PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE
ESCUELA DE INGENIERÍA

ATTENTION-DRIVEN OVERRREACTION TO POSITIVE AND NEGATIVE EARNINGS SURPRISES

DIEGO ANTONIO MARTÍNEZ MUNZENMAYER

Thesis submitted to the Office of Research and Graduate Studies
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering

Advisor:
TOMÁS REYES

Santiago de Chile, July 2018

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Gratefully to my parents

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ABSTRACT

We argue for a unifying mechanism that combines the most relevant theories in the prior literature to link investor attention to stock prices. We propose a directional and compound effect of attention on stock prices: high attention is associated with both an overreaction effect and faster information discovery. Both associations depend on the type of new information driving the increase in attention: high attention to very positive (negative) new information generates positive (negative) price pressure and a subsequent partial price reversal. We test this novel mechanism in the context of quarterly earnings announcements. Data in earnings announcements cover a wide range of events, from very positive to very negative earnings surprises. We find strong evidence to support this mechanism, even after controlling for well-known predictors of financial performance around earnings announcements.

Keywords: Earnings announcements, market-pricing anomaly, limited attention, event study.

RESUMEN

En esta tesis se plantea un mecanismo que relaciona la atención de los inversionistas con los precios de las acciones, y que combina las teorías más relevantes presentes en la literatura previa. Se propone un mecanismo direccional y compuesto de la atención sobre el precio de las acciones, en el cual una alta atención está asociada con una sobrerreacción y con un descubrimiento de precios más veloz. Ambas asociaciones dependen del tipo de nueva información que conduce ese aumento de atención: alta atención ante nueva información muy positiva (negativa) genera una presión de precios positiva (negativa) y una subsecuente reversión parcial. Testeamos este nuevo mecanismo en el contexto de anuncios de utilidades trimestrales. Los datos disponibles de estos anuncios cubren un amplio rango de eventos: desde aquellos en que la sorpresa de utilidades fue muy positiva, hasta aquellos en los que fue muy negativa. Encontramos evidencia robusta que respalda el mecanismo propuesto, incluso después de controlar por variables que en la literatura se plantean como predictores del desempeño financiero en el contexto de anuncios de utilidades.

Palabras Claves: Anuncios de utilidades, anomalías de mercado, atención limitada, estudio de eventos.

1. INTRODUCTION

1.1. Introduction

In 1973, Kahneman described attention has a limited resource, arguing that people can allocate attention only to part of the vast amount of available information. Extensive evidence suggests that investors' attention to economic and financial events is related to their behavior, and, therefore, it affects asset prices. That is, limited attention influences the way that investors process information and react to it, which affects variables such as stock prices, expected returns, and volatilities.

Previous authors have studied the relationship between limited attention and investor's behavior. Concretely, there are three main different mechanisms that try to explain this relation, and that are not fully consistent with each other. First, Barber and Odean (2007) find that individual investors are net buyers of attention-grabbing stocks, regardless of whether the attention is driven by positive or negative information.

Another strand of the literature argues that attention promotes the faster incorporation of new information into capital markets and helps reduce market inefficiencies. Drake, Roulstone, and Thornock (2012), an exponent of this strand, show that an increase in investors' demand for information accelerates price discovery (i.e., high attention driven by positive (negative) information is associated with higher (lower) prices).

Finally, Reyes and Waissbluth (2018) argue for a third mechanism. In the context of bankruptcy filings, they find that investors negatively overreact to attention-grabbing stocks. They posit that, in the context of very negative news, firms receiving high attention exhibit a more negative price reaction than firms receiving low attention and a subsequent reversal

In this paper, we propose a unifying mechanism for attention on stocks prices. We argue that attention is associated with faster information discovery as well as an overreaction effect. The directions of both effects depend on whether the information driving the increase in attention has a clearly positive or negative connotation. That is, high attention to very positive (negative) new information generates positive (negative) price pressure and a subsequent partial price reversal.

We test this mechanism in the context of quarterly earnings announcements. Earnings announcements provide a suitable framework for studying the effect of attention associated with very positive or negative new information on stock prices. Additionally, earnings announcements have been studied extensively, which allows us to build upon a solid and well-known strand of literature.

1.2. Literature Review

This paper studies the effect of investor attention on firms' financial performance around quarterly earnings announcements. Our contribution is related to two main strands of the literature. First, we delve into the literature that relates attention to investor behavior. Additionally, we contribute to the literature that explains stock performance around earnings announcements.

First, we review the three main mechanisms through which attention seems to affect stock prices. First, Barber and Odean (2007) find that individual investors are net buyers of stocks that grab investors' attention, independent of whether the circumstances that triggered such attention have a positive or negative connotation. They argue that since it is impossible for investors to pay attention to each stock available in the market, individual investors tend to buy stocks that have recently caught their attention. That is, an increase in investor attention produces positive price pressure on average, which then partially reverses over time.

Another strand of the literature suggests that attention accelerates the incorporation of new information into stock prices. That is, attention promotes price discovery. DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Drake et al. (2012) provide evidence consistent with this mechanism.

Finally, Reyes and Waissbluth (2018) argue for a third mechanism through which attention affects investors' behavior. They study the relation between attention and stock prices in the context of bankruptcy filings and find that investors negatively overreact to high-attention filings. Reyes and Waissbluth (2018) argue that neither of the above mechanisms fully apply in their setting because bankruptcy news have extremely negative connotations.

In order to measure investors' attention, several variables have been used. Usual ones are trading volume (Gervais, Kaniel, & Mingelgrin, 2001; Barber & Odean, 2007; Lin, Wu, & Chiang, 2014; and Adra & Barbopoulos, 2018), news coverage (Barber & Odean, 2007; Boulland & Dessaint, 2017; and Chemmanur & Yan, 2017), advertising expenses (Grullon, Kanatas, & Weston, 2004; Ding, Jia, Wu, & Yuan, 2017), price limits (Seasholes & Wu, 2007; D. Peng, Rao, & Wang, 2016), and extreme returns (Barber & Odean, 2007; Reyes, 2018).

We follow an emerging strand of literature and use Google Search Volume Index (SVI) as a proxy for attention. Since people searching in Google need to be paying attention to what they search, SVI is a more direct measure of attention than the alternatives in the literature. Additionally, since Google is a popular and massive search engine, SVI provides a more representative proxy for investor attention than alternative measures.

In the literature about financial performance in the context of earnings announcements, financial researchers find that these events produce various effects in the capital markets. Ball and Brown (1968) document the so called post-earnings-announcement drift. This drift is defined as the tendency for a stock's cumulative abnormal returns to follow an upward or downward trend over several weeks after an earnings announcement, depending on whether the earnings surprise is positive or negative, respectively. Some researchers characterize this anomaly as a market inefficiency (see for instance, Lev & Ohlson, 1982; Bernard & Thomas, 1989; Chordia, Goyal, Sadka, Sadka, & Shivakumar, 2009; Ramiah, Xu, & Moosa, 2015 among others).

Some authors have also studied the magnitude of post-earnings-announcement drift, finding that the magnitude of the drift could be related to firm size (Foster, Olsen, & Shevlin, 1984), earnings surprise associated to the announcement (Bernard & Thomas, 1989), transaction costs (Bhushan, 1994), and institutional ownership (Bartov, Radhakrishnan, & Krinsky, 2000). Additionally, antecedents have proposed several variables to explain the size of the cumulative abnormal returns observed empirically. They have also propose psychological biases as explanations for post-earnings-announcement drift. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) develop a theoretical model in which investors overestimate the precision of their private information and underestimate the precision of public information (earnings announcements).

In this thesis, we use investors' attention as a variable to explain abnormal returns after earnings announcements.

1.3. Objective and Hypotheses

The main objective of this thesis is to provide a robust mechanism that explains the relationship between investors' attention and investors' behavior.

Concretely, we propose a unifying mechanism for attention's directional and compound effect on stock performance. We argue that attention is associated with faster information discovery as well as an overreaction effect. The directions of both effects depend on whether the information driving the increase in attention has a clearly positive or negative connotation. That is, high attention to very positive (negative) new information generates positive (negative) price pressure and a subsequent partial price reversal.

To verify this mechanism in the context of earnings announcement, we use *Earnings Surprise* variable to distinguish between earnings announcement with different connotations. An earnings surprise (ES) is defined as the difference between announced earnings per share and the median of the analysts' forecasts, standardized by the stock price at the end of the fiscal quarter in which the announcement was made.

To test our mechanism we present three specific hypotheses: (i) when an earnings surprise is very positive, abnormal attention to the announcement is positively related to post-announcement abnormal returns; (ii) when an earnings surprise is very negative, abnormal attention to the announcement is negatively related to post-announcement abnormal returns; and (iii) the initial effects of abnormal attention on abnormal returns are subsequently partially reversed. In other words, the post-announcement price reaction to a strong earnings surprise is exacerbated for firms receiving greater attention before and during the announcement. This reaction initially follows the direction of the earnings surprise, but partially reverses in the subsequent period. Therefore, investors exhibit attention-driven overreactions to both very positive and very negative earnings surprises.

1.4. Methodology

In this thesis, we use the event study methodology to test our hypotheses. The objective of an event study methodology, first proposed by Fama (1969), is to evaluate the effect that an specific event has on firms' performance. This methodology is widely used in financial researches, since it allows to isolate this specific event and quantify its effect over relatively short periods of time.

In general, firms' performance is measured using abnormal returns in a time window around (or after) the event. To compute abnormal returns, it is necessary to define a benchmark return, that should represent the return in a normal scenario (without the event). In this thesis, we perform an event study for abnormal returns after quarterly earnings announcements from 2004 to 2016, and for firms that were at least once in the S&P 500 in those years. As benchmark, we use the average return of firms that were similar, based on size and on book-to-market ratios. This is a standard benchmark and it is also used by Hirshleifer et al. (2009) and Drake et al. (2012).

For statistical analysis, the main explanatory variable is abnormal attention, measured using search volume of Google Trends of the firm doing the announcement. We include several other variables that antecedents suggest, such as explanatory variables of financial performance in the context of earnings announcement. Additionally, we deal with some difficulties that statistical models currently present: endogeneity issues and heteroscedasticity issues, among others.

1.5. Main Results and Conclusions

To study how investor attention relates to stock returns depending on the connotation of the earnings news, we partition a full sample of earnings announcements using the variable *Earnings Surprise*. We focus on the highest and lowest quintiles of *Earnings Surprise* and define: (i) the *Highest ES* sample as the subsample of earnings announcements with *Earnings Surprise* in the highest quintile, which have a very positive connotation; and (ii) the *Lowest ES* sample as the subsample consisting of earnings announcements with *Earnings Surprise* in the lowest quintile, which have a very negative connotation.

For each of the events in these subsamples, we estimate weekly *Cumulative Abnormal Return* (CAR) for the four weeks following the announcement. Additionally, using Google Trends, we compute a variable to measure abnormal investors' attention, which is called *Abnormal SVI* ($ASVI$).

Our main results strongly support our hypotheses. When the earnings surprise is positive in the *Highest ES*, abnormal investor attention, $ASVI$, is related to a positive price reaction in the first week after the announcement ($CAR[1,5]$). In contrast, when the earnings surprise is negative in the *Lowest ES* sample, $ASVI$ is negatively related to $CAR[1,5]$. In both cases, this effect is partially reversed in third week following the announcement, in which the relationships between $ASVI$ and $CAR[11,15]$ are smaller in magnitude and have opposite signs.

1.6. Further Research

There are some extensions that could help overcome some limitations of this study. First of all, we do not include in our sample firms whose tickers have ambiguous meanings since searches for these terms are unlikely to be related to financial phenomena. To resolve this issue objectively, we keep a firm in the sample only if a Google search for its ticker symbol provides specific financial information on the first page of results. This procedure may not be completely accurate, since we are implicitly assuming that if nowadays this criteria is met for a firm, it was also met on the date of the announcement.

Another extension of this thesis is related to the size of the sample. Following Drake et al. (2012), we only consider firms that were part of the S&P 500 at least once during our sample period (2004 to 2016), since small — less searched — firms are unlikely to have SVI available. In the future, if Google Trends reports data for a wide set of terms, this study may incorporate a larger number of firms and hopefully reconfirm our hypothesis.

A third extension consists in the implementation of a trading strategy that take advantage of the patterns we propose in our mechanism, and simulate the construction of a portfolio based on this strategy. Comparing this portfolio to a benchmark portfolio should give us more evidence that further supports our mechanism. This methodology is widely used by financial researches other contexts, since it is a realistic way to compute the return that an investor could effectively get considering our mechanism.

Finally, in this study we could include a long-term analysis. To test our mechanism, we only require to compute attention on the two days before the announcement and abnormal return on the month after the announcement since long-term abnormal returns provide different empirical challenges. In the future, we can seize the sample used in this study and include larger time windows in the analysis. This would allow us to delve into some long-term implications of our mechanism and obtain additional conclusions.

2. ATTENTION-DRIVEN OVERRREACTION TO POSITIVE AND NEGATIVE EARNINGS SURPRISES

2.1. Introduction

Extensive evidence suggests that investors' attention to economic and financial events is related to their behavior, and, therefore, affects asset prices. Kahneman (1973) is the first to describe attention as a limited cognitive resource and to argue that attention has a strong influence on individuals' decision making. More recently, several authors have related investors' limited attention to diverse financial phenomena, showing that limited attention influences the way that investors process information and react to it, which affects variables such as stock prices, expected returns, and volatilities.[1]

In the literature, we can identify three main mechanisms through which attention impacts asset prices. These mechanisms are not fully consistent with each other. First, Barber and Odean (2007) find that individual investors are net buyers of attention-grabbing stocks, regardless of whether the spike in attention is driven by positive or negative information. That is, an increase in investor attention produces positive price pressure, which then partially reverses over time. Da, Engelberg, and Gao (2011) and Joseph, Wintoki, and Zhang (2011) also provide evidence to support this theory.

