratitude to my supervisor Professor Jerry Coakley. I am forever indebted for his continuous support throughout my doctoral studies not only in professional but personal level as well. I could not have asked for a better supervisor to guide me through all the ups and downs the PhD journey entails. Without his patience and advice, the stimulating discussions and the immense knowledge, the completion of this thesis would not have been possible. I am grateful to my second supervisor Professor Andrew Wood for providing me with useful advice, feedback, and encouragement over the past years.

I am also grateful to the Essex Business School for providing me with the scholarship to undertake my PhD studies. I thank all of the School's academic as well as administrative staff for their unwavering support and assistance. I would also like to express my appreciation to all of my fellow PhD colleagues; thank you for the wonderful memories we have had together in the past few years.

And last, but certainly not least, I am much obliged to my family – thank you for encouraging me in all of my pursuits and inspiring me to follow my dreams. I always knew that you believed in me and wanted the best for me. Thank you for teaching me that my job in life was to learn, to be happy, and to know and understand myself; only then could I know and understand others. I would like to dedicate this work to my mother whose dreams for me have resulted in this achievement. Had it not been for my mother's unflinching insistence and support, my dreams of excelling in education would have remained mere dreams.

Contents

List of Tables

"In an information rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes. What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it."

- Herbert A. Simon, Nobel-laureate in 1978

Chapter1

Introduction

Over the past few decades, expansion of the Internet has provided investors with a growing number of platforms for information acquisition. In addition to improving ongoing processes within the stock markets such as facilitating brokerage transactions, the Internet has also developed new processes and interactions like stock message boards and forums. Hence, it may be said that the efficiency of stock markets is greatly attributable to the efficient dissemination of information. Under conventional asset pricing theories, rational investors instantly incorporate newly available information into the stock prices. Hence, it is likely to be the case that Internet plays a significant role in the stock markets.

However, recent literature suggests that information must attract investor attention before it can be processed and incorporated into stock prices. At the same time, attention is a scarce cognitive resource (Kahneman, 1973), and attention to one task calls for the exchange of cognitive resources from other tasks. In regard to investment decisions, considering the wealth of information available in today's digital world and inevitability of limited cognitive resources, investors must be selective in information processing. This thesis investigates the role of investor attention in a variety of settings and its impact on the financial markets.

Barber and Odean (2008) were the first to show that investors limit their investment choice set to attention-grabbing stocks. Investor inattention can lead to mispricing associated with public accounting information (Hirshleifer and Teoh, 2003), processing market-wide rather than market-specific information (Peng and Xiong, 2006), earlier information incorporation by larger than by smaller stocks (Peng, 2005), slower stock price and volume reactions to earnings surprises (Hirshleifer et al., 2009) , and neglect of long-term public information (DellaVigna and Pollet, 2005). Firms may exploit limited investor attention by disclosing negative news at times when other firms are making salient disclosures (Hirshleifer et al., 2004), or on Fridays rather than on regular weekdays as the weekend approaches (DellaVigna and Pollet, 2009). Similarly, investor attention to Friday M&A announcements is muted, as evidenced by lower levels of trading volume and abnormal return (Louis and Sun, 2010).

To measure the attention a firm receives from investors, the existing literature suggests variety of proxies. Grullon et al. (2004) and Lou (2008) measure investor attention using advertising expenditure, considering it to reflect a firm's overall visibility with investors. Fang and Peress (2009) employ media coverage on the grounds that investor attention should be higher the more stock comes to light in the newspaper articles. Kim and Meschke (2011) quantify the attention a firm attracts by counting the firm's CEO interviews on television or general news coverage. Barber and Odean (2008) find that investors are net buyers of attention-grabbing stocks, such as those in the news, with abnormal trading volumes, or extreme returns. However, these proxies and identification strategies for attention are best described as passive, considering that they may be driven by factors unrelated to investor attention.

In their seminal paper, Da et al. (2011) propose a direct measure of investor attention based on users' activity on Google search engine known as Search Volume Index (SVI). Unlike previous passive attention measures, SVI reflects investors' active information gathering and therefore offers a direct measure of active investor attention. The relation between SVI and financial markets has recently attracted a lot of attention, with Google's measure now recognised as a significant investor attention and investor sentiment proxy. The literature employs SVI to analyse effects of investor attention in a variety of settings including stock liquidity (Ding and Hou, 2015), market volatility (Vlastakis and Markellos, 2012), price adjustments to earnings announcements (Drake et al., 2012), biased attention towards local stocks (Mondria and Wu, 2011), FX market volatility (Goddard et al., 2015), mergers and acquisitions (Siganos, 2013), and profitable trading strategies (Preis et al., 2013).

When considering the impact of investor attention on stock market reactions, we must decide whether to focus on retail investors, institutional investors, or both. Consistent with intuition, Da et al. (2011) show that the SVI proxy captures the attention of retail investors, given the strong association between SVI changes and trading by individual investors. In contrast to individuals who request information on Google, those using Bloomberg platform are more likely to be institutional investors for a number of reasons. On those grounds, Ben-Rephael et al. (2017) propose a direct measure of abnormal institutional attention (AIA) founded on users' news reading and news searching activity for stocks on Bloomberg terminals. While both SVI and AIA measures are correlated with abnormal trading volume, only AIA has a significantly higher correlation with abnormal institutional trading rather than total trading volume, supporting the view that AIA directly measures institutional investor attention.

This thesis explores retail and institutional investor attention in different contexts. The goal of the thesis is threefold. First, it revisits the impact of retail investor attention on a cross-section of stocks' liquidity and seasonal patterns in investor attention. Second, it examines investor attention on a recent sample of S&P 500 index additions prior to their inclusions on the basis of anticipatory trading effects. Finally, it investigates the well-documented target firm pre-bid price run up anomaly in an M&A announcements framework from a novel angle, re-examining the market anticipation hypothesis.

1.1 Contributions

One of the main findings in current thesis (Chapter 2) is that active retail investor attention has a positive effect on stock liquidity, as measured by the relative bid-ask spread, which is particularly prominent for stocks of small market capitalisation firms, while larger firms benefit far less from the increased investor attention. Our results remain robust to alternative liqudity measures including relative effective spread and turnover. While these measures consider the inventory aspect of liquidity, we also address the price impact aspect of liquidity by employing the Amihud's (2002) illiquidity ratio measure. We find that active retail investor attention is insignificantly related to the illiquidity ratio, implying that it cannot mitigate the price impact aspect of stock illiquidity. The underlying reason is likely to be due to the choice of attention proxy, since SVI generally captures attention of retail investors who are unlikely to have outstanding impact on stock prices. In line with Da et al. (2011), we find media coverage and advertising expenditure to be positively related to the SVI, although the relationship is relatively weak. Our empirical results also show that retail investor attention exhibits strong seasonality pattern, being considerably higher during the month of July. Consistent with our findings, Hong and Yu (2009) show that most retail investors take holidays during the months of August and September. Hence, our results are consistent with the "pre-holiday" effect, suggesting that investors tend to be most attentive to the markets at times preceding the holiday. We attribute the divergence in our findings from those of Liu and Peng (2015) to the shift in retail investor attention over the post-crisis period.

The second contribution of this thesis is that it investigates the role of institutional and individual investor attention in the S&P game, in the context of anticipatory trading effects (Chapter 3). To the best of my knowledge, this is the first study to explore investor attention in this capacity. The empirical results show that investor attention levels measured by AIA significantly increase a week ahead of the announcement of firm addition to the S&P 500 index, and are positively associated with abnormal trading volumes and abnormal returns. This implies that sophisticated investors such are hedge funds and other risk arbitrageurs seek to anticipate the outcome of index review and purchase stocks that have high likelihood of becoming new index members, in an effort to exploit the 3% mean price increase that comes with the addition announcement. We refer to these findings as the pre-announcement index effect. Moreover, we report that attention measured by the AIA precedes the attention proxied by SVI during the pre-announcement period, showing that institutional investors have greater resources and higher incentives to react rapidly to information, in line with Ben-Rephael et al. (2017). We also add to the literature on trading strategies, showing that investors bet against beta as a part of their statistical arbitrage, documenting that most of the pre-announcement index effect is driven by low beta stocks. Our study provides fresh insights on the S&P game, showing that opposed to the existing assumption of announcement day being the foundation of it, the index effect begins much ahead of the announcement of firm addition to the index.

The final contribution of this thesis is that it revisits the well-documented pre-bid price run up for target firms in the context of M&A announcements, analysing institutional investor attention levels and price-volume dynamics prior to the official takeover announcement (Chapter 4). To the best of my knowledge, no other study has previously tested institutional investor attention in this regard. We find that institutional attention to target firms significantly increases from two weeks prior to the M&A announcement. Given that significant increase in attention must be supported by a large number of platform users, our findings suggest that observed run-up may be caused by investors who seek to anticipate impending takeovers and take positions early, but speculate more aggressively as the announcement day approaches. We provide further evidence in support of this view by analysing the dynamics of trading volume and return over the period preceding the takeover announcement, under the competitive trading model of He and Wang (1995). Our results suggest that target firms experience significantly positive and rising abnormal trading volumes as early as two weeks prior to the M&A announcement, unaccompanied by abnormal returns. Positive and significant abnormal returns arise just shortly ahead of the event, exhibiting pattern inconsistent with illegal insider trading hypothesis but in line with the predictions for market anticipation. These findings are in line with Gao and Oler (2012) and King and Padalko (2009). Our results also contribute to the literature on investor attention allocation and its impact on stock market reactions, showing that stock returns and trading volume is higher when investors pay more attention.

1.2 Preview of chapters

The remainder of this thesis is structured as follows. Chapter 2 considers all firms that have ever been included in the S&P 500, S&P 400, and S&P 600 indices between January 2010 and December 2018. The Ding and Hou (2015) results suggest that increased investor attention results in a reduced bid-ask spread for large market capitalisation firms during the period preceding and including the most recent financial crises. Following Merton's (1987) investor recognition hypothesis, smaller firms that are less known to the public should benefit more from being in investors' sight. Hoffmann et al. (2013) document that retail investor perceptions and behaviour change significantly during the financial crisis, driving trading and risk-taking behaviour. This is the motivation for including the complete set of S&P 1500 stocks to examine the effects of investor attention on a cross-section of stocks' liquidity and seasonal attention patterns during the post-crisis period. The results show that increased investor attention leads to a reduction in a bid-ask spread as well as alternative liquidity measures, which is particularly striking for stocks of smaller firms, while retail investor attention has no significant effect on the price impact aspect of liquidity. In line with Hong and Yu (2009) who show that most retail investors take holidays during summer, we show that investors are most attentive to markets during the month of July.

Chapter 3 examines the roles of retail and institutional investor attention on a sample of S&P 500 index additions that took place between January 2004 and December 2018. The first contribution of this chapter is the discovery of the pre-announcement index effect, suggesting that hedge funds and other risk arbitrageurs anticipate the likely candidates for index inclusion. Following Beneish and Whaley (1996), literature's common approach considered the announcement day of firm's addition to the index to be the foundation of the S&P game. We provide novel insights, showing that the S&P game begins on average a week ahead of the inclusion announcement. Consistent with Ben-Rephael et al. (2017), we report that institutional investor attention leads retail investor attention during the pre-announcement period, confirming that institutional investors have greater resources and higher incentives to react rapidly to information. Secondly, we show that most of the effect is driven by low-beta stocks, in line with betting-against-beta investment style of Frazzini and Pedersen (2014). In other words, investors overweight on low beta stocks and underweight on high beta stocks as a part of their statistical arbitrage, in an effort to add BAB returns on top of the profits from anticipating index additions. Lastly, we show that abnormal trading volumes and a considerable part of abnormal returns remain permanent until the end of our event window, in line with attention hypothesis.

Chapter 4 re-evaluates the market anticipation hypothesis from an angle of investor overreaction as a possible explanation for the significantly positive pre-bid price run up in target firm's stock, that is almost uniformly documented in the prior literature. To do so, we employ a novel approach by testing the levels of active institutional investor attention during the period preceding the official takeover announcement. For the most part, prior studies primarily focus on the rumours published in the newspaper media, which may not necessarily reflect attention especially of institutional investors, providing wide-ranging findings. This chapter finds that attention of sophisticated investors to target firms significantly increases two weeks prior to the M&A announcement, implying increased demand for information and hence suggesting anticipation of impending deals, given that significant increase in information acquisition on Bloomberg terminals must be supported by a large number of users. Our main findings are confirmed by analysing the price-volume dynamics of target stocks over the pre-event window in the framework of competitive trading model of He and Wang (1995).

Chapter 5 briefly summarises the key findings of this thesis.

Chapter2

Retail investor attention and stock liquidity

Traditional asset pricing models assert that investors are rational and that all newly available information is immediately reflected in the stock prices. However, recent studies show that important news or information is not fully reflected by prices until investors pay attention to it. Nonetheless, attention is a scarce cognitive resource (Kahneman, 1973), and investors must be selective in information processing. Merton (1987) notes that given the vast amount of available information in financial markets and the inevitability of limited cognitive capacity, investors choose only a subset of stocks to learn about and trade. Put differently, investors limit their choice set to attention-grabbing stocks (Barber and Odean, 2008). This study aims to provide some fresh insights into the capital market effects of retail investor attention.

Merton (1987) introduces the idea of investor recognition, demonstrating that investor attention can be relevant for stock pricing and liquidity. As a practical matter, however, it is quite challenging to capture investor attention. Grullon et al. (2004) employ advertising expenditure as a way of reaching a broad population of investors, and explore its impact on stock liquidity. Fang and Peress

(2009) use media coverage to proxy for investor attention, where a number of published news articles measures attention attracted by a firm. However, there is no reliable information concerning the degree to which investors pay attention to advertisements or newspaper articles. Other measures including analyst coverage, institutional holdings, extreme returns, trading volume and price limits suffer from similar shortcomings. These proxies generally assume that if a stock's return or turnover was extreme, or firm's name was mentioned in the media, investors should have paid attention to it. Yet, newspaper articles do not guarantee attention unless investors actually read it. This is especially true in the so-called information age where "a wealth of information creates a poverty of attention."

In this paper we employ passive measures of attention including advertising expenditure and news articles, as well as the more recently proposed direct measure of active retail investor attention based on the aggregate search frequency on Google, known as the Search Volume Index (henceforth SVI). Suggested by Da et al. (2011), SVI as a gauge of general public interest has a number of enriched features in comparison to the previous attention measures. The significance of Internet has grown steadily over the past decades, presenting the largest pool of freely available information ever. As a result, online search for information reveals attention: if we search for a firm online, we are undoubtedly paying attention to it. Hence, SVI is a direct measure of active investor attention. While Da et al. (2011) focus on the search frequency using firm's ticker, we employ a more general method and measure attention by the search volume of firm names. This approach is likely to seize attention the firm is getting from a wider, and possibly relevant crowd, considering little chance that ordinary user searches for firm on Google using its stock symbol or ISIN number.

Building on the studies by Ding and Hou (2015) and Liu and Peng (2015), we explore effects of retail investor attention on stock liquidity, as well as seasonal patterns in attention. While Ding and Hou (2015) base their analysis solely on the sample of large and well-known S&P 500 stocks, we hypothesise that firms less known to the public should benefit more from the increased investor attention. Hence, in addition to large firms, we also examine the effect of investor attention on liquidity of small-cap S&P 600 index stocks and mid-cap S&P 400 index stocks. Moreover, their findings are based on the relatively short period of six years, preceding the 2008 financial crisis. We extend our sample and focus on the post-crisis period, testing for any changes in investors' behaviour in the subsequent years.

We find that increased investor attention measured by the SVI results in a reduction of a bid-ask spread, that is, improved liquidity. Our results are robust to the alternative liquidity measures, including relative effective spread and stock turnover. Empirical results also hold after controlling for the previously used measures of attention including advertising expenditure and media coverage, firm characteristics, and year and month fixed effects. What is more, our findings affirm that larger and well-established firms benefit far less from the increased attention as compared to the small-cap and medium-cap firms.

While relative bid-ask spread, effective spread, and stock turnover consider the inventory aspect of liquidity, Amihud's (2002) illiquidity ratio reflects the price impact aspect of stock illiquidity. We find that active retail investor attention is insignificantly related to the illiqudity ratio measure, suggesting that it cannot mitigate the price impact aspect of illiquidity. This is unsurprising, given that SVI measure captures attention of retail investors who are less likely to have significant impact on stock prices in comparison to the institutional investors.

In line with Da et al. (2011), we find media coverage and advertising expenditure to be positively related to the SVI, although the relationship is relatively weak. Our empirical results report considerably higher levels of retail investor attention during July, in comparison to the other months of the year. In line with our findings, Hong and Yu (2009) show that most retail investors take holidays during the months of August and September. Hence, our results are consistent with the "pre-holiday" effect documented by Lakonishok and Smidt

(1988) and Ariel (1990), where investors tend to be particularly attentive to the markets at times preceding the holiday. We attribute the divergence in our findings from those of Liu and Peng (2015) to the shift in retail investor attention over the post-crisis period.

Our study contributes to the emerging literature on the role of investor attention in asset pricing dynamics, including Barber and Odean (2008) on investor attention and investor trading behaviour; Siganos (2013) on mergers and acquisitions; Ding and Hou (2015) on stock liquidity and shareholder base, and Liu and Peng (2015) on seasonal attention patterns. We also extend the literature on investor recognition hypothesis, in line with Grullon et al. (2004) and Fang and Peress (2009). Stocks of less recognised firms tend to be less liquid in markets with asymmetric information and have to offer higher returns to make up for their illiquidity. At the same time, stocks attracting more investor attention allow to be better recognised, resulting in improved liquidity. Hence, our findings also add credence to the investor recognition hypothesis. Lastly, we provide some fresh insights on the seasonal patterns of retail attention, documenting a change in investor attention allocation during the post-crisis period, consistent with Hoffmann et al. (2013).

The remainer of the paper is organised as follows. Section 2.1 reviews the related literature. Section 2.2 describes the data and research method. Section 2.3 presents empirical findings. Section 2.4 concludes.

2.1 Related literature

2.1.1 Traditional investor attention approach

Gervais et al. (2001) find that investors pay attention to stocks with abnormally high trading volumes as trading shocks to one stock may influence its market visibility. They argue that if changes in visibility account for subsequent higher returns, high volume return premium should not depend upon high coexisting return shocks. They also posit that visibility should be more far-reaching for neglected stocks or stocks that are out of favour. Grullon et al. (2004) employ advertising expenditure to examine its impact on firm's visibility. Given that advertising does not distribute genuinely new information, investors who react to it may best be described as the uninformed investors. As a result, a big upsurge in the number of investors due to advertising should reduce asymmetric information costs.[1] Grullon et al. (2004) confirm this hypothesis by showing that firms with larger advertising expenses have a greater number of investors and better stock liquidity. In a similar manner, Frieder and Subrahmanyam (2001) document a positive relationship between investors' decision to invest in firm's stock and attention paid to its products. Chemmanur and Yan (2009) analyse advertising expenditure and IPO underpricing as signs of firm's intrinsic value in an IPO market characterised by asymmetric information, showing that these two indicators may serve as substitutes for signalling in the IPO market.

Barber and Odean (2008) were the first to show that investor attention triggers positive short-term buying pressure for stocks that are in the news, stocks facing large abnormal trading volume, or stocks with extreme one-day reruns.[2] Furthermore, they discover asymmetry in the impact of attention on market patterns in buys and sells. They argue that attention effect is stronger for buyers compared to sellers, considering that investors can pick from a large set of stocks when purchasing but facing limited choices when selling the assets. Barber and Odean (2008) provide empirical evidence that retail investors are net buyers of attention-grabbing stocks, in line with prior study by Grullon et al. (2004). Moreover, they state that stock's improved visibility may appeal to new

[1]Considering that market makers cannot tell apart between the informed and uninformed investors, they will anticipate acquiring profits when trading with uninformed investors who possess less information about the true value of assets.

[2]Several studies do not concentrate on investor attention by its very nature but report interesting anecdotal evidence. For instance, Lee (1992) finds that "acquisition decisions of small trader are related to news events that bring the security to small traders' attention." Graham and Kumar (2006) find that some investors are inclined to acquire stocks following certain attention-grabbing events like dividend initiations. Alternative examples include Choe et al. (1999), Gervais et al. (2001), Huberman and Regev (2001), Grinblatt and Keloharju (2001) among many others.

investors, as argued by the Gervais et al. (2001). Seasholes and Wu (2007) revisit this hypothesis using the Shangai Stock Exchange data. They demonstrate that attention-grabbing events, characterised by high media coverage, returns and trading volumes, trigger investors to purchase stocks they have not previously owned. They further show that upper price limit events are synchronised with initial stock price increases, followed by significant price mean reversion over the following five days. Brandt et al. (2009) document changes in idiosyncratic volatility levels to be associated with investors' limited attention, particularly around the attention-grabbing events. Liu et al. (2014) find that speculative activities in the warrants market during the China's warrants bubble period attracted attention from investors, prompting them to speculate more on the underlying stocks.

Fang and Peress (2009) measure investor attention using media coverage, on the grounds that it should be higher the more stock comes to light in the newspapers. They demonstrate that stocks with a lower media coverage display greater abnormal returns, even after controlling for the widely known risk factors. Authors attribute this negative relationship to the effect of investor recognition, in the spirit of Merton's (1987) study. Considering implications of the abnormal returns, their empirical findings suggest that investor attention improves market efficiency. In a similar fashion but closely related to Barber and Odean (2008), Yuan (2011) examines the ability of market wide attention-grabbing events to predict trading patterns and market returns, using the front page news events and record breaking events of the Dow Jones Industrial Average Index. He finds that increased attention triggers retail investors to radically decrease their positions when the market level is high, and modestly increase their positions when the market level is low. As the attention effect is not solely confined to retail investors, abnormal selling behaviour lowers the market price and induces institutional investor to trade, reducing market returns in days following the events.

Investor attention continually fluctuates over time. Whereas high levels of attention lead to buying pressure and hasty price reactions, limited investor attention is frequently associated with slow dissemination of information and under-reaction to news.[3] DellaVigna and Pollet (2009) study reactions to earnings announcements made on Fridays, when investors are relatively inattentive to work related activities. They show that announcements made on Friday generally exhibit lower immediate and a higher subsequent response from investors, in line with the inattention hypothesis. Namely, distractions cause investors to underreact to information given their limited attention, however, they eventually become aware of the mispricing and incorporate information into their decision-making process.[4] These results are consistent with the post-earnings announcement drift explanations based on the underreaction to information, resulting from limited investor attention.

Hirshleifer et al. (2004) report that firms exploit limited investor attention by altering their financial reporting decisions at times when other firms make salient disclosures. They report that in the context of multiple arenas of disclosure, disclosure in one arena influences perception in fundamentally unrelated arenas as a result of competition, salience, and analytic inference; and that disclosure in one arena may crowd out disclosure in another. Hong and Yu (2009) argue that investors "go fishing" during summer and are less observant to the stock market, documenting considerably lower trading activity over summer months as compared to the rest of the year. Liu and Peng (2015) extend their work by analysing weekly and monthly patterns of investor attention, showing that investor attention levels are significantly lower on Fridays and during the summer.

The empirical challenge in testing the attention theories comes in the form of

[3] Hirshleifer and Teoh (2003) show that market prices are influenced by the way in which accounting information are presented at times when investors are not fully attentive. Peng and Xiong (2006) find that limited attention gives rise to category learning, and hence causes return patters that cannot be untangled within rational expectations framework. Hirshleifer et al. (2011) put forward a theoretical framework that assimilates investors' inattentiveness to information when forecasting returns. Other examples include Cohen and Frazzini (2008), Hirshleifer et al. (2009), Hendershott et al. (2010), Da et al. (2014), Chen et al. (2016b), among many others.

[4] Hirshleifer et al. (2009) report similar results when several different announcements are in the running for investors' attention.

electing the appropriate proxy. The above cited studies employ different measures including media coverage (Fang and Peress, 2009), advertising expenditure (Grullon et al., 2004), trading volume (Gervais et al., 2001), extreme returns (Barber and Odean, 2008), price limits (Seasholes and Wu, 2007), state of business cycle (Kacperczyk et al., 2009), brand familiarity (Kent and Allen, 1994), number of CEO interviews on TV (Kim and Meschke, 2011), number of user requests on EDGAR online system (Drake et al., 2015), among others. Overall, these proxies belong to the group of passive measures of investor attention. The underlying assumption on which these measures are based is that if a firm's name was mentioned in the media or stock return was extreme, investors should have paid attention to it. However, newspaper articles do not guarantee attention unless investors actually read them, and returns can be driven by factors unrelated to attention. This is particularly true in today's world where "a wealth of information creates a poverty of attention."

2.1.2 More recent approach

The lack of appropriate attention proxy was ultimately addressed in the seminal paper by Da et al. (2011). They propose a measure of active investor attention based on the search frequency on Google, which they refer to as the Search Volume Index (henceforth SVI). Da et al. (2011) argue that SVI as a measure of general public interest has a number of enriched features in comparison to the previous attention proxies. The importance of Internet has grown steadily over the past decades, now presenting the largest pool of freely available information ever. More importantly, search for information directly reveals attention: if we search for a firm online, we are undoubtedly paying attention. Da et al. (2011) show that correlations between SVI and passive attention proxies such as media coverage, returns, and turnover are positive on average, although relatively low. Accordingly, Da et al. (2011) argue that SVI provides direct measure of active individual investor attention. Choi and Varian (2012) support this claim showing that search data can forecast home and car sales as well as tourism, while Ginsberg et al. (2009) report that influenza related searches forecast flu epidemics couple of weeks before the Centres for Disease Control and Prevention reports. Da et al. (2011) also document that increasing SVI can predict higher stock prices in the short-run and price reversals in the long-run, conforming to findings of Barber and Odean (2008).

Following seminal work of Da et al. (2011), a vast number of studies began to explore effects of SVI in a range of different settings. Drake et al. (2012) broaden the literature by exploring the factors that impact investor attention around earnings announcements, reporting that higher SVI ahead of the announcement day leads to lower announcement day abnormal stock returns and trading volumes. Their findings demonstrate that when investors demand more information regarding a particular firm, the informational content of firm's earnings announcement is partly anticipated. Bank et al. (2011) explore implications of the SVI on German stock returns, trading volume, and liquidity. They find increased SVI to be associated with higher trading activity, better liquidity, and increase in stock returns in the short run. Moreover, large fluctuations in the SVI are associated with small changes in illiquidity as measured by the Amihud's (2002) illiquidity ratio, and vice versa. Based on the premise that negative relationship between the SVI and illiquidity results from variations in the cost of asymmetric information, consistent with Da et al. (2011) but differently from Drake et al. (2012), Bank et al. (2011) conclude that SVI predominantly measures interest of uninformed investors. Ding and Hou (2015) report that investor attention considerably improves liquidity of stocks as measured by the relative bid-ask spread, but find insignificant results based on the Amihud's (2002) illiquidity ratio.