Another strand of the literature argues that attention promotes faster incorporation of new information into capital markets and helps reduce market inefficiencies. Drake et al. (2012) show that an increase in investors' demand for information accelerates price discovery (i.e., high attention driven by positive (negative) information is associated with higher (lower) prices).[2] Importantly, none of these studies argue or provide evidence for a reversal effect. DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) argue that

[1]See, for example, L. Peng and Xiong (2006), Barber and Odean (2007), DellaVigna and Pollet (2009), Hirshleifer et al. (2009), Cumming and Dai (2011), Mamun and Mishra (2012), Borghesi, Houston, and Naranjo (2014), and Boulland, Degeorge, and Ginglinger (2017).

[2]Drake et al. (2012) find that a high level of attention before an earnings announcement partially preempts the effect of the announcement.

investors take longer to react to new information in contexts of inattention (e.g., when their attention is focused elsewhere or they are simultaneously tracking numerous stocks).

Finally, Reyes and Waissbluth (2018) argue for a third mechanism. In the context of bankruptcy filings, they find that investors (negatively) overreact to attention-grabbing stocks. They posit that, in the context of very negative news, firms receiving high attention exhibit a more negative price reaction than firms receiving low attention. They also show that this effect is partially reversed during the days after the bankruptcy filing. This third role of attention has also been suggested by Hou, Xiong, and Peng (2009); Peress and Schmidt (2016).

In this paper, we propose a unifying mechanism for attention's directional and compound effect on stock performance. We argue that attention is associated with faster information discovery as well as an overreaction effect. The directions of both effects depend on whether the information driving the increase in attention has a clearly positive or negative connotation. That is, high attention to very positive (negative) new information generates positive (negative) price pressure and a subsequent partial price reversal.

This mechanism combines the three main theories suggested in the prior literature. We argue that all news with strong connotations, regardless of whether the connotations are positive or negative, lead to faster incorporation of information into prices, which is consistent with DellaVigna and Pollet (2009), Hirshleifer et al. (2009), and Drake et al. (2012). However, we also point to an overreaction effect. When new information is very positive, this overreaction effect is consistent with Barber and Odean (2007), Da et al. (2011), and Joseph et al. (2011), i.e., high attention is related to positive price pressure and a subsequent partial reversal. On the other hand, when new information is very negative, this overreaction is consistent with Reyes and Waissbluth (2018), i.e., high attention is related to negative price pressure and a subsequent partial reversal.

We test this mechanism in the context of quarterly earnings announcements. Earnings announcements provide a suitable framework for studying the effect of attention associated with very positive or negative new information on stock prices. Data in earnings announcements provide a wide range of events to test our mechanism, from announcements with very positive earnings surprises (i.e., a release of information with very positive connotations) to those with very negative earnings surprises (i.e., a release of information with very negative connotations). An earnings surprise (ES), or unexpected earnings, is defined as the difference between announced earnings per share and the median of analysts' forecasts, standardized by the stock price at the end of the fiscal quarter. Additionally, earnings announcements have been studied extensively, which allows us to build upon a solid and well-known strand of literature.[3]

In the context of earnings announcements, our main hypotheses are: (i) when an earnings surprise is very positive, abnormal attention to the announcement is positively related to post-announcement abnormal returns; (ii) when an earnings surprise is very negative, abnormal attention to the announcement is negatively related to post-announcement abnormal returns; and (iii) the initial effects of abnormal attention on abnormal returns are subsequently partially reversed. In other words, the post-announcement price reaction to a strong earnings surprise is exacerbated for firms receiving greater attention before and during the announcement. This reaction initially follows the direction of the earnings surprise, but partially reverses in the subsequent period. Therefore, investors exhibit attention-driven overreactions to both very positive and very negative earnings surprises.

[3]Ball and Brown (1968) were the first to notice the so-called post-earnings-announcement drift. They show that, after annual earnings announcements, cumulative abnormal returns tend to increase or decrease based on whether the earnings surprise was positive or negative, respectively, and tend to stay high or low for several weeks afterward. Bernard and Thomas (1989) justify post-earnings-announcement drift as a delayed response to the announcement. Other authors have tried to explain post-earnings-announcement drift with variables such as firm size (Foster et al., 1984), transaction costs (Ng, Rusticus, & Verdi, 2008; Bhushan, 1994), institutional ownership (Bartov et al., 2000), and such psychological traits as investors' over- and under-confidence in information (Daniel et al., 1998; Liang, 2003) and limited attention (Hou et al., 2009).

We use quarterly earnings announcement data from IBES.[4] We complement this data with accounting information, financial information, media coverage, and institutional ownership information from Compustat, CRSP[5] and Kenneth French's website,[6] LexisNexis, and Thomson Reuters Institutional Holdings, respectively. Additionally, we proxy for investor attention using Google's Search Volume Index (SVI).[7] We measure investor attention to an earnings announcement as abnormal SVI between days -2 and 0 relative to the announcement date ($ASVI[-2, 0]$) for the ticker symbol of the firm making the announcement. To measure stock performance, we analyze post-announcement cumulative abnormal returns for the four weeks following each announcement (i.e., $CAR[1, 5]$, $CAR[6, 10]$, $CAR[11, 15]$, and $CAR[16, 20]$). We also include in our analyses other well-known predictors of stock performance around earnings announcements. Our final sample contains 8,734 quarterly earnings announcements with complete data and made by firms located in the U.S. between 2004 and 2016.

In our main tests, we focus on earnings announcements with very positive or negative connotations, using the highest and lowest quintiles of earnings surprises, respectively. More specifically, the *Highest ES* sample comprises earnings announcements with *Earnings Surprise* in the highest quintile, while the *Lowest ES* sample consists of earnings announcements with *Earnings Surprise* in the lowest quintile.[8]

Visual inspection of daily average post-announcement CARs for the *Highest ES* and *Lowest ES* samples provides preliminary evidence supporting our mechanism. During the first week after the announcement, the price reaction of firms with high abnormal attention, $ASVI[-2, 0]$, intensifies in the direction of the announcement's connotation. That is,

[4]Thomson Reuters Institutional Brokers' Estimate System.

[5]Center for Research in Security Prices

[6]`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[7]Da et al. (2011), Joseph et al. (2011), Drake et al. (2012), and Reyes and Waissbluth (2018) have all used search volume to measure investor attention to firms and relate these measures with stock price performance in different contexts.

[8]The distribution of earnings surprises is not symmetrical. Our sample includes more announcements with positive ES than with negative ES. However, all announcements in the *Highest ES* (*Lowest ES*) sample do in fact have positive (negative) ES.

high-attention firms in the *Highest ES* (*Lowest ES*) sample have higher (lower) CARs than low-attention firms. Moreover, this effect partially reverses during the following weeks, suggesting that investors tend to overreact positively or negatively based on the sign of the earnings surprise.

Bivariate correlations among key variables also provide consistent evidence for our mechanism. In the *Highest ES* sample, abnormal attention, $ASVI[-2, 0]$, has a positive and significant correlation with one-week post-announcement cumulative abnormal return, $CAR[1, 5]$. In the *Lowest ES* sample, $ASVI[-2, 0]$ has a negative and significant correlation with $CAR[1, 5]$. Moreover, after computing correlations between $ASVI[-2, 0]$ and weekly CARs over subsequent weeks, we find that $ASVI[-2, 0]$ is also significantly correlated with CAR $[11, 15]$ in both samples. Importantly, these correlations are smaller in magnitude than those between $ASVI[-2, 0]$ and $CAR[1, 5]$, and have the opposite signs, suggesting a reversal effect.

We next use regression models to test whether our mechanism holds after controlling for other known predictors of performance around earnings announcements. For the *Highest ES* sample, regression results confirm that abnormal attention, $ASVI[-2, 0]$, has a positive and significant relationship with cumulative abnormal returns over the first week after the announcement, $CAR[1, 5]$. In contrast, for the *Lowest ES* sample, regression results show that $ASVI[-2, 0]$ has a negative and significant relationship with $CAR[1, 5]$. That is, high attention seems to exacerbate the price reaction in the direction of the earnings surprise, providing evidence consistent with our first two hypotheses.

Additionally, regression results suggest that the relationship between $ASVI[-2, 0]$ and $CAR[1, 5]$ partially reverses when considering CARs computed after the first week post-announcement in both samples. We find that $ASVI[-2, 0]$ has a significant relationship with $CAR[11, 15]$ in both samples; these associations are smaller in magnitude than those between abnormal attention and one-week post-announcement CAR and have the opposite signs. This evidence suggests a reversal effect, providing evidence consistent with our third hypothesis of an attention-driven overreaction to positive and negative earnings surprises.

Finally, we perform several robustness checks. We verify that our results are robust to different definitions of abnormal attention, and to wider definitions of the *Highest ES* and *Lowest ES* samples. Then, we analyze the effect of abnormal attention on post-announcement CARs for the complete sample of earnings announcements. Additionally, we corroborate that the effect of abnormal attention on post-announcement earnings performance tends to be driven by individual rather than institutional investors. Finally, we analyze the effect of abnormal attention on post-announcement CARs for samples of earnings announcements that release information with neutral or weaker connotations.

The rest of the paper is organized as follows: Section 2 summarizes the related literature; Section 3 describes data sources, provides variable definitions, and presents descriptive statistics of the sample; Section 4 shows our main results; Section 5 provides various robustness tests; and Section 6 concludes.

2.2. Literature Review

This paper studies the effect of investor attention on firms' financial performance around quarterly earnings announcements. Our contribution is related to two main strands of the literature. First, we build on the literature that relates attention to investor behavior. Additionally, we contribute to the literature that explains stock performance around earnings announcements.

2.2.1. Attention and Investor Behavior

Antecedents have long studied the ways in which attention affects investors' decisions. Kahneman (1973) was the first to argue that attention is a limited resource. Since Kahneman (1973), several authors have proposed mechanisms through which attention impacts asset prices and other financial phenomena. For example, prior studies claim that attention constraints can induce return predictability (L. Peng & Xiong, 2006; Cohen & Frazzini, 2008; Cao, Chordia, & Lin, 2016),[9] impact stock liquidity (Corwin and Coughenour (2008)),[10] and lead to systematic mispricing (Daniel, Hirshleifer, & Teoh, 2002; L. Peng & Xiong, 2006).[11]

In the rest of this subsection, we review the three main mechanisms through which attention seems to affect stock prices. First, Barber and Odean (2007) find that individual investors are net buyers of stocks that grab investors' attention (as proxied by trading volume, media coverage, and extreme returns), independent of whether the circumstances that triggered such attention have a positive or negative connotation. They argue that since it is impossible for investors to pay attention to each stock available in the market, individual investors tend to buy stocks that have recently caught their attention. In contrast, individual investors' selling behavior is not driven by attention, since they tend to sell only the stocks that they already hold, which represent a small subset of all stocks. In sum, an increase in investor attention produces positive price pressure on average, which then partially reverses over time.

Another strand of the literature suggests that attention accelerates the incorporation of new information into stock prices. That is, attention promotes price discovery. Drake et al. (2012) show that investor attention is positively related to incorporation of new information into prices and to higher trading volume. DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) also provide evidence consistent with this mechanism.[12] This second role of

[9] L. Peng and Xiong (2006) provide a theoretical model to show that, due to limited attention, investors tend to be more informed at the sector level than at the firm-specific level. This leads to higher-than-normal return correlations between firms within a sector, which affects return predictability and asset mispricing. Cohen and Frazzini (2008) propose that attentional constraints generate delays in the transmission of information across economically linked firms. Cao et al. (2016) suggest that investor inattention induces firms to underreact to their strategic partners' returns.

[10] Corwin & Coughenour, 2008 show that a specialist's ability to provide liquidity to a stock in a portfolio is reduced by the attention requirements of other stocks in the same portfolio.

[11] Daniel et al. (2002) suggest that limited attention leads to investor credulity, which generates asset mispricing.

[12] We review DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) in more detail in Section 2.2.2.1.

attention has also been suggested in Bushee, Core, Guay, and Hamm (2010) and Soltes (2009).

Finally, Reyes and Waissbluth (2018) argue for a third mechanism through which attention affects investors' behavior. They study the relation between attention and stock prices in the context of bankruptcy filings. They find that attention is negatively related to abnormal returns in the period prior to and during a bankruptcy filing, and that this effect is partially reversed in the days after the filing. In other words, in the context of bankruptcies, investors (negatively) overreact to high-attention filings. Reyes and Waissbluth (2018) argue that neither of the above mechanisms fully apply in their setting because bankruptcy news have extremely negative connotations.

In this paper, we argue that attention has a directional and compound effect on stock performance. That is, high attention is associated with faster incorporation of information into prices as well as an overreaction effect; both of these effects depend on the connotation of the new information driving the increase in attention. Specifically, high attention to very positive (negative) new information generates positive (negative) price pressure and a partial subsequent reversal.

This proposed mechanism combines the three main theories previously suggested in the literature. For all extreme news, regardless of connotation, we argue that attention accelerates the incorporation of new information into stock prices, as Drake et al. (2012), DellaVigna and Pollet (2009), and Hirshleifer et al. (2009) suggest. However, we also propose an overreaction effect. When information is very positive, this overreaction effect is consistent with Barber and Odean (2007), Da et al. (2011), and Joseph et al. (2011), i.e., high attention is related to positive price pressure and a subsequent partial reversal. In contrast, when information is very negative, this overreaction is consistent with Reyes and Waissbluth (2018), i.e., high attention is related to negative price pressure and a subsequent partial reversal.

2.2.1.1. Google Searches as a Proxy for Attention

Measuring investor attention is a challenging task, for which antecedents have proposed several proxies. For instance, Gervais et al. (2001), Barber and Odean (2007), Lin et al. (2014), and Adra and Barbopoulos (2018) use trading volume as a proxy for attention, suggesting that a direct relationship exists between high trading volume and investor attention to a stock. Additionally, Barber and Odean (2007), Boulland and Dessaint (2017), and Chemmanur and Yan (2017) use news coverage to measure attention, suggesting that firms that are in the news are more likely to catch investors' attention. Nofsinger (2001) has also used news coverage to study the trading behavior of individual and institutional investors. Other proxies for attention proposed in the literature are advertising expenses (Grullon et al., 2004; Ding et al., 2017), price limits (Seasholes & Wu, 2007; D. Peng et al., 2016), and extreme returns (Barber & Odean, 2007; Reyes, 2018).

In recent years, an emerging strand of the literature has used search volume from Google to measure attention in different contexts. Choi and Varian (2012) use Google searches to predict economic indicators such as unemployment claims, travel destination planning, and consumer confidence. Reyes, Majluf, and Ibañez (2018) use Google searches to measure social perceptions. In finance, Da, Engelberg, and Gao (2014) use internet searches to proxy for investor sentiment in order to predict aggregate market returns and Vozlyublennaia (2014) uses searches to measure investors' attention to stock market indexes such as the Dow Jones, S&P 500, and NASDAQ. More closely related to our study, Da et al. (2011) and Joseph et al. (2011) measure attention paid to individual firms using search volume and find evidence to support Barber and Odean's positive price pressure hypothesis, Drake et al. (2012) use it to proxy for information demand around earnings announcements, and Reyes and Waissbluth (2018) use internet searches to measure attention paid to firms around bankruptcy filings.

We follow this latter strand of literature and use the Google Search Volume Index (SVI) as a proxy for attention. Since individuals performing Google searches must be paying attention to their search terms, SVI is a more direct measure of attention than the alternatives in the literature. Additionally, since Google is a popular and massive search engine, SVI provides a more representative proxy for investor attention than alternative measures.

2.2.2. Stock Performance around Earnings Announcements

Financial researchers have studied earnings announcements extensively, identifying various effects of these announcements in the capital markets. Beaver (1968) was among the first to report some of these effects. He confirms that earnings announcements provide new information that is not fully incorporated in current prices. He also shows that, in the weeks in which firms announce their earnings, their stocks experience higher-than-normal trading volume and volatility. More importantly, Ball and Brown (1968) document the so called post-earnings-announcement drift. This drift is defined as the tendency for a stock's cumulative abnormal returns to follow an upward or downward trend over several weeks after an earnings announcement, depending on whether the earnings surprise is positive or negative, respectively. Some researchers characterize this anomaly as a market inefficiency (see for instance, Lev & Ohlson, 1982; Bernard & Thomas, 1989; Chordia et al., 2009; Ramiah et al., 2015 among others).

Several authors have tried to determine the cause of post-earnings-announcement drift. Bernard and Thomas (1989) find evidence supporting two potential explanations, both of which justify drift as a delayed response to the announcement. One explanation is that investors are not immediately able to recognize the full implications of earnings information. Therefore, prices cannot instantaneously and completely incorporate the new information provided by the announcement. Another explanation for the delay relates to transaction costs, which prevent the immediate incorporation of information into prices. Ng et al. (2008) provide further evidence supporting this explanation.[13]

[13] Ng et al. (2008) find that, for firms with higher transaction costs, stock prices drift less just after earnings announcements but subsequently drift more.

Some authors have also studied the magnitude of post-earnings-announcement drift, proposing several variables to explain the size of the cumulative abnormal returns observed empirically. Foster et al. (1984) show that the magnitude of the drift varies inversely with firm size. Bernard and Thomas (1989) add that the magnitude of the drift is positively correlated with the size of the earnings surprise. Bhushan (1994) suggests that transaction costs are positively related to the magnitude of the drift. Finally, Bartov et al. (2000) find that the proportion of stocks held by institutional investors (used as a proxy for investor sophistication) is inversely related to the magnitude of the drift. They also show that, after controlling for institutional ownership, variables such as firm size and transaction costs lose their influence.

Antecedents also propose psychological biases as explanations for post-earnings-announcement drift. Daniel et al. (1998) develop a theoretical model in which investors overestimate the precision of their private information and underestimate the precision of public information (earnings announcements). Under this framework, investors underreact to earnings announcements, failing to fully incorporate the new information into prices, which Daniel et al.argue leads to post-earnings-announcement drift. Liang (2003) provides empirical evidence supporting this theory.

2.2.2.1. Attention and Earnings Announcements

Some authors have also explored the relationship between investor attention and stock price performance around earnings announcements. DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) focus on stock price reactions to earnings announcements in contexts of low attention. DellaVigna and Pollet (2009) compare earnings announced on Fridays to those announced on other weekdays. They argue that investors are more distracted on Fridays and find that Friday earnings announcements result in weaker immediate stock price reactions but stronger delayed reactions. Hirshleifer et al. (2009) present similar results by using days with more earnings announcements as proxies for high-distraction days. These two studies argue for an inattention-driven slow initial reaction to earnings announcements, which is followed by a larger reaction in the subsequent weeks. Similarly, Drake et al. (2012) show that an increase in investor attention before an earnings announcement helps to preempt the information contained in that announcement. In particular, they find that, when attention prior to the announcement is high, price changes and trading volume are higher prior to the announcement and lower after it.[14]

2.3. Data

In this section, we first present our data sources and formally define each variable. Then, we specify the composition of our sample and provide descriptive statistics.

2.3.1. Data Sources and Variable Definitions

Earnings Announcements. We gather information about earnings announcements from IBES. This database includes quarterly earnings per share announced by firms and analysts' ex ante estimates of these earnings. Data obtained from IBES includes: date and fiscal quarter of each announcement; quarterly earnings per share; and analysts' forecasts of earnings per share, including the date each forecast is made and if and when that forecast is revised.

With this data, we compute the following variables: *4th Quarter*, which is set to 1 if the announcement is made on the last quarter of the fiscal year; *Revisions*, which is the logarithm of 1 plus the number of revisions made to the analysts' forecasts; *Earnings Surprise*, which is defined as the difference between announced earnings per share and the

[14]Additionally, in one of their robustness checks, Reyes and Waissbluth (2018) find some evidence suggesting that investors negatively overreact to negative earnings surprises. However, in their empirical setup, abnormal attention and abnormal returns are measured over the same time period, generating potential endogeneity concerns.

median of the analysts' forecasts, scaled by the stock price at the end of the fiscal quarter;[15,16] *Loss*, set to 1 if the value of announced earnings is negative; and *Friday*, which is set to 1 if the announcement is made on a Friday. Additionally, following Hirshleifer et al. (2009) and Drake et al. (2012), we compute *Earnings Volatility* as the standard deviation of seasonal earnings changes (i.e., the deviations of quarterly earnings from 1-year-ago earnings) over the four-year period ending on the fiscal end date (a minimum of four observations required) and *Earnings Persistence* as the first auto-correlation coefficient of quarterly earnings over the four-year period ending on the fiscal end date (a minimum of four observations required). Finally, we define $Rank\ of\ Announcement$ as the decile rank of the number of other firms announcing quarterly earnings on the same day.

Investor Attention. To construct our proxy for investor attention, we use data from Google Trends.[17] This tool provides a Search Volume Index (SVI) for any frequently searched term on Google, showing how searches for that term evolved over time since 2004 within a specified geographical region. SVI is normalized by Google to a range of 0-100, which conceals the raw number of searches made but allows us to obtain relative values of, and compute relative changes in, search volume.

Following Joseph et al. (2011) and Drake et al. (2012), we only consider firms that were part of the S&P 500 at least once during our sample period, since small — less searched — firms are unlikely to have SVI available. To examine attention around earnings announcements involving these companies, we download daily U.S. SVI around the announcement date for the ticker symbol of the company making the announcement.[18]

[15]Following Hirshleifer et al. (2009), we consider only analyst estimates (or revisions) made within the 60 days preceding the announcement date. If an analyst made multiple revisions during this period, only the last forecast is used. Additionally, following Hirshleifer et al. (2009) and Drake et al. (2012), we only consider earnings announcements with earnings per share lower than stock price and with stock price above $1 at the end of the most recent fiscal quarter.

[16]We obtain daily stock prices from CRSP and fill in missing CRSP information with data from Compustat's Security Daily Database.

[17]`www.google.com/trends`

[18]Due to random sampling performed daily by Google Trends, SVI data for the same term may differ depending on the day on which it is downloaded. Therefore, we download SVI data on ten different days and use the average to construct a single and more robust daily SVI series.

We remove firms with ambiguous ticker symbols from the sample. For instance, we exclude firms with ticker symbols such as “LEG”, “SUN”, and “LIFE”, since searches for these broad terms are unlikely to be related to financial phenomena. To resolve this issue objectively, we keep a firm in the sample only if a Google search for its ticker symbol provides specific financial information on the first page of results, as shown in Figure 2.1. Appendix A presents our final list of firms and their ticker symbols.

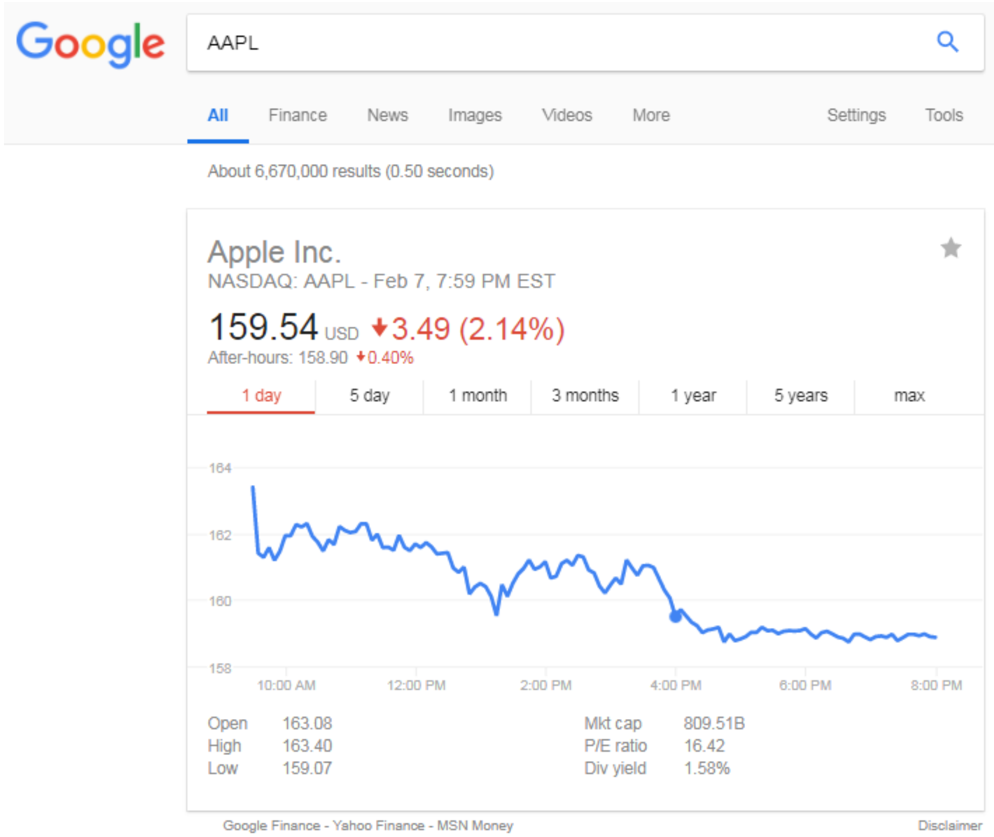


Figure 2.1. Example of Google results showing explicit financial information for the ticker symbol "AAPL".

Figure 2.2 shows the average daily SVI for our final sample of earnings announcements. The numbers on the horizontal axis represent days relative to the announcement date. The figure shows a clear spike in search volume starting approximately two days before the announcement date and ending two days after. The figure also shows a clear weekly trend, even after averaging all announcements, which are made on different weekdays.[19]

We are interested in measuring the abnormal attention associated with an earnings announcement. Similar to Drake et al. (2012), we do so in two steps. First, for each day t around an earnings announcement, we compute *Abnormal Search(t)* as the ratio between: (i) SVI on day t minus average SVI on the same weekday over the past 8 weeks, and (ii) average SVI on the same weekday over the past 8 weeks. This definition avoids potential weekday biases stemming from weekly trends in SVI.

[19]Specifically, 8.23% of announcements are made on Mondays, 22.69% are made on Tuesdays, 28.33% are made on Wednesdays, 34.30% are made on Thursdays, and 6.45% are made on Fridays. If the distribution of announcements were homogeneous over all weekdays, we would expect no weekly trend in Figure 2.2.