Vlastakis and Markellos (2012) show that demand for information is positively associated with return volatility and trading volume for 30 major stocks traded on the NYSE and NASDAQ. Moreover, they document positive relationship between demand for information and investor risk aversion. Predictive power of the SVI on stock trading volume is also documented by Preis et al (2010), while further evidence of the impact of SVI on stock volatility is reported by Goddard et al. (2015). Dimpfl and Jank (2016) show that investor attention is not only correlated but also predicts volatility of the US stock market. Aouadi et al. (2013) find that SVI is correlated to trading activity and that it determines volatility of the French stock market. Vozlyublennaia (2014) finds that attention affects performance of market indices of stocks, bonds, and commodities. Moreover, higher levels of SVI decrease return predictability, suggesting improvement in market efficiency. Overall, prior studies document that increased investor attention has a positive effect on short-run stock returns, liquidity, turnover, and volatility.

2.2 Data and research methods

2.2.1 Sample selection

Our sample includes all stocks that appear in the S&P 500, S&P 400, and S&P 600 indices between January 2010 and December 2018. We extend the study of Ding and Hou (2015) by focusing on the period following the 2008 financial crisis, to examine for any changes in retail investors' perceptions, following Hoffmann et al. (2013). The S&P 500 index is considered to be the best single gauge of large cap US equities, S&P 400 provides investors with a benchmark for medium sized firms, while S&P 600 index represents small-cap sector of the US equity market. We elect these S&P 1500 stocks in an effort to achieve cross-sectional variation in the type of stocks used in this study. To rule out survivorship bias and impact of index additions and deletions, we start with all of the 1, 964 firms ever included in the S&P 1500 index over the sample period.

Our main variable of interest, SVI, comes from the Google's service Google Trends; news data is collected from the LexisNexis database; company fundamental information from Compustat; and stock-related data from CRSP. Considering that main focus of our study is on investor attention captured by the SVI, we exclude firms for which Google Trends returns a value of zero. Table 2.1 presents composition and summary statistics of our final sample. Out of 1, 964 firms we begin with, about 51% make it to our final sample: 42% of the S&P 500 stocks, 28% of the S&P 400 stocks, and 30% of the S&P 600 stocks. Google does not generate valid SVI if a firm is seldom searched for, which more frequently happens for medium and small-cap stocks, resulting in a greater loss of firms belonging to the S&P 400 and S&P 600 indices.

< Table 2.1 around here >

2.2.2 Direct measure of investor attention (SVI)

Google makes the Search Volume Index (SVI) data available through the product called Google Trends, which is a real time index of the volume of searches users enter in the Google search engine. It is defined as the term's search volume relative to the highest number of searches over the selected time period.[5] Google Trends uses a scaled score of 0 to 100, where 100 defines the highest query volume over the selected time. The platform also provides non-real time data, pertaining to historical data from 2004 up to 36 hours in advance of search activity.[6] We conduct our study using the weekly SVI data.

We don't employ raw SVI in our analysis given that its value depends on the period over which the data is downloaded. For instance, SVI for the first week of January 2010 depends on whether we obtain data from 2008 to 2010, or from 2009 to 2011. Hence, we calculate abnormal SVI (henceforth ASVI) as follows:

$$ASVI_{i,t} = \frac{SVI_{i,t} - AverageSVI_{i,(t-52,t-4)}}{AverageSVI_{i,(t-52,t-4)}} \tag{2.1}$$

[5]Available at: http://www.google.com/trends/.

[6]Non-real time data can be downloaded in various time ranges: past hour, past 4 hours, past week, past month, past quarter, past year, past 5 years, 2004 to present, and custom time ranges. However, time frequency varies according to the time range selected by the user. For instance, hourly data may be downloaded at most for one day only, while daily data may be downloaded at once only for the time range up to 90 days.

The past year average SVI captures the baseline level of attention that is free of low-frequency seasonality, while skipping the most recent month accounts for any attention spillover effect. Hence, ASVI captures deviations from the usual level of investor attention and any possible time trends. Lastly, we convert the weekly ASVI into monthly observations by taking the average in each calendar month.

Da et al. (2011) state that using stock ticker to obtain SVI is a more appropriate way to capture attention than using firm names, as search queries prompted by firm names may be motivated by various reasons unrelated to investments. On the other hand, Bank et al. (2011) and Vlastakis and Markellos (2012) argue that although searching by firm names may add some noise, it is random and should not impact variable in a systematic way. Using firm names allows acquiring a more extensive measure of demand for information, since investors are more likely to use firm names as keywords when searching for firm related information rather than for stocks solely. Moreover, Bijl et al. (2016) find that firm name searches have stronger relationship with stock returns than ticker searches. Hence, we employ firm names as given by the CRSP database to acquire SVI for the sample of firms in our study.

2.2.3 Indirect measures of investor attention

In addition to the direct measure of investor attention captured by the SVI, we also control for the passive measures of attention including media coverage (Fang and Peress, 2009) and advertising expenditure (Grullon et al., 2004), so that incremental value of the SVI can be unravelled. We download the total number of monthly relevant newspaper articles for each firm in our sample from the LexisNexis database.[7] Yearly data on firm's advertising expenditure comes from

[7]For each company in our sample, we obtain its associated indexing keywords from LexisNexis database. We then manually match these company names with other data sets. LexisNexis uses a "relevance score" to measure the quality of the match between an article and a company. To capture articles with primary focus on a company, we retain articles with a relevance score of 90% or above, which LexisNexis describes as "major references".

Compustat. Many firms, however, do not provide information on their advertising expenditure. In an effort to maintain sample size, studies in the literature tend to replace missing data with zeros (Grullon et al., 2004; Bank et al., 2011). Since we use natural logarithm of advertising expenditure, we replace the missing figures by $0.01 instead.

2.2.4 Research method

In order to explore investor attention effect on stock liquidity, we combine active and passive measures of attention in the model of Grullon et al. (2004), as follows:

$$\begin{aligned} RBAS = \delta_0 + &\delta_1 LnASVI + \delta_2 LnNews + \delta_3 LnAdvertising\ Expenditure \\ &+ \delta_4 LnFirm\ Age + \delta_5 Return \\ &+ \delta_6 Return\ on\ Assets + \delta_7 LnMarket\ Capitalisation + \delta_{\mathrm{s}} \left(\frac{1}{P_t}\right) \\ &+ \delta_{\mathrm{g}} Turnover + \delta_{10} Volatility + \varepsilon \end{aligned} \tag{2.2}$$

where relative bid-ask spread (RBAS) is regressed against the ASVI, number of newspaper articles, advertising expenditure, and a set of control variables. We hypothesise that stock liquidity improves with increased investor attention, which is particularly prominent for smaller and less known firms, while firms that exhibit high visibility should benefit considerably less from increased investor attention. Hence, we expect to find significantly negative δ_1 in Equation 2.2, that is larger in magnitude for firms belonging to the S&P 600 or S&P 400 indices in comparison to those belonging to the S&P 500 index.

Comparison of mean and median values reveals a common skewness for some of our variables, so we follow the approach suggested by Grullon et al. (2004) and Ring and Hou (2015) and use log-transformations as presented in Equation 2.2. We also include year and month fixed effects to control for the unknown factors that may influence stock liquidity. Our final sample counts 45, 114 monthly observations for the S&P 500 index; 30, 456 monthly observations for the S&P 400 index; and 32, 184 monthly observations for the S&P 600 index.

We define the relative bid-ask spread as the monthly average of the ratio of daily inside spread to the midpoint of daily inside spread. Chung and Zhang (2014) argue that the bid-ask spread is a good alternative for the TAQ-based spread as it accounts for the higher percentage of the cross-sectional variation in stocks. We exclude any observations greater than 50% of the midpoint to filter data from any errors. We then convert daily data into monthly data by taking the average in each calendar month. We replicate the analysis using the relative effective spread and stock turnover to ensure that our results are not specific to the choice of liquidity measure.

We also include a set of control variables that may have an impact on stock liquidity. Specifically, we control for stock turnover as Ho and Stoll (1980) report that high trading volume lowers inventory cost per trade, and accordingly, leads to a smaller bid-ask spread. Therefore, firms that exhibit greater trading activity have higher chance of exhibiting smaller spreads. We also control for the market capitalisation as big businesses generally have high trading volumes and consequently smaller spreads. Since transaction costs may induce investors to stocks within a certain price range, we include the reciprocal value of the stock price. Return volatility and company age proxy for variations in total risk across our sample. We also include return on assets and average monthly return to control for the market performance and profitability. Definitions of all variables are provided in Appendix A.

2.3 Empirical results

2.3.1 Active and passive attention measures

Table 2.2 presents results of the relationship between active investor attention captured by the SVI, and passive attention measures proxied by media coverage and advertising expenditure. News coverage is positively associated with the SVI across all three S&P's indices, suggesting that firms with better visibility in terms of media coverage attract more attention. Advertising expenditure also positively predicts SVI, although it is significant at the 10% level of significance only, across all three groups of stocks.

< Table 2.2 around here >

The coefficients of turnover, return on assets, market capitalisation, and return volatility are positive and significant, implying that firms with good operational efficiency, actively traded securities, large market value, and higher uncertainty draw more attention from individual investors. This is consistent with Seasholes and Wu (2007), who show that riskier stocks enjoy more press coverage and therefore gain more investor attention.

The results presented in Table 2.2 exemplify the difference between active investor attention captured by the SVI and passive investor attention captured by the news coverage and advertising expenditure. In spite of the significance of the regressors, however, the model has a very low explanatory value for all three indices.

2.3.2 Active attention and stock liquidity

In this section we analyse the effect of investor attention on liquidity of stocks belonging to the S&P 500, S&P 400 and S&P 600 indices. We regress the relative bid-ask spread against the active measure of investor attention, passive measures of investor attention, and a set of control variables proposed by the prior literature, as shown in the Equation 2.2. Findings for the S&P 500, S&P 400 and S&P 600 indices are reported in Tables 2.3, 2.4, and 2.5, respectively.

<<< Tables 2.3, 2.4 & 2.5 around here >>>

Model I only includes the active measure of investor attention and a set of control variables suggested by Grullon et al. (2004). Conforming to our hypothesis, coefficient of the ASVI is negative and significant in all three S&P's indices, demonstrating that active investor attention leads to reduction in a bid-ask spread, or simply put, improved liquidity. We also note that the δ_1 coefficient is considerably larger in magnitude for the sample of S&P 600 stocks in comparison to the other two indices. An increase of one standard deviation in abnormal attention leads to a decrease in bid-ask spread by 1.91% for S&P 500 large-cap stocks. This effect is about four times stronger for the S&P 600 small-cap stocks, where one standard deviation increase in ASVI leads to improvement in liquidity of about 6.97%. The attention effect on the mid-cap stocks is also stronger in comparison to the effect on the S&P 500 stocks, validating our hypothesis that stocks of smaller, less known firms, benefit more from increased attention.

We incorporate news coverage and advertising expenditure in models II and III, respectively. The effect of ASVI remains significant with very similar magnitude of coefficients after controlling for the passive attention measures. News coefficient is negative and statistically significant for the sample of large stocks, although much smaller in magnitude compared to the ASVI, implying that S&P 500 index constituents that are widely covered in the press exhibit better liquidity. Nonetheless, the coefficient of news in the sample of S&P 400 and S&P 600 firms is statistically insignificant. Our second measure of passive investor attention, advertising expenditure, is statistically insignificant across all three indices.

Model IV combines both active and passive attention measures along with the set of control variables. We show that effect of ASVI remains similar in magnitude and statistically significant across all three indices, while both of the passive attention measures become insignificant. Our results are also economically significant. The volatility coefficient is positive and significant in all three indices, illustrating that safer firms enjoy better stock liquidity. Older, more profitable, and larger firms within the S&P 500 index have more liquid stocks, while S&P 400 firms with higher stock turnover exhibit improved liquidity.

Overall, our results support the notion that increase in active investor attention leads to an improvement in stock liquidity, and that smaller firms benefit lot more from the raised investor attention in comparison to the larger firms. In line with Da et al. (2011), we note that SVI captures investor attention in a more direct way relative to the passive attention proxies such as media coverage or advertising expenditure. To rule out the possibility that our findings are subject to the choice of liquidity measure, we replicate the analysis using the alternative measures of stock liquidity including relative bid-ask spread, turnover, and Amihud's (2002) illiqudity ratio. Findings are presented in the following section.

2.3.3 Alternative liquidity measures

Liquidity has a number of important elements. Relative bid-ask spread considers the inventory angle. According to the Stoll (1978) and Ho and Stoll (1980), investors buy stocks at the "bid" price that is below the true price, and sell stocks at the "ask" price that is above the true price, in order to offset cost of holding the inventory which creates the bid-ask spread. At the same time, other dimensions of liquidity may not be best captured by the bid-ask spread. For instance, Grossman and Miller (1988) argue that liquidity is defined by the demand and supply of immediacy, that is, willingness to sell rather than wait. Yet, the bid-ask spread does not reflect the cost of supplying immediacy to the market. Kyle (1985) suggests that due to market makers not being able to differentiate between the order flows generated by informed traders and those generated by noise traders, they set prices as an increasing function of the imbalance in the order flow which can indicate informed trading. This leads to a positive relationship between the transaction volume and price change, known as the price impact. Amihud (2002) defines it as the daily price reaction associated with one dollar of trading volume, computed as the daily ratio of absolute return to dollar trading volume, averaged over all positive volume days.

In order to examine whether active investor attention also influences other aspects of stock liquidity such as the price impact, we substitute relative bid-ask spread with the Amihud's (2002) illiquidity ratio. As a robustness check, we also replace the dependent variable with the monthly standard deviation of illiquidity ratio, following Lang and Maffett (2011). We further replicate the analysis by substituting relative bid-ask spread with the relative effective spread, which also considers the inventory angle of stock liquidity, consistent with Grullon et al. (2004). Lastly, we employ turnover as an alternative liquidity proxy following Datar et al. (1998). Regression results of the effect of ASVI on these alternative measures of liquidity for stocks belonging to the S&P 500, S&P 400 and S&P 600 indices are reported in Tables 2.6, 2.7, and 2.8, respectively.

<<< Tables 2.6, 2.7 & 2.8 around here >>>

The regression coefficient of ASVI is statistically insignificant at all conventional levels of significance when regressed on the illiquidity ratio measure and standard deviation of the illiquidity ratio measure, for stocks of all three S&P's indices. These results suggest that while active investor attention can successfully reduce the adverse selection kind of illiquidity, it cannot alleviate the price impact aspect of illiquidity. Amihud (2002) also states that whilst bid-ask spread is a better liquidity proxy, there is no single proxy that grasps all elements of stock liquidity. Moreover, as Da et al. (2011) show, SVI reflects attention of retail investors given that institutional investors take advantage of more sophisticated information vendors such as Bloomberg and Reuters terminals. Considering that average retail investor's trading volume is unlikely to be particularly large, individual trading behaviour may have diminished impact on the stock price reaction to trading.

However, ASVI is negative and highly statistically significant when regressed against relative effective spread across the stocks of all three indices, providing further evidence in support of our findings based on the inventory angle of stock liquidity. Moreover, the effect is largest in magnitude for stocks belonging to the S&P 600 index, conforming to our investor recognition hypothesis. In line with former findings, passive attention measures are insignificant when added to the model. Our findings remain robust when ASVI is regressed on the stock turnover as well.

These empirical results provide evidence in support of the argument that retail investors' active attention positively influences stock liquidity, as measured by the relative bid-ask spread. We also show that impact is particularly strong for stocks of smaller firms, in line with the investor recognition hypothesis. Our results remain robust to alternative liquidity measures including relative effective spread and turnover. While these measures consider the inventory aspect of liquidity, we also address the price impact aspect of liquidity by employing the Amihud (2002) illiquidity ratio measure. We find insignificant relationship between the active retail investor attention and stock illiquidity ratio across our whole sample, suggesting that SVI proxy cannot alleviate the price impact aspect of illiquidity. The underlying reason is likely to be due to the choice of attention proxy, since SVI generally captures attention of individual investors who are unlikely to have outstanding impact on stock prices.

2.3.4 Seasonality of investor attention

Hong and Yu (2009) find that both retail and institutional investors "go fishing'" during the summer, while DellaVigna and Pollet (2009) show that investors exhibit lower attention on Fridays compared to the other days of the week. More recent study by Liu and Peng (2015) examines seasonal patterns of investor attention during the most recent financial crisis, and reports that retail investor attention is significantly lower on Fridays and during the summer months. Hoffmann et al. (2013) note that perceptions and behaviour of retail investors considerably change during the financial crisis, which motivates us to investigate monthly patterns of ASVI following the recent financial collapse. We report the mean and median values of ASVI for each month of the year for all three indices in Table 2.9. The differences are tested using difference of means test and Mood's non-parametric median test.

< Table 2.9 around here >

Table 2.9 reveals that ASVI is consistently higher during the month of July when compared to the ASVI values over the other months of the year, with statistical difference in means of around 3.5% across all three indices. We obtain similar results when testing for the difference in medians. On the flip side, we find that investors are least alert during December, in line with Liu and Peng (2015).

These findings are contrary to findings of Liu and Peng (2015) who argue that investors are inattentive to financial markets during the summer. However, it is worth noting that Hong and Yu (2009) define summer as the third quarter of the year, but emphasise that most investors take summer holidays during the months of August and September rather than July. They arrive at these conclusions by studying the airline passenger travel and hotel occupancy rates over the period defined, showing that their results are mostly driven by these two months. Hence, in the spirit of Hong and Yu (2009), found results are consistent with the "pre-holiday" effect. These findings are in line with those of Lakonishok and Smidt (1988) and Ariel (1990), who explain that investors tend to be most attentive to the markets at times preceding the holiday. We attribute the divergence in our findings from those of Liu and Peng (2015) to shift in retail investors' attention patterns over the post-crisis period.

2.4 Conclusion

Unlike institutional investors who have access to more sophisticated information vendors such as Bloomberg or Reuters terminals, retail investors increasingly search for financial information on Google, which is a worldwide dominant online search engine. We obtain Google's search volume index (SVI) data for stocks belonging to the S&P 500, S&P 400, and S&P 600 indices over the period between

January 2010 and December 2018 to proxy for active retail investor attention, and analyse its impact on the stock liquidity.

We find that increased investor attention leads to improved stock liquidity, as measured by the relative bid-ask spread. We also show that stocks of smaller, or less known firms, particularly benefit from increased attention. Our results remain robust after controlling for the passive measures of investor attention including advertising expenditure and media coverage, following Grullon et al. (2004) and Fang and Peress (2009). We demonstrate that in spite of the SVI being positively correlated with media coverage and advertising expenditure, less than 1% of variation in the SVI can be explained by the passive measures of investor attention. Our findings are robust to alternative measures of liquidity, including relative effective spread and turnover.

However, there are several aspects of liquidity, and relative bid-ask spread addresses the inventory aspect. To analyse other aspects such as the price impact, we replicate the analysis based on the illiquidity ratio measure proposed by Amihud (2002), and measure's monthly standard deviation. Active investor attention proxy is statistically insignificant across all indices when regressed against these liquidity measures, suggesting that it cannot alleviate the price impact aspect of illiquidity. The possible reason lays in the SVI measure which generally captures attention from retail investors. Trading behaviour of average retail investor is unlikely to have an outstanding impact on the stock price, which may explain why active measure of retail investor attention is insignificantly related to the Amihud's (2002) illiquidity ratio.

Finally, we show that investor attention is significantly higher during the month of July. Consistent with our findings, Hong and Yu (2009) show that most retail investors take holidays during the months of August and September. Hence, our results are in line with the "pre-holiday" effect documented by Lakonishok and Smidt (1988) and Ariel (1990), who argue that investors tend to be most attentive to markets at times preceding a holiday. We attribute the divergence in our findings from those of Liu and Peng (2015) to shift in attention patterns over the post-crisis period.

Results of our study provide clear suggestions for firms aiming to encourage investor recognition. Firms may take advantage of investor attention by making their presence more noticeable online, particularly on the search engine such as Google. Our findings may also be beneficial for liquidity traders and other market participants that may gain from more refined models that integrate investor information acquisition behaviour into the forecast of stock liquidity.

Table 2.1: Descriptive statistics

This table reports the summary statistics of our sample which includes constituents of the S&P 500, S&P 400, and S&P 600 indices over the period between January 2010 and December 2018. The ASVI is computed as the difference between weekly SVI and average value of weekly SVI over the previous year skipping the most recent month, scaled by the value of average weekly SVI over the previous year skipping the most recent month. News are defined as the total number of monthly newspaper articles obtained from the LexisNexis database. Advertising expenditure data is gathered from Compustat. Relative bid-ask spread is the monthly average of the ratio of daily inside spread to the midpoint of daily inside spread. Relative effective spread is computed as twice the difference between the transaction price and the spread midpoint scaled by the midpoint of the spread. Turnover is monthly average of share trading volume divided by the number of outstanding shares. Firm age is constructed as the number of years for which the firm has been included in CRSP database. Return is the monthly average of daily stock returns. Return on assets is calculated as the annual operating income before depreciation scaled by total assets. Firm size is the product of total number of outstanding shares and closing stock price. Price inverse is the reciprocal of monthly stock price. Return volatility is a monthly average of the standard deviation of daily stock returns.

	S&P 500			S&P 400			S&P 600		
	Mean	Std.	Median	Mean	Std.	Median	Mean	Std.	Median
Investor attention									
ASVI	-0.003	0.094	0.001	-0.004	0.093	0.004	-0.001	0.093	0.002
Number of news	2, 572	6, 086	864	541	600	394	263	246	196
Advertising expenditure	683	1, 300	207	78	151	23	29	43	13
Liquidity measures									
RBAS	0.034	0.041	0.024	0.055	0.073	0.038	0.124	0.266	0.073
Relative effective spread	0.034	0.041	0.024	0.055	0.073	0.038	0.124	0.266	0.073
Turnover	11.132	10.657	8.274	12.239	11.960	8.866	9.556	9.259	7.050
Firm characteristics									
Firm age	37	23	31	28	17	22	24	15	21
Return	0.053	0.390	0.065	0.057	0.456	0.068	0.063	0.005	0.001
ROA	0.627	0.590	0.466	0.493	0.458	0.389	0.388	0.377	0.282
Firm size	32, 517	58, 987	14, 485	4, 486	5, 168	3, 294	1, 539	2, 404	1, 064
1/Share price	0.029	0.050	0.019	0.041	0.085	0.026	0.060	0.129	0.035
Return volatility	0.016	0.009	0.014	0.019	0.011	0.016	0.022	0.012	0.019

Table 2.2: Active and passive investor attention measures

This table presents results of the extent to which active measure of retail investor attention, measured by the SVI, can be explained by the passive attention measures including media coverage and advertising expenditure, along with the firm characteristics proposed in Grullon et al. (2004). The SVI data is obtained from Google Trends. The number of news is from LexisNexis database. Advertising expenditure data comes from Compustat. Firm age is defined as the number of years for which the firm has been included in CRSP database. Return on assets is constructed as the annual operating income before depreciation scaled by total assets. Firm size is the product of total number of outstanding shares and closing stock price. Return volatility is a monthly average of standard deviation of daily returns from CRSP. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	S&P 500	p-value	S&P 400	p-value	S&P 600	p-value
Ln (News)	0.064***	0.000	0.027**	0.030	0.026**	0.035
Ln (Advertising)	0.017*	0.076	0.011*	0.071	0.010*	0.057
Turnover	0.046***	0.007	0.019*	0.059	0.019*	0.058
Firm age	-0.009	0.195	-0.002	0.683	-0.002	0.790
ROA	0.015	0.674	0.049*	0.072	0.042*	0.063
Ln (Firm size)	0.016	0.391	0.029**	0.045	0.016	0.152
Return volatility	0.044*	0.057	0.021*	0.075	0.015*	0.092
Observations	45, 144		30, 456		32, 184	
$Adj.R^2$	0.012		0.004		0.002	

Table 2.3: Active investor attention and stock liquidity for the S&P 500 index stocks

This table reports estimates from the panel regressions relating the relative bid-ask spread to the active retail investor attention measured by the SVI. The sample includes constituents of the S&P 500 index over the period between January 2010 and December 2018. Relative bid-ask spread is the monthly average of the ratio of daily inside spread to the midpoint of daily inside spread. The ASVI is computed as the difference between weekly SVI and average value of weekly SVI over the previous year skipping the most recent month, scaled by the value of average weekly SVI over the previous year skipping the most recent month. News are defined as the total number of monthly newspaper articles obtained from the LexisNexis database. Advertising expenditure data comes from Compustat. Firm age is constructed as the number of years for which the firm has been included in CRSP database. Return on assets is calculated as the annual operating income before depreciation scaled by total assets. Firm size is the product of total number of outstanding shares and closing price. Price inverse is the reciprocal value of stock price obtained from CRSP. Turnover is monthly average of share trading volume divided by the number of outstanding shares. Return volatility is a monthly average of the standard deviation of daily stock returns. Standard errors are clustered and adjusted for heteroskedasitcity. *, **, and *** represent significance at 10%, 5%, and 1% level of significance, respectively.

	Model I	p-value	Model II	p-value	Model III	p-value	Model IV	p-value
Ln (ASVI)	-0.203***	0.000	-0.203***	0.000	-0.234***	0.000	-0.233***	0.000
Ln (News)	-	-	-0.039***	0.000	-	-	0.023	0.230
Ln (Advertising)	-	-	-	-	0.012	0.200	0.009	0.367
Firm age	-0.064***	0.000	-0.063***	0.000	-0.079***	0.000	-0.079***	0.000
ROA	0.003	0.833	-0.001	0.966	-0.150***	0.000	-0.149***	0.000
Ln (Firm size)	-0.075***	0.000	-0.046***	0.000	-0.103***	0.000	-0.119***	0.000
Price inverse	0.656***	0.000	0.659***	0.000	0.535***	0.000	0.533***	0.000
Turnover	0.071***	0.000	0.079***	0.000	0.126***	0.000	0.122***	0.000
Return volatility	0.145***	0.000	0.143***	0.000	0.074**	0.013	0.074**	0.013
Month effect	YES		YES		YES		YES	
Year effect	YES		YES		YES		YES	
Observations	45, 144		45, 144		45, 144		45, 144	

Table 2.4: Active investor attention and stock liquidity for the S&P 400 index stocks

This table reports estimates from the panel regressions relating the relative bid-ask spread to the active retail investor attention measured by the SVI. The sample includes constituents of the S&P 400 index over the period between January 2010 and December 2018. Relative bid-ask spread is the monthly average of the ratio of daily inside spread to the midpoint of daily inside spread. The ASVI is computed as the difference between weekly SVI and average value of weekly SVI over the previous year skipping the most recent month, scaled by the value of average weekly SVI over the previous year skipping the most recent month. News are defined as the total number of monthly newspaper articles obtained from the LexisNexis database. Advertising expenditure data comes from Compustat. Firm age is constructed as the number of years for which the firm has been included in CRSP database. Return on assets is calculated as the annual operating income before depreciation scaled by total assets. Firm size is the product of total number of outstanding shares and closing price. Price inverse is the reciprocal value of stock price obtained from CRSP. Turnover is monthly average of share trading volume divided by the number of outstanding shares. Return volatility is a monthly average of the standard deviation of daily stock returns. Standard errors are clustered and adjusted for heteroskedasitcity. *, **, and *** represent significance at 10%, 5%, and 1% level of significance, respectively.

	Model I	p-value	Model II	p-value	Model III	p-value	Model IV	p-value
Ln (ASVI)	-0.298***	0.000	-0.297***	0.000	-0.248***	0.005	-0.283***	0.005
Ln (News)	-	-	-0.133	0.147	-	-	0.048	0.584
Ln (Advertising)	-	-	-	-	0.003	0.959	0.002	0.963
Firm age	0.003	0.878	0.002	0.908	0.024	0.482	0.025	0.469
ROA	-0.739***	0.000	-0.788***	0.000	-0.613**	0.048	-0.598**	0.039
Ln (Firm size)	-0.163	0.528	-0.108	0.711	-0.435	0.173	-0.507*	0.075
Price inverse	0.963***	0.000	0.967***	0.000	0.923***	0.000	0.922***	0.000
Turnover	-0.235***	0.000	-0.203***	0.000	-0.301***	0.000	-0.312***	0.000
Return volatility	0.057	0.507	-0.054	0.538	0.288***	0.002	0.290***	0.002
Month effect	YES		YES		YES		YES	
Year effect	YES		YES		YES		YES	
Observations	30, 456		30, 456		30, 456		30, 456	

Table 2.5: Active investor attention and stock liquidity for the S&P 600 index stocks

This table reports estimates from the panel regressions relating the relative bid-ask spread to the active retail investor attention measured by the SVI. The sample includes constituents of the S&P 600 index over the period between January 2010 and December 2018. Relative bid-ask spread is the monthly average of the ratio of daily inside spread to the midpoint of daily inside spread. The ASVI is computed as the difference between weekly SVI and average value of weekly SVI over the previous year skipping the most recent month, scaled by the value of average weekly SVI over the previous year skipping the most recent month. News are defined as the total number of monthly newspaper articles obtained from the LexisNexis database. Advertising expenditure data comes from Compustat. Firm age is constructed as the number of years for which the firm has been included in CRSP database. Return on assets is calculated as the annual operating income before depreciation scaled by total assets. Firm size is the product of total number of outstanding shares and closing price. Price inverse is the reciprocal value of stock price obtained from CRSP. Turnover is monthly average of share trading volume divided by the number of outstanding shares. Return volatility is a monthly average of the standard deviation of daily stock returns. Standard errors are clustered and adjusted for heteroskedasitcity. *, **, and *** represent significance at 10%, 5%, and 1% level of significance, respectively.

	Model I	p-value	Model II	p-value	Model III	p-value	Model IV	p-value
Ln (ASVI)	-0.748**	0.048	0.771**	0.043	-0.661*	0.059	-0.710**	0.048
Ln (News)	-	-	0.531	0.296	-	-	0.967	0.198
Ln (Advertising)	-	-	-	-	0.234	0.354	0.182	0.480
Firm age	-0.322	0.244	-0.341	0.219	0.155	0.773	0.123	0.819
ROA	-0.853	0.381	-0.762	0.409	-0.411	0.591	-0.162	0.665
Ln (Firm size)	0.344	0.569	0.245	0.692	0.577	0.446	0.408	0.603
Price inverse	0.789***	0.000	0.787***	0.000	0.723***	0.000	0.720***	0.000
Turnover	-0.917	0.491	-0.982	0.470	-0.505	0.463	-0.606	0.441
Return volatility	0.751	0.236	0.732	0.244	0.643*	0.095	0.631*	0.097
Month effect	YES		YES		YES		YES	
Year effect	YES		YES		YES		YES	
Observations	32, 184		32, 184		32, 184		32, 184	

Table 2.6: Active investor attention and alternative liquidity measures for the S&P 500 index stocks

This table presents results of the impact of active retail investor attention on the alternative measures of stock liquidity, including the Amihud (2002) illiquidity ratio, its standard deviation, relative effective spread, and turnover. Illiquidity ratio is calculated as the monthly average of daily ratio of absolute stock return to the dollar volume of stock. Following Lang and Maffett (2012) we also compute its standard deviation. In line with Grullon et al. (2004), relative effective spread is defined as twice the difference between the transaction price and the spread midpoint scaled by the midpoint of the spread. Turnover is calculated as the monthly average of share trading volume divided by the number of outstanding shares. Standard errors are clustered and adjusted for heteroskedasticity. *, **, and *** represent significance at 10%, 5%, and 1% level of significance, respectively.

	Illiquidity ratio	*p*-value	Std. Illiq.	*p*-value	Relative effective spread	*p*-value	Turnover	*p*-value
Ln (ASVI)	0.007	0.303	0.008	0.240	-0.220***	0.000	-0.108**	0.013
Ln (News)	-0.046	0.325	-0.037	0.296	0.030	0.258	0.040	0.217
Ln (Advertising)	0.034	0.185	0.025	0.140	0.007	0.324	0.010	0.323
Firm age	-0.034	0.173	-0.025	0.140	-0.108***	0.000	-0.086***	0.002
ROA	-0.052	0.182	-0.047	0.116	-0.144***	0.000	-0.120***	0.004
Ln (Firm size)	-0.032	0.290	-0.024	0.114	-0.127***	0.001	0.099*	0.090
Price inverse	-0.089	0.232	-0.064	0.135	0.677***	0.000	-0.344**	0.011
Turnover	-0.158	0.512	-0.120	0.300	0.155***	0.000	-	-
Return volatility	0.162	0.310	0.105	0.219	0.150***	0.000	0.039***	0.000
Month effect	YES		YES		YES		YES	
Year effect	YES		YES		YES		YES	
Observations	45, 144		45, 144		45, 144		45, 144	

Table 2.7: Active investor attention and alternative liquidity measures for the S&P 400 index stocks

This table presents results of the impact of active retail investor attention on the alternative measures of stock liquidity, including the Amihud (2002) illiquidity ratio, its standard deviation, relative effective spread, and turnover. Illiquidity ratio is calculated as the monthly average of daily ratio of absolute stock return to the dollar volume of stock. Following Lang and Maffett (2012) we also compute its standard deviation. In line with Grullon et al. (2004), relative effective spread is defined as twice the difference between the transaction price and the spread midpoint scaled by the midpoint of the spread. Turnover is calculated as the monthly average of share trading volume divided by the number of outstanding shares. Standard errors are clustered and adjusted for heteroskedasticity. *, **, and *** represent significance at 10%, 5%, and 1% level of significance, respectively.

	Illiquidity ratio	*p*-value	Std. Illiq.	*p*-value	Relative effective spread	*p*-value	Turnover	*p*-value
Ln (ASVI)	-0.324	0.335	-0.596	0.318	-0.250**	0.012	-0.181**	0.047
Ln (News)	-0.084	0.378	-0.170	0.307	0.066	0.372	0.051	0.284
Ln (Advertising)	0.172	0.388	0.342	0.336	0.010	0.748	0.021	0.521
Firm age	0.131	0.310	0.230	0.314	0.041	0.316	0.033	0.112
ROA	0.505	0.531	1.182	0.408	-0.433**	0.021	-0.221	0.216
Ln (Firm size)	-0.061	0.450	0.034	0.810	-0.613*	0.091	0.437	0.346
Price inverse	-0.118	0.255	-0.044	0.579	0.903***	0.000	-0.432	0.418
Turnover	-0.696	0.314	-0.597	0.248	-0.273***	0.000	-	-
Return volatility	0.257	0.264	-0.076	0.848	0.362***	0.000	0.172***	0.000
Month effect	YES		YES		YES		YES	
Year effect	YES		YES		YES		YES	
Observations	30, 456		30, 456		30, 456		30, 456	

Table 2.8: Active investor attention and alternative liquidity measures for the S&P 600 index stocks

This table presents results of the impact of active retail investor attention on the alternative measures of stock liquidity, including the Amihud (2002) illiquidity ratio, its standard deviation, relative effective spread, and turnover. Illiquidity ratio is calculated as the monthly average of daily ratio of absolute stock return to the dollar volume of stock. Following Lang and Maffett (2012) we also compute its standard deviation. In line with Grullon et al. (2004), relative effective spread is defined as twice the difference between the transaction price and the spread midpoint scaled by the midpoint of the spread. Turnover is calculated as the monthly average of share trading volume divided by the number of outstanding shares. Standard errors are clustered and adjusted for heteroskedasticity. *, **, and *** represent significance at 10%, 5%, and 1% level of significance, respectively.

	Illiquidity ratio	*p*-value	Std. Illiq	*p*-value	Relative effective spread	*p*-value	Turnover	*p*-value
Ln (ASVI)	-0.715	0.828	2.006	0.756	-0.597**	0.038	-0.201*	0.076
Ln (News)	0.656	0.767	4.528	0.264	0.832	0.210	0.248	0.319
Ln (Advertising)	0.754	0.208	1.001	0.278	0.202	0.392	0.150	0.274
Firm age	0.133	0.936	2.528	0.467	0.107	0.413	0.082	0.137
ROA	6.568	0.337	23.085	0.139	-0.109	0.367	0.104	0.326
Ln (Firm size)	0.557	0.970	0.359	0.359	0.352	0.244	-0.318	0.409
Price inverse	0.164	0.484	0.508	0.285	0.633**	0.021	-0.230	0.211
Turnover	-4.111	0.451	-2.620	0.804	-0.450	0.309	-	-
Return volatility	-0.295	0.896	-2.973	0.484	0.436*	0.050	0.236*	0.071
Month effect	YES		YES		YES		YES	
Year effect	YES		YES		YES		YES	
Observations	32, 184		32, 184		32, 184		32, 184	

Table 2.9: Patterns in abnormal retail investor attention

This table presents monthly mean and median values of the abnormal active retail investor attention, measured by the ASVI, for the sample of stocks belonging to the S&P 500, S&P 400, and S&P 600 indices over the period between January 2010 and December 2018. In testing the differences in mean and median values, standard errors are adjusted for heteroskedasticity and clustered by date. *, **, and *** indicate significance at the 10%, 5%, and 1% level of significance, respectively.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Diff. (Jul - rest of year)	Diff. (Dec-rest of year)
Panel A: S&P 500 Index														
Mean	1.460	1.153	0.617	0.181	0.201	0.124	3.189	-0.406	-0.173	0.269	-1.813	-8.583	3.823***	-9.020***
Median	1.993	1.100	1.037	0.140	0.315	0.118	2.718	-0.571	-0.256	0.251	-1.896	-8.798	3.315**	-9.248***
Panel B: S&P 400 Index														
Mean	2.214	2.030	0.961	0.173	0.432	0.104	2.911	-0.268	-0.508	0.105	-2.269	-10.540	3.599**	-11.075***
Median	1.573	1.874	1.042	0.702	0.434	0.657	2.956	-0.301	-0.535	0.200	-1.904	-10.997	3.616**	-11.606***
Panel C: S&P 600 Index														
Mean	1.770	1.283	1.080	0.218	0.817	0.429	2.751	-0.156	-1.221	0.321	-1.770	-6.378	3.079***	-6.880***
Median	1.974	1.503	1.349	0.246	1.002	0.979	2.586	-0.202	-1.201	0.210	-1.556	-6.425	2.779**	-7.051***

Chapter3

Investor attention and the S&P 500 pre-announcement index effect

Changes to the Standard & Poor's (S&P) 500 index constituents have long attracted attention owing to their theoretical implications. The pioneering studies of Shleifer (1986) and Harris and Gurel (1986) initiated an extensive literature that uniformly finds a positive abnormal stock return and trading volume immediately after the S&P's announcement of a change. This initial price increase is then followed by at least a partial reversal over the several weeks following the stock inclusion in the index. This anomaly is referred to in the literature as the index effect. Up until 1989, Standard & Poor's followed the practice of changing the composition of the index overnight, where the announcement of the change and the effective change would occur simultaneously. However, beginning October 1989, they began pre-announcing the changes several days ahead of the implementation day. This new announcement procedure resulted in the S&P game, changing the way stock prices react.

In their seminal study, Beneish and Whaley (1996) find that stock prices do not settle as soon as the addition announcement is made public. They show that most index trackers wait to rebalance their positions until the day before the effective change date in an effort to maintain tracking error at a minimum. This in turn creates an opportunity for risk arbitrageurs, who purchase the stocks on the announcement day and sell them at a higher price several days later. Therefore, stock inclusions to the S&P 500 Index are not solely of interest to the index trackers who must rebalance their portfolios, but also risk arbitrageurs who exploit these opportunities.

This paper investigates the S&P game from a new angle, focusing on the immediate pre- as well as post-announcement periods. Beneish and Whaley (1996) overlook the prominent role of leverage unconstrained investors such as hedge funds in the S&P game. Instead of purchasing stock of the new index addition on the announcement day, it can potentially be very profitable to trade in anticipation of new additions. A possible strategy would be to predict the outcome of the index review and purchase stock of firms with high probability of inclusion. By doing so, arbitrageurs exploit the 3% mean price increase that comes with the addition announcement. Before proceeding with the transaction, however, they need to carry out an extensive research to determine likely inclusion candidates. Based on the complexity of capturing all available information, most may use online search engines to look for relevant information.

We explore four questions in this paper. First, we analyse the timing and magnitude of investor attention around the inclusion announcement to determine whether sophisticated investors look for information in an effort to anticipate the identity of new index constituents ahead of it. Information seeking on online platforms captures investor attention in a timely and accurate way: if investors search for a company, they are undoubtedly paying attention to it (Da et al., 2011). Hence, we employ two attention measures: one based on users' search volume on Google platform (SVI), and the novel measure of abnormal institutional attention based on users' news searching and news reading activity on Bloomberg (AIA). If investors predict impending additions, we expect to observe increased search volume for firm-related information in the days prior to the announcement, reflecting increased investor attention. Our findings confirm this, showing that attention to new inclusions increases at least four days prior to the S&P's announcement, and peaks on the announcement day. The abnormal attention effect based on the Bloomberg's AIA measure begins even earlier, demonstrating significantly positive levels a week before the announcement. Bloomberg's AIA measure picking up the effect earlier than Google's SVI confirms that institutional investors have greater resources and higher incentives to quickly react to information. It is also in line with the Ben-Rephael et al. (2017), who find that AIA leads retail attention.

Our second question concerns the implications of pre-announcement attention on trading volumes and stock returns. If hedge funds and other risk arbitrageurs in pursuit of new arbitrage opportunities trigger abnormal attention in the pre-announcement period, we expect to find increased trading volume ultimately leading to price pressure over the same period. We find that trading volume significantly increases ten days ahead of the announcement. Subsequently, stock price begins to increase around five days before the announcement of a new S&P 500 index addition. These results provide novel insights on the index effect, given that current literature considers the announcement day to be the focus of analysis. Findings of abnormal pre-announcement attention, trading volume and return levels put together provide striking evidence in favour of a pre-announcement index effect driven by investor attention.

At the forefront with AQR Capital Management[1], many actively managed funds follow the approach of betting against beta, as suggested by Frazzini and Pedersen (2014). Founded on the idea that betas tend to converge to one, investors are likely to overweight on stocks of index additions that have low betas as they are expected to have increasing betas, and underweight on stocks with high betas. By doing so, they magnify their profits by adding BAB returns on top of the arbitrage profits. We split our sample of firm additions into low and high beta stocks based

[1]AQR, a large hedge fund founded by famed investor Cliff Asness is one of the most well-known funds that employ this strategy. They have constructed market neutral betting against beta factors that can be used to measure this idea (Available at www.acq.com/education).

on their pre-announcement betas and examine pre-announcement effects for the two groups. The results show that our findings are largely driven by low-beta stocks consistent with the BAB approach.

Lastly, we investigate whether the observed effects are permanent or temporary. Abnormal search values measured on both platforms become statistically insignificant shortly after the effective inclusion takes place, in line with attention hypothesis. On the other hand, abnormal volume ratios remain elevated and significant until the end of the post inclusion window, suggesting that investors continue to trade on new information. We note a generally negative trend in the daily levels of abnormal returns following the effective addition which is suggestive of a price reversal. However, cumulative abnormal returns show that although there is some level of price reversal, considerable part of the effect remains positive and highly statistically significant in the twenty days following the firm addition in the index. These permanent effects are suggestive of reversal being a long run process.

This paper sits at the juncture of two literatures, one on investor attention and the other on index effect. To the best of my knowledge, no other study explores investor attention in this framework. We employ a novel measure of abnormal institutional attention (AIA) in order to directly capture attention of sophisticated investors surrounding the event. As Bloomberg terminals are crucial in disseminating news to institutional investors, our paper contributes to the extensive literature linking news media to stock price movements. Using the most recent sample of firm additions to S&P 500 index, we find that contrary to the conventional notion, index effect starts well ahead of the announcement day. Hence, our main contribution comes from the discovery of the media-driven anticipatory effects.

The rest of the chapter proceeds as follows. Section 3.1 reviews the literature and development of hypotheses. Section 3.2 describes the data. Section 3.3 outlines the methodology. Empirical results are discussed in Section 3.4. Section

3.5 summarises and concludes.

3.1 Related literature

Interest in index revision effects has been increasing concurrently with the growing use of stock indices as benchmarks. Shleifer (1986) and Harris and Gurel (1986) were the first to note that stock returns of firms added to the S&P 500 index jump on average around 3% on the day after the announcement, followed by abnormal levels of trading volume. The initial price increase is subsequently followed by a partial reversal over the several weeks following the inclusion. Literature also documents that stocks added to the S&P 500 index display subsequent increases in their beta coefficients. These synchronised beta changes are referred to as comovement. In general, existing literature can be grouped into two categories: studies that aim to provide an explanation by focusing on the stock returns and trading volumes, and those that explore risk measures.

Considering that index effect cannot be addressed in the efficient market framework, the first group of studies attempts to explain price and volume effects by advancing alternative hypotheses.[2] Five competing hypotheses have been proposed thus far, including the price pressure hypothesis, imperfect substitutes hypothesis, index certification hypothesis, improved liquidity hypothesis, and investor awareness hypothesis. One important difference between them relates to the question of whether the effect on stock price and trading volume is deemed to be temporary or permanent. Table 3.1 illustrates characteristics of each hypothesis.

< Table 3.1 around here >

Harris and Gurel (1986) find that additions result in an increase in stock prices that fully reverses within two weeks of the revision effective date. Along

[2] As stated by the S&P 500 index committee, changes in the S&P 500 index composition do not carry any new information regarding the prospects of the underlying stock. Hence, changes in index constituents should not trigger any volatility in stock price.

with the price effect, they find a similar temporary increase in trading volume for stocks added to the index. They propose the price pressure hypothesis to explain these temporary effects. The underlying principle behind the theory is that investors who provide market liquidity without having any incentive to trade ought to be remunerated in a form of a premium, which accounts for added expenses and risk of these trades. Following the event period, prices revert back to the long run equilibrium level. However, many studies challenge the full reversal and find at least a portion of the stock price effect that is permanent and therefore unexplained by the price pressure hypothesis.[3] Dhillon and Johnson (1991) suggest that disagreement may be due to their findings being specific to the method of risk adjustment they employ.

In a seminal study, Shleifer (1986) pioneers the imperfect substitutes hypothesis predicting a permanent stock price effect. According to this hypothesis, changes in index constituents give rise to abnormal demand for stocks given that index funds have to purchase (sell) stocks that are added (removed) to the index in order to minimize the tracking error. The only condition under which this excess demand can be met without causing a change in the price is if stocks have perfect substitutes. Hence, in the absence of alternative explanation, Shleifer (1986) concludes that stocks belonging to the S&P 500 index do not have perfect substitutes and have downward-sloping demand curves in both short and the long run, in contrast to the price pressure hypothesis which assumes a downward sloping demand curve only in the short run. In other words, Shleifer's (1986) theory states that stock prices shift to wipe out excess demand and no reversal is expected in the long run.[4]

Shleifer's (1986) seminal study predates the S&P's practice of pre-announcing changes to the S&P 500 Index which began in 1989. The first to examine the

[3]Studies by Arnott and Vincent (1986), Dhillon and Johnson (1991), Lynch and Mendenhall (1997), Malkiel and Radisich (2001), and Madhavan (2003) all find partial support for the price pressure hypothesis. Elliott and Warr (2003) document price pressure but solely around the effective day of the stock inclusion.

[4]Shleifer (1986) defines long-run window as only ten days following the effective change date for the early period sub-sample in his study.

impact of the new announcement policy were Beneish and Whaley (1996), who find that stocks added to the Index experience positive abnormal returns between the announcement date and effective change date. They find abnormal return effect to be only partially revered after the change is made, which they ascribe to the price pressure of risk arbitrageurs that purchase stocks ahead of the index funds. In a similar manner, Lynch and Mendenhall (1997) find significant but minor stock return reversal. Further support for the imperfect substitutes hypothesis comes from Wurgler and Zhuravskaya (2002) who argue that stocks included in the S&P 500 do not have perfect substitutes and investors who engage in arbitrage expose themselves to certain amounts of risk; Blume and Edelen (2004) who show that index managers are unlikely to front run index changes as they seek to minimise tracking error and are inclined to purchase stocks on the inclusion day; and Kaul et al. (2000) who report results consistent with this theory but based on the stock value changes in response to the re-weighting of the Toronto Stock Exchange 300 Index.[5]

Dhillon and Johnson (1991) present results that are inconsistent with both price pressure and imperfect substitutes hypotheses, proposing the alternative certification hypothesis. They show that firm inclusion in the S&P 500 affects not just the stock price, but also the price of its bonds and options. Since stocks and bonds are imperfect substitutes, their findings suggest that firm's addition to the Index conveys new affirmative information.[6] Denis et al. (2003) provide further support in this view, showing that firm addition to the S&P 500 flags positive prospects and potential for prolonged existence on the market, or industry as a whole. They demonstrate that inclusion results in a greater scrutiny of management, which increases effort and cost of managerial reputation should the status of inclusion be lost. Their results show that stocks of newly added firms

[5]This hypothesis is also supported by evidence from other US indices such as the Russell 2000 Index Biktimirov et al. (2004), the TSE 300 index Chung and Kryzanowski (1998), the FTSE 100 index Mase (2007), and the ISE-100 and ISE -300 indices Bildik and Gülay (2008).

[6]This is contrary to the S&P's claims that their potential candidate considerations are purely based on the analysis of the information open to the public.

experience upward revisions in earnings estimates.

Mikkelson and Partch (1985) and Amihud and Mendelson (1986) propose the improved liquidity hypothesis under which stocks of firms added to the S&P 500 index become cheaper for investors, given that increased liquidity reduces transaction costs and attracts more interest from investors. Hence, firm inclusion guarantees a permanent increase in stock's liquidity, leading to permanent increase in price and trading volume.[7] By the same token, stocks removed from the S&P 500 index experience decline in liquidity over the three months following the deletion. Various other studies find similar patterns that they attribute to improved liquidity including Edmister et al. (1996), Erwin and Miller (1998), and Hegde and McDermott (2003) among others.

Investor awareness hypothesis or "shadow cost" falls under the Merton's (1987) framework, which states that investors hold incompletely diversified portfolios in segmented markets. Chen et al. (2004) develop this hypothesis where firm's addition to the S&P 500 index alerts investors to its existence.[8] Their findings are inconsistent with the previous explanations of the index effect as they uniformly find symmetric price responses. Chen et al. (2004) find that changes in investors' awareness are asymmetric, as there is an increased investor awareness for index additions, but a relatively smaller decrease in awareness for index deletions. In other words, investors do not become unaware of the stock following its deletion from the index.[9]

Index effect may also be explained through attention hypothesis proposed by Odean (1999). He suggests that investors shape their decisions on attention-

[7] On the flip side, however, some may argue that indexing can contribute towards the reduction in stock liquidity as index funds are passive buy-and-hold investors and decrease in the accessible float can negatively influence stock liquidity.

[8] According to CAPM, investors hold stocks in their portfolios in the same ratio as they appear in the market portfolio and therefore diversify away any non-systematic risk. According to Merton (1987) investor recognition theory, however, investors only hold a subset of stocks they are aware of and require a premium for non-systematic risk they are exposed to.

[9] Investor awareness hypothesis is the only theory that explains asymmetric changes in stock price and trading volume, as all the other theories assume symmetric change for stock additions and deletions. Chen et al. (2004) state their key finding is that deletions are not associated with a permanent excess return. However, given that their deletion sample is quite small (62 deletions), some may argue that their findings are questionable.

grabbing stocks simply because they do not have the ability to evaluate all available stocks during their investment process. Although they do not purchase every stock that catches their attention, for the most part they purchase the stocks that do. Analysing investor trading behaviour using media coverage, abnormal trading volume and returns as proxies for attention, Barber and Odean (2008) confirm the attention hypothesis. Hence, although no prior study directly tests this hypothesis in the framework of index additions, it is plausible to believe that positive abnormal returns may be triggered by increased investor attention. We contribute to this gap in the literature by being the first to directly test investor attention hypothesis in the context of S&P 500 index additions.