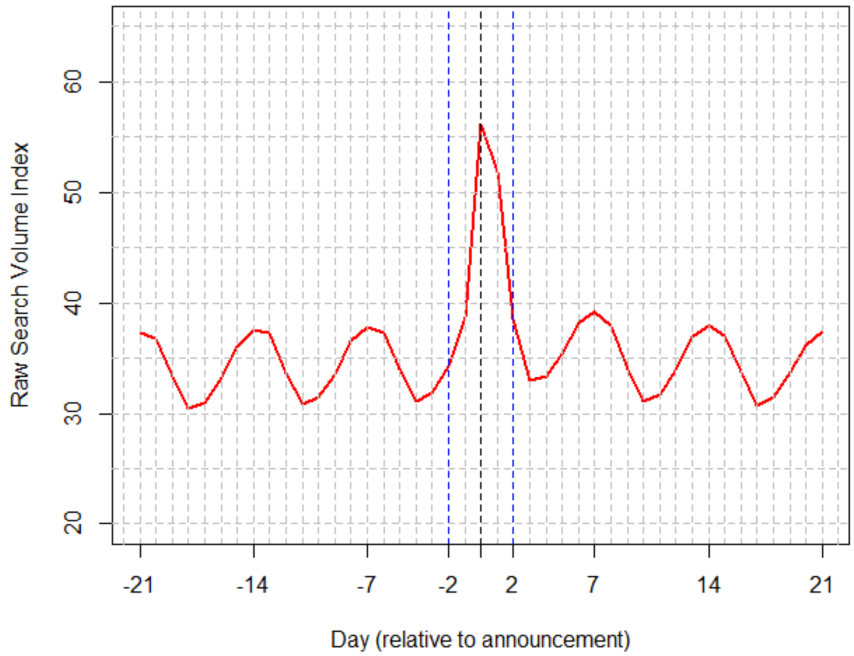


Figure 2.2. Average daily SVI for our final sample of earnings announcements. The numbers on the horizontal axis are days relative to the announcement date.

Next, to compute abnormal attention ($ASVI$) during a particular window relative to the announcement, we define $ASVI[t_1, t_2]$ as the logarithm of 1 plus the average of $Abnormal\ Search(t)$ from days t_1 to t_2 relative to the announcement. To reduce endogeneity concerns, we want to capture abnormal attention over a window that does not overlap with the post-announcement period, over which we will compute abnormal returns. Therefore, we choose day 0 (i.e., $t_2 = 0$) relative to the announcement date as the upper bound of the window.[20] Additionally, we need a window wide enough to capture the increase in attention related to the announcement, but not any wider than that. Figure 2.2 depicts that the average search volume before day -2 seems to have the same pattern as it does in the preceding days and weeks. Therefore, we choose day -2 (i.e., $t_1 = -2$) as the lower bound of the window. That is, we proxy for abnormal attention using $ASVI[-2, 0]$.[21]

Financial and Accounting Information. We collect financial and accounting information from CRSP, Compustat, and Kenneth French's website. From CRSP we obtain daily stock prices, trading volume and, when not available from Compustat, number of shares outstanding. From Compustat we obtain total stockholders' equity, total preferred stock, redemption value of preferred stock, liquidation value of preferred stock, deferred taxes and investment tax credit, total assets and total liabilities. Additionally, when not available from CRSP, we obtain stock prices and trading volume from Compustat's Security Daily Database. From Kenneth French's website, we obtain daily returns of benchmark portfolios.

With this information, we compute the following variables: *Market Equity*, defined as stock price multiplied by number of shares outstanding; *Rank of Market Equity*, defined as the decile rank of *Market Equity*; *Book Equity*, for which we follow French's definition;[22]

[20] Cumulative abnormal returns are computed starting on day 1 after the announcement.
[21] In Section 2.5.1, we show that our main results are robust to different specifications of the window used to compute $ASVI$.
[22] The precise definition of *Book Equity* is available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/variable_definitions.html`.

Book-to-Market, defined as *Book Equity* divided by *Market Equity*; and *Rank of Book-to-Market*, defined as the decile rank of *Book-to-Market*.

To compute cumulative abnormal returns, we first define $AR(t)$ as the abnormal return on day t relative to a given company's announcement, which is computed as the difference between the return on the firm's stock and the return on a benchmark portfolio on day t. Following Hirshleifer et al. (2009) and Drake et al. (2012), we match each firm with one of 25 benchmark portfolios formed based on *Market Equity* and *Book-to-Market* quintiles.[23]

We define $CAR[t_1, t_2]$ as the cumulative abnormal return between trading days t_1 and t_2 relative to the announcement. $CAR[t_1, t_2]$ is computed as the sum of $AR(t)$s from t_1 to t_2. We focus on weekly CARs for the four weeks following the announcement date, i.e., we compute $CAR[1, 5]$, $CAR[6, 10]$, $CAR[11, 15]$, and $CAR[16, 20]$.

Finally, we measure $Turnover$ as the average of daily turnover over the same window we use to measure $ASVI$, i.e., from trading day -2 to day 0 relative to the announcement date, $Turnover[-2, 0]$. Daily turnover is defined as the ratio between trading volume and total shares outstanding.

News Coverage. We use LexisNexis to gather information about media coverage. We determine the number of news stories that mention each firm making an earnings announcement over the same window we use to measure $ASVI$. Specifically, we compute the variable $News[-2, 0]$ as the natural logarithm of one plus the average number of news stories that mention the firm and are published in the *The New York Times*, *The Wall Street Journal*, *USA Today*, or *The Washington Post* between days -2 and 0 relative to the announcement date.

[23]Each stock is matched to one of these portfolios at the end of June of each year. Kenneth French's website provides daily returns for each of these 25 portfolios.

Institutional Ownership. We gather data about institutional ownership from the Thomson Reuters Institutional Holdings (13F) database. This database includes the quarterly holdings of each institutional manager with $100 million or more in assets. With this data, we compute for each firm the variable *Institutional Ownership* as the fraction of total outstanding shares held by institutional investors at the end of the most recent fiscal quarter.

Table 2.1 shows, in alphabetical order, the full list of variables, including their definitions and data sources.

Table 2.1. Variable definitions and data sources

Name	Description	Source
$4th\ Quarter$	Set to 1 if the announcement is made on the last quarter of the fiscal year.	IBES
$Abnormal\ Search(t)$	The ratio between: (i) the SVI on day t minus the average SVI on the same weekday over the past 8 weeks, and (ii) the average SVI on the same weekday over the past 8 weeks.	Google Trends
$AR(t)$	Abnormal return. The difference between the return on the firm's stock and the return on a benchmark portfolio on day t.	CRSP, Compustat, and French's portfolios
$ASVI[t_1, t_2]$	Abnormal SVI. The logarithm of 1 plus the average of $Abnormal\ Search(t)$ from day t_1 to day t_2 relative to the announcement.	Google Trends
$Book\ Equity$	We follow French's definition, available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/variable_definitions.html`.	Compustat
$Book\text{-}to\text{-}Market$	Book Equity divided by Market Equity.	CRSP and Compustat
$CAR[t_1, t_2]$	Cumulative abnormal return. The sum of $AR(t)$s from t_1 to t_2. That is, $CAR[t_1, t_2] = \sum_{t_1}^{t_2} AR(t)$.	CRSP and French's portfolios
$Earnings\ Persistence$	The first auto-correlation coefficient of quarterly earnings over the four-year period ending on the fiscal end date (a minimum of four observations required)	IBES
$Earnings\ Surprise$	The difference between announced earnings per share and the median of the analysts' forecasts, scaled by the stock price at the end of the fiscal quarter.	IBES and CRSP
$Earnings\ Volatility$	The standard deviation of seasonal earnings changes (i.e., the deviations of quarterly earnings from 1-year-ago earnings) over the four-year period ending on the fiscal end date (a minimum of four observations required).	IBES
$Friday$	Set to 1 if the announcement is made on a Friday	IBES
$Institutional\ Ownership$	The fraction of total outstanding shares held by institutional investors at the end of the most recent fiscal quarter.	Thomson Reuters Institutional (13f) Holdings Database
$Loss$	Set to 1 if the value of announced earnings is negative.	IBES
$Market\ Equity$	Stock price multiplied by number of shares outstanding	CRSP and Compustat
$News[t_1, t_2]$	The natural logarithm of one plus the average number of news stories that mention the firm and are published in the *The New York Times*, *The Wall Street Journal*, *USA Today*, or *The Washington Post* between days t_1 and t_2 relative to the announcement date.	LexisNexis

Table 2.1. Variable definitions and data sources,continuation

Name	Description	Source
$Rank\ of\ Announcement$	The decile rank of the number of other firms announcing quarterly earnings on the same day.	IBES
$Rank\ of\ Book\text{-}to\text{-}Market$	The decile rank of $Book\text{-}to\text{-}Market$.	CRSP and Compustat
$Rank\ of\ Market\ Equity$	The decile rank of $Market\ Equity$.	CRSP and Compustat
$Revisions$	The logarithm of 1 plus the number of revisions made to the analysts' forecasts.	IBES
$Turnover[t_1, t_2]$	The average of daily turnover from trading day t_1 to day t_2 relative to the announcement date.	CRSP and Compustat

2.3.2. Sample Characteristics

The final sample is composed of 8,734 earnings announcements with complete data. Table 2.2 presents summary statistics. Columns 1, 2, and 3 present the average, standard deviation, and median of each variable, respectively. Average $ASVI[-2,0]$ is 0.211, meaning that average daily SVI in the window $[-2,0]$ is approximately 23% higher than in previous weeks. Average *Earnings Surprise* is 0.001, and is positive for 69.41% of earnings announcements in the sample, negative for 22.29% of earnings announcements in the sample, and zero for the remaining 8.30% of announcements. Average CAR is 0.126% over the first week after the announcement. Average CARs over the subsequent weeks are -0.004%, -0.053%, and -0.061%, for the second, third, and fourth week, respectively. Average $News[-2,0]$ is 0.391, showing that the average number of news stories associated with each announcement in the window $[-2,0]$ is 0.478. Average $Turnover[-2,0]$ is 1.758%, i.e., on average, 1.758% of total shares outstanding are traded between days -2 and 0 relative to the announcement date.

Table 2.2. Summary statistics of the sample

	(1) Average	(2) Standard Deviation	(3) Median	(4) Correlation with *ASVI*
ASVI[-2,0]	0.211	0.358	0.171	-
Earnings Surprise	0.001	0.003	0.000	-0.016
CAR[1,5]	0.126%	5.673%	0.030%	0.002
CAR[6,10]	-0.004%	3.241%	-0.070%	0.007
CAR[11,15]	-0.053%	3.252%	-0.140%	0.007
CAR[16,20]	-0.061%	3.243%	-0.140%	-0.02*
News[-2,0]	0.391	1.062	0.000	0.096***
Turnover[-2,0]	1.758%	1.306%	1.360%	0.120***
Earnings Volatility	25.991%	33.780%	14.680%	-0.009
Earnings Persistence	-24.573%	27.777%	-24.440%	0.002
Rank of Market Equity	0.550	0.288	0.500	0.093***
Rank of Book-to-Market	0.549	0.288	0.500	-0.138***
Revisions	2.359	0.637	2.485	0.060***
Rank of Announcement	0.757	0.186	0.800	-0.112***
4th Quarter	0.243	0.429	0.000	0.017
Loss	0.054	0.227	0.000	-0.016
Friday	0.064	0.246	0.000	-0.009
Institutional Ownership	76.722%	16.426%	78.160%	-0.036***

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
All variables are defined in Table 2.1. Our full sample consists of 8,734 earnings announcements with complete data between 2004 and 2016.

Average *Earnings Volatility* is 25.991%, and average *Earnings Persistence* is -24.573 $\%$. Average *Rank of Book-to-Market* and *Rank of Market Equity* are 0.549 and 0.55, respectively.[24] Average *Revisions* is 2.359, implying that the average number of revisions is 9.5 per announcement. Additionally, average *Rank of Announcement* is 0.757.[25] The table also shows that 24.3% of announcements are from the fourth fiscal quarter ($4th\ Quarter$), only 5.4% of announcements are negative ($Loss$), and 6.4% of announcements are made on Fridays ($Friday$). Finally, average *Institutional Ownership* is 76.722%.

Column 4 of Table 2.2 presents pairwise correlations between abnormal attention, $ASVI[-2, 0]$, and each of the other variables. In the full sample, $ASVI$ $[-2, 0]$ has very low correlations with post-announcement CARs; the only significant correlation is -0.02 with $CAR[16, 20]$ $(p < 0.1)$. Additionally, $ASVI[-2, 0]$ has positive and significant correlations with $News[-2, 0]$ and $Turnover[-2, 0]$: 0.096 $(p < 0.01)$ and 0.12 $(p < 0.01)$, respectively. This is expected, given that the latter two variables are also related to attention.

$ASVI[-2, 0]$ is positively correlated with *Rank of Market Equity* (correlation of 0.093, $p < 0.01$), showing that larger firms attract more investor attention. In contrast, $ASVI$ $[-2, 0]$ is negatively correlated with *Rank of Book-to-Market* (correlation of -0.138%, $p < 0.01$), suggesting that growth firms attract more attention. $ASVI[-2, 0]$ is also positively correlated with $Revisions$ (correlation of 0.06, $p < 0.01$), showing that firms whose earnings estimates are more frequently revised by financial analysts attract more investor attention. Additionally, we observe that $ASVI[-2, 0]$ is negatively correlated with *Rank of Announcement* (correlation of -0.112, $p < 0.01$), which is consistent with Hirshleifer et al. (2009), who argue that investors are more distracted on days with more earnings

[24]These values are slightly above of 0.5 since they were calculated using all firms with market equity numbers available, before removing firms with incomplete data.