The second major group of studies in the literature focuses on explaining the index effect through stock betas and comovement. On the whole, comovement literature agrees that stocks added (deleted) from the S&P 500 index experience subsequent increases (decreases) in their beta coefficients. In his seminal paper, Vijh (1994) reports that stock betas increase upon their inclusion in the index, at both daily and weekly frequency over the full sample period. However, decreasing betas during a sub-sample period suggest that stock betas do not consistently increase following the index addition. Barberis et al. (2005) find significant beta increases for stocks added to the S&P 500, arguing that non-fundamental factors explain the effect better than fundamental factors.[10] Kasch and Sarkar (2011) similarly document significant increases in beta following addition to the index. Chen et al. (2016a) report further increases in betas following the addition, that holds over their full sample period, based on the increasing beta assumption for added stocks. They show that different trading strategies may trigger changes in stock betas by impacting demand for specific stocks in the index.

[10]Barberis et al. (2005) distinguish between two views on return comovement: traditional view, which holds that comovement in prices, reflects comovement in fundamental values; and alternative behavioural finance view in which frictions or sentiment delink it from fundamental values.

3.1.1 Hypothesis development

An extensive literature on the index effect considers the announcement day to be focus of observed anomaly. This assumption overlooks the prominent role of ever-growing hedge funds and other unconstrained investors in the S&P game. They are inclined to trade in markets where temporary deviations of prices from fundamentals are large and enter and exit trades as pricing and liquidity shifts (Aragon and Strahan, 2012). Therefore, it is plausible to assume that they are incentivised to purchase some of the new index addition stocks ahead of the announcement, exploiting the 3% mean price increase that comes with the announcement. In contrast to existing studies, we also consider the period preceding the announcement day to address this question.

Investors need to analyse a variety of information including firm and industry analysis, analyst forecasts, technical analysis, or rumours in the financial media in order to determine most likely candidates for inclusion. Most will resort to online search engines such as Google or Bloomberg to look for relevant information, or they can use machine learning to identify potential addition candidates. Formally, we hypothesise:

H1: Attention to new index addition stocks begins to increase ahead of the S&P's announcement reflecting investors' increased search for firm related information in an effort to anticipate identity of new additions ahead of the event.

Upon collection of relevant information, investors should begin to purchase stocks of new index additions. This should consequently influence stock price movements ahead of the announcement of firm inclusion to the S&P 500 index. It follows that:

H2: New index additions should exhibit abnormal levels of trading volume and price increases ahead of the announcement day.

Existing studies generally focus on index trackers who account for the majority of institutional investors. However, the latter are unconstrained investors including hedge funds and other risk arbitrageurs, likely to employ completely different strategies. Specifically, many hedge funds can follow statistical arbitrage by taking a long position in low beta stocks and short position in high beta stocks, on the presumption that stock betas converge towards one. Betting against beta (BAB) investment strategy, developed by Frazzini and Pedersen (2014), builds on the idea that defensive stocks should experience increasing betas and aggressive stocks should produce decreasing betas. Therefore, unconstrained investors may overweight on index additions that exhibit low beta stocks ($\beta < 1$) and underweight on those with high beta stocks ($\beta > 1$), based on their historical betas. In doing so, they earn the BAB returns as well as taking advantage of the mean price increase that comes with the S&P's announcement of additions. It follows that excess demand for the low beta stocks would mainly drive the return effects in the period preceding the announcement in our sample. By contrast, there should be far less price pressure for the high beta stocks added to the S&P 500 index. Our average abnormal returns should reflect these two trends. We hypothesise:

H3: Leverage unconstrained investors will overweight on low beta stocks, driving most of the pre-announcement effects, and underweight on high beta stocks.

Lastly, we explore persistence of effects following the effective firm inclusion in the S&P 500 index. In line with attention being a scarce cognitive resource, we expect temporary abnormal search levels surrounding the firm addition to the S&P 500 index. At the same time, return and volume effects are more likely to be permanent given that they begin from a lower (pre-announcement) base level than those in the existing literature. Moreover, investor attention increases upon firm's addition to the S&P 500 due to greater coverage from analysts, media, and other financial intermediaries, leading to permanently elevated trading volumes and returns. In other words:

H4: Cumulative abnormal return and trading volume effects are more likely to be permanent for low beta index additions.

3.2 Data

This section briefly describes the S&P 500 index, its selection rules, the sample selection process, data sources, and some basic features of our final sample.

3.2.1 The S&P 500 index

To carry our analysis, we employ one of the most frequently referenced indices in the world, the S&P 500 index. Established in 1957, the S&P 500 was the first US market cap-weighted index. It was designed to measure the performance of the domestic economy through changes in the aggregate market value of 500 stocks, representing all major industries.

Changes in the constituents of the S&P 500 index are generally prompted by the need to delete a company. The most common reasons for company deletion from the index are event-driven, such as mergers, acquisitions, bankruptcies, spin-offs, suspension of trading, and similar corporate events. In addition to these involuntary deletions, stocks may also be deleted from the index when they represent an industry that is declining in importance or when a stock is no longer appropriate representative of an important industry. Hence, in order to maintain 500 stocks in the index, company additions are generally announced along with the deletions.

Up until 1989, Standard & Poor's followed the practice of changing the composition of the index overnight, where the announcement of the change and the effective change would occur simultaneously. However, beginning in October 1989, Standard & Poor's began their practice of pre-announcing the changes several days ahead. This new policy reveals the identity of the companies to be added and removed from the index in addition to the dates on which the changes will become effective. They can be made at any time and are usually announced around one to five days before they are implemented. When picking a candidate company for the inclusion in the index, however, Standard & Poor's follows criteria that may be somewhat subjective and not strictly enforced. For instance, according to the Standard & Poor's, a good company candidate must have sufficient liquidity, be profitable, be leader in an important industry, and its ownership must not be focused on a single or few entities.

3.2.2 Sample construction

The primary data sources used in this paper are Standard & Poor's directory, CRSP database, Google's service Google Trends, and the Bloomberg terminal. The Standard & Poor's directory is the key source for the announcement and effective dates of stock inclusions to the S&P 500 in our sample. Data on daily closing prices, stock trading volumes, and S&P 500 index trading volume come from CRSP database. Blomberg and Google platforms provide data used to construct measures of attention.

This study considers the sample period between January 2004 and December 2018. The start date is dictated by the fact that Google attention data became available from January 2004 onwards. Standard and Poor's provides the complete list of firm additions to the S&P 500 index over this period. We remove firm additions that occurred due to mergers, spinoffs, and corporate restructuring. In addition, to estimate abnormal returns and betas we require that any firm added to the index has at least 250 trading days available pre- and post- announcement date. These requirements, along with the data availability, produce a final sample of 287 firm additions, comparable to Shleifer's (1986) sample size. Table 3.2

presents the distribution of our sample according to the year addition took place and industry that firm belongs to.

< Table 3.2 around here >

On average, our sample yields 17 firm additions each year. The year that boasts most index additions was 2007, while most index inclusions come from manufacturing industry. Standard & Poor's generally announces index changes up to five days before they become effective. The mean and median number of days between the announcement and effective day in our sample is three. Our event window goes from 20 days prior to the announcement [AD-20] to 20 days after the date of change coming into effect [ED+20]. It is worth mentioning that existing studies provide different definitions of the post-inclusion windows. For instance, Shleifer (1986) defines the long-run window as ten days following the effective change date, while Harris and Gurel (1986) define it as two weeks following the announcement.

3.3 Research methods

We investigate stock return, trading volume, and attention effects in an event study framework. Following Lynch and Mendenhall (1997), we employ two event dates: the announcement date [AD], when the first official announcement is made by Standard and Poor's regarding the upcoming addition, and the effective change date [ED], when the addition effectively comes into place. This section describes the research design.

3.3.1 Abnormal returns

In line with the previous research, we use closing stock prices to calculate daily returns. To estimate abnormal returns various methods have been suggested in the literature including the simple model, market model, 3-factor model, and many others.[11] We employ the most widely used, market model, with the following linear specification for any security i at time t:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{it} \tag{3.1}$$

The model builds on the actual returns of a reference market and the correlation of company's stock with it. Therefore, abnormal return denotes the difference between the actual stock return ($R_{i,t}$) and the expected return on any given day. This is estimated based on two inputs: typical relationship between the company's stock and its reference index (showed by the α and β parameters), and the actual return on the market i.e. S&P 500 index ($R_{m,t}$). Simply put, abnormal return for each stock is given by:

$$AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t} \tag{3.2}$$

Following MacKinlay (1997), we choose estimation window of 250 trading days starting 270 days prior to the announcement date and ending 21 days before the announcement to estimate model parameters. Coefficient estimates over the estimation window together with the S&P 500 index returns are employed in Equation (3.2) to calculate abnormal returns. Abnormal returns are then averaged across all stocks in the sample to calculate average abnormal return (AAR_t) for each day t of the event window, as follows:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{3.3}$$

For testing $H_0 : AAR = 0$, the test is given by:

$$t_{AAR_t} = \frac{AAR_t}{\sigma_{AAR_t}}\sqrt{N} \tag{3.4}$$

where σ_{AAR_t} is the standard deviation across firms at time t:

[11]Brown and Warner (1985) and Shankar and Miller (2006) argue that more complicated models have not significantly improved upon the simple model.

$$\sigma^2_{AAR_t} = \sum_{i=1}^{N}(AR_{i,t} - AAR_t)^2 \frac{1}{N-1} \tag{3.5}$$

Abnormal returns are compounded to cumulative abnormal returns (CARs), which are then averaged across all stocks in the sample to calculate cumulative average abnormal returns (CAARs), as follows:

$$CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i \tag{3.6}$$

For testing $H_0 : CAAR = 0$, the test is given by:

$$t_{CAAR} = \frac{CAAR}{\sigma_{CAAR}}\sqrt{N} \tag{3.7}$$

where σ_{CAAR} is the standard deviation of the cumulative abnormal returns across the sample:

$$\sigma^2_{CAAR} = \sum_{i=1}^{N}(CAR_i - CAAR)^2 \frac{1}{N-1} \tag{3.8}$$

3.3.2 Abnormal trading volumes

Abnormal volume performance is estimated using volume ratios, a method also employed in the seminal work of Harris and Guerl (1986) and Beneish and Whaley (1996). To avoid biases or inflated volume figures due to potential market anticipation, we first produce base volume ratios for each stock added to the index (BVR_i), by estimating the average stock to S&P 500 index volume ratio over the 60 days estimation window, that starts 80 days before the announcement and ends 21 days before the announcement:

$$BVR_i = \frac{1}{60}\sum_{AD-80}^{AD-21} \frac{V_{i,t}}{V_{m,t}} \tag{3.9}$$

We then compare these figures to daily stock to index trading ratios, as follows:

$$VR_{i,t} = \frac{V_{i,t}}{V_{m,t}} \div BVR_i \tag{3.10}$$

where $V_{i,t}$ and $V_{m,t}$ are trading volumes of each individual stock and S&P 500 index at the day t of the event window, respectively. The volume ratios are then averaged across all stocks in the sample to calculate average volume ratios AVR_t for each day t of the event window, as follows:

$$AVR_t = \frac{1}{N}\sum_{i=1}^{N} VR_{i,t} \tag{3.11}$$

The null hypothesis is that the AVR_t equals to one. If average volume ratio is significantly higher than one (lower than one) on any given day, it is an indication that trading volume on that day is significantly higher than usual (lower than usual). The significance of AVR_t is measured by the t-mean test defined as follows:

$$t_{AVR} = \frac{AVR}{\sigma_{AVR}}\sqrt{N} \tag{3.12}$$

3.3.3 Abnormal attention

We employ two measures of active investor attention. The first one is based on the aggregate search volume index (SVI) provided by Google, measuring retail investor attention; while latter is based on user news searching and news reading activity on Bloomberg terminal which measures institutional attention. The following sections describe the construction of both measures.

3.3.3.1 Google abnormal attention (ASVI)

Google's search engine is a widely utilised information gathering platform, with many firms counting on being highly ranked in their search results to attract attention from potential investors. Google's service Google Trends provides data on the number of times a specific term is searched for on Google, using a standardised scale of 0 to 100, 100 being the maximum search volume over the selected period. This measure is known as the Search Volume Index (SVI).[12]

We start our analysis using daily Google search data. Vlastakis and Markellos (2012) and Bijl et al. (2016) conclude that firm name searches have a stronger relationship to financial markets than ticker searches. Accordingly, we collect daily raw SVIs on the basis of firm names in our sample. Raw SVIs are then used to compute abnormal SVI (henceforth ASVI). We first calculate the baseline level of attention for each stock over the period of 250 trading days, skipping the most recent 20 days relative to the announcement day to avoid potential spillover effects in attention:

$$Baseline\ Attention_i = \frac{1}{250}\sum_{AD-270}^{AD-21} SVI_i \tag{3.13}$$

We consider this baseline level of attention to reflect the normal amount of attention each company gets on average. We then compare daily SVI values to these values in order to calculate ASVI, as follows:

$$ASVI_{i,t} = \frac{(SVI_{i,t} - Baseline\ Attention)}{Baseline\ Attention} \tag{3.14}$$

where $ASVI_{i,t}$ measures the deviation of attention from the normal level, as a percentage, and any potential time trends. For instance, an $ASVI_{i,t}$ value of 10% suggests that search interest on a particular day is 10% greater than its previous year's average. $ASVI_{i,t}$ is then averaged across all stocks to calculate average abnormal search volume index (AASVI) for each day t of the event window, as follows:

$$AASVI_t = \frac{1}{N}\sum_{i=1}^{N} ASVI_{i,t} \tag{3.15}$$

Under the null hypothesis, $AASVI_t$ equals to zero. The significance is measured as follows:

[12]More information on Google measure of attention is provided in the paragraph 2.1.1. and 2.2.2.

$$t_{AASVI} = \frac{AASVI}{\sigma_{AASVI}}\sqrt{N} \tag{3.16}$$

3.3.3.2 Bloomberg abnormal attention (AIA)

The Bloomberg terminal operates as a single point of information distribution for many professional investors. Bringing together a variety of user-friendly features including newsfeed, analyst recommendations, valuation and monitoring tools, and many others made it a one-stop-shop for the vast majority of sophisticated investors. A search of terminal users' profiles reveals that around 80% work in financial industry services. Furthermore, unlike the Google search engine that is open to the public, Bloomberg terminal licence comes with a hefty price tag. Based on the above arguments and tending to directly measure attention of sophisticated investors, Ben-Rephael et al. (2017) propose a novel measure based on news searching and news reading user activity on Bloomberg terminal.

Bloomberg records the number of times users actively search for news as well as the number of times users read news articles regarding a particular stock. Putting more significance on deliberate news seeking, Bloomberg assigns a score of ten when users search for news and one when users read a news article. These scores are then aggregated into hourly counts which Bloomberg uses to create a numerical attention score each hour. This is done by comparing the mean hourly count over the previous eight hours to all hourly counts over the previous month for a particular stock. A score of 0 is given if the rolling average is in the lowest 80% of the hourly counts over the previous thirty days. Likewise, scores of 1, 2, 3 or 4 are given if average is between 80% and 90%, 90% and 94%, 94% and 96%, or higher than 96% of the previous thirty days' hourly counts, respectively. We refer to this measure as the abnormal institutional attention (AIA).[13]

Ben-Rephael et al. (2017) show that Bloomberg and Google attention measures are positively correlated, although they weakly explain each other's vari-

[13] Further information on this measure and how it compares to Google attention measure is provided in chapter 4.2.1.

ation. Although we acknowledge that AIA rather than ASVI is more likely to capture the attention of institutional investors, Bloomberg provides data that includes transformed measures of news reading and news searching activity starting February 2010. Hence, based on data availability, we are able to examine cross-sectional AIA for 150 index additions which is slightly over half of the companies in our sample. Considering that AIA is an ordinal variable taking values of 0 to 4, we test for difference in medians using the non-parametric Wilcoxon signed-rank test. To test for the presence of abnormal attention, we compare daily levels of AIA to the levels of AIA during the estimation period [-21, -250].

3.4 Empirical results

The main focus of this study is on the period preceding the S&P's announcement of firm addition to the index, during which we investigate the timing and magnitude of attention, trading volumes, and stock returns. We refer to these as the pre-announcement S&P 500 index effects. In the second part, we explore the post inclusion effects.

3.4.1 Pre-announcement effects

We consider two different event dates surrounding the addition to the S&P 500 index: the announcement day (AD), and the day when change effectively takes place (ED). The extant literature considers the announcement day to be the focus of the index effect. By contrast, our primary focus is on the period preceding the announcement day in order to explore possible anticipatory patterns of the documented anomaly. Hence, we first analyse pre-announcement effects during the period that ranges from 20 days before the announcement (AD-20) to the effective inclusion day (ED). Table 3.3 reports daily values of AASVI and AAIA for our full sample of firm additions during this window.

< Table 3.3 around here >

Both measures indicate that attention to firms reaches its peak on the announcement day. AASVI is highly statistically significant, with nearly 70% of firms in the sample experiencing increased attention on the day. Similarly, results of the Wilcoxon sign-rank test strongly reject the null in favour of significantly higher median values of AAIA on the announcement day in comparison to the AAIA levels over the estimation window. Following the announcement day, the two measures generally mirror each other: they are both positive and highly statistically significant, suggesting that the announcement of firm addition to the index attracts investor attention in the days that follow it as well. However, the dynamics between the two measures slightly differ over the period preceding the announcement.

We find that AASVI is positive and statistically significant in 4 days prior to the announcement, monotonically increasing from 3% on day -4 to 11% on the pre-announcement day. During these days, close or more than 60% of firms in our sample experience abnormally high attention. These results reflect intensified search for firm related information in advance of addition announcement, which suggests that investors anticipate likely candidates for inclusion to the S&P 500 index. As we hypothesise, collection of relevant information and thorough research is of vital importance to investors, considering that successful arbitrage outcome depends on the correct speculation of new additions. What is more, levels of AAIA are significantly higher 7 days ahead of the announcement, preceding the abnormally higher levels of AASVI by 3 days. These findings present evidence that AIA leads attention measured by Google's SVI, affirming that institutional investors have greater resources and higher incentives to react rapidly to information. Nevertheless, post-announcement attention levels confirm that the two measures are positively correlated. Considering that cross-sectional significant increase in attention during the pre-announcement period must be caused by a high number of platform users, our novel findings reveal investors' increased interest in firms about a week before announcement of their addition to the S&P

500, implying investor anticipation.

In view of the significant pre-announcement abnormal attention effects, we proceed to examine daily levels of cross-sectional trading volume ratio, abnormal returns, and cumulative abnormal returns during the pre-announcement window. We predict that investors begin to purchase stocks of the likely additions ahead of the announcement, subsequently impacting stock prices. Table 3.4 reports daily average volume ratios (AVRs), average abnormal returns (AARs), and cumulative average abnormal returns (CAARs) during the pre-announcement window.

< Table 3.4 around here >

On the announcement day, 92% of firms in our sample experience increased trading activity with the average volume ratio more than doubled, revealing a common surge in trading volume. Similarly, AAR is 2.65% with more than 80% of firms exhibiting positive announcement day abnormal return. Positive and highly statistically significant abnormal volumes and returns on the announcement day are in line with the existing literature on index effect, evincing an increased stock demand for newly announced firm additions, subsequently leading to increase in stock price. Between the announcement and effective addition days, average abnormal trading volume is persistently positive and highly statistically significant although considerably smaller in magnitude compared to the announcement day level, demonstrating that investors slowly begin to rebalance their positions following the announcement. However, as reported by Beneish and Whaley (1996), index trackers postpone the greater majority of their position rebalancing until the day before the effective change day in order to minimise tracking error. All firms in our sample experience positive abnormal trading volume on this day, with volume ratios being more than 15 times greater in size than normal. This conforms with the findings of Hegde and McDermott (2003) who also find trading volume to be approximately 15 times higher on the day preceding the effective change in index constituents. Kappou et al. (2010) show that volume levels on the day before effective change were almost 16 times higher than normal, with most trading activity concentrated towards the last five minutes of the trading day, suggesting that index trackers are more concerned with tracking error than with firm performance during the event window.

It is interesting to compare figures of trading volume during the rebalancing period with those for AARs over the same time. In particular, it is worth noting that although trading volume reaches its peak on the day preceding the effective inclusion, cross-sectional abnormal return on the same day is statistically insignificant. This may be attributed to the fact that leverage unconstrained investors like hedge funds take on role of liquidity providers taking long and short position trades as pricing and liquidity dynamics change. Specifically, vast buying pressure resulting from index trackers on the day preceding the effective inclusion leads to a positive price effect. However, hedge funds and other risk arbitrageurs sell off most of their holdings as a part of strategy to satisfy the increased demand, ultimately offsetting the positive price effect. Accordingly, this results in culmination in trading volume and insignificant abnormal returns on the day preceding the effective index change.

Our main findings, however, come from the period preceding the announcement. Contrary to the conventional understanding, our results show that index effect starts well ahead of the announcement day. In particular, we find weakly statistically significant levels of abnormal trading volumes commencing 10 days ahead of the announcement, during which more than 40% of firms display abnormal trading activity. The abnormal trading volume then drastically increases, displaying highly statistically significant levels of AVR with close or more than 50% of firms manifesting abnormal trading activity during the 5 days prior to the announcement. We should highlight that while AIA measure leads Google attention measure by several days and directly captures attention of sophisticated investors, we could only obtain it for half of firms in our sample. Hence, one may argue that attention effect would reveal itself even earlier if we had the AIA measure for our full sample of index additions. Together with findings of pre-event buying, these patterns likely reflect arbitrage motivated trading of unconstrained investors such as hedge funds and other arbitrageurs, as a part of their S&P game strategy.

The implication of the pre-announcement trading is that the stock price of new additions begins to increase ahead of the announcement day. We find positive and statistically significant AARs that are monotonically increasing from five days before the announcement, in the course of which around 60% of firms generate positive abnormal returns. CAARs cumulated over the window [AD-20, ED] pick up the effect slightly earlier, showing significant positive levels week before the announcement. These results provide novel insights on the anomaly, taking into account that current literature considers the announcement day to be the focus of index effect. Findings of abnormal pre-announcement attention, trading volume and return levels put together provide striking evidence in favour of the pre-announcement index effect.

Sophisticated investors may further magnify their arbitrage profits by taking advantage of stock beta as a self-correcting process that tends to mean revert towards one (Frazzini and Pedersen, 2014), and particularly overweight on likely candidates for inclusion that exhibit defensive betas prior to their addition. Given that these stocks are likely to experience increasing prices following inclusion, together with the demand coming from index trackers, they will be particularly fruitful for risk arbitrageurs. By contrast, candidates with pre-addition aggressive betas are expected to have decreasing prices, so there will be far less pressure for these added stocks. We employ CAPM to estimate historical betas using a year worth of daily data before the S&P's announcement, skipping the most recent 20 days. We then divide our firms into low beta ($\beta < 1$) and high beta ($\beta > 1$) stocks, and examine the pre-announcement abnormal attention, volume, and return levels. Table 3.5 reports attention based on Google and Bloomberg measures for the sub-samples of defensive and aggressive stocks over the pre-announcement window.

< Table 3.5 around here >

While attention patterns on the announcement day and the days that follow manifest similar trend in defensive and aggressive stocks, slight advantage goes to high-beta stocks when it comes to pre-announcement abnormal attention. The AASVI of defensive stocks is positive and significant three days ahead of the announcement, while the effect begins a day earlier for aggressive stocks. Consistent with prior findings, the institutional attention measure leads the Google attention measure for both groups of stocks. Results of the Wilcoxon sign-rank test strongly reject the null in favour of significantly higher AIA medians over the five days ahead of the announcement for defensive stocks, and seven days ahead of the announcement for aggressive stocks. However, the positive difference in AIA medians for aggressive stocks is only weakly statistically significant on days -7 and -6. Overall, one possible reason for high beta stocks enjoying marginally higher attention in the pre-announcement period may be due to them being glamour stocks. We then calculate abnormal volume ratios and returns based on the two groups over the pre-announcement window and present results in Table 3.6.

< Table 3.6 around here >

The two groups' trading volume and abnormal return effects are comparable in size on the announcement day, as well as in the days that follow, with a slight advantage in favour of the low beta stocks. However, there are some striking differences in the days preceding the announcement. Low beta stocks' volume ratio becomes positive and weakly statistically significant beginning day -10, gradually increasing and reaching higher statistically significant levels six days ahead of the announcement. By contrast, aggressive stocks' volume ratio levels display positive significant levels considerably later. Precisely, high beta stocks' volume ratio becomes weakly significant five days ahead of the announcement, monotonically increasing and reaching higher statically significant level at day -2. Accordingly, defensive stocks AARs are positive and statistically significant five days ahead of the announcement, while aggressive stocks abnormal returns significantly increase only two days before the announcement.

Splitting the sample into high and low beta firms clearly demonstrate that our pre-announcement trading volume and abnormal returns are mostly driven by defensive beta stocks, while aggressive beta stocks trigger later and far less prominent effects. These results support our hypothesis that investors bet against beta as a part of their arbitrage strategy, following Frazzini and Pedersen (2014). A point still open for discussion is whether the observed effects may be described as permanent or temporary. We address this in the following section.

3.4.2 Post-inclusion effects

To examine the persistence of the documented effects, we define the post inclusion window as 20 days following the effective day of firm addition to the S&P 500 index. Given that our findings show that index effects begin from a lower pre-announcement base level than in extant announcement date studies, they have to mean revert more to be defined as temporary. Daily levels of post-inclusion abnormal attention, trading volume, and returns are reported in Table 3.7.

< Table 3.7 around here >

Post-inclusion abnormal attention levels are positive and statistically significant for the first three days following the effective change as measured by AASVI, and the first two days as measured by the AAIA. Subsequently, no clear pattern emerges for neither measures, although the overall trend is that post addition daily levels of abnormal attention are insignificant. These test results are consistent with the attention hypothesis. Kahneman (1973) shows that limited attention requires investors to allocate their cognitive resources across tasks, so that attention spent on one task must decrease attention available for other tasks. Therefore, following index addition, sophisticated investors redirect their limited cognitive resources to search for the next profit opportunity. Hence, we conclude that the attention effect is temporary, mostly surrounding the period ahead of the event and event itself, reflecting increased attention coming from sophisticated investors. Following the firm inclusion to the index, investor attention rapidly dissolves.

The effect of firm addition to the S&P 500 index on trading activity is fairly clear: abnormal trading volume is positive and highly statistically significant at each daily level following the effective change, until the end of the post-inclusion window. These findings provide support in favour of permanent volume effects. Post inclusion AAR point estimates generally exhibit negative values, although they are mostly statistically insignificant. AARs are only sporadically significant over the period following first ten days after the effective inclusion, suggesting at least a partial reversal.

To get a clearer view on the persistence of the effect, we consider post-inclusion CAARs. Given that CAARs are sensitive to periods over which they are cumulated, we create three different windows for the full sample of stocks, as well as for the high and low beta stocks, including [AD-20, AD+20], [AD-5, ED+20] and [AD, ED+20]. Results are reported in Table 3.8.

< Table 3.8 around here >

All three windows over which CAARs are cumulated suggest some reversal in the 20 days following the effective inclusion. Nonetheless, CAAR is positive and highly statistically significant in all three windows, ranging from 4.62% in CAAR [AD-20, ED+20] to 1.54% in CAAR [AD, ED+20]. This implies that the documented reversal is only partial, and a considerable part of price effect remains permanent. Post-inclusion cumulative returns based on the high and low beta stocks are particularly interesting, reiterating our betting against beta hypothesis. CAARs of low beta stocks outperform CAARs of high beta stocks across all three windows, implying that low beta stocks exhibit higher prices following the inclusion. We therefore conclude that no full reversal is observed during the 20 days following the effective index change.

3.5 Conclusion

The index effect, or tendency of firm additions to the S&P 500 index to cause changes in stock prices and trading volumes of underlying stocks, has been extensively documented in the literature. Firm inclusion in index may be caused by the firm meeting (or no loner meeting) the relevant criteria, or by variety of different corporate events including bankruptcy, merger, delisting and so on. An important dimension that contributes to the index effect size is the way that index changes are announced, and subsequently, the level of anticipation of the relevant changes. In this study we investigate investor attention on a recent sample of stocks added to the S&P 500 index in the context of anticipatory trading effects. In defiance of efficient market hypothesis predicting that changes in index constituents should not have an effect on stock prices, numerous studies have documented significant price and volume changes connected to the event. Accordingly, a number of theories have emerged to justify these results, mainly referring to whether the effects are permanent or temporary.

Beneish and Whaley (1996) show that index trackers rebalance their positions the day before the effective change date, which creates an opportunity for risk arbitrageurs who purchase the stocks on the announcement day and sell them at a higher price several days later. However, they overlook the prominent role of non-leveraged investors such as hedge funds in this S&P game. For risk arbitrageurs aware of the opportunity index revision presents, it can potentially be very profitable to trade in anticipation of the new additions, by predicting the outcome of the index review and purchasing stocks ahead of the announcement. By doing so, they exploit the 3% mean price increase that comes with the addition announcement. Moreover, as a part of their statistical arbitrage strategy, most hedge funds and other risk arbitrageurs will overweight on low-beta stocks, given that they are expected to have increasing betas and hence prices.

We find significantly positive abnormal trading volume and return close to

3% on the announcement day of firm addition to the index, in line with the existing literature. However, contrary to the conventional understanding, our findings document that index effect starts much ahead of the announcement day. In particular, we find statistically significant levels of abnormal trading volumes commencing ten days ahead of the announcement, causing a significant price increases that begin five days prior to the announcement. What is more, we document that this effect is mostly driven by stocks that exhibit pre-announcement low stock betas ($\beta < 1$), confirming that hedge funds bet against beta as a part of their arbitrage strategy. We refer to these findings are the as the pre-announcement index effect.

To verify that documented pre-announcement effects suggest anticipation of index revision by leverage unconstrained investors such as hedge funds, we study their attention allocation surrounding the event. Based on the complexity of capturing all information required for investors to determine likely candidates for inclusion, it can be expected that they will rely on online search engines to collect variety of relevant information including firm and industry analysis, analyst forecasts, technical analysis, rumours in the financial media, and so on. Moreover, search undoubtedly reveals investor attention to a particular firm. To the best of our knowledge at the time of writing, no other study directly examines investor attention in this framework.

We employ two measures of investor attention, one based on user search volume on Google, and the other based on news reading and news searching user activity on Bloomberg terminal. Our results show that investor attention measured by Google is significantly increased over the four days ahead of the announcement, reflecting increased search volume for firm-related information during this period. Bearing in mind that that cross-sectional significant increase in attention must be caused by a high number of platform users rather than few individuals, these findings confirm investor anticipation hypothesis. Limited attention requires investors to allocate their cognitive resources across tasks, so that attention spent on one task must reduce attention available for other tasks. Concentrated attention in days preceding the announcement, therefore, undoubtedly depicts that investors' cognitive resources are entertained by these firms at the expense of other available investment opportunities. What is more, Bloomberg attention measure that captures institutional attention in a more direct way than attention captured by Google, exhibits significantly positive levels week before the announcement. These findings present evidence that AIA leads attention measured by Google's SVI, affirming that institutional investors have greater resources and higher incentives to react rapidly to information. Our results suggest that investor attention play a role in abnormal trading volume and price patterns observed prior to the announcement of index revision.

Given that our findings show that index effects begin from a lower base level than in extant announcement date studies, they have to mean revert more to be defined as temporary. Abnormal search levels on both platforms become statistically insignificant shortly after the effective inclusion in the index, in line with attention hypothesis. Post-addition levels of abnormal trading volume are elevated and highly statistically significant at, providing evidence for permanent volume effect. We document a partial reversal following the effective inclusion; however, a good portion of abnormal return effect remains positive and significant in 20 days following the announcement. These permanent effects are conforming to attention hypothesis, as well as improved liquidity and certification hypotheses. Amount of firm related information increases upon its addition to the S&P 500 due to greater attention from investors and greater coverage from analysts, media, and other financial intermediaries. Accordingly, information asymmetry declines and more liquidity become available. Stock addition to the index attracts attention from investors, who will hold it to achieve diversification, resulting in an increase in stock price. Moreover, as institutional investors follow constituent stocks more closely, they will exert pressure on the firm to improve its performance, resulting in permanent volume and price effects.

Table 3.1: Summary of index effect competing hypotheses

This table summarises five existing hypotheses in the literature that aim to explain the index effect and their characteristics with regard to the duration of stock price and trading volume effects.

	Revision	Stock returns	Duration	Trading volume	Duration
Price pressure hypothesis	addition	increase	temporary	increase	temporary
	deletion	decrease	temporary	increase	temporary
Imperfect substitutes hypothesis	addition	increase	permanent	increase	temporary
	deletion	decrease	permanent	increase	temporary
Certification hypothesis	addition	Increase	permanent	increase	permanent
	deletion	increase	permanent	increase	permanent
Improved liquidity hypothesis	addition	increase	permanent	increase	permanent
	deletion	decrease	permanent	decrease	permanent
Investor awareness hypothesis	addition	increase	permanent	increase	temporary
	deletion	decrease	permanent	increase	temporary

Table 3.2: Distribution of the sample of S&P 500 index

This table presents distribution of final sample of firm additions to the S&P 500 index between January 2004 and December 2018 across industries and years, based on the first two digits of the SIC code. Data on index additions comes from Standard & Poor's directory. After removing additions due to mergers, spinoffs, and corporate restructuring, our final sample counts 287 firm additions. Most index additions in our sample occurred in 2007, with yearly average of 17 index additions.

Year of addition	Mineral industries and construction	Manufacturing	Transportation and communications	Wholesale trade and retail trade	Finance, insurance, and real estate	Service industries	Total index additions
2004	1	4	0	0	6	3	14
2005	2	4	0	1	4	1	12
2006	3	9	3	1	6	4	26
2007	1	8	7	2	9	2	29
2008	3	10	4	1	3	6	27
2009	3	6	4	4	3	4	24
2010	2	2	3	2	2	2	13
2011	2	6	0	3	1	1	13
2012	1	6	2	3	0	1	13
2013	1	7	2	0	2	3	15
2014	1	1	1	2	2	5	12
2015	0	5	4	4	2	4	19
2016	1	7	4	4	9	1	26
2017	0	5	2	0	5	10	22
2018	0	10	0	1	2	9	22
Total	21	90	36	28	56	56	287

Table 3.3: Abnormal attention measures during the pre -announcement period

This table reports values for two measures of abnormal attention during the pre-announcement period, starting 20 days ahead of the S&P's announcement of firm addition to the index until the effective change day. ASVI is calculated based on the full sample of 287 index additions from January 2004 to December 2018. AIA is calculated based on the smaller sample of 150 index additions from February 2010 to December 2018, due to data availability. For Google attention measure, we first calculate the baseline level of attention over the estimation window of 250 days skipping the most recent 20 days prior to the announcement, and then compare daily SVI values to calculate ASVI. ASVI is then averaged across stocks to calculate AASVI. We report t-statistics using a two-tail to test the null hypothesis under which there is no abnormal attention on a given day. For Bloomberg attention measure, we perform Wilcoxon sing-rank test to test for the difference in medians of AIA during the pre-announcement period and estimation period of 250 days before the announcement of firm addition to the index, skipping the most recent 20 days. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Trading day	AASVI	t-stat.	% ASVI > 0	AIA	p $\|Z\|$
-20	1.256	0.528	45	0.202	0.840
-19	-0.401	-0.144	48	1.017	0.309
-18	-2.266	-0.904	44	1.007	0.314
-17	1.815	0.560	51	0.717	0.473
-16	0.139	0.050	45	1.651	0.099
-15	2.560	1.082	53	0.695	0.487
-14	-3.726	-1.542	47	-0.292	0.770
-13	3.444	1.302	52	0.290	0.772
-12	-0.621	-0.249	47	1.296	0.195
-11	0.096	0.040	45	0.353	0.724
-10	3.081	1.282	51	1.394	0.164
-9	3.503	1.465	51	1.554	0.120
-8	-0.597	-0.295	45	1.597	0.110
-7	-1.239	-0.600	50	-1.894*	0.058
-6	2.309	0.934	48	-2.473**	0.013
-5	3.120	1.345	49	-3.748***	0.000
-4	3.087*	1.666	55	-4.101***	0.000
-3	7.945***	4.051	66	-8.777***	0.000
-2	9.959***	4.992	66	-14.398***	0.000
-1	10.759***	4.677	64	-16.678***	0.000
AD	17.977***	8.021	69	-28.005***	0.000
AD+1	14.370***	4.796	61	-14.210***	0.000
AD+2	9.237***	3.532	63	-5.261***	0.000
ED-1	11.109***	4.244	57	-10.302***	0.000
ED	17.884***	4.631	69	-27.815***	0.000

Table 3.4: Average volume ratios and average abnormal returns in the pre-announcement period

This table reports daily average volume ratios (AVR), average abnormal returns (AAR), and cumulative average abnormal returns (CAAR) during the pre-announcement period, starting 20 days ahead of the S&P's announcement of firm addition to the index until the effective change day. AVR is calculated based on the full sample of 287 index additions from January 2004 to December 2018. We first obtain base volume ratios for each firm by estimating the average stock to S&P 500 index volume ratio over the estimation window of 60 days before the announcement of firm addition to the index, skipping the most recent 20 day. We then compare these figures to daily stock to index trading ratios to calculate volume ratios, which are then averaged across all stocks to compute AVR. Abnormal returns are estimated for all 287 firms in our sample using the market model and averaged across firms to calculate AAR. Abnormal returns are compounded to cumulative abnormal returns and then averaged to calculate cumulative average abnormal returns (CAARs). *, **, *** indicate statistical significance at the 10%, 5%, and 1% level for two-tail test, respectively.

Trading day	AVR	t-stat.	% VR > 1	AAR	t-stat.	% AR > 0	CAAR [AD-20, -
-20	1.014	0.427	38	0.215	1.546	54	0.215
-19	1.034	1.312	44	0.202*	1.739	52	0.417**
-18	1.074	1.502	39	0.191	1.347	54	0.608***
-17	1.034	0.809	37	0.169	1.379	50	0.777***
-16	1.031	1.071	40	0.047	0.363	53	0.824***
-15	1.013	0.399	38	0.136	1.113	54	0.960***
-14	1.043	1.105	40	-0.148	-1.179	46	0.812***
-13	1.019	0.500	39	-0.216	-1.589	48	0.596
-12	1.029	1.028	40	-0.063	-0.547	46	0.534
-11	1.033	1.119	41	-0.159	-1.214	47	0.374
-10	1.045*	1.698	45	-0.118	-0.939	50	0.257
-9	1.081*	1.865	43	0.261*	1.921	55	0.518
-8	1.051*	1.777	46	0.156	1.262	50	0.675
-7	1.082*	1.832	44	0.134	0.922	49	0.809*
-6	1.059*	1.885	44	0.188	1.267	55	0.996*
-5	1.074***	2.598	47	0.227*	1.949	54	1.223***
-4	1.134***	3.011	48	0.242*	1.819	56	1.465***
-3	1.164***	4.024	52	0.269***	2.598	58	1.735***
-2	1.200***	5.411	55	0.513***	4.336	60	2.248***
-1	1.242***	5.905	52	0.792***	5.788	62	3.040***
AD	3.204***	14.064	92	2.652***	15.768	82	5.692***
AD+1	1.991***	12.333	86	0.223	1.559	54	5.870***
AD+2	1.797***	9.613	87	-0.231	-1.603	46	5.709***
ED-1	16.437***	24.075	100	0.091	0.546	52	5.868***
ED	2.763***	11.921	97	-0.141	-1.107	47	5.727***

Table 3.5: Abnormal attention measures for defensive and aggressive beta stocks

This table reports daily levels of abnormal attention based on the Google and Bloomberg platforms for low beta ($\beta < 1$) and high beta ($\beta > 1$) firm additions over the period starting 20 days prior to the announcement of addition until the effective change day. Betas are estimated from the CAPM over the estimation window of 250 days before the announcement of index addition, skipping the most recent 20 days. Out of our full sample of 287 index additions from January 2010 to December 2018, 157 firms exhibit defensive betas and 130 firms exhibit aggressive betas prior to the index addition. For Google attention measure, we first calculate the baseline level of attention over the estimation window of 250 days skipping the most recent 20 days prior to the announcement, and then compare daily SVI values to calculate ASVI. ASVI is then averaged across stocks to calculate AASVI. We report t-statistics using a two-tail to test the null hypothesis under which there is no abnormal attention on a given day. For Bloomberg attention measure, we perform Wilcoxon sing-rank test to test for the difference in medians of AIA during the pre-announcement period and estimation period of 250 days before the announcement of firm addition to the index, skipping the most recent 20 days. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Trading day	AASVI	t-stat.	AIA	$p\|Z\|$	AASVI	t-stat.	AIA	$p\|Z\|$
	Defensive beta stocks				Aggresive beta stocks			
-20	-1.624	-0.449	-0.359	0.720	3.641	1.155	0.604	0.546
-19	-3.422	-0.753	1.359	0.174	2.100	0.611	0.141	0.888
-18	-1.742	-0.419	0.334	0.738	-2.701	-0.891	1.052	0.293
-17	-3.129	-0.931	0.621	0.534	5.909	1.133	0.403	0.687
-16	-1.656	-0.456	1.360	0.174	1.626	0.390	1.003	0.316
-15	3.124	1.007	0.801	0.423	2.094	0.600	0.217	0.828
-14	-3.199	-0.831	-0.341	0.733	-4.163	-1.356	-0.063	0.950
-13	1.006	0.257	0.790	0.430	5.463	1.521	-0.334	0.739
-12	-3.427	-0.840	1.251	0.211	1.701	0.556	0.604	0.546
-11	-2.003	-0.573	0.667	0.505	1.834	0.563	-0.121	0.904
-10	1.678	0.444	1.255	0.210	4.242	1.371	0.744	0.457
-9	2.607	0.775	1.014	0.311	4.246	1.256	1.189	0.234
-8	2.403	0.824	0.832	0.405	-3.080	-1.102	1.405	0.160
-7	-0.745	-0.256	-0.899	0.369	-1.649	-0.566	-1.755*	0.079
-6	1.053	0.265	-1.568	0.117	3.349	1.077	-1.938*	0.053
-5	1.093	0.330	-2.514**	0.012	4.800	1.482	-2.787***	0.005
-4	-2.213	-0.874	-2.210**	0.027	7.475***	2.858	-3.539***	0.000
-3	5.521**	2.111	-6.437***	0.000	9.952***	3.486	-6.022***	0.000
-2	10.615***	3.132	-9.734***	0.000	9.416***	4.025	-10.637***	0.000
-1	13.395***	3.959	-11.923***	0.000	8.577***	2.735	-11.743***	0.000
AD	18.838***	5.838	-20.137***	0.000	17.265***	5.544	-19.541***	0.000
AD+1	20.587***	3.375	-9.264***	0.000	8.447****	2.481	-10.787***	0.000
AD+2	11.242***	2.629	-4.536***	0.000	9.394***	2.296	-2.940***	0.000
ED-1	12.711***	2.412	-6.975***	0.000	9.744***	2.430	-7.577***	0.000
ED	20.089***	2.612	-19.811***	0.000	16.059***	5.231	19.588***	0.000

Table 3.6: Volume ratios and abnormal returns for defensive and aggressive beta stocks

This table reports daily average volume ratios (AVRs) and average abnormal returns (AARs) for low beta ($\beta < 1$) and high beta ($\beta > 1$) firm additions over the period starting 20 days prior to the announcement of addition until the effective change day. Betas are estimated from the CAPM over the estimation window of 250 days before the announcement of index addition, skipping the most recent 20 days. We first obtain base volume ratios for each firm by estimating the average stock to S&P 500 index volume ratio over the estimation window of 60 days before the announcement of firm addition to the index, skipping the most recent 20 day. We then compare these figures to daily stock to index trading ratios to calculate volume ratios, which are then averaged across all stocks to compute AVR. Abnormal returns are estimated using the market model and averaged across firms to calculate AAR. Abnormal returns are compounded to cumulative abnormal returns and then averaged to calculate cumulative average abnormal returns (CAARs). *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Trading day	AVR	t-stat.	AAR	t-stat.	AVR	t-stat.	AAR	t-stat.
	Defensive beta stocks				Aggresive beta stocks			
-20	1.029	0.598	0.269	1.139	1.001	0.021	0.171	1.044
-19	1.074*	1.919	0.123	0.643	1.000	0.006	0.267*	1.884
-18	1.089	1.290	0.083	0.597	1.063	0.885	0.281	1.206
-17	1.001	0.029	-0.027	-0.202	1.061	0.877	0.332*	1.706
-16	1.022	0.667	-0.256	-1.556	1.039	0.849	0.298	1.554
-15	1.011	0.322	0.177	1.189	1.015	0.281	0.102	0.546
-14	1.045	0.892	-0.070	-0.400	1.041	0.716	-0.213	-1.190
-13	1.031	0.781	-0.275	-1.566	1.008	0.136	-0.167	-0.827
-12	1.056	1.362	-0.286*	-1.896	1.006	0.154	0.123	0.737
-11	1.062	1.209	-0.213	-0.987	1.010	0.292	-0.115	-0.716
-10	1.066*	1.824	-0.130	-0.822	1.029	0.738	-0.107	-0.570
-9	1.149*	1.846	0.101	0.825	1.024	0.576	0.394*	1.736
-8	1.084*	1.918	-0.030	-0.212	1.024	0.631	0.311	1.619
-7	1.158*	1.893	-0.028	-0.169	1.018	0.431	0.268	1.176
-6	1.102**	2.166	0.144	0.940	1.024	0.562	0.224	0.934
-5	1.085**	1.981	0.270*	1.908	1.066*	1.702	0.192	1.075
-4	1.203***	2.495	0.411*	1.853	1.077*	1.693	0.102	0.641
-3	1.268***	3.839	0.332**	2.081	1.079*	1.700	0.218	1.597
-2	1.315***	5.716	0.720***	4.296	1.104**	2.150	0.342**	2.070
-1	1.363***	5.845	1.390***	6.019	1.142***	2.661	0.296***	1.966
AD	3.485***	10.907	2.798***	14.246	2.972***	9.192	2.531***	9.693
AD+1	2.220***	9.565	0.181	0.900	1.795***	8.061	0.260	1.278
AD+2	1.969***	7.232	-0.234	-1.200	1.647***	6.455	-0.228	-1.085
ED-1	18.911***	19.405	-0.079	-0.297	14.290***	15.987	0.239	1.156
ED	3.374***	7.947	-0.162	-0.794	2.257***	13.598	-0.122	-0.768

Table 3.7: Post index addition effects

This table reports daily levels of AASVI, difference in medians of AIA measure, AVRs, AARs and CAARs for the first 20 days following firm's effective addition date (ED) to the S&P 500 index. Reported results are for our full sample of 287 firm additions between January 2004 and December 2018. For Google attention measure, we first calculate the baseline level of attention over the estimation window of 250 days skipping the most recent 20 days prior to the announcement, and then compare daily SVI values to calculate ASVI. ASVI is then averaged across stocks to calculate AASVI. We report t-statistics using a two-tail to test the null hypothesis under which there is no abnormal attention on a given day. For Bloomberg attention measure, we perform Wilcoxon sing-rank test to test for the difference in medians of AIA during the pre-announcement period and estimation period of 250 days before the announcement of firm addition to the index, skipping the most recent 20 days. To calculate AVR, we first obtain base volume ratios for each firm by estimating the average stock to S&P 500 index volume ratio over the estimation window of 60 days before the announcement of firm addition to the index, skipping the most recent 20 day. We then compare these figures to daily stock to index trading ratios to calculate volume ratios, which are then averaged across all stocks. Abnormal returns are estimated using the market model and averaged across firms to calculate AAR. Abnormal returns are compounded to cumulative abnormal returns beginning 20 days before the announcement. CARs are then averaged across all stocks to calculate cumulative average abnormal returns (CAARs). *, **, *** indicate statistical significance at the 10%, 5%, and 1% level for two-tail test, respectively.

Trading day	AASVI	AIA	AVR	AAR
ED	17.884***	-27.815***	2.763***	-0.141
1	6.840***	-11.675***	1.944***	-0.115
2	4.129**	-0.579	1.710***	-0.108
3	2.418	0.231	1.600***	-0.127
4	-1.933	1.001	1.570***	-0.142
5	-0.404	0.994	1.492***	-0.111
6	0.248	0.846	1.405***	-0.101
7	1.062	0.610	1.436***	-0.105
8	-1.991	0.893	1.321***	0.140
9	-0.461	0.778	1.420***	0.132
10	0.697	0.941	1.361***	-0.226*
11	2.264	0.769	1.316***	-0.124
12	-1.515	0.465	1.270***	-0.292***
13	-0.415	1.017	1.220***	-0.108
14	0.874	0.873	1.277***	0.153
15	2.224	0.546	1.289***	-0.115
16	2.157	0.904	1.219***	-0.239***
17	2.621	1.022	1.238***	0.119
18	0.162	-0.202	1.224***	0.177*
19	1.989	0.742	1.255***	0.236*
20	-1.112	0.516	1.259***	-0.157

Table 3.8: Persistence of abnormal stock returns following index addition

This table reports CAARs over different windows for our full sample of index additions, sub-sample based on low-beta stocks ($\beta < 1$), and high-beta stocks ($\beta > 1$. Betas are estimated from the CAPM over the estimation window of 250 days before the announcement of index addition, skipping the most recent 20 days. Abnormal returns are estimated using the market model and averaged across firms to calculate AAR. Abnormal returns are compounded to cumulative abnormal returns and then averaged to calculate cumulative average abnormal returns (CAARs). Since CAARs are sensitive to window over which they are cumulated, we present CAARs cumulated over three different windows: from 20 days before the announcement to the 20 days following the effective revision day; from 5 days before the announcement to the 20 days 20 days following the effective revision day; and from announcement day to the 20 days following the effective revision day. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level for two-tail test, respectively.

	Full sample, N = 287			Defensive beta stocks, N = 130			Aggressive beta stocks, N = 157		
Trading day	CAAR [AD-20, -	CAAR [AD-5, -	CAAR [AD, -	CAAR [AD-20, -	CAAR [AD-5, -	CAAR [AD, -	CAAR [AD-20, -	CAAR [AD-5, -	CAAR [AD, -
ED	5.727***	4.731***	2.687***	5.099***	5.518***	2.395***	6.248***	4.079***	2.929***
1	5.612***	4.616***	2.572***	5.104***	5.523***	2.400***	6.033***	3.865***	2.715***
2	5.504***	4.508***	2.464***	4.862***	5.281***	2.158***	6.036***	3.868***	2.717***
3	5.377***	4.381***	2.338***	4.710***	5.130***	2.007***	5.930***	3.761***	2.611***
4	5.270***	4.229***	2.181***	4.526***	4.946***	1.823***	5.889***	3.631***	2.480***
5	5.159***	4.118***	2.070***	4.590***	5.009***	1.886***	5.633***	3.375***	2.224***
6	5.058***	4.017***	1.970***	4.140***	4.560***	1.437***	5.823***	3.565***	2.414***
7	4.954***	3.913***	1.865***	4.231***	4.650***	1.528***	5.556***	3.298***	2.147***
8	5.093***	4.052***	2.005***	4.509***	4.928***	1.805***	5.581***	3.322***	2.171***
9	5.225***	4.184***	2.137***	4.830***	5.249***	2.126***	5.555***	3.296***	2.145***
10	4.999***	3.958***	1.910***	4.812***	5.231***	2.108***	5.155***	2.897***	1.745***
11	4.875***	3.834***	1.787***	4.708***	5.127***	2.004***	5.015***	2.757***	1.606***
12	4.584***	3.542***	1.495***	4.452***	4.871***	1.748***	4.693***	2.435***	1.284*
13	4.475***	3.434***	1.387***	4.230***	4.649***	1.526***	4.679***	2.421***	1.270*
14	4.628***	3.587***	1.540***	4.365***	4.785***	1.662***	4.847***	2.589***	1.438**
15	4.513***	3.472***	1.425***	4.109***	4.528***	1.405**	4.850***	2.592***	1.441**
16	4.274***	3.233***	1.186***	3.982***	4.401***	1.278**	4.518***	2.259***	1.108
17	4.393***	3.352***	1.304***	4.063***	4.482***	1.359**	4.668***	2.410***	1.259*
18	4.545***	3.479***	1.463***	4.087***	4.471***	1.374**	4.929***	2.648***	1.537**
19	4.781***	3.715***	1.699***	4.324***	4.708***	1.612***	5.164***	2.883***	1.772***
20	4.624***	3.558***	1.542***	4.271***	4.655***	1.558***	4.920***	2.639***	1.528**

Chapter4

Institutional investor attention around M&A announcements

An extensive literature has documented that limited attention affects investors' trading behaviour and movements in stock prices. Investor inattention can lead to mispricing that is associated with public accounting information (Hirshleifer and Teoh, 2003), processing market-wide rather than market-specific information (Peng and Xiong, 2006), earlier information incorporation by larger rather than by smaller stocks (Peng, 2005), slower stock price and volume reactions to earnings surprises (Hirshleifer et al., 2009), and neglect of long-term public information (DellaVigna and Pollet, 2009). Firms may exploit limited investor attention by disclosing negative news at times when other firms are making salient disclosures (Hirshleifer et al., 2004), or on Fridays rather than on regular weekdays as the weekend approaches (DellaVigna and Pollet, 2009). These findings generally come from empirical studies carried out on the period around pre-scheduled corporate events, most notably, earnings announcements. However, only very limited previous research has considered attention in the framework of unscheduled announcements around major corporate events. This chapter investigates this issue for a large sample of US merger and acquisitions – hereafter M&As.