[25]This value is higher than 0.5 since the number of earnings announcements with a high rank (those of firms announcing earnings on the same day than many other firms) is much larger than the number of those with a low rank (those of firms announcing earnings on the same day than few other firms).

announcements. Finally, $ASVI[-2,0]$ is negatively correlated with *Institutional Ownership* (correlation of −0.036, $p < 0.01$), which is consistent with previous antecedents suggesting that effect of attention is partially driven by individual investors.[26]

2.4. Results

To determine how the relation between investor attention and stock returns is affected by the connotation of earnings news, we partition the full sample using the variable *Earnings Surprise*. We focus on the highest and lowest quintiles of *Earnings Surprise* and define: (i) the *Highest ES* sample as the subsample of earnings announcements with *Earnings Surprise* in the highest quintile, which have a very positive connotation; and (ii) the *Lowest ES* sample as the subsample of earnings announcements with *Earnings Surprise* in the lowest quintile, which have a very negative connotation.[27]

We do not consider the middle quintiles of *Earnings Surprise* in our main analysis, since the new information provided by those earnings announcements has less extreme connotations, and therefore, is not optimal for testing our hypotheses. However, in Section 2.5.2 we show that our results are robust to widening the *Highest ES* and *Lowest ES* samples to include a larger number of earnings announcements. Additionally, in Section 2.5.5 we analyze what happens if we consider a *Neutral ES* sample, consisting of earnings announcements in quintiles 2, 3, and 4 of *Earnings Surprise*.

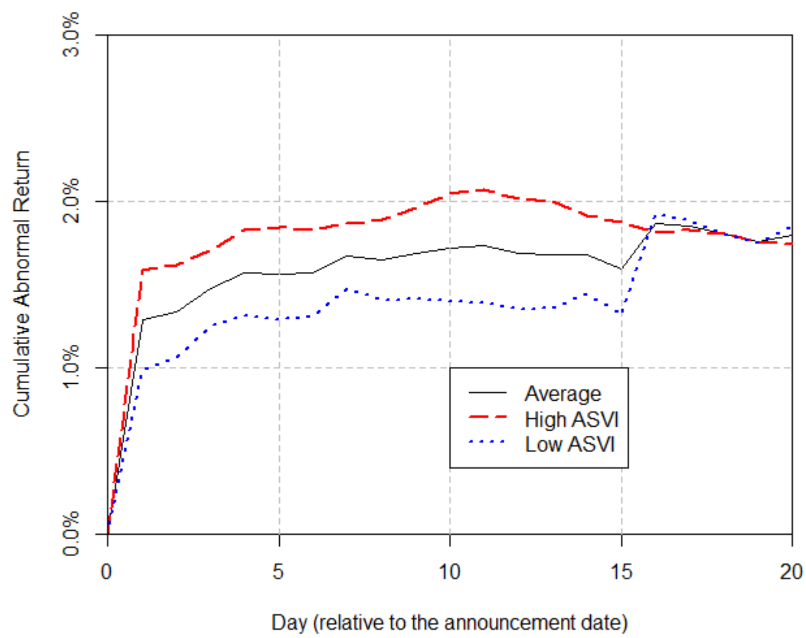
2.4.1. Preliminary Evidence

In this section, we visually inspect how average CARs for all earnings announcements, as well as for those with high and low $ASVI[-2,0]$, evolve through time after the announcement date. Specifically, Panel A of Figure 2.3 shows average CAR for the *Highest ES* sample (solid line), for earnings announcements from the *Highest ES* sample with

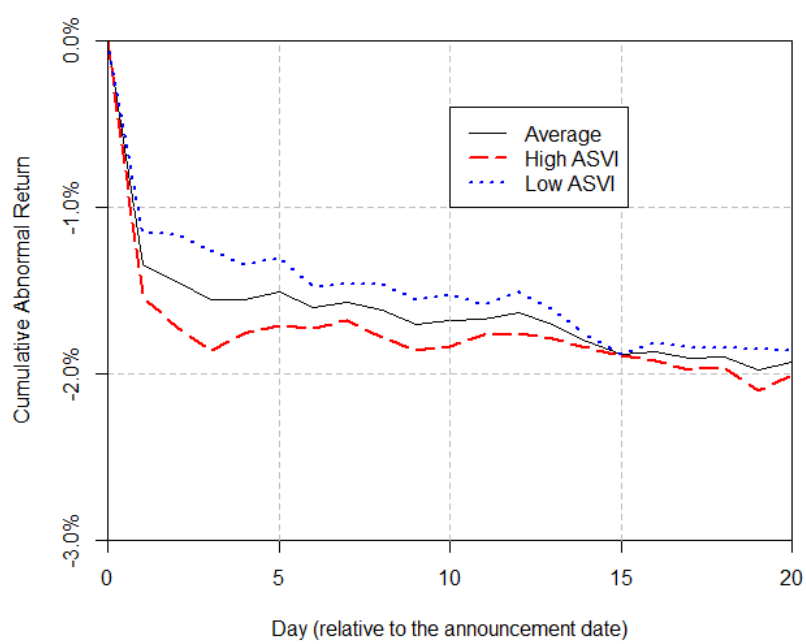
[26]See, among others, Barber and Odean (2007), Da et al. (2011), Jacobs and Weber (2011), Irresberger, Mühlnickel, and Weiß (2015), Reyes and Waissbluth (2018), and Dzieliński, Rieger, and Talpsepp (2018).

[27]Using the highest and lowest quintiles ensures that all events in the *Highest ES* and *Lowest ES* groups have only positive and negative $Earnings\ Surprise$, respectively.

$ASVI[-2,0]$ above its median (red dashed line), and for earnings announcements from the ***Highest ES*** sample with $ASVI[-2,0]$ below its median (blue dotted line). Panel B of Figure 2.3 shows analogous CARs for the ***Lowest ES*** sample. All CARs are computed starting on the announcement day.



Panel A. CARs for the *Highest ES* sample



Panel B. CARs for the *Lowest ES* sample

Figure 2.3. Daily cumulative abnormal returns for the *Highest ES* and *Lowest ES* samples. *High ASVI* and *Low ASVI* denote earnings announcements with abnormal attention ($ASVI[-2,0]$) above and below its median, respectively.

The solid line in Panel A shows that cumulative abnormal returns for the *Highest ES* sample increase sharply on the day after the announcement and then tend to follow an upward trend that lasts up to four weeks (i.e., 20 trading days).[28] More importantly, just after the announcement, firms receiving high attention realize higher abnormal returns than the average firm, while firms receiving low attention realize lower-than-average abnormal returns. These differences with respect to the average CAR tend to increase for approximately two weeks (i.e., around 10 trading days) and then begin to revert. During the last week plotted in the figure (i.e., trading days 16 to 20), CARs for the high- and low-attention groups converge to the average CAR.

In contrast, the solid line in Panel B shows that cumulative abnormal returns for the *Lowest ES* sample decrease sharply on the day after the announcement and then tend to follow a downward trend that lasts up to four weeks. Moreover, just after the announcement, firms receiving high attention realize lower abnormal returns than the average firm and firms receiving low attention realize higher abnormal returns than the average. These differences with respect to the average CAR increase for a few days (i.e., until day 3 or 4) and then start reverting steadily until trading day 15, on which the CARs for both subgroups get very close to the average CAR.

Figure 2.3 provides initial evidence that, in the days after earnings announcements, investors exhibit an attention-driven positive or negative overreaction depending on the sign of the extreme earnings surprise. That is, for earnings announcements with high levels of attention, the price reaction intensifies — with respect to the average — in the direction of the announcement's connotation during the days immediately following the announcement; this effect is subsequently reversed.

2.4.2. Pairwise Correlations

Before turning to regression models, we present pairwise correlations between the variables. Analyzing correlations provides further evidence on the relationship between

[28]This is consistent with post-earnings announcement drift (Ball and Brown (1968)).

abnormal attention and abnormal returns. Table 2.3 and Table 2.4 show pairwise correlations for the *Highest ES* and the *Lowest ES* samples, respectively.

Table 2.3. Bivariate correlations for the *Highest ES* sample

	CAR [1,5]	*CAR* [6,10]	*CAR* [11,15]	*CAR* [16,20]	*ASVI* [-2,0]	*News* [-2,0]	*Turnover* [-2,0]	*Earnings Volatility*
CAR [6,10]	-0.01							
CAR [11,15]	0.04*	-0.03						
CAR [16,20]	0.02	-0.03	-0.02					
ASVI[-2,0]	0.08***	0.01	-0.05**	-0.02				
News[-2,0]	-0.04*	0.01	0.01	0.00	0.07***			
Turnover[-2,0]	0.06**	0.05**	-0.02	-0.02	0.09***	-0.11***		
Earnings Volatility	-0.02	-0.02	-0.01	-0.01	-0.01	-0.06***	0.12***	
Earnings Persistence	-0.03	0.01	0.01	0.00	-0.01	-0.17***	0.10***	-0.19***
Rank of Market Equity	-0.10***	-0.04	0.00	-0.01	0.10***	0.41***	-0.44***	-0.01
Rank of Book-to-Market	-0.04*	-0.02	-0.05**	-0.03	-0.13***	-0.03	-0.11***	0.17***
Revisions	-0.04	0.03	-0.02	0.01	0.05**	0.16***	0.03	0.00
Rank of Announcement	0.06***	-0.05**	0.01	0.03	-0.10***	0.00	-0.15***	-0.07***
4th quarter	-0.02	0.01	0.00	-0.02	0.03	-0.03	0.04	0.00
Loss	0.01	0.00	0.01	0.03	-0.03	-0.08***	0.14***	0.17***
Friday	-0.06***	0.04*	-0.01	-0.03	0.01	0.00	-0.03	0.04

	Earnings Persistence	*Rank of Market Equity*	*Rank of Book-to-Market*	*Revisions*	*Rank of Announce-ment*	*4th quarter*	*Loss*
Rank of Market Equity	-0.17***						
Rank of Book-to-Market	0.01	0.03					
Revisions	0.03	0.39***	0.13***				
Rank of Announcement	0.08***	0.05**	0.03	0.00			
4th quarter	0.02	-0.04*	-0.01	0.01	-0.14***		
Loss	0.04	-0.26***	-0.07***	-0.10***	0.05**	-0.02	
Friday	-0.01	0.08***	0.07***	0.01	-0.32***	-0.02	-0.06**

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$
All variables are defined in Table 2.1. The *Highest ES* sample consists of earnings announcements with earnings surprises in the highest quintile.

Table 2.4. Bivariate correlations for the *Lowest ES* sample

	CAR [1,5]	*CAR* [6,10]	*CAR* [11,15]	*CAR* [16,20]	*ASVI* [-2,0]	*News* [-2,0]	*Turnover* [-2,0]	*Earnings Volatility*
CAR [6,10]	-0.02							
CAR [11,15]	0.01	-0.07***						
CAR [16,20]	-0.02	0.01	-0.04*					
ASVI[-2,0]	-0.06**	0.01	0.06***	-0.02				
News[-2,0]	-0.04	-0.01	0.00	0.00	0.11***			
Turnover[-2,0]	0.04	0.01	-0.03	-0.01	0.14***	-0.07***		
Earnings Volatility	0.06***	-0.03	-0.05**	-0.01	-0.01	-0.01	0.14***	
Earnings Persistence	-0.03	-0.03	-0.05**	0.02	-0.04*	-0.06**	0.08***	-0.16***
Rank of Market Equity	-0.02	-0.03	0.02	0.01	0.09***	0.37***	-0.36***	-0.06**
Rank of Book-to-Market	0.02	-0.05**	-0.01	0.02	-0.14***	-0.01	-0.01	0.17***
Revisions	-0.03	0.01	-0.02	0.03	0.01	0.16***	0.09***	-0.07***
Rank of Announcement	-0.02	0.00	-0.01	-0.01	-0.14***	-0.04*	-0.13***	-0.09***
4th quarter	-0.02	0.01	0.04*	0.04	0.03	0.04	0.02	-0.04
Loss	0.00	0.02	-0.02	0.02	0.03	-0.05*	0.23***	0.36***
Friday	0.04	0.02	-0.03	-0.02	0.00	0.04*	-0.01	0.01

	Earnings Persistence	*Rank of Market Equity*	*Rank of Book-to-Market*	*Revisions*	*Rank of Announce-ment*	*4th quarter*	*Loss*
Rank of Market Equity	-0.09***						
Rank of Book-to-Market	-0.03	-0.07***					
Revisions	0.12***	0.30***	0.07***				
Rank of Announcement	0.07***	0.00	0.04	0.06**			
4th quarter	0.04*	0.02	0.00	0.04	-0.10***		
Loss	0.06**	-0.32***	-0.02	-0.09***	-0.05**	0.00	
Friday	0.07***	0.14***	0.06***	0.05**	-0.23***	0.02	-0.03

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
All variables are defined in Table 2.1. The *Lowest ES* sample consists of earnings announcements with earnings surprises in the lowest quintile.

***Highest ES* Sample.** For the *Highest ES* sample, Table 2.3 shows that the correlation between $ASVI[-2, 0]$ and $CAR[1, 5]$ is positive and significant, with a value of 0.08 ($p \leq 0.01$). $ASVI[-2, 0]$ is also positively correlated with $CAR[6, 10]$; however, this correlation is not statistically significant. More importantly, the correlation between $ASVI[-2, 0]$ and $CAR[11, 15]$ is negative and significant, with a value of -0.05 ($p \leq 0.1$). Finally, $ASVI[-2, 0]$ is also negatively correlated with $CAR[16, 20]$, though the relationship is not statistically significant.

***Lowest ES* Sample.** For the *Lowest ES* sample, Table 2.4 shows that the correlation between $ASVI[-2, 0]$ and $CAR[1, 5]$ is negative and significant, at -0.06 ($p \leq 0.05$). Then, $ASVI[-2, 0]$ becomes positively correlated with $CAR[6, 10]$; however, this correlation is not statistically significant. In contrast, the correlation between $ASVI[-2, 0]$ and $CAR[11, 15]$ is positive and statistically significant, with a value of 0.06 ($p \leq 0.01$). Finally, the correlation between $ASVI[-2, 0]$ and $CAR[16, 20]$ is not statistically significant.