Arguably, M&As are a prime example of unexpected or unscheduled corporate events that are of equal or higher importance than earnings announcements. They attract sufficient investor attention to lead to immediate price discovery, although their informational content is generally more complex and challenging to process. They require investors to analyse various aspects of deals including their value, the possible synergy from the merger deals, and the probability of successful deal completion. Moreover, the Wall Street phenomenon "Merger Monday" describes the recurrence of many firms announcing mergers on a Monday to attract attention to their transactions. Hence, as M&A announcements frequently come in waves, investors must decide to which deals to allocate their attention to. It is plausible that attention allocation, therefore, will have an impact on their trading behaviour and stock prices.

The distinctive feature of our paper is that we distinguish between the retail and institutional investor attention and employ a novel measure for capturing the latter. Given that institutional investors are more likely than retail investors to understand the complexities of M&As, it is important to examine the influence of their attention on stock market reactions. The abnormal institutional attention (AIA) measure was suggested by Ben-Rephael et al. (2017) to address the shortcomings of existing measures used to proxy for institutional attention. This measure is based on news searching and reading activity for stocks on Bloomberg terminals and it differs from retail investor attention measured using abnormal Google search volume. Although positively and significantly correlated, they explain less than 2% of each other's variation. Unlike the Google search-based measure, AIA is highly correlated with institutional trading measures. It is related to but different from other investor attention proxies to the extent that it reacts more rapidly to major news events, leads retail attention, and potentially facilitates permanent price adjustments.

This chapter examines AIA within the context of M&As and its implications for the related stock market reactions. Prior M&A studies almost uniformly document a significantly positive pre-bid price run up in target firm stocks that is generally accompanied by abnormal levels of trading volume. While some studies use the information leakage hypothesis as an explanation for the pre-bid run up, others propose the market anticipation hypothesis. This states that sophisticated investors may be able to predict impending takeovers through legitimate sources – publicly available information. M&As are generally less predictable than other corporate events, and therefore can be highly profitable to investors who correctly anticipate them. In this paper we focus on the latter, exploring whether institutional investors' demand for information, abnormal trading volume and abnormal return patterns are consistent with the market anticipation hypothesis, the Friday effect, the Monday effect, and study the implications of attention on stock market reactions.

We first examine the timing and magnitude of institutional attention to target and acquirer firms prior to the merger announcement. We employ a large recent sample of M&A announcements for publicly listed US firms. This includes 730 target and 860 acquirer firms covering the period between February 2010 and February 2018. The empirical findings show that AIA is significant in the two weeks prior to the merger announcement for target firms, and three days prior to the announcement for acquirer firms. Attention to both target and acquirer firms reaches its peak on the announcement day. These results suggest that targets attract more attention than acquirers on average, which is plausible given that target firms generally exhibit significantly positive returns and considerable structural changes, while acquirers do not (Betton et al., 2008). Findings are suggestive of a market anticipation view, considering that significant AIA must be supported by a body of active investors and is unlikely to be driven by a few corporate insiders. These results hold in a multivariate analysis as well.

We also investigate whether attention varies in the cross-section of target and acquirer firms with different attributes. We find that investor attention to acquirers increases with firm size and transaction value, showing that large, well-known firms are more likely to receive media coverage (Ahern and Sosyura, 2014). Interestingly, less profitable acquirers attract more attention, but attention to acquirers is higher when they acquire more profitable targets. Consistent with DellaVigna and Pollet (2009) and Louis and Sun (2010), we find that institutional investors pay most attention to both target and acquirer firms on Mondays, and least on Fridays.

Based on the competitive trading model of He and Wang (1995), the relationship between abnormal returns and abnormal volume during the period before the merger announcement reveals the source of informed trading and differentiates between the market anticipation and insider trading explanations. Hence, to empirically test for the market anticipation hypothesis, we explore the dynamics between daily levels of abnormal volume and abnormal returns in the pre-announcement period. The average abnormal returns become positive and significant shortly before the merger announcement, while average abnormal trading volumes become consistently and significantly positive at the 1% level around two weeks prior to the merger announcement. Abnormally high trading volume is not associated with significant share price movement until close to the announcement day, in line with the predictions of the market anticipation hypothesis.

Institutional attention facilitates information incorporation around earnings announcements, where earnings announcements with abnormal institutional attention exhibit larger returns during the announcement day (Ben-Rephael et al., 2017). Within the framework of unscheduled corporate events, we examine the impact of institutional attention on market reactions, in particular announcement day trading volumes and stock returns. Barber and Odean (2008) show that investors are net buyers of attention-grabbing stocks, wherefore buying pressure prompted by investor attention may lead to overreaction to information. On the other hand, some studies argue that limited attention leads to underreaction to news (Hirshleifer et al., 2009; DellaVigna and Pollet, 2009). Both arguments predict a positive relationship between investor attention and announcement returns. We assign firms into quartiles according to the attention they receive on the announcement day to analyse trading volumes and returns. Our results show that stock returns and trading volumes are higher when investors pay more attention. These findings hold in the multivariate analysis as well.

The issue of reverse causality is relevant here. Instead of investor attention affecting stock returns, higher announcement returns could be possibly inducing higher investor attention. To tackle this concern, we assign firms into groups according to their announcement day abnormal returns and then look at the announcement day attention. We find no significant difference in attention between the highest return group and other groups, ruling out the reverse causality issue.

To the best of our knowledge, investor attention has been linked to the literature on M&As previously only by Louis and Sun (2010) and Siganos (2013). Using publicly available financial and corporate information available from Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system to proxy investor attention, Louis and Sun (2010) find that stock-for-stock acquirers' abnormal trading volumes are substantially lower for Friday M&A announcements than for non-Friday announcements. Using a sample of UK M&As, Siganos (2013) studies whether Google search activity can predict impending deals before takeover signals are reported in the Financial Times. While he reports that Google indicators are better than the Financial Times in explaining price increases in target firms, nonetheless Google can explain only 36% of the target price pre-bid run up. This chapter builds upon and extend this research by using a novel measure of institutional investor attention to address the shortcoming of the previous studies. As Bloomberg terminals are crucial in disseminating news to institutional investors, our paper contributes to the extensive literature linking news media to asset price movements.

The remainder of the paper is organised as follows. Section 4.1 reviews the literature and development of hypotheses. Section 4.2 describes the data. Section

4.3 outlines the empirical methods. Empirical results are discussed in Section 4.4. Section 4.5 summarises and concludes.

4.1 Related literature

The prior literature on M&As consistently documents pre-bid price run ups in a target firm's stock which is statistically significant in days or even weeks prior to the bid being publicly announced. This is not only the case in the US market, as studies that employ UK, Canadian, and Australian data report similar findings.[1] The run up is accompanied by abnormal trading volume which can lead the price run up by more than a week (King and Padalko, 2005; Gao and Oler, 2012). Two hypotheses have been proposed to explain this phenomenon, namely the insider trading and market anticipation hypotheses. According to the former, corporate insiders are aware of impending mergers and purchase shares of these firms to benefit from the expected premium (Keown and Pinkerton, 1981). Corporate insiders may be staff working at the target or bidding firm, or even at the financial institution that organises the merger. According to the alternative market anticipation hypothesis, sophisticated investors can predict a takeover bid using legitimate public sources such as company and market analysis, rumours in the financial media, and analyst forecasts (Jensen and Ruback, 1983).

In this paper we focus on the latter, analysing whether pre-bid run ups documented in the literature may be driven by publicly available information. Previous studies mostly employ media coverage in the Wall Street Journal (WSJ), Financial Times (FT), and other business and trade newspapers and journals to proxy for investor attention. In line with the attention hypothesis developed by Barber and Odean (2008), investors rely on media coverage when identifying firms for long run transactions considering large selection of firms available. It follows that buying pressure prompted by investor attention may lead to overreaction to

[1] For representative studies that use UK data, see Franks and Harris (1989), Holland and Hodgkinson (1994), Siganos (2013); for Canada, see Eckbo and Thorburn (2000), King and Padalko (2009); for Australia, see Clarkson et al. (2006), Aspris et al. (2014)

information.

Pound and Zeckhauser (1990) investigate if the market overreacts to takeover rumours published in Heard on the Street column of WSJ. They find that market reacts efficiently to rumours, as no abnormal returns could be realized through buying rumoured target stocks. They conclude that trading on rumours is not profitable for a holding period of one year. However, as pointed by Chou et al. (2010), they do not distinguish between rumours more likely to be followed by a formal bid from rumours less likely to lead to a bid. Their findings are also challenged by Zivney et al. (1996), who argue that the use of takeover rumours published in the Heard on the Street column might be contaminated because most rumours appear weeks earlier in the Abreast of the Market column of the WSJ, suggesting that the surprise component is limited.

Holland and Hodgkinson (1994) use articles published in UK national and regional newspapers, business and trade journals to proxy for the market's information set related to the takeover bid, and find that rumours give a significant rise to the pre-bid price run up. In a more recent study, Siganos and Papa (2015) employ news coverage in the FT and show that rumours can explain a portion of the price run up in UK target firms. Louis and Sun (2010) use publicly available financial and corporate information available from Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system to proxy investor attention in a framework of merger announcements.

Overall, the majority of previous studies agrees that media coverage in the WSJ or FT can explain some portion of the run up observed. However, the advent of the internet provided a new outlet for news dissemination, implying that older studies do not necessarily capture all publicly available information. Clarkson et al. (2006) examine the market reaction to takeover rumour postings in the Australian Hotcopper online discussion website, showing that a rumour is often associated with abnormal returns and trading volume during the 10-minute posting interval and abnormal trading volume in the 10-minute immediately preceding its posting. Chou et al. (2010) show that merger rumours of this type have a significant impact on firms' stock returns. Siganos (2013) is the only study in the literature that employs Google search volume measure to proxy for investor attention, although this measure mostly captures retail attention. As shown by Ben-Rephael et al. (2017), this does not facilitate information incorporation into stock prices around earnings announcements. Therefore, it is plausible that previous findings may be biased as a result of limited news coverage, as well as consideration of inappropriate sources of information for institutional investors.

The main challenge in distinguishing empirically between the market anticipation and insider trading hypothesis is that both explanations are based on informed trading. However, different patterns in abnormal trading volume and abnormal returns can be useful in distinguishing between the origins of informed trading. While the strategic trading model of Kyle (1985) portrays how insiders trade strategically to exploit their insider information, the competitive trading model of He and Wang (1995) describes the behaviour of sophisticated investors with heterogeneous information regarding the state of the economy and their investment opportunities. In this study we focus on the latter, considering not only the abnormal return and trading volume dynamics, but also the timing and magnitude of institutional attention in the pre-announcement period.

4.1.1 Hypothesis development

In the context of M&As, sophisticated investors are institutional investors that actively manage stock portfolios, or risk arbitrageurs that construct long/short portfolios of target and acquirer firms. Under the competitive trading model of He and Wang (1995), institutional investors obtain information regarding a potential takeover through analysis of publicly available information rather than through corporate insiders. Previous studies employ the traditional news media coverage in the WSJ or FT to account for all public information accessible to investors, and hence proxy investor attention.

However, these studies assume that a firm's mention in the news media automatically infers attention. Yet, a news article in WSJ or FT does not guarantee attention unless investors actually read it. To address this issue, we employ the abnormal institutional attention (AIA) measure, based on news searching and news reading activity for stocks on sophisticated investors' favourite platform for information collection - Bloomberg. Unlike previous measures, AIA is a direct and unambiguous measure of institutional attention given that if investors look for news regarding specific stocks on Bloomberg, then they are undoubtedly paying attention to it. Hence, we use AIA to proxy sophisticated investors' attention allocation in a setting when they have full access to all publicly available information. Investors' increased demand for information in the pre-announcement period should illustrate their information gathering process in an effort to anticipate upcoming takeover candidates. The first hypothesis is:

H1: Institutional attention prior to M&A announcements should be higher than normal to reflect increased demand for information by sophisticated investors in their attempt to anticipate impending takeovers. Hence, we should observe statistically higher levels of AIA during the pre-announcement period.

He and Wang (1995) model how sophisticated investors trade ahead of an unscheduled announcement to either rebalance their portfolios for risk-sharing, or to exploit proprietary information regarding future stock payoffs. They consider two components that make up the total stock value: the fundamental component, regarding which sophisticated investors possess proprietary information; and the residual component regarding which they do not. While the fundamental component's true value is gradually exposed through trading, the value of the residual component remains unrevealed until the announcement. Hence, residual uncertainty regarding the stock value remains until the announcement.

Long before a merger announcement, high uncertainty and investor heterogeneity generate low speculative trading and pattern of return reversals on high volume days, suggesting the presence of both hedging and speculative trading. Simply put, if information heterogeneity is high, high trading volumes should not influence changes in stock prices (Harris and Raviv, 1993; Kim and Verrecchia, 1994). As the announcement date approaches, the amount of information increases and uncertainty decreases, causing investors to anticipate more aggressively. Hence, returns should display positive autocorrelation with high trading volume as market anticipation becomes integrated into stock prices, giving rise to a run up.

H2: Pre-bid run ups ahead of the M&A announcement should exhibit abnormal volume but no clear pattern in abnormal returns long before the official announcement, followed by intense trading and positively autocorrelated price and volume just shortly before the merger announcement.

As residual uncertainty regarding the stock value remains until the announcement, a target's stock price should react significantly to the official takeover announcement. Investors will also be prompted to update their prior anticipations more aggressively following the announcement. While empirical evidence on average announcement returns for acquirer firms is wide ranging, from negative to insignificantly positive depending on the payment method, size, and whether the targets are public or private firms (Bradley and Sundaram, 2006; Moeller et al., 2007), the literature uniformly agrees that target firms' announcement returns are significantly positive (Betton et al., 2008; Bargeron et al., 2008).

In line with the attention theory of Barber and Odean (2008), investors are net buyers of attention-grabbing stocks, wherefore buying pressure prompted by investor attention may lead to overreaction to information. Hirshleifer et al. (2009) and DellaVigna and Pollet (2009), on the other hand, argue that investor's limited attention causes underreaction to news. They show that immediate price discovery is weaker and post earnings announcement drift is stronger when investors are distracted. Overall, both overreaction and underreaction arguments predict a positive relationship between the announcement returns and investor attention. We focus on target firms because the prior literature agrees that target firm's average announcement returns are significantly positive, and hypothesise as follows:

H3: M&A announcement generates a significantly positive reaction in the target firm's stock price and trading volume levels. The target firms' stock returns and trading volumes should both increase with investor attention following an M&A announcement.

4.2 Data

4.2.1 Abnormal institutional attention (AIA)

The onset of the digital revolution cultivated a new way of accessing information, promoting the most credible digital information source in the financial industry, rivalling traditional news outlets such as the WSJ and FT. Bloomberg is a cutting-edge information platform, primarily used by institutional investors. A search of terminal users' profiles shows that around 80% work in financial industries, including banking, asset management, and institutional financial services. Their prevailing job titles include fund/portfolio managers, analyst, traders, and managing directors.

Bloomberg records the number of times users actively search for news as well as the number of times users read news articles regarding a particular stock. To put more significance on deliberate news seeking, Bloomberg assigns a score of ten when users search for news and one when users read a news article. These scores are then aggregated into hourly counts which Bloomberg uses to create a numerical attention score each hour. This is done by comparing the mean hourly count over the previous eight hours to all hourly counts over the previous month for a particular stock. A score of 0 is given if the rolling average is in the lowest 80% of the hourly counts over the previous thirty days. Likewise, scores of 1, 2, 3 or 4 are given if average is between 80% and 90%, 90% and 94%, 94% and 96%, or higher than 96% of the previous thirty days' hourly counts, respectively. We refer to this measure as the abnormal institutional attention (AIA).

Virtually all AIA can be related to news regarding the firm, including CEO turnover, analyst recommendation change, large price movement and so on (Ben-Rephael et al., 2017). News media coverage and AIA are positively correlated. However, news coverage does not guarantee attention, while AIA directly pinpoints the news that engages institutional attention. The only two studies that previously considered investor attention within the context of M&As include Siganos (2013) and Louis and Sun (2010). While Siganos (2013) uses Google search-based measure to proxy attention, Louis and Sun (2010) employ user requests at Electronic Data Gathering, Analysis, and Retrieval (EDGAR) online system. Neither of these two measures captures institutional attention directly.

Although the AIA and Google search-based proxies are positively correlated, they explain less than 2% of each other's variation. When correlated with contemporaneous measures of abnormal trading volume, only AIA has a significantly higher correlation with abnormal institutional trading volume than with abnormal total trading volume (Ben-Rephael et al., 2017). In other words, AIA and not the Google search volume proxy directly captures institutional investor attention. Ben-Rephael et al. (2017) also show that AIA leads retail attention measured by Google search volume, affirming that institutional investors have greater resources and higher incentives to react rapidly to news.

In comparison to those who look for information on Google, users seeking information on EDGAR are more likely to be institutional investors. Although

EDGAR's proxy for attention has a significantly positive relationship with AIA, its explanatory power is weak compared to the news occurrence (Ben-Rephael et al., 2017). It is also worth noting that AIA is based on all news searching and reading activity on Bloomberg, while hits on EDGAR are focused on regulatory filings only.

4.2.2 Sample construction

Our sample consists of US public firm M&A announcements that took place between February 2010 and February 2018. The beginning date of our sample is dictated by the fact that the data used to create AIA measure started being available from February 2010 onwards.

The sample of merger announcements, data on target and acquirer financial characteristics, as well as on deal characteristics for each transaction in our sample is from Thomson Financial Securities Data Company (SDC) Platinum database. Stock prices and trading volume data come from CRSP. Data on earnings announcements is obtained from Compustat. Although we only include public companies in our data sample, we are unable to acquire measure of abnormal attention for all target firms and acquirer firms in our final sample due to data availability.

Following Betton et al. (2008), we start by downloading all mergers (form M), acquisitions of majority interest (AM), acquisitions of partial interest (AP), and acquisitions of remaining interest (AR). We exclude all transactions classified as exchange offers (EO), acquisitions of assets (AA), acquisitions of certain assets (AC), buybacks (B), recaps (R), and acquisition (A). The final sample includes 730 target companies and 860 acquirer companies. It has the AIA measure for target firms but not acquirer firms for 730 announcements, acquirer firms but not target firms for 860 announcements, and both target and acquirer firms for 517 announcements. This study employs the most recent sample of M&A announcements in the literature, covering a larger number of firms in relation to the prior studies (see Appendix B).

4.2.3 Summary statistics

Table 4.1 presents the distribution of our sample according to acquirer and target industry and year the merger took place, respectively. During our sample period, the 2015 year witnessed the most mergers followed by 2016 and 2014. Most of the acquirers and targets are in the manufacturing industry (34% of acquirers, 41% of targets); and finance, insurance and real estate (37% of acquirers, 24% of targets). Since our sample period ends in February 2018, we only observe 5 acquiring companies (3 target companies) in 2018.

< Table 4.1 around here >

Table 4.2 presents descriptive statistics for our data sample. Several features are worth noting. The mean firm market capitalisation is around \$7 *billion*(3 billion median) for acquirers, and \$1 *billion*(376 million) for target companies, showing that on average acquiring companies are much larger in size. Acquirers' return on equity is 7% in mean while targets' return on equity is slightly negative at -0.2%, implying that acquiring companies are much more profitable in comparison to targets. Around 40% of both targets and acquirers in our sample belong to high tech industry. The average value of the deal is around \$2 billion, with nearly 60% of the deals fully financed by cash.

< Table 4.2 around here >

4.3 Research methods

We begin empirical analysis by investigating the timing and magnitude of AIA around the M&A announcements in the pre-event window that starts 20 days before the announcement, on the announcement day, and in the post-event period including 20 days following the event. Considering that our main variable of interest, AIA, is an ordinal variable taking values of 0 to 4, we test for difference in medians using the non-parametric Wilcoxon signed-rank test. To test for the presence of abnormal attention in the pre-announcement period, we compare daily levels of AIA in the pre-event window to the levels of AIA during the estimation period [-21, -250].

Using the Google attention proxy in the scheduled corporate event setting, Drake et al. (2012) show that abnormal investor attention is significantly positive on the earnings announcement day, as well as in the first five days before and after the event. Hence, to control for other potential drivers of the institutional attention, we perform multivariate analysis in which we include separate indicator variables for the period around merger announcement, period around earnings announcement, and a set of control variables. We estimate an ordered logit model for target and acquirer firms separately, as follows:

$$\begin{aligned} AIA = \beta_0 + \beta_1\ &Merger\ Ann.\ [-20,-1] + \beta_2\ Merger\ Ann.\ [0] \\ &+ \beta_3\ Merger\ Ann.\ [+1,+5] + \beta_4\ Earnings\ Ann.\ [-5,-1] \\ &+ \beta_5\ Earnings\ Ann.\ [0] + \beta_6\ Earnings\ Ann.\ [+1,+5] \\ &+ \beta_7\ Controls + \varepsilon \end{aligned} \tag{4.1}$$

where a set of control variables includes firm size, book to market ratio, abnormal return, abnormal trading volume, market return, day of week dummies, and month of year dummies. To make cross-sectional comparisons, we examine if AIA varies among firms with different attributes. This approach is in line with the methodology used in trading volume literature, in which firm specific characteristics explain within-firm abnormal volume[2]. The ordered logit model is estimated separately for target and acquirer firms, as follows:

[2]See Bamber et al. (2010) for the review of this literature.

$$AIA = \beta_0 + \beta_1 \; Target \; characteristics \; + \beta_2 \; Acquirer \; characteristics \\ + \beta_3 \; Deal \; characteristics \; + \varepsilon \tag{4.2}$$

where acquirer firm characteristics include acquirer firm size, acquirer ROE, and an indicator variable that shows whether the acquirer is a high-tech firm; Target characteristics include target firm size, target ROE, and an indicator variable that shows whether target is a high tech firm; and deal related characteristics include transaction value, offer premium, tender offer dummy, diversifying merger dummy, all cash dummy, and Monday and Friday dummies. All variables are defined in Appendix C.

We carry out an event study following the methodology in MacKinlay (1997) to study abnormal trading volumes and abnormal returns. The "day zero" is the date of the M&A announcement. Our event window starts 20 trading days before the announcement and ends 20 trading days after that date [-20, 20]. We use an estimation window starting 250 trading days before the announcement and ending 21 days before the zero day [-250, -21]. We calculate daily abnormal returns (ARs) for firm i and event date t in our sample according to the following equation:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t) \tag{4.3}$$

where $AR_{i.t}, R_{i,t}$, and $E(R_{i,t}|X_t)$ represent abnormal, actual, and normal returns for time period t, respectively. We estimate normal returns over the estimation window [-250, -21] using the market model, as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{4.4}$$

where $R_{i,t}, R_{m,t}$ and ε_i are period t returns on stock i and market portfolio, and error term with zero mean and constant variance, respectively. We use S&P 500 index to proxy for the market. We aggregate individual abnormal returns across all stocks in the sample to compute average abnormal returns (AARs). The sample AARs for day t and its variance are given by:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{4.5}$$

$$\sigma^2(AAR_t) = \frac{1}{N^2}\sum_{i=1}^{N} MSE_i \tag{4.6}$$

where MSE_i is mean squared errors from the estimation regression for each firm i. AARs are then aggregated over the event window to compute the cumulative average abnormal return (CAAR) for each security i in the sample. For any interval in the event window (T_1, T_2), the CAAR and its variance are computed as follows:

$$CAAR_{T_1,T_2} = \sum_{t=T_1}^{T_2} AAR_t \tag{4.7}$$

$$\sigma^2(CAAR_{T_1,T_2}) = \sum_{t=T_1}^{T_2} \sigma^2(AAR_t) \tag{4.8}$$

We perform a cross-sectional test of the null hypothesis that AARs and CAARs are zero. Following Chae (2005), we calculate abnormal trading volume for stock i at time t as follows:

$$AV_{i,t} = V_{i,t} - \frac{1}{n}\sum_{n=-250}^{-21} V_{i,n} \tag{4.9}$$

where $V_{i,t}$ is the turnover for firm i on day t, calculated as daily trading volume scaled by the number of outstanding shares. The estimation period for de-meaning each firm's turnover is [-250,-21]. A positive and statistically significant value for a given day suggest that, on average, firm experiences higher turnover on day t than it did on the average day over the window [-250, -21]. The average abnormal volumes (AAVs), the cumulative average abnormal volumes (CAAVs), and their statistical significance are computed in a similar fashion to that of AARs and

CAARs.

Consistent with DellaVigna and Pollet (2009) and Hirshleifer et al. (2009), we measure the market reaction to announcements over the day of, and the day after the announcement (days 0 and 1), to account for the possibility that takeover announcements may be made when the market is closed. To control for the possible determinants of announcement day abnormal returns and abnormal volumes other than attention, we perform multivariate analysis. We create an indicator variable "High AIA" that equals to 1 if firm's AIA on the announcement day equals to three or four and 0 otherwise. We regress average CAR [0, 1] and CAV [0, 1] on an indicator variable and a set of control variables, as follows:

$$\begin{aligned} CAR[0,1] &= \beta_0 + \beta_1 High\ AIA + \beta_2 Tar.\ Characteristics \\ &+ \beta_3 Acq.\ Characteristics + \beta_4\ Deal\ Characteristics + \varepsilon \end{aligned} \tag{4.10}$$

$$\begin{aligned} CAV[0,1] &= \beta_0 + \beta_1 High\ AIA + \beta_2 Tar.\ Characteristics \\ &+ \beta_3 Acq.\ Characteristics + \beta_4\ Deal\ Characteristics + \varepsilon \end{aligned} \tag{4.11}$$

where control variables are same as the ones in Equation 4.2.

4.4 Empirical results

Table 4.3 presents findings on timing and magnitude of AIA to target and acquirer firms, starting from 20 days before the M&A announcement to several days following the event. Using non-parametric Wilcoxon signed-rank test, we reject the null hypothesis of zero difference in medians between level of AIA to target firms up to 14 days prior to the M&A announcement and level of AIA to target firms during the estimation window [-21, -250]. The test shows that target firms experience statistically significant higher levels of AIA for two weeks prior to the merger announcement. The magnitude of AIA also seems to steadily increase approaching the announcement. These results imply presence of pre-announcement run-up in the AIA to target firms, which may possibly explain the well documented target pre-bid price run up.