In sum, the correlation between $ASVI[-2, 0]$ and $CAR[1, 5]$ is statistically significant in both the *Highest ES* and *Lowest ES* samples and has the same sign as the earnings surprise. That is, during the first week after the announcement, abnormal returns are more extreme and move in the same direction as the earnings surprise for companies receiving higher attention in the preceding period. Moreover, the correlation between $ASVI[-2, 0]$ and $CAR[11, 15]$ is also statistically significant in both samples, but its sign is the opposite of that of the earnings surprise. Taken together, these findings support the idea that investors display an attention-driven overreaction to earnings surprises.

As for the relationship between abnormal attention and the remaining variables, $ASVI$ $[-2, 0]$ is positively correlated with $News[-2, 0]$ and $Turnover[-2, 0]$ in both samples. This is expected, given that the latter two variables are also related to attention. $ASVI[-2, 0]$ is also positively correlated with *Rank of Market Equity* in both samples, confirming that larger firms attract more attention. In contrast, $ASVI[-2, 0]$ is negatively correlated with

Rank of Book-to-Market in both samples, suggesting that growth firms attract more attention. $ASVI[-2,0]$ is also negatively correlated with *Rank of Announcement* in both samples. This is consistent with Hirshleifer et al. (2009): on days with more earnings announcements, investors are more distracted and pay less attention to any given announcement.

Finally, the correlations among the rest of the variables are, in general, lower than 30% in absolute value in both the *Highest ES* and *Lowest ES* samples, with a few exceptions. $News[-2,0]$ and *Rank of Market Equity* are positively correlated in both samples, showing that larger firms appear in the news more often. $Revisions$ and *Rank of Market Equity* are positively correlated in both samples, suggesting that analysts revise earnings forecasts for larger firms more frequently. $Turnover[-2,0]$ is negatively correlated with *Rank of Market Equity* in both samples, implying that the stocks of bigger firms are traded less (in terms of volume) on days prior to earnings announcements. In the *Highest ES* sample, we find that *Friday* and *Rank of Announcement* are negatively correlated, showing that fewer firms announce earnings on Fridays. In the *Lowest ES* sample, *Earnings Volatility* and *Loss* are positively correlated, implying that firms whose earnings are more volatile are more likely to announce negative earnings. Finally, *Rank of Market Equity* and *Loss* are negatively correlated in the *Lowest ES* sample, meaning that smaller firms tend to announce more negative earnings.

2.4.3. Financial Performance after Earnings Announcements

In this section, we use regression models to analyze the relationship between abnormal attention, $ASVI[-2,0]$, and post-announcement abnormal returns. Again, we compare the *Highest ES* and *Lowest ES* samples, focusing on CARs for the four weeks after the announcement, that is, on $CAR[1,5]$, $CAR[6,10]$, $CAR[11,15]$, and $CAR[16,20]$. In the regression models, we control for several factors that are known to affect financial performance in the context of earnings announcements.[29] The full regression specification is as follows:

$$\begin{aligned} CAR_i[t_1,t_2] = {} & \beta_0 + \beta_1 ASVI_i[-2,0] + \beta_2 News_i[-2,0] + \beta_3 Turnover_i[-2,0] \\ & + \beta_4 Earnings\ Volatility_i + \beta_5 Earnings\ Persistence_i \\ & + \beta_6 Rank\ of\ Market\ Equity_i + \beta_7 Rank\ of\ Book\text{-}to\text{-}Market_i \\ & + \beta_8 Revisions_i + \beta_9 Rank\ of\ Announcement_i + \beta_{10} 4th\ Quarter_i \\ & + \beta_{11} Loss_i + \beta_{12} Friday_i + \varepsilon_i \end{aligned} \tag{2.1}$$

We estimate model (2.1) on the *Highest ES* sample and the *Lowest ES* sample separately. In all specifications, we measure abnormal attention in the same fixed window $[-2,0]$, which does not overlap with any of the windows used to measure abnormal returns ($[1,5]$, $[6,10]$, $[11,15]$, or $[16,20]$). This helps to avoid endogeneity concerns and guarantees that all observed effects are driven by the same spike in attention. We also cluster standard errors by announcement date.

[29]See for instance, Hirshleifer et al. (2009), DellaVigna and Pollet (2009), and Drake et al. (2012)

Table 2.5 presents estimation results for the *Highest ES* sample (columns 1 to 4) and for the *Lowest ES* sample (columns 5 to 8). Overall, these results provide strong support for our hypotheses.[30]

***Highest ES* Sample**. Columns 1 to 4 of Table 2.5 present the results of model (2.1) with CARs computed in the windows $[1,5]$, $[6,10]$, $[11,15]$, and $[16,20]$, as the dependent variable, respectively. In column 1, the coefficient for $ASVI[-2,0]$, β_1, is 0.017 and statistically significant at the 1% level. This relationship is also economically significant: a one-standard-deviation increase in $ASVI[-2,0]$ is associated with an increase of 0.56% in $CAR[1,5]$; this is substantial considering that the average $CAR[1,5]$ in the *Highest ES* sample is 1.49%.

In column 2, the coefficient β_1 is still positive but not significantly different from 0. In column 3, β_1 becomes negative, with a value of -0.006, and is statistically significant at the 5% level. The economic significance of the relationship between $ASVI[-2,0]$ and $CAR[11,15]$ is -0.20%, which is large considering that the average $CAR[11,15]$ in the *Highest ES* sample is -0.15%. Moreover, this latter relationship is smaller in magnitude than the relationship between $ASVI[-2,0]$ and $CAR[1,5]$, which is consistent with our hypothesis of a partial overreaction. In column 4, the coefficient β_1 is still negative but not significantly different from 0.

Only a few of the control variables have statistically significant relationships with any cumulative abnormal returns. Among them, *Earnings Persistence* has a negative and significant relationship with $CAR[1,5]$ ($\beta_5 = -0.013, p < 0.05$), showing that firms with more autocorrelated earnings have lower cumulative abnormal returns in our sample. *Rank of Market Equity* has a negative and significant relationship with $CAR[1,5]$ ($\beta_6 = -0.024, p < 0.01$) and $CAR[6,10]$ ($\beta_6 = -0.007, p < 0.1$), showing that larger firms have lower cumulative abnormal returns during those weeks in our sample. *Rank*

[30]Low R^2 values are common in this type of event study (see, for example, Hirshleifer et al., 2009; DellaVigna & Pollet, 2009).

Table 2.5. Regression results

	Highest ES				*Lowest ES*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR[1,5]	CAR[6,10]	CAR[11,15]	CAR[16,20]	CAR[1,5]	CAR[6,10]	CAR[11,15]	CAR[16,20]
ASVI[-2,0]	0.017^{***}	-0.0002	-0.006^{**}	-0.001	-0.010^{***}	0.0003	0.006^{**}	-0.002
	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
News[-2,0]	-0.001	0.001	0.0005	0.0001	-0.002	-0.00000	-0.001	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Turnover[-2,0]	0.068	0.056	-0.066	-0.066	0.223	-0.021	-0.053	-0.037
	(0.132)	(0.092)	(0.085)	(0.079)	(0.142)	(0.089)	(0.088)	(0.094)
Earnings Volatility	-0.004	-0.002	0.001	-0.0003	0.009^{*}	-0.003	-0.005^{*}	-0.001
	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Earnings Persistence	-0.013^{**}	0.0004	0.002	-0.001	-0.005	-0.007^{**}	-0.006^{**}	0.002
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
Rank of Market Equity	-0.024^{***}	-0.007^{*}	-0.0005	-0.003	0.003	-0.006	0.002	0.002
	(0.007)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)
Rank of Book to Market	-0.005	-0.003	-0.007^{*}	-0.004	-0.001	-0.006^{*}	0.001	0.003
	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)
Revisions	0.001	0.003^{*}	-0.0003	0.001	-0.003	0.001	-0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Rank of Announcement	0.025^{***}	-0.007	-0.001	0.004	-0.002	0.002	-0.001	-0.003
	(0.008)	(0.005)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.005)
4th quarter	-0.003	0.001	0.0005	-0.001	-0.002	0.001	0.003	0.003
	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Loss	-0.006	-0.001	0.001	0.004	-0.006	0.002	0.001	0.003
	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)	(0.003)	(0.004)	(0.004)
Friday	-0.008^{*}	0.005^{*}	-0.001	-0.003	0.009^{**}	0.005	-0.005	-0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Constant	0.005	0.004	0.007	-0.002	-0.013	-0.0004	-0.002	-0.003
	(0.011)	(0.007)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)	(0.006)
Observations	1,747	1,747	1,747	1,747	1,747	1,747	1,747	1,747
R^2	0.031	0.010	0.007	0.004	0.014	0.008	0.013	0.005

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The table presents the results of estimating model (2.1). All variables are defined in Table 2.1. The *Highest ES* sample consists of earnings announcements with earnings surprises in the highest quintile and the *Lowest ES* sample consists of earnings announcements with earnings surprises in the lowest quintile. Standard errors are in parentheses and clustered by announcement date.

of Book to Market has a negative and significant relationship with $CAR[11, 15]$, showing that in the third week after the announcement, growth firms have higher cumulative abnormal returns. *Rank of Announcement* has a positive and significant relationship with $CAR[1, 5]$ ($\beta_9 = 0.025, p < 0.01$), suggesting that firms announcing earnings on days when more earnings announcements occur have higher cumulative abnormal returns over the following week. Additionally, $Friday$ has a significantly negative relationship with $CAR[1, 5]$ ($\beta_{12} = -0.008, p < 0.1$) and a significantly positive relationship with $CAR[6, 10]$ ($\beta_{12} = 0.005, p < 0.1$). This is consistent with DellaVigna and Pollet (2009)'s argument about the Friday distraction.[31]

***Lowest ES* Sample**. Columns 5 to 8 of Table 2.5 present the results of model (2.1) using CARs computed in the windows $[1, 5]$, $[6, 10]$, $[11, 15]$, and $[16, 20]$, as the dependent variable, respectively. In column 5, the coefficient for $ASVI[-2, 0]$, β_1, is -0.010 and statistically significant at the 1% level. A one-standard-deviation increase in $ASVI[-2, 0]$ is associated with a decrease of 0.36% in $CAR[1, 5]$; this is relatively large considering that the average CAR[1,5] in the *Lowest ES* sample is -1.38%.

In column 6, the coefficient β_1 is positive but not significantly different from 0. In column 7, β_1 is positive, with a value of 0.006, and is statistically significant at the 5% level. The economic significance of the relationship between $ASVI[-2, 0]$ and $CAR[11, 15]$ is 0.22%, which is substantial considering that the average $CAR[11, 15]$ in the *Lowest ES* sample is -0.18%. Moreover, this latter relationship is smaller in magnitude that the initial relationship with $CAR[1, 5]$, which is consistent with our hypothesis of a partial overreaction. In column 8, the coefficient β_1 is still negative but not significantly different from 0.

Only a few of the control variables have statistically significant relationships with any cumulative abnormal returns. Among them, *Earnings Volatility* has a significantly positive

[31]DellaVigna and Pollet (2009) find that the price reaction to earnings announced on a Friday is generally delayed. Our results suggest that, in the *Highest ES* sample, the positive price reaction to earnings announced on a Friday is delayed from the window $[1, 5]$ (in which $Friday$ has a negative relationship with CAR) to the window $[6, 10]$ (in which $Friday$ has a positive relationship with CAR).

relationship with $CAR[1,5]$, and a significantly negative relationship with $CAR[11,15]$ ($\beta_4 = 0.009, p < 0.1$ and $\beta_4 = -0.005, p < 0.1$, respectively). ***Earnings Persistence*** has significantly negative relationships with $CAR[6,10]$ and with $CAR[11,15]$ ($\beta_5 = -0.007, p < 0.05$ and $\beta_5 = -0.006, p < 0.05$, respectively), suggesting that firms with more autocorrelated earnings have lower cumulative abnormal returns in the ***Lowest ES*** sample. We also find that $Friday$ has a positive relationship with $CAR[1,5]$ ($\beta_{12} = 0.009, p < 0.05$). As in the ***Highest ES*** sample, this is consistent with DellaVigna and Pollet (2009), since, for earnings announcements released on a Friday, the negative price reaction is dampened in the days just after the announcement. Finally, ***Rank of Book to Market*** has a negative and significant relationship with $CAR[6,10]$ ($\beta_7 = -0.006, p < 0.1$), implying that growing firms experience higher cumulative abnormal returns in the second week after the announcement.

In sum, the results in this section strongly support our hypotheses. When the earnings surprise is positive (the ***Highest ES*** sample), abnormal investor attention before and during the announcement, $ASVI[-2,0]$, is related to a positive price reaction in the first week after the announcement, measured by $CAR[1,5]$. In contrast, when the earnings surprise is negative (the ***Lowest ES*** sample), $ASVI[-2,0]$ is negatively related to $CAR[1,5]$. In both cases, this effect is partially reversed in the third week following the announcement, in which the relationships between $ASVI[-2,0]$ and $CAR[11,15]$ are smaller in magnitude and have opposite signs.

2.5. Robustness Tests

In this section, we perform several additional analyses to verify the robustness of our results and to help address potential endogeneity issues. If abnormal attention is an endogenous variable, the estimated coefficients of the different specifications of model (2.1) presented in previous sections may be biased and inconsistent, and therefore, our conclusions may be at risk. Unfortunately, robust methods for dealing with endogeneity, such as instrumental variables estimation, are difficult to apply to search volume data. In fact, to the best of our knowledge, prior studies do not provide a convincing method for addressing potential endogeneity issues in similar contexts (see, for instance, Da et al., 2011; Joseph et al., 2011; Drake et al., 2012; Reyes & Waissbluth, 2018).

In previous sections, we have already taken steps to prevent endogeneity concerns. Endogeneity issues are reduced by relying on a lagged window to measure abnormal attention (i.e., $[-2, 0]$), which does not overlap with the windows used to compute CARs (i.e., $[1, 5]$, $[6, 10]$, $[11, 15]$, and $[16, 20]$). Additionally, maintaining $ASVI[-2, 0]$ as the key independent variable to explain all post-announcement CARs guarantees that all effects found in post-announcement CARs are driven by the same spike in attention. Additionally, controlling for $News[-2, 0]$ and $Turnover[-2, 0]$ helps ensure that $ASVI[-2, 0]$ does not simply reflect incoming news or high trading volume, and that these factors are not driving the observed price reactions.

The remainder of this section shows that the patterns found in Section 2.4.3 continue to hold when we change the window in which attention is measured, as well as when we modify the definitions of the *Highest ES* and *Lowest ES* samples to incorporate additional earnings surprises. We also analyze the relationship between abnormal attention and CARs in the complete sample and relate our findings with those of antecedents. After that, we corroborate that the relationship between abnormal attention and post-announcement CARs tends to be driven by individual investors rather than institutional investors. Finally, we analyze the relationship between abnormal attention and CARs in samples of earnings announcements with a more neutral or weaker connotation than those in the *Highest ES* and *Lowest ES* samples.

2.5.1. Window for Measuring Attention

In our main analyses, we measure abnormal attention in the window $[-2, 0]$ due to several reasons. First, it does not overlap with the post-announcement period, in which we compute abnormal returns. We also choose this window because average search volume before day -2 shows the same pattern as search volume over previous weeks. Hence, it is unlikely to measure abnormal attention related to the earnings announcement (see Figure 2.2). In this subsection, we confirm that our results are robust to reasonable variations in the time window in which attention is measured. We estimate model (2.1) using attention measured in the windows $[-3, 0]$ and $[-1, 0]$ and present results in Panels A and B of Table 2.6 for the *Highest ES* and *Lowest ES* samples, respectively. We do not attempt to increase the upper bound of the window, which is 0, to avoid overlapping with the post-announcement windows in which we compute CARs.

***Highest ES* sample.** Columns 1 and 2 of Panel A show results using $CAR[1, 5]$ and $CAR[11, 15]$ as dependent variables, respectively, and measuring attention in the window $[-1, 0]$. Columns 3 and 4 show results using $CAR[1, 5]$ and $CAR[11, 15]$ as dependent variables, respectively, and measuring attention in the window $[-3, 0]$. We focus on the windows $[1, 5]$ and $[11, 15]$ since our main analyses suggest that abnormal attention has a significant relationship with abnormal returns in these particular windows (see Table 2.5).

Table 2.6. Regression results for different windows for measuring abnormal attention

Panel A: Results for the *Highest ES* sample

	ASVI[-1,0]		ASVI[-3,0]	
	(1)	(2)	(3)	(4)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI	0.011^{**}	-0.004^{*}	0.013^{**}	-0.004
	(0.005)	(0.002)	(0.006)	(0.003)
Controls	Yes	Yes	Yes	Yes
Observations	1,749	1,749	1,737	1,737
R^2	0.027	0.006	0.028	0.005

Panel B: Results for the *Lowest ES* sample

	ASVI[-1,0]		ASVI[-3,0]	
	(1)	(2)	(3)	(4)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI	-0.008^{**}	0.004	-0.007^{*}	0.005^{**}
	(0.004)	(0.002)	(0.004)	(0.003)
Controls	Yes	Yes	Yes	Yes
Observations	1,749	1,749	1,736	1,736
R^2	0.014	0.011	0.011	0.012

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
The table presents the results of estimating model (2.1) with $ASVI$ measured over different windows as the main covariate. All variables are defined in Table 2.1. The *Highest ES* sample consists of earnings announcements with earnings surprises in the highest quintile and the *Lowest ES* sample consists of earnings announcements with earnings surprises in the lowest quintile. Standard errors are in parentheses and clustered by announcement date.

Columns 1 and 2 show that, if we measure abnormal attention in the window $[-1, 0]$, our results are similar to those obtained in Section 2.4.3 (columns 1 and 3 of Table 2.5). In column 1, $ASVI[-1, 0]$ has a positive and statistically significant relationship with $CAR[1, 5]$ ($\beta_1 = 0.011, p < 0.05$). In column 2, there is evidence of a partial reversal: $ASVI[-1, 0]$ has a negative and statistically significant relationship with $CAR[11, 15]$ ($\beta_1 = -0.004, p < 0.1$). Analogously, we find a similar pattern in columns 3 and 4, when we measure attention in the window $[-3, 0]$. In this case, we find a positive and statistically significant relation between $ASVI[-3, 0]$ and $CAR[1, 5]$ ($\beta_1 = 0.013, p < 0.05$) and a negative relation between $ASVI[-3, 0]$ and $CAR[11, 15]$ ($\beta_1 = -0.004$). However, the latter is not statistically significant.

***Lowest ES* sample.** Columns 1 and 2 of Panel B show results using $CAR[1, 5]$ and $CAR[11, 15]$ as the dependent variables, respectively, and measuring attention in the window $[-1, 0]$. Columns 3 and 4 show results using $CAR[1, 5]$ and $CAR[11, 15]$ as the dependent variables, respectively, and measuring attention in the window $[-3, 0]$. Columns 1 and 2 confirm that, if we measure abnormal attention in the window $[-1, 0]$, we get results similar to those obtained in the previous section (columns 5 and 7 of Table 2.5). In column 1, $ASVI[-1, 0]$ has a negative and statistically relationship with $CAR[1, 5]$ ($\beta_1 = -0.008, p < 0.05$). Column 2 suggests a partial reversal: $ASVI[-1, 0]$ presents a positive, albeit marginally significant, relationship with $CAR[11, 15]$ ($\beta_1 = 0.004, p < 0.12$). Analogously, we find the same pattern in columns 3 and 4, when we measure attention in the window $[-3, 0]$: a significantly negative relationship between $ASVI[-3, 0]$ and $CAR[1, 5]$ ($\beta_1 = -0.007, p < 0.1$) followed by a subsequent partial reversal in the window $[11, 15]$ ($\beta_1 = 0.005, p < 0.05$).

In sum, Table 2.6 provides evidence suggesting that our proposed mechanism is robust to different windows for measuring abnormal attention (i.e., $[-3, 0]$, $[-2, 0]$, or $[-1, 0]$).

2.5.2. Definition of *Highest ES* and *Lowest ES* Samples

In this section, we show that our results are robust to the percentage of earnings announcements included in the *Highest ES* and *Lowest ES* samples.

In our main analyses, the *Highest ES* and *Lowest ES* samples include earnings announcements with *Earnings Surprise* in the highest and lowest quintiles, respectively. In this subsection, we test the robustness of our results to these specific definitions, repeating our regression estimations for definitions of the *Highest ES* and *Lowest ES* samples that include earnings announcements in (i) the highest and lowest 30% and (ii) the highest and lowest 40% of *Earnings Surprise*.

We present results in Panels A and B of Table 2.7 for the *Highest ES* and *Lowest ES* samples, respectively. Overall, our results hold for wider *Highest ES* and *Lowest ES* samples. However, the relationship between abnormal attention with abnormal returns decreases for wider samples. This is consistent with our proposed mechanism, since enlarging each sample requires events with weaker connotations, which weaken the average relationship between abnormal attention and cumulative abnormal returns.

Table 2.7. Regression results using alternate definitions of the *Highest ES* and *Lowest ES* samples

Panel A: Results for broader *Highest ES* Sample

	Top 30% of $Earnings\ Surprise$		Top 40% of $Earnings\ Surprise$	
	(1)	(2)	(3)	(4)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	0.010^{**}	-0.004^{*}	0.007^{*}	-0.002
	(0.004)	(0.002)	(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes
Observations	2,620	2,620	3,494	3,494
R^2	0.022	0.006	0.016	0.003

Panel B: Results for broader *Lowest ES* Sample

	Bottom 30% of $Earnings\ Surprise$		Bottom 40% of $Earnings\ Surprise$	
	(1)	(2)	(3)	(4)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	-0.010^{***}	0.005^{**}	-0.006^{**}	0.003^{**}
	(0.004)	(0.002)	(0.003)	(0.002)
Controls	Yes	Yes	Yes	Yes
Observations	1,947	1,947	3,494	3,494
R^2	0.013	0.010	0.006	0.007

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The table presents the results of estimating model (2.1) for different definitions of the *Highest ES* and *Lowest ES* samples. All variables are defined in Table 2.1. Standard errors are in parentheses and clustered by announcement date.

***Highest ES* Sample.** Columns 1 and 2 of Panel A present results for earnings announcements with *Earnings Surprise* in the highest 30%. Similarly, columns 3 and 4 present results for earnings announcements with *Earnings Surprise* in the highest 40%. Each pair of columns presents results for both $CAR[1,5]$ and $CAR[11,15]$.

In columns 1 and 3 of Panel A, we find the same pattern as in our main analysis (column 1 of Table 2.5). $ASVI[-2,0]$ has a positive and statistically significant relationship with $CAR[1,5]$. This relationship is significant at the 5% and 10% levels in columns 1 and 3, respectively. Moreover, the coefficient β_1 decreases in magnitude as we widen the sample: the magnitude of β_1 decreases from 0.010 ($p < 0.05$) in column 1 to 0.007 ($p < 0.1$) in column 3 (both smaller than 0.017 ($p < 0.01$), the coefficient for β_1 in column 1 of Table 2.5). The same pattern holds for the economic significance of these coefficients.

In columns 2 and 4 of Panel A, the previously described effect partially reverses. $ASVI$ $[-2,0]$ has a negative relationship with $CAR[11,15]$, although this relationship is only statistically significant in column 2 ($p < 0.1$). Additionally, the coefficient β_1 decreases in magnitude from 0.004 ($p < 0.1$) to 0.002 as we widen the sample. Both values are smaller than 0.006 ($p < 0.05$), the coefficient for β_1 in column 3 of Table 2.5). The economic significance of the relationship between $ASVI[-2,0]$ and $CAR[11,15]$ also decreases in magnitude as we widen the sample.

***Lowest ES* Sample.** Columns 1 and 2 of Panel B present results for earnings announcements with *Earnings Surprise* in the lowest 30%. Similarly, columns 3 and 4 present results for earnings announcements with *Earnings Surprise* in the lowest 40%. Each pair of columns presents results for both $CAR[1,5]$ and $CAR[11,15]$.

In columns 1 and 3 of Panel B, we find the same pattern as in our main results (column 5 of Table 2.5). $ASVI[-2,0]$ has a negative and statistically significant relationship with $CAR[1,5]$. This relationship is significant at the 1% and 5% levels for columns 1 and 3, respectively. Furthermore, the coefficient β_1 decreases in magnitude as we widen the sample: the magnitude of β_1 decreases from 0.010 ($p < 0.01$) in column 1 to 0.006

($p < 0.05$) in column 3 (both smaller than 0.0101 ($p < 0.01$), the coefficient for β_1 in column 5 of Table 2.5). The same pattern holds for the economic significance of these coefficients.

In columns 2 and 4 of Panel B, the previously described effect partially reverses. $ASVI\,[-2,0]$ has a positive and statistically significant relationship with $CAR[1,5]$. This relationship is significant at the 5% level in both columns. Additionally, the coefficient β_1 decreases in magnitude from 0.005 ($p < 0.05$) to 0.003 ($p < 0.05$) as we widen the sample. Both values are smaller than 0.006 ($p < 0.05$), the coefficient for β_1 in column 7 of Table 2.5). The economic significance of the relationship between $ASVI[-2,0]$ and $CAR[1,5]$ also decreases in magnitude as we widen the sample.

In sum, this section verifies that our results continue to hold when widening the *Highest ES* and *Lowest ES* samples. Moreover, consistent with our proposed mechanism, the relationship between abnormal attention and abnormal returns weakens as we include announcements with weaker connotations.

2.5.3. The Complete Sample

In this section, we analyze the relation between abnormal attention and cumulative abnormal returns for the complete sample of earnings announcements. The complete sample is composed of earnings announcements with all kinds of connotations: some with very positive connotations (e.g., announcements in the *Highest ES* sample), some with very negative connotations (e.g., announcements in the *Lowest ES* sample), and some with more intermediate levels of *Earnings Surprise* and, therefore, more neutral and weaker connotations.

We estimate model (2.1) using all earnings announcements and present results in columns 1 to 4 of Table 2.8 using $CAR[1,5]$, $CAR[6,10]$, $CAR[11,15]$, and $CAR[16,20]$ as dependent variables, respectively.

Table 2.8. Regression results for the complete sample

	(1)	(2)	(3)	(4)	(5)
	CAR[1,5]	CAR[6,10]	CAR[11,15]	CAR[16,20]	CAR[1,5]
ASVI[-2,0]	0.001	0.0004	0.001	-0.001	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)	
Earnings Surprise					2.275
					(1.799)
ASVI[-2,0] $\times$*Earnings Surprise*					3.195^{***}
					(0.882)
Controls	Yes	Yes	Yes	Yes	Yes
Controls $\times$*Earnings Surprise*	No	No	No	No	Yes
Observations	8,734	8,734	8,734	8,734	8,734
R^2	0.005	0.003	0.002	0.002	0.032

Note: $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01

The table presents results of estimating model (2.1) in columns 1-4 and model (2.2) in column 5. All variables are defined in Table 2.1. Our full sample consists of 8,734 earnings announcements with complete data between 2004 and 2016. Standard errors are in parentheses and clustered by announcement date.