< Table 4.3 around here >

In the case of acquirer firms, we document statistically higher levels of AIA only three days prior to the M&A announcement. Significant levels of AIA to acquirer firms only shortly before the M&A announcement do not automatically suggest that acquirer identity is not anticipated. A possible explanation is that targets attract more attention than acquires in general, since target firms exhibit significantly positive returns and possible structural changes while acquirer firms have insignificant returns and minimal adjustments in firm structure. AIA to both target and acquirer firms reaches its peak on the announcement day, demonstrating the importance of the announcement. Following the event, attention to target firms remains statically higher for the next couple of days, although much smaller in magnitude compared to the previous days. Attention to acquirers remains significantly higher only for one day following the announcement.

Results of the univariate analysis document that institutional investors give more attention than usual to target firms starting as early as 14 days prior to the M&A announcement. Institutional attention is also higher in magnitude and precedes attention to acquirer firms by around 10 days. To the extent that significant increase in Bloomberg news searching and news reading activity two weeks prior to the announcement must be supported by a large population and is implausible to be driven by few corporate insiders, our findings suggest that the observed price run-up may be explained by market anticipation of the deals. This is hardly surprising, as the average M&A process begins three months prior to the official announcement with numerous parties involved. With the advent of digital revolution, it is quite difficult to lock up the information.

To check the robustness of our findings, we carry out multivariate analysis by estimating the model in Equation 4.1. Estimation results for target and acquirer firms are reported in Table 4.4 and Table 4.5, respectively. Consistent with the univariate analysis results, target firms attract significant attention in the pre-event period that is higher in magnitude relative to attention that acquirer firms receive. In line with Drake et al. (2012), earnings announcements attract abnormal level of attention several days prior to the pre-scheduled event, as well as on the announcement day itself. However, we do not find significant AIA in the five days following the event either for target nor acquirer firms. The possible reason could be that, unlike prior studies, we employ direct measure that captures attention of strictly sophisticated investors. Given that attention is a scarce cognitive resource, sophisticated investors quickly shift their resources to other opportunities in the market. Overall, target firms attract significant pre-announcement attention, that is higher in magnitude compared to attention acquirer firms receive. Abnormal attention to targets precedes abnormal attention to acquirers by more than a week. These findings provide evidence in favour of our first hypothesis.

<<< Tables 4.4 & 4.5 around here >>>

We also examine the possible drivers of the cross-sectional AIA using the model from the Equation 4.2. We report results for target and acquirer firms in Table 4.6 and Table 4.7, respectively[3]. We find that AIA to acquirers increases with the firm size and transaction value, showing that large, well-known firms are more likely to receive media coverage (Ahern and Sosyura, 2014). Coefficient on the acquirer ROE is negative and significant, suggesting that less profitable acquirers attract more attention on average. A possible reason could be that high ROE reduces the likelihood of a transaction being successful, as argued by Beitel et al. (2004) and Pilloff (1996). However, coefficient on the target's ROE is significantly positive while coefficient on the target firm size is significantly negative, showing that investors pay more attention to acquirer firms when they acquire smaller, more profitable firms.

<<< Tables 4.6 & 4.7 around here >>>

[3]As the regression analysis requires target financial information, acquirer financial information, and deal related information, a smaller sample containing 517 deals is used.

Transaction value also positively predicts investor attention to targets. Significantly positive acquisition premium and tender offer coefficients may be interpreted as investors' increased demand for information in an effort to determine overall benefit from the potential merger arbitrage when M&A deals exhibit larger difference between the target's real and estimated value. Our cross-sectional findings also support the notion that investors are less attentive to Friday announcements, consistent with DellaVigna and Pollet (2009) and Louis and Sun (2010). At the same time, coefficient on a Monday dummy is positive and highly statistically significant, showing that M&A deals that take place on a Monday attract most institutional attention. Interestingly, firms in our sample classified as non-high-tech according to the SDC classification receive on average more institutional attention.

To provide further evidence for the market anticipation view, in addition to the documented pre-announcement run-up in AIA, we look at the alternative angle by considering abnormal return and trading volume dynamics within the competitive trading model of He and Wang (1995). Table 4.8 reports daily levels of average abnormal returns (AARs), average abnormal trading volumes (AAVs), and cumulative average abnormal returns and volumes (CAARs; CAAVs) over the window [-20, 1], although the CAARs and CAAVs are based on the window [-20, 20]. We focus on the target firm stock returns and trading volumes since these companies attract most attention and as documented in the literature experience the pre-bid price run up.

< Table 4.8 around here >

AARs show weak and episodic statistical significance over the window [-20, -5], on days -20 and -16, when AARs are negative at the 10% level of significance. Up to this point, percentage of positive abnormal returns on any given day oscillates around 50% alongside with the number of reversals, in line with the predictions of the market anticipation hypothesis. The AARs become positive and statistically significant at the 1% level of significance only shortly prior to the M&A announcement. Consistent with the M&A literature, there is a significant reaction on the announcement day with an AAR of around 20%, while it is worth noting that 15% of the sample has negative abnormal returns on the day. Displaying similar pattern, CAARs are positive and statistically significant from day -4, very close to the announcement day. CAARs peak at about 28.5% on day 1, and then continuously decrease to about 25% by day 20, while remaining statistically significant at the 1% level. These results show target pre-bid run up starts merely in the days preceding the M&A announcement. Under the competitive trading model, the timing of the run up is conforming to the market anticipation hypothesis as speculative trading intensifies close to the announcement, reflecting decrease in uncertainty.

The pattern of daily AAVs during the pre-event window, however, looks much different. We observe positive AAVs at the 10% level of significance two weeks prior to the M&A announcement, when the percentage of firms with positive abnormal trading volume was not above 50%. AAV becomes steadily positive at the 1% level of significance starting from day -11, when the percentage of firms with positive abnormal trading volume on a day increases near to or above 60%. High levels of abnormal volume are not linked with high levels of abnormal returns until near the announcement day, as stated by the predictions of the market anticipation hypothesis. Gao and Oler (2004) discover the same pattern where abnormal volume precedes abnormal returns by five days on average. They attribute significant pre-announcement trading volume to market's processing of highly uncertain information in M&A rumour, in line with model of He and Wang (1995). Using a sample of Canadian M&As, King and Padalko (2005) find similar pattern which they ascribe to market anticipation of the upcoming M&A deals.

Dramatic increase of AAV on the announcement day depicts enhanced adjustments of investors' prior forecasts, which is in line with the information heterogeneity assumption under competitive trading model. AAVs remain significantly positive until the end of the post-event window, indicating that investors keep on trading on the new information after the uncertainty is diminished. This is consistent with the findings reported by Chae (2005) and King and Padalko (2005). Contrary to abnormal returns, CAAVs are statistically significant from day -15, demonstrating that target firms exhibit abnormal turnover ahead of the M&A announcement. In accordance with the competitive trading model predictions, the steady run up in abnormal volume accelerates around the announcement day, suggesting that institutional investors take positions early, but speculate in a more aggressive manner closer the announcement day gets. Meanwhile, lack of statistically significant AARs over most of this period seems to indicate that trading has limited informational value as it does not give rise to the run up in stock price.

To present a more formal test of the relationship between abnormal return and abnormal trading volume, we regress abnormal returns on abnormal volumes over different windows, including dummy variables for the year in which the M&A took place, and dummy variables for the industries included in our sample. Table 4.9 reports the results. In all instances, abnormal returns are highly statistically related to abnormal trading volume, despite the fact that small estimated coefficient and the poor fit of the model indicate that the relationship is not economically significant. Column 1 demonstrates estimation over the pre-announcement period [-20, -1], showing that one standard deviation increase in abnormal trading volume results in an increase in abnormal stock returns of 0.012%. The fit of the regression over this window is also very low. Column 2 demonstrates the relationship between the abnormal return and trading volume over the window [0, 1], where the overall R-square is 27.5%. An increase of one standard deviation in abnormal volume over event window comes with an increase in abnormal returns of 0.257%. Therefore, we can conclude that during our pre-announcement window, abnormal returns are not importantly associated with abnormal volumes. This return-volume dynamic is contrast to the pattern documented in insider trading studies but is in line with the predictions for the market anticipation hypothesis. Hence, alongside our findings of the pre-bid run up in attention, it may be concluded that the recorder pre-bid run-ups are result of market anticipation.

< Table 4.9 around here >

Lastly, we investigate the impact of AIA on stock market reactions. We focus on the stock returns and trading volumes of target firms as prior literature uniformly agrees that that target average announcement returns are significant and positive, while evidence on the acquirer average announcement returns is mixed. We firstly sort all target firms in our sample into quartiles based on the level of AIA they receive on event day, and then determine the CAAR [0, 1] for each of the four groups. We then test the difference in CAAR [0, 1] between the top quartile group and other groups. Results of this univariate analysis are reported in Table 4.10.

< Table 4.10 around here >

Our findings show that CAAR [0, 1] increases with attention in a monotonous manner, from 16.60% in the bottom quartile to 31.97% in the top quartile. Similar dynamics are observed in stock return medians, going from 9.36% in the bottom quartile to 27.71 in the top quartile. The difference between the top quartile and other firms is highly statistically significant at 15%. We also carry out multivariate analysis by estimating the model in Equation 4.10, to account for other possible drivers of target announcement day returns. Results are reported in Table 4.11. High AIA dummy coefficient is positive and statistically significant, implying that target announcement day returns rise with investor attention. Firms involved in large deals exhibit lower announcement returns, while deals fully financed by cash experience higher stock returns. Unsurprisingly, higher acquisition premium increases target announcement day returns.

< Table 4.11 around here >

One may be concerned regarding the reverse causality issue; such that higher announcement day returns give rise to abnormal attention instead of high levels of attention leading to higher announcement day returns. To deal with this issue, we split firms into quartiles based on their event day returns and then calculate medians of AIA for each group. If causality is present, we should expect AIA medians in the top quartile group to be significantly higher than AIA medians in other groups. Using Wilcoxon sign-rank test, we show that although the top quartile group has higher AIA median compared to that of the other groups, the difference is not significant at any conventional level of significance. Results are reported in Table 4.12.

< Table 4.12 around here >

In a similar fashion to abnormal returns, we conduct univariate analysis to test for the difference in abnormal trading volume means between the portfolio of companies that receive highest level of institutional attention on the announcement day and other firms. We report the results in Table 4.13. Abnormal trading volume increases with AIA, from 17.48% in the bottom quartile to 38.16% in the top quartile. Medians display a very similar pattern. We show that the difference between the top quartile and other firms is 21%, and it is highly statistically significant. We estimate the model from the Equation 4.11 as a robustness check of our results and report the results of the multivariate analysis in Table 4.14. High AIA dummy coefficient is positive and statistically significant, confirming our previous findings. We conclude that trading volume is higher when investors pay more attention.

<<< Tables 4.13 & 4.14 around here >>>

These findings provide evidence in support of our last hypothesis, although we unable to differentiate between the market overreaction and market underreaction explanations. In contrast to the earnings announcement framework where we can study post earnings announcement price reaction, M&As are involved with constant information streams where stock prices correct accordingly. The stock price may plummet following the announcement when the merger is disapproved by shareholders or stopped by regulators. Similarly, the stock price may continue to rise if bidders increase the offer price or new bidder appears. At best we can study a sample of completed M&As without any further streams of information, however, the size of the relevant sample would be limited preventing us from making valid arguments.

4.5 Conclusion

This paper investigates institutional investor attention within the framework of M&A announcements, and its implications on the stock market reactions. A number of previous studies document significantly positive pre-bid price run up in target firms, developing two hypotheses to explain this phenomenon. According to the insider trading hypothesis, corporate insiders trade in these firms before the announcement, while according to the market anticipation hypothesis investors manage to predict the identity of target firms before their merger announcements. In this paper we focus on the latter, exploring the institutional investors' demand for information, abnormal trading volume and abnormal return patterns in the pre-event window, and implications of attention on stock market reactions. We revisit the pre-bid price run up issue from another angle, joining together literature on investor attention and literature on M&As.

Previous studies that linked the run up to the market anticipation hypothesis mostly used media coverage such as rumours published in WSJ or FT as a proxy, with investors managing to anticipate a merger as long as the rumour was reported ahead of the announcement day. Based on the difficulty of seizing all public information available to investors, particularly in more recent times when online resources and chat discussions are massively used, we follow an alternative approach. In the event of coming across a rumour of a potential M&A, it is plausible to believe that most sophisticated investors may search for further information on the target company before proceeding with a transaction. As shown by Ben-Rephael et al. (2017), Bloomberg platform is a first choice of sourcing information for institutional investors. Hence, firms that feature in a rumour are likely to experience abnormal levels of activity on Bloomberg platform to reflect increased demand for information.

Our findings show that target firms attract significantly higher attention from institutional investors commencing two weeks prior to the M&A announcement, while acquirer firms receive significantly higher attention only shortly before the announcement. The results show that investors' attention to target firms commences earlier and is higher in magnitude compared to that of acquirers, which is plausible given that targets generally exhibit significantly positive returns and considerable changes in firm structure, while acquirers do not. Multivariate analysis confirms these results These findings are suggestive of a market anticipation, given that significant AIA must be supported by a large number of platform users and not a few corporate insiders.

We provide further evidence in support of the market anticipation view by considering the abnormal return and abnormal trading volume dynamics within the competitive trading model of He and Wang (1995). We find that target firms experience significantly positive and rising abnormal trading volumes beginning as early as two weeks prior to the M&A announcement. Abnormal volume is unaccompanied by abnormal returns, implying information heterogeneity among investors. We observe a pattern of reversals with abnormal return levels oscillating around zero, mirroring random walk. Positive and significant abnormal returns arise just shortly ahead of the event, accompanied by significantly positive abnormal trading volumes. Target's stock price reacts significantly to the M&A announcement, exhibiting both positive and negative abnormal returns, accompanied by very high levels of abnormal trading volume. This pattern is inconsistent with the patter of illegal insider trading but is in line with the predictions for the market anticipation hypothesis. Alongside findings of significantly positive run-up in attention in the pre-event window, we conclude that pre-bid price run ups are caused by market anticipation and not insider trading.

Lastly, we provide evidence on investors' attention allocation and its impact on the stock prices and trading behaviour. We find that stock return is more positive and trading volume is higher when investors pay more attention. These results also hold in the multivariate analysis setting that includes acquirer characteristics, target characteristics, and deal characteristics. We also address the reverse causality issue, ruing out the possibility that higher returns result in a higher attention.

Table 4.1: Distribution of sample by year and industry

Our sample includes US public firm M&A announcements made between February 2010 and February 2018. The sample of M&As comes from Thomson Financial Securities Data Company (SDC) Platinum database. We start by downloading all mergers (form M), acquisitions of majority interest (AM), acquisitions of partial interest (AP), and acquisitions of remaining interest (AR). We exclude all transactions classified as exchange offers (EO), acquisitions of assets (AA), acquisitions of certain assets (AC), buybacks (B), recaps (R), and acquisition (A). We extract 1, 200 unique merger announcements that met these criteria. Our final sample counts 860 acquirer firms, and 730 target firms. Industry classification is based on the first two digits of the SIC code.

Year	Agriculture, forestry & fisheries (01-09)	Mineral & construction industries (10-17)	Manufacturing (20-39)	Transportation & communications (40-49)	Wholesale & retail trade (50-59)	Finance, insurance & real estate (60-67)	Service industries (70-89)	Total
Panel A. Acquirer industry								
2010	0	8	40	10	3	25	11	97
2011	0	5	21	10	4	18	11	69
2012	0	1	35	8	7	30	13	94
2013	0	4	28	9	5	45	15	106
2014	0	6	36	11	5	48	15	121
2015	1	4	53	13	5	48	11	135
2016	0	7	38	12	1	52	18	128
2017	0	6	37	5	3	47	7	105
2018	0	0	3	1	0	1	0	5
Total	1	41	291	79	33	314	101	860
Panel B. Target industry								
2010	0	1	7	0	1	5	0	14
2011	0	3	14	9	1	13	5	45
2012	0	5	42	4	6	26	14	97
2013	0	3	33	10	8	26	16	96
2014	0	6	48	12	6	28	15	115
2015	1	9	60	17	9	24	17	137
2016	0	5	56	11	6	29	25	132
2017	0	6	35	9	5	24	12	91
2018	0	0	2	1	0	0	0	3
Total	1	38	297	73	42	175	104	730

Table 4.2: Descriptive statistics

In this table we provide summary statistics for the key variables in our sample. Data on target financial characteristics, acquirer financial characteristics, and deal characteristics is from Thomson Financial Securities Company (SDC) Platinum database, All the variable definitions are presented in Appendix C.

	Mean	St.Dev.	1^{st} Quartile	Median	3^{rd} Quartile	Observations
Acquirer market cap ($ mil.)	7, 408	11, 402	667	2, 504	8, 446	118, 973
Acquirer ROE	0.065	0.528	0.002	0.011	0.053	132, 903
High tech acquirer	0.402	0.490	0	0	1	134, 472
Target market cap ($ mil.)	1, 078	1, 619	115	376	1, 165	116, 137
Target ROE	-0.002	0.083	-0.002	0.001	0.007	129, 767
High tech target	0.400	0.490	0	0	1	134, 472
Transaction value ($ mil.)	1, 937	2, 661	277	812	2, 448	119, 005
Acquisition premium	0.341	0.768	0.124	0.256	0.414	124, 151
Tender offer	0.191	0.393	0	0	0	134, 472
Diversifying merger	0.279	0.449	0	0	1	134, 472
All cash deal	0.558	0.497	0	1	1	97, 928

Table 4.3: Univariate analysis of AIA to target and acquirer firms around M&A announcements

This table reports differences in medians between the daily levels of AIA in the event window against the levels of AIA during the estimation window [-21, -250] for target and acquirer firms. To test for differences in medians, we employ non-parametric Wilcoxon sign-rank test. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Target firms		Acquirer firms	
Trading day	Z	$p\|Z\|$	Z	$p\|Z\|$
-20	-0.619	0.536	0.767	0.443
-19	-0.717	0.473	0.614	0.539
-18	-0.788	0.431	0.744	0.457
-17	-0.958	0.338	0.651	0.515
-16	-1.161	0.246	0.801	0.423
-15	-1.784*	0.075	0.471	0.638
-14	-2.361**	0.018	0.308	0.758
-13	-7.795***	0.000	0.245	0.807
-12	-10.945***	0.000	0.403	0.687
-11	-14.452***	0.000	0.195	0.846
-10	-17.460***	0.000	-0.069	0.945
-9	-15.905***	0.000	-0.285	0.775
-8	-17.797***	0.000	-0.599	0.549
-7	-17.330***	0.000	-0.727	0.468
-6	-17.882***	0.000	-0.995	0.320
-5	-19.147***	0.000	-1.256	0.209
-4	-22.574***	0.000	-1.443	0.149
-3	-23.245***	0.000	-1.871*	0.061
-2	-26.881***	0.000	-2.725***	0.006
-1	-30.408***	0.000	-12.261***	0.000
0	-41.051***	0.000	-32.810***	0.000
1	-11.918***	0.000	-10.465***	0.000
2	-2.463**	0.014	-1.143	0.253
3	-1.258	0.209	-0.190	0.849
4	-1.532	0.126	1.545	0.122
5	-1.078	0.281	1.352	0.176

Table 4.4: Multivariate analysis of AIA to target firms

This table presents the results of the heteroscedastic ordered logit model presented in Equation (1), which models the timing and magnitude of the institutional attention to M&A announcements. The dependent variable is target firm AIA. All variables are defined in Appendix C. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Coefficient	p-value
Merger AD [-20, -1]	0.692***	0.000
Merger AD	2.662***	0.000
Merger AD [1, 5]	0.222***	0.000
Earnings AD [-5, -1]	0.426***	0.000
Earnings AD	0.884***	0.000
Earnings AD [1, 5]	-0.197	0.112
Firm size	0.079***	0.000
Book-to-market	-0.001***	0.000
Abnormal return	-0.197	0.554
Abnormal trading volume	3.147***	0.000
Market return	0.196	0.919
Day of week fixed effects		YES
Month of year fixed effects		YES

Table 4.5: Multivariate analysis of AIA to acquirer firms

This table presents the results of the heteroscedastic ordered logit model presented in Equation (1), which models the timing and magnitude of the institutional attention to M&A announcements. The dependent variable is acquirer firm AIA. All variables are defined in Appendix C. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Coefficient	p-value
Merger AD [-20, -1]	0.208***	0.000
Merger AD	2.880***	0.000
Merger AD [1, 5]	0.159***	0.002
Earnings AD [-5, -1]	0.413***	0.001
Earnings AD	0.730***	0.000
Earnings AD [1, 5]	0.037	0.758
Firm size	0.030***	0.000
Book-to-market	-0.003	0.416
Abnormal return	1.159	0.174
Abnormal trading volume	31.166***	0.000
Market return	1.794	0.328
Day of week fixed effects		YES
Month of year fixed effects		YES

Table 4.6: Cross-section of AIA to target firms

This table presents the results of the model specified in Equation (2), which models the determinants of cross -sectional attention that includes acquirer characteristics, target characteristics, and deal characteristics. The dependent variable is target firm AIA. All variables are defined in Appendix C. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Coefficient	p-value
Acquirer firm size	-0.002	0.288
High tech acquirer	-0.263***	0.000
Acquirer ROE	-0.059*	0.059
Target firm size	-0.022	0.256
High tech target	-0.171***	0.005
Target ROE	0.129	0.599
Transaction value	0.056***	0.000
Acquisition premium	0.124**	0.046
Tender offer (dummy)	0.099**	0.037
Diversifying merger (dummy)	-0.042	0.382
All cash deal (dummy)	-0.065	0.170
Monday	0.220***	0.000
Friday	-0.114*	0.071
Year fixed effect		YES

Table 4.7: Cross-section of AIA to acquirer firms

This table presents the results of the model specified in Equation (2), which models the determinants of cross -sectional attention that includes acquirer characteristics, target characteristics, and deal characteristics. The dependent variable is acquirer firm AIA. All variables are defined in Appendix C. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Coefficient	p-value
Acquirer firm size	0.028***	0.000
High tech acquirer	-0.179***	0.003
Acquirer ROE	-0.082***	0.006
Target firm size	-0.068***	0.000
High tech target	-0.166***	0.006
Target ROE	0.539**	0.045
Transaction value	0.063***	0.000
Acquisition premium	0.105*	0.089
Tender offer (dummy)	0.268***	0.000
Diversifying merger (dummy)	0.092*	0.052
All cash deal (dummy)	-0.033	0.494
Monday	0.236***	0.000
Friday	-0.303***	0.000
Year fixed effect		YES

Table 4.8: Average and cumulative abnormal returns and trading volumes of target firms

Average and cumulative abnormal returns are estimated using the market model. Average and cumulative abnormal trading volumes are estimated using a firm-detrended model. CAARs and CAAVs are accumulated over the window [-20, 20]. The columns % positive ARs and % positive AVs show the percentage of M&A deals where the abnormal returns (trading volumes) were positive for a given day. Standard errors are adjusted using a heteroscedasticity-consistent covariance matrix estimator. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Trading day	Abnormal returns			Abnormal trading volumes		
	AAR (%)	% positive ARs	CAAR (%)	AAV (%)	% positive AVs	CAAV (%)
-20	-0.221*	49	-0.221	0.063	33	0.063
-19	-0.111	48	-0.333	0.033	28	0.099
-18	0.141	55	-0.199	0.041	27	0.138
-17	0.074	47	-0.056	0.049	27	0.190
-16	-0.171*	48	-0.329	0.049	30	0.220
-15	0.186	49	-0.074	0.047	32	0.310
-14	0.217	49	0.115	0.079*	34	0.348**
-13	0.083	53	0.039	0.097*	42	0.358**
-12	0.213	50	0.43	0.212**	44	0.700***
-11	0.169	50	0.698	0.73***	53	1.293***
-10	0.275	52	0.566	1.030***	50	2.415***
-9	0.107	50	1.125	1.321***	56	3.606***
-8	-0.154	46	0.687	1.652***	58	5.270***
-7	0.097	49	0.923	1.932***	59	7.005***
-6	0.133	50	1.022	2.309***	68	8.695***
-5	-0.089	47	0.778	2.674***	71	12.112***
-4	0.192*	51	1.078*	2.912***	79	15.076***
-3	0.347**	54	1.284***	3.488***	82	18.477***
-2	0.934***	57	2.490***	4.575***	88	22.327***
-1	1.971***	60	4.263***	6.653***	95	29.211***
0	20.209***	85	24.432***	21.751***	99	50.635***
1	3.319***	59	27.905***	7.057***	98	57.768***
2	0.857***	56	28.493***	3.458***	96	60.681***

Table 4.9: Panel regressions of abnormal returns and trading volumes

Panel A of this table presents results of the panel regressions of abnormal returns and abnormal trading volume over different windows. The dependent variable is abnormal return for each target firm at time t, where abnormal returns are estimated using the market model. The independent variables are abnormal trading volume for each target firm at time t, dummy variables for the year in which M&A takes place, and dummy variables for different industries covered in our sample. Panel B of this table presents summary statistics of abnormal return and abnormal trading volume over different windows. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A	CAR [-20, -1]	CAR [0, 1]	CAR [-20, 1]
Abnormal trading volume	0.003	0.013	0.009
p-value	(0.000)	(0.00)	(0.000)
Year dummies	YES	YES	YES
Industry dummies	YES	YES	YES
Number of target firms	494	494	494
Adj. R-square	0.012	0.275	0.017

Panel B	Mean	St. Dev.	Observations
Abnormal return [-20, -1]	0.002	0.033	9, 965
Abnormal trading volume [-20, -1]	0.015	0.041	9, 965
Abnormal return [0, 1]	0.119	0.299	1, 023
Abnormal trading volume [0, 1]	0.145	0.198	1, 023

Table 4.10: Univariate analysis of the AIA impact on announcement day return

This table reports results of the univariate analysis of the impact of institutional investor attention on target stock announcement day returns. We first assign target firms into quartiles based on the level of attention they receive on the announcement day. We then calculate the average CAAR [0, 1] for each of the four groups and test the difference in CAAR [0, 1] between the top quartile group and other groups. When testing the difference in mean, standard errors are adjusted for heteroskedasticity and clustered by data. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Rank of AIA	Mean	St.Dev.	1^{st} Quartile	Median	3^{rd} Quartile	Number of firms
1	16.603	21.580	1.324	9.364	28.114	142
2	20.753	16.989	11.820	17.481	23.634	100
3	27.492	84.432	4.904	23.739	27.787	71
4	31.973	29.491	10.426	27.707	47.376	195
Diff. (High-Low) (4-1,2,3)	15.4***					

Table 4.11: Multivariate analysis of the AIA impact on announcement day return

In this table we analyse the determinants of announcement day returns for target stock. We regress average CAR [0, 1] on a high attention dummy, acquirer characteristics, target characteristics, and deal characteristics. High AIA is a dummy variable that takes value of 1 if firm's AIA on the announcement day equals to three or four and 0 otherwise. All variables are defined in Appendix C. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Coefficient	p-value
High AIA	0.033**	0.023
Acquirer firm size	0.001**	0.011
Acquirer ROE	0.006	0.611
High tech acquirer	-0.006	0.749
Target firm size	0.004	0.658
Target ROE	0.065	0.396
High tech target	0.023	0.229
Transaction value	-0.007***	0.000
Acquisition premium	0.467***	0.000
Tender offer	0.005	0.765
Diversifying merger	0.005	0.739
All cash deal	0.048***	0.002
Year fixed effects		YES
Number of companies		660
Adj. R-square		0.87

Table 4.12: Univariate analysis of the impact of announcement day returns on AIA

In this table we test whether target firm announcement day returns affect investor attention. We first assign target firms into quartiles based on their event day returns over the window [0, 1] and then calculate medians of AIA for each group. Using Wilcoxon sing-rank test we test the difference in medians of AIA between the top quartile group and other groups.

Rank of CAR [0,1]	(Z)	p(Z)
1	1.625	0.104
2	-0.382	0.703
3	-0.500	0.617
4	-0.743	0.458

Table 4.13: Univariate analysis of the AIA impact on announcement day trading volume

This table reports results of the univariate analysis of the impact of institutional investor attention on target stock announcement day trading volumes. We first assign target firms into quartiles based on the level of attention they receive on the announcement day. We then calculate the CAAV [0, 1] for each of the four groups and test the difference in CAAV [0, 1] between the top quartile group and other groups. When testing the difference in mean, standard errors are adjusted for heteroskedasticity and clustered by data. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Rank of AIA	Mean	St.Dev.	1^{st} Quartile	Median	3^{rd} Quartile	Number of firms
1	17.477	20.194	3.647	9.334	26.073	142
2	24.476	21.413	8.957	18.029	33.082	100
3	26.451	22.389	8.070	22.430	36.824	71
4	38.159	30.788	16.144	31.829	50.523	195
Diff. (High-Low) (4-1,2,3)	20.7***					

Table 4.14: Multivariate analysis of the AIA impact on announcement day trading volume

In this table we analyse the determinants of announcement day trading volumes for target stock. We regress average CAV [0, 1] on a high attention dummy, acquirer characteristics, target characteristics, and deal characteristics. High AIA is a dummy variable that takes value of 1 if firm's AIA on the announcement day equals to three or four and 0 otherwise. All variables are defined in Appendix C. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Coefficient	p-value
High AIA	0.083***	0.000
Acquirer firm size	0.002	0.547
Acquirer ROE	0.003	0.855
High tech acquirer	0.017	0.566
Target firm size	-0.003	0.106
Target ROE	-0.069	0.551
High tech target	0.053*	0.070
Transaction value	-0.001	0.437
Acquisition premium	0.026**	0.024
Tender offer	0.164***	0.000
Diversifying merger	0.011	0.622
All cash deal	0.083***	0.000
Year fixed effects		YES
Number of companies		660
Adj. R-square		0.198

Chapter5

Concluding Remarks

Investor attention plays a significant role in information processing and consequently in the pricing of assets. While traditional asset pricing models make the assumption that information newly available to investors is quickly processed and reflected in the stock prices, more recent literature documents that information is not embedded in prices until investors pay close attention to them. We investigate retail and institutional investor attention from three different perspectives.

This thesis makes several contributions. First, it contributes to the broad literature on the investor recognition hypothesis (*see* Merton, 1987; Grullon et al., 2004; Fang and Peress, 2009) and role of investor attention in the stock markets (*see* Barber and Odean, 2008; Da et al., 2011; Ben-Rephael et al., 2017). Firm's stock visibility is related to its price, publicity, and popularity of the products and social image, although we suggest that these proxies are passive. Our research is built on active measures of investor attention, considering that if one searches for information related to a firm, one is undoubtedly paying attention to it (Da et al., 2011). Furthermore, ASVI and AIA capture attention in a timelier manner than passive attention proxies. When investors search for a firm online, they may obtain valuable news in relation to the stock, which alleviates informational asymmetry. Hence, smaller stocks and stocks of firms less known to the public will benefit more from being recognised and from drawing investors' attention.

Second, it contributes to the stream of literature studying the S&P 500 index effect anomaly, by examining the role of investor attention in the context of anticipatory trading effects. The pioneering studies of Shleifer (1986) and Harris and Gurel (1986) find that stocks of firms added to the S&P 500 index exhibit abnormal returns of 3% immediately following the Standard & Poor's announcement of a change. Beneish and Whaley (1996) show that risk arbitrageurs play the S&P game by purchasing the stocks following the announcement and then selling them several days later to the index trackers, exploiting the new Standard & Poor's policy of announcing the change in advance. Our findings contribute to the literature by showing that the actual effect begins ahead of the announcement, where risk arbitrageurs anticipate the likely candidates for inclusion. Significantly positive levels of investor attention during the pre-announcement period imply increased information acquisition that aids arbitrageurs in targeting the most likely candidates for inclusion. Moreover, we report that attention measured by the AIA precedes the attention proxied by SVI during the pre-announcement period, showing that institutional investors have greater resources and higher incentives to react rapidly to information, in line with Ben-Rephael et al. (2017). Significantly positive abnormal trading volumes and abnormal returns five days ahead of the announcement support the pre-announcement index effect hypothesis. We also show that investors bet against beta as a part of their statistical arbitrage, with most of the pre-announcement effect being driven by low beta stocks.

Lastly, it makes a contribution to the literature that attempts to explain the widely known pre-bid price run up in target firm's stock from the perspective of the market anticipation hypothesis. It examines institutional investor attention and price-volume dynamics within the competitive trading model of He and Wang (1995) over the period ahead of the takeover announcement to shed light on the documented price run-up. The empirical results show that pre-announcement institutional investor attention levels are significantly higher two weeks ahead of the announcement and monotonically increase approaching the announcement day, which suggests that sophisticated investors take positions early but speculate more aggressively over time. Considering that significant increase in AIA must be supported by a large population of users instead of few corporate insiders, as well as the price-volume dynamics during the pre-event window, our results favour market anticipation hypothesis over the insider trading explanation. The study highlights the importance of our proxy since existing studies mostly employ passive measures like rumours in news media to proxy for anticipatory effects. This improves the previous results and provides stronger support for the market anticipation view.

5.1 Future research

An immediate avenue for future research emerges from the results in Chapter 3. One could investigate a control sample of firms of similar characteristics to those included in the S&P 500 index, to examine whether they exhibit the similar behaviour over the pre-announcement period. In other words, instead of considering only the successful addition candidates, a sample of firms that did not end up in the S&P 500 but had a high likelihood could be considered.

It would also be interesting to gain some further insights between the market overreaction and market underreaction explanations in Chapter 4. Unlike earnings announcements where we can study post-event stock price reactions, M&As are characterised by constant flow of information where stock prices correct accordingly. It would be interesting to obtain a sufficiently big sample of completed M&As without any further streams of information following the event in an effort to distinguish between the two explanations.

Appendix A

Variable definitions

Attention measures	
SVI	Weekly search volume index downloaded from Google Trends based on the firm's name as given by the CRSP database.
ASVI	Abnormal search volume index computed as the difference between weekly SVI and average value of weekly SVI over the previous year skipping the most recent month, scaled by the value of average weekly SVI over the previous year skipping the most recent month. Weekly ASVI is converted to monthly values by taking the average in each calendar month.
News	Number of news is total number of monthly newspaper articles relevant to a firm downloaded from the LexisNexis database.
Advertising expenditure	Annual cost of advertising media including radio, television, and promotional expenses downloaded from Compustat database ($ million).
Liquidity measures	
Relative bid-ask spread	Monthly average of the ratio of daily inside spread to the midpoint of daily inside spread downloaded from CRSP database.

Relative effective spread	Twice the difference between the transaction price and the spread midpoint scaled by the midpoint of the spread downloaded from CRSP database.
Turnover	Monthly average of share trading volume divided by the number of outstanding shares from CRSP database.
Amihud illiquidity ratio	Monthly average of daily absolute stock return divided by its daily dollar trading volume downloaded from CRSP database.
Firm characteristics	
Firm Age	Number of years for which the firm has been included in the CRSP database.
Return	Monthly average of daily stock returns obtained from CRSP database.
Return on assets	Annual operating income before depreciation scaled by total assets downloaded from Compustat database.
Market capitalisation	Monthly average of the product of total number of outstanding shares and closing stock price downloaded from CRSP database.
Price inverse	Reciprocal of monthly stock price downloaded from CRSP database.
Volatility	Monthly average of the standard deviation of daily returns downloaded from CRSP database.

Appendix B

Media coverage in target pre-bid price run-up literature

Study	*Period*	*Country*	*Number of firms*
Chou et al. (2010)	1990/2008	US	260
Gao and Oler (2012)	1990/2001	US	976
Gupta and Misra (1989)	1985/1986	US	87
Hallett (2007)	2003/2006	US	431
Jarrell and Poulsen (1989)	1981/1985	US	172
Mathur and Waheed (1995)	1981/1989	US	233
Pound and Zeckhauser (1990)	1983/1985	US	42
Zivney et al. (1996)	1985/1988	US	271
Holland and Hodgkinson (1994)	1988/1989	UK	86
Siganos (2013)	2004/2010	UK	430
Siganos and Papa (2012)	1998/2010	UK	783
Aspris et al. (2014)	2001/2009	Australia	450
Clarkson et al. (2006)	1999/2000	Australia	118
Murray (1994)	1988/1992	Australia	60
King and Padalko (2005)	1985/2002	Canada	420

Appendix C

Variable definitions

AIA	Abnormal institutional attention measure obtained from Bloomberg platform, as defined in paragraph 3.1.
Market return	Returns on the S&P 500 index from CRSP.
Abnormal return	Estimated using the market model.
CAR [0, 1]	Cumulative abnormal return over the window [0,1] in days relative to the merger announcement day.
Turnover	Trading volume divided by the number of shares outstanding from CRSP.
Abnormal trading volume	The difference between the turnover on a particular day and the average daily turnover for the past 250 days, skipping the most recent 20 trading days.
Book/Market ratio	Book value scaled by the market capitalisation from Thomson Financial SDC
Target financial characteristics	
Target firm size	Market capitalisation from CRSP.
Target ROE	Net income of the target firm scaled by the book value of common equity of the target firm from Thomson Financial SDC.

High tech acquirer	Dummy variable that equals 1 if acquirer firm operates in a high-tech industry according to Thomson Financial SDC classification and 0 otherwise.
Acquirer financial characteristics	
Acquirer firm size	Market capitalisation from CRSP.
Acquirer ROE	Net income of the acquirer firm scaled by the book value of common equity of the acquirer firm from Thomson Financial SDC.
High tech target	Dummy variable that equals 1 if target firm operates in a high-tech industry according to Thomson Financial SDC classification and 0 otherwise.
Deal characteristics	
Transaction value	Value of the transaction as disclosed in the Thomson Financial SDC
Offer premium	Difference between initial offer price and target firm's stock price on the day before the announcement, scaled by the target firm's stock price on the day before the announcement.
Tender offer	Dummy variable that equals 1 if deal is a tender offer and 0 otherwise.
Diversifying merger	Dummy variable that equals 1 if the acquirer and target have different four digits SIC code and 0 otherwise.
All cash deal	Dummy variable that equals 1 if deal is fully financed by cash and 0 otherwise.
Event day indicator variables	
Merger announcement (Target) [i,j]	Dummy variable for the window [i,j] in days relative to the day when a firm is announced to be the target of the merger deal.

Merger announcement (Acquirer) [i,j]	Dummy variable for the window [i,j] in days relative to the day when a firm is announced to be the acquirer of the merger deal.
Earnings announcement [i,j]	Dummy variable for the window [i,j] in days relative to the earnings announcement date.

Bibliography

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1):31–56.

Amihud, Y. and Mendelson, H. (1986). Liquidity and stock returns. *Financial Analysts Journal*, 42(3):43–48.

Aouadi, A., Arouri, M., and Teulon, F. (2013). Investor attention and stock market activity: Evidence from france. *Economic Modelling*, 35:674–681.

Ariel, R. A. (1990). High stock returns before holidays: Existence and evidence on possible causes. *The Journal of Finance*, 45(5):1611–1626.

Arnott, R. D. and Vincent, S. J. (1986). S&p additions and deletions: A market anomaly. *The Journal of Portfolio Management*, 13(1):29–33.

Aspris, A., Foley, S., and Frino, A. (2014). Does insider trading explain price run-up ahead of takeover announcements? *Accounting & Finance*, 54(1):25–45.

Bamber, L. S., Barron, O. E., and Stevens, D. E. (2010). Trading volume around earnings announcements and other financial reports: Theory, research design, empirical evidence, and directions for future research. *Research Design, Empirical Evidence, and Directions for Future Research.*

Bank, M., Larch, M., and Peter, G. (2011). Google search volume and its influence on liquidity and returns of german stocks. *Financial markets and portfolio management*, 25(3):239.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies*, 21(2):785–818.

Barberis, N., Shleifer, A., and Wurgler, J. (2005). Comovement. *Journal of financial economics*, 75(2):283–317.

Beitel, P., Schiereck, D., and Wahrenburg, M. (2004). Explaining m&a success in european banks. *European Financial Management*, 10(1):109–139.

Ben-Rephael, A., Da, Z., and Israelsen, R. D. (2017). It depends on where you search: Institutional investor attention and underreaction to news. *The Review of Financial Studies*, 30(9):3009–3047.

Beneish, M. D. and Whaley, R. E. (1996). An anatomy of the "s&p game": The effects of changing the rules. *The Journal of Finance*, 51(5):1909–1930.

Betton, S., Eckbo, B. E., and Thorburn, K. S. (2008). Corporate takeovers. In *Handbook of empirical corporate finance*, pages 291–429. Elsevier.

Bijl, L., Kringhaug, G., Molnár, P., and Sandvik, E. (2016). Google searches and stock returns. *International Review of Financial Analysis*, 45:150–156.

Biktimirov, E. N., Cowan, A. R., and Jordan, B. D. (2004). Do demand curves for small stocks slope down? *Journal of Financial Research*, 27(2):161–178.

Bildik, R. and Gülay, G. (2008). The effects of changes in index composition on stock prices and volume: Evidence from the istanbul stock exchange. *International Review of Financial Analysis*, 17(1):178–197.

Blume, M. E. and Edelen, R. M. (2004). S&p 500 indexers, tracking error, and liquidity. *The Journal of Portfolio Management*, 30(3):37–46.

Brandt, M. W., Brav, A., Graham, J. R., and Kumar, A. (2009). The idiosyncratic volatility puzzle: Time trend or speculative episodes? *The Review of Financial Studies*, 23(2):863–899.

Brown, S. J. and Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of financial economics*, 14(1):3–31.

Chae, J. (2005). Trading volume, information asymmetry, and timing information. *The journal of finance*, 60(1):413–442.

Chemmanur, T. and Yan, A. (2009). Product market advertising and new equity issues. *Journal of Financial Economics*, 92(1):40–65.

Chen, H., Noronha, G., and Singal, V. (2004). The price response to s&p 500 index additions and deletions: Evidence of asymmetry and a new explanation. *The Journal of Finance*, 59(4):1901–1930.

Chen, H., Singal, V., and Whitelaw, R. F. (2016a). Comovement revisited. *Journal of Financial Economics*, 121(3):624–644.

Chen, J., Liu, Y.-J., Lu, L., and Tang, Y. (2016b). Investor attention and macroeconomic news announcements: Evidence from stock index futures. *Journal of Futures Markets*, 36(3):240–266.

Choe, H., Kho, B.-C., and Stulz, R. M. (1999). Do foreign investors destabilize stock markets? the korean experience in 1997. *Journal of Financial Economics*, 54(2):227–264.

Choi, H. and Varian, H. (2012). Predicting the present with google trends. *Economic Record*, 88:2–9.

Chou, H.-I., Tian, G. Y., and Yin, X. (2010). Rumors of mergers and acquisitions: Market efficiency and markup pricing. In *23rd Australasian Finance and Banking Conference*.

Chung, K. H. and Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets*, 17:94–120.

Chung, R. and Kryzanowski, L. (1998). Are the market effects associated with revisions to the tse300 index robust? *Multinational Finance Journal*, 2(1):1–36.

Clarkson, P. M., Joyce, D., and Tutticci, I. (2006). Market reaction to takeover rumour in internet discussion sites. *Accounting & Finance*, 46(1):31–52.

Cohen, L. and Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, 63(4):1977–2011.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5):1461–1499.

Da, Z., Gurun, U. G., and Warachka, M. (2014). Frog in the pan: Continuous information and momentum. *The review of financial studies*, 27(7):2171–2218.

Datar, V. T., Naik, N. Y., and Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1(2):203–219.

DellaVigna, S. and Pollet, J. M. (2009). Investor inattention and friday earnings announcements. *The Journal of Finance*, 64(2):709–749.

Denis, D. K., McConnell, J. J., Ovtchinnikov, A. V., and Yu, Y. (2003). S&p 500 index additions and earnings expectations. *The Journal of Finance*, 58(5):1821–1840.

Dhillon, U. and Johnson, H. (1991). Changes in the standard and poor's 500 list. *Journal of Business*, pages 75–85.

Dimpfl, T. and Jank, S. (2016). Can internet search queries help to predict stock market volatility? *European Financial Management*, 22(2):171–192.

Ding, R. and Hou, W. (2015). Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutions and Money*, 37:12–26.

Drake, M. S., Roulstone, D. T., and Thornock, J. R. (2012). Investor information demand: Evidence from google searches around earnings announcements. *Journal of Accounting research*, 50(4):1001–1040.

Eckbo, B. E. and Thorburn, K. S. (2000). Gains to bidder firms revisited: Domestic and foreign acquisitions in canada. *Journal of Financial and Quantitative Analysis*, 35(1):1–25.

Edmister, R. O., Graham, A. S., and Pirie, W. L. (1996). Trading cost expectations: Evidence from s&p 500 index replacement stock announcements. *Journal of Economics and Finance*, 20(2):75–85.

Elliott, W. B. and Warr, R. S. (2003). Price pressure on the nyse and nasdaq: Evidence from s&p 500 index changes. *Financial Management*, pages 85–99.

Erwin, G. R. and Miller, J. M. (1998). The liquidity effects associated with addition of a stock to the s&p 500 index: Evidence from bid/ask spreads. *Financial Review*, 33(1):131–146.

Fang, L. and Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance*, 64(5):2023–2052.

Franks, J. R. and Harris, R. S. (1989). Shareholder wealth effects of corporate takeovers: the uk experience 1955–1985. *Journal of financial Economics*, 23(2):225–249.

Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1):1–25.

Frieder, L. and Subrahmanyam, A. (2001). Brand perceptions and the market for common stock, forthcoming, journal of financial and quantitative.

Gao, Y. and Oler, D. (2012). Rumors and pre-announcement trading: why sell target stocks before acquisition announcements? *Review of Quantitative Finance and Accounting*, 39(4):485–508.

Gervais, S., Kaniel, R., and Mingelgrin, D. H. (2001). The high-volume return premium. *The Journal of Finance*, 56(3):877–919.

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., and Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, 457(7232):1012.

Goddard, J., Kita, A., and Wang, Q. (2015). Investor attention and fx market volatility. *Journal of International Financial Markets, Institutions and Money*, 38:79–96.

Graham, J. R. and Kumar, A. (2006). Do dividend clienteles exist? evidence on dividend preferences of retail investors. *The Journal of Finance*, 61(3):1305–1336.

Grinblatt, M. and Keloharju, M. (2001). What makes investors trade? *The Journal of Finance*, 56(2):589–616.

Grossman, S. J. and Miller, M. H. (1988). Liquidity and market structure. *the Journal of Finance*, 43(3):617–633.

Grullon, G., Kanatas, G., and Weston, J. P. (2004). Advertising, breadth of ownership, and liquidity. *The Review of Financial Studies*, 17(2):439–461.

Harris, L. and Gurel, E. (1986). Price and volume effects associated with changes in the s&p 500 list: New evidence for the existence of price pressures. *the Journal of Finance*, 41(4):815–829.

He, H. and Wang, J. (1995). Differential information and dynamic behavior of stock trading volume. *The Review of Financial Studies*, 8(4):919–972.

Hegde, S. P. and McDermott, J. B. (2003). The liquidity effects of revisions to the s&p 500 index: An empirical analysis. *Journal of Financial Markets*, 6(3):413–459.

Hendershott, T., Menkveld, A. J., Praz, R., and Seasholes, M. S. (2010). Asset price dynamics with limited attention. In *23rd Australasian Finance and Banking Conference*.

Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38:297–331.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, 64(5):2289–2325.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2011). Limited investor attention and stock market misreactions to accounting information. *The Review of Asset Pricing Studies*, 1(1):35–73.

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics*, 36(1-3):337–386.

Ho, T. and Stoll, H. R. (1980). On dealer markets under competition. *The Journal of Finance*, 35(2):259–267.

Hoffmann, A. O., Post, T., and Pennings, J. M. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, 37(1):60–74.

Holland, K. and Hodgkinson, L. (1994). The pre-announcement share price behaviour of uk takeover targets. *Journal of Business Finance & Accounting*, 21(4):467–490.

Hong, H. and Yu, J. (2009). Gone fishin': Seasonality in trading activity and asset prices. *Journal of Financial Markets*, 12(4):672–702.

Huberman, G. and Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *The Journal of Finance*, 56(1):387–396.

Kahneman, D. (1973). *Attention and effort*, volume 1063. Citeseer.

Kappou, K., Brooks, C., and Ward, C. (2010). The s&p500 index effect reconsidered: Evidence from overnight and intraday stock price performance and volume. *Journal of Banking & Finance*, 34(1):116–126.

Kasch, M. and Sarkar, A. (2011). Comovement revisited. *Federal Reserve Bank of New York Staff Reports No*, 484.

Kaul, A., Mehrotra, V., and Morck, R. (2000). Demand curves for stocks do slope down: New evidence from an index weights adjustment. *The Journal of Finance*, 55(2):893–912.

Kim, Y. H. and Meschke, F. (2011). Ceo interviews on cnbc. In *Fifth Singapore International Conference on Finance*.

King, M. R. and Padalko, M. (2009). Prebid run-ups ahead of canadian takeovers: How big is the problem? *Financial Management*, 38(4):699–726.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, pages 1315–1335.

Lakonishok, J. and Smidt, S. (1988). Are seasonal anomalies real? a ninety-year perspective. *The review of financial studies*, 1(4):403–425.

Lang, M. and Maffett, M. (2011). Transparency and liquidity uncertainty in crisis periods. *Journal of accounting and economics*, 52(2-3):101–125.

Lee, C. M. (1992). Earnings news and small traders: An intraday analysis. *Journal of Accounting and Economics*, 15(2-3):265–302.

Liu, H. and Peng, L. (2015). Investor attention: seasonal patterns and endogenous allocations. Technical report, Working paper.

Liu, Y.-J., Zhang, Z., and Zhao, L. (2014). Speculation spillovers. *Management Science*, 61(3):649–664.

Louis, H. and Sun, A. (2010). Investor inattention and the market reaction to merger announcements. *Management Science*, 56(10):1781–1793.

Lynch, A. W. and Mendenhall, R. R. (1997). New evidence on stock price effects associated with changes in the s&p 500 index. *The Journal of Business*, 70(3):351–383.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, 35(1):13–39.

Madhavan, A. (2003). The russell reconstitution effect. *Financial Analysts Journal*, 59(4):51–64.

Malkiel, B. G. and Radisich, A. (2001). The growth of index funds and the pricing of equity securities. *The Journal of Portfolio Management*, 27(2):9–21.

Mase, B. (2007). The impact of changes in the ftse 100 index. *Financial Review*, 42(3):461–484.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The journal of finance*, 42(3):483–510.

Mikkelson, W. H. and Partch, M. M. (1985). Stock price effects and costs of secondary distributions. *Journal of Financial Economics*, 14(2):165–194.

Odean, T. (1999). Do investors trade too much? *American economic review*, 89(5):1279–1298.

Peng, L. and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3):563–602.

Pilloff, S. J. (1996). Performance changes and shareholder wealth creation associated with mergers of publicly traded banking institutions. *Journal of Money, Credit and Banking*, 28(3):294–310.

Pound, J. and Zeckhauser, R. (1990). Clearly heard on the street: The effect of takeover rumors on stock prices. *Journal of Business*, pages 291–308.

Seasholes, M. S. and Wu, G. (2007). Predictable behavior, profits, and attention. *Journal of Empirical Finance*, 14(5):590–610.

Shankar, S. and Miller, J. M. (2006). Market reaction to changes in the s&p smallcap 600 index. *Financial Review*, 41(3):339–360.

Siganos, A. (2013). Google attention and target price run ups. *International Review of Financial Analysis*, 29:219–226.

Siganos, A. and Papa, M. (2015). Ft coverage and uk target price run-ups. *The European Journal of Finance*, 21(12):1070–1089.

Stoll, H. R. (1978). The supply of dealer services in securities markets. *The Journal of Finance*, 33(4):1133–1151.

Vijh, A. M. (1994). S&p 500 trading strategies and stock betas. *The Review of Financial Studies*, 7(1):215–251.

Vlastakis, N. and Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance*, 36(6):1808–1821.

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking & Finance*, 41:17–35.

Wurgler, J. and Zhuravskaya, E. (2002). Does arbitrage flatten demand curves for stocks? *The Journal of Business*, 75(4):583–608.

Yuan, Y. (2011). Attention and trading. *Working Paper, University of Pennsylvania*.

Zivney, T. L., Bertin, W. J., and Torabzadeh, K. M. (1996). Overreaction to takeover speculation. *The Quarterly Review of Economics and Finance*, 36(1):89–115.