Results show that, for the complete sample, the regression coefficients of abnormal attention are not statistically different from 0.[32] That is, when we mix events with all kinds of connotations, the relationship between abnormal attention and cumulative abnormal returns fades out. These results suggest that the positive attention-driven overreaction associated with highly positive earnings surprises cancels out the negative overreaction related to highly negative earnings surprises, while announcements with more intermediate earnings surprises, and more neutral and weaker connotations, do not generate any overreaction effect.

2.5.3.1. Interacting *Earnings Surprise* with $ASVI$ and Control Variables

We also estimate a model using $CAR[1,5]$ as the dependent variable and including interaction terms between *Earnings Surprise* and all other variables. We include the same controls used in model (2.1). The full specification is as follows:

$$\begin{aligned} CAR_i[1,5] = \alpha_0 + \alpha_1 ASVI_i[-2,0] + \alpha_2 Earnings\ Surprise_i \\ + \alpha_3 ASVI_i[-2,0] \times Earnings\ Surprise_i + \sum_j \gamma_j Controls_{i,j} \\ + \sum_j \delta_j Controls_{i,j} \times Earnings\ Surprise_i + \varepsilon_i \end{aligned} \tag{2.2}$$

We estimate this model since it is similar to one of Drake et al. (2012)'s key models, the results of which can be found in column 3 of Table 6 of their paper. The main differences between model (2.2) and Drake et al. (2012)'s model are that the latter measured $ASVI$ and CAR during the same pre-announcement window and also included as a control a long-term pre-announcement measure of attention. In their model, Drake et al. (2012) find a positive relationship between the interaction of pre-announcement $ASVI$ and *Earnings*

[32]However, their signs are consistent with Barber and Odean (2007). That is, over the first three weeks following the announcement, abnormal attention has a positive relationship with CARs, which reverses during the fourth week.

Surprise (termed $Unexpected\ Earnings$ in their paper) and pre-announcement CAR. They conclude that investor attention is positively related to faster incorporation of new information into prices.

We present the estimation results for model (2.2) in column 5 of Table 2.8. Similar to Drake et al. (2012)'s findings, we observe that the interaction between $ASVI[-2, 0]$ and *Earnings Surprise* has a positive and statistically significant relationship with $CAR[1, 5]$ ($\alpha_3 = 3.195, p < 0.01$). Also consistent with our findings in Section 2.4.3, this result suggests that the relationship between $ASVI[-2, 0]$ and $CAR[1, 5]$ is more positive (negative) for earnings announcements with higher (lower) values of *Earnings Surprise*. However, estimating model (2.2) with $CAR[6, 10]$, $CAR[11, 15]$, or $CAR[16, 20]$ as dependent variables (rather than $CAR[1, 5]$) does not provide statistical evidence of a reversal effect.

2.5.4. Institutional Ownership Level

Some authors suggest that the effects of attention on financial phenomena are mainly driven by individual investors rather than institutional investors. Barber and Odean (2007) explain that institutional investors are less likely to be guided by attention, since they have more sophisticated resources for making investment decisions. Additionally, Da et al. (2011) suggest that measuring attention using SVI provides a proxy for individual investors' attention, since individual investors are more likely to search for financial information on Google. Reyes and Waissbluth (2018) find that the effect of abnormal SVI on the performance of bankrupt companies is stronger for firms with a low proportion of institutional ownership than for firms with a high proportion of institutional ownership.

This section tests whether the findings presented in the previous sections are mainly driven by individual investors. To verify this, we split the *Highest ES* and *Lowest ES* samples into two groups based on the institutional ownership level of the firms announcing earnings (i.e., whether the variable *Institutional Ownership* is below its median (*Low Institutional Ownership* group) or above its median (*High Institutional Ownership* group)). For each group, we estimate model (2.1) as in Section 2.4.3. Additionally, we analyze the effect of increasing the number of events in the *Highest ES* and *Lowest ES* samples, as in Section 2.5.2. We present results in Table 2.9.

Table 2.9. Regression results for the *Highest ES* and the *Lowest ES* samples by level of *Institutional Ownership*

Panel A: Results for the *Highest ES* Sample and Low *Institutional Ownership*

	Top 20% of $Earnings\ Surprise$		Top 30% of $Earnings\ Surprise$		Top 40% of $Earnings\ Surprise$	
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	0.012	−0.005	0.011*	−0.004	0.009*	−0.003
	(0.007)	(0.004)	(0.006)	(0.003)	(0.005)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	874	874	1,310	1,310	1,747	1,747
R^2	0.021	0.016	0.015	0.017	0.011	0.015

Panel B: Results for the *Highest ES* Sample and High *Institutional Ownership*

	Top 20% of $Earnings\ Surprise$		Top 30% of $Earnings\ Surprise$		Top 40% of $Earnings\ Surprise$	
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	0.021***	−0.008**	0.010	−0.004	0.005	−0.001
	(0.008)	(0.004)	(0.006)	(0.003)	(0.005)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	873	873	1,310	1,310	1,747	1,747
R^2	0.040	0.021	0.030	0.010	0.020	0.003

Panel C: Results for the *Lowest ES* Sample and Low *Institutional Ownership*

	Bot. 20% of $Earnings\ Surprise$		Bot. 30% of $Earnings\ Surprise$		Bot. 40% of $Earnings\ Surprise$	
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	−0.013**	0.011***	−0.015***	0.009***	−0.007*	0.005**
	(0.006)	(0.003)	(0.005)	(0.003)	(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	874	874	974	974	1,747	1,747
R^2	0.029	0.027	0.029	0.021	0.013	0.011

Table 2.9. Regression results for the *Highest ES* and the *Lowest ES* samples by level of *Institutional Ownership*, continuation

Panel D: Results for the *Lowest ES* Sample and High *Institutional Ownership*

	Bot. 20% of $Earnings\ Surprise$		Bot. 30% of $Earnings\ Surprise$		Bot. 40% of $Earnings\ Surprise$	
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	−0.007	0.002	−0.005	0.002	−0.006	0.002
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	873	873	973	973	1,747	1,747
R^2	0.014	0.016	0.012	0.013	0.010	0.009

Note: $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01

The table presents results of estimating model (2.1) for different definitions of the *Highest ES* and *Lowest ES* samples and firms with *Institutional Ownership* above and below its median. All variables are defined in Table 2.1. Standard errors are in parentheses and clustered by announcement date.

***Highest ES* Sample.** In Table 2.9, Panels A and B present results for the *Highest ES* sample. Panel A shows results for firms with low values of *Institutional Ownership*, and Panel B shows results for firms with high values of *Institutional Ownership*. Both panels first present results for earnings announcements with *Earnings Surprise* in the highest 20% (columns 1 and 2), then for announcements with *Earnings Surprise* in the highest 30% (columns 3 and 4), and finally for announcements with *Earnings Surprise* in the highest 40% (columns 5 and 6).

Comparing the first two columns of Panels A and B, we observe that, surprisingly, the relationship between abnormal attention and CAR in the *Highest ES* sample seems stronger for firms with a high level of *Institutional Ownership*. In contrast, when we expand the *Highest ES* sample to include announcements with *Earnings Surprise* in the highest 30% and 40% (columns 3-4 and 5-6, respectively, of both Panel A and Panel B), we find what we originally expected. That is, that the relationship between abnormal attention and CARs tends to be stronger in magnitude (and also in significance for $CAR[1, 5]$) in firms with a low level of *Institutional Ownership*.[33]

***Lowest ES* Sample.** In Table 2.9, Panels C and D present results for the *Lowest ES* sample. Panel C shows results for firms with low values of *Institutional Ownership*, and Panel D shows results for firms with high values of *Institutional Ownership*. Both panels first present results for earnings announcements with *Earnings Surprise* in the lowest 20% (columns 1 and 2), then for announcements with *Earnings Surprise* in the lowest 30% (columns 3 and 4), and finally for announcements with *Earnings Surprise* in the lowest 40% (columns 5 and 6).

Panels C and D strongly confirm our hypothesis. That is, in the *Lowest ES* sample, the relationship between abnormal attention and CAR is consistently stronger in firms with low levels of *Institutional Ownership*. Specifically, the relationship between $ASVI[-2, 0]$ and both $CAR[1, 5]$ and $CAR[11, 15]$ is stronger in magnitude and significance in firms

[33]Untabulated results show that the relationship between abnormal attention and $CAR[1, 5]$ is higher in magnitude in firms with lower *Institutional Ownership* even when the *Highest ES* sample includes events with *Earnings Surprise* in the highest 80%.

with low levels of *Institutional Ownership* than in firms with high levels of *Institutional Ownership*, regardless of how we define the *Lowest ES* sample.

In sum, our results in this section suggest that the relationship between abnormal attention and abnormal returns is at least partially driven by individual investors. Except for the sample composed of earnings announcements with *Earnings Surprise* in the highest quintile, firms with a low level of *Institutional Ownership* show stronger relationships between abnormal attention and CARs.

2.5.5. *Neutral ES* Samples

In this section, we estimate model (2.1) in subsamples consisting of earnings announcements with intermediate levels of *Earnings Surprise*. These announcements have more neutral and weaker connotations than those included in the *Highest ES* and *Lowest ES* samples, which have more extreme positive and negative connotations, respectively.

Panel A of Table 2.10 shows results for the sample of earnings announcements with values of *Earnings Surprise* within the three middle quintiles – in other words, all earnings announcements not considered in our main results presented in Section 2.4.3. For robustness, Panel B of Table 2.10 presents analogous results for the sample of earnings announcements with *Earnings Surprise* falling between the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles. In both panels, columns 1 to 4 present the results of model (2.1) using $CAR[1, 5]$, $CAR[6, 10]$, $CAR[11, 15]$, and $CAR[16, 20]$ as the dependent variable, respectively.

Consistent with our proposed mechanism and similar to our results for the complete sample, presented in Section 2.5.3, Table 2.10 shows that the regression coefficients of abnormal attention on CARs are not statistically different from 0. That is, when we focus on announcements with more intermediate earnings surprises and, therefore, more neutral and weaker connotations, the effect of abnormal attention on cumulative abnormal returns fades out and there is no evidence of an overreaction.[34]

[34]In columns 1 to 4 of Panel B, we observe that, though the coefficients are not statistically significant, their signs are consistent with the positive price pressure hypothesis proposed by Barber and Odean (2007).

Table 2.10. Regression results for *Neutral ES* Sample

Panel A: Results for earnings announcements with values of *Earnings Surprise* between the 20^{th} and 80^{th} percentiles

	(1)	(2)	(3)	(4)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	-0.0004	0.001	0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Observations	5,240	5,240	5,240	5,240
R^2	0.005	0.003	0.004	0.004

Panel B: Results for earnings announcements with values of *Earnings Surprise* between the 30^{th} and 70^{th} percentiles

	(1)	(2)	(3)	(4)
	CAR[1,5]	CAR[11,15]	CAR[1,5]	CAR[11,15]
ASVI[-2,0]	0.001	0.0005	0.001	-0.0001
	(0.003)	(0.001)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes
Observations	3,442	3,442	3,442	3,442
R^2	0.005	0.005	0.008	0.002

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
The table presents the results of estimating model (2.1) for different definitions of the *Neutral ES* sample. All variables are defined in Table 2.1. Standard errors are in parentheses and clustered by announcement date.

That is, in the first week after the announcement, abnormal attention is positively associated with CAR, a relationship that subsequently reverses.

2.6. Conclusion

We propose a novel mechanism to explain the effect of attention on stock performance when new information with a strong positive or negative connotation becomes publicly available. Our mechanism partially integrates Barber and Odean (2007), Drake et al. (2012), and Reyes and Waissbluth (2018)'s findings on this topic, describing a directional and compound effect of abnormal attention on stock performance. That is, we argue that attention is associated with faster information discovery and an overreaction effect, both of which depend on the connotation of the new information driving the increase in attention. Specifically, high attention to very positive (negative) new information generates positive (negative) price pressure and a partial subsequent reversal.

We test this mechanism in the context of quarterly earnings announcements. Our main tests focus on earnings announcements with earnings surprises in the highest and lowest quintiles, i.e., what we call the *Highest ES* and *Lowest ES* samples, respectively. Visual inspection of daily average post-announcement CARs and bivariate correlations among abnormal attention and CARs for the *Highest ES* and *Lowest ES* samples provide preliminary evidence supporting our mechanism, suggesting that investors exhibit an attention-driven positive or negative overreaction based on the sign of the earnings surprise. Additionally, the analysis of pairwise correlations shows that during the first week after the announcement, abnormal returns are more extreme and move in the same direction as the earnings surprise for companies receiving higher attention in the preceding period. Furthermore, during the third week after the announcement, the previous relationship partially reverses. Taken together, these findings support the idea that investors display an attention-driven overreaction to earnings surprises.

We also use regression models to analyze the relationship between abnormal attention and abnormal returns after controlling for well-known predictors of financial performance in the context of earnings announcements. Results strongly support our hypotheses.

When the earnings surprise is positive, in the *Highest ES* sample, the first-week post-announcement CAR is positively related to abnormal attention in the preceding period. In contrast, when the earnings surprise is negative, in the *Lowest ES* sample, the first-week post-announcement CAR is negatively related to abnormal attention in the preceding period. In both cases, this relationship is partially reversed in the third week following the announcement, in which the relationships between cumulative abnormal returns and attention are smaller in magnitude and have the opposite signs.

Finally, we perform several additional analyses to verify the robustness of our results and to address potential endogeneity issues. We verify that our results are robust to different definitions of abnormal attention, and to wider definitions of the *Highest ES* and *Lowest ES* samples. Then, we analyze the effect of abnormal attention on post-announcement CARs for the complete sample of earnings announcements. Additionally, we corroborate that the effect of abnormal attention on post-announcement earnings performance tends to be driven by individual investors rather than institutional investors. Finally, we analyze the effect of abnormal attention on post-announcement CARs for samples of earnings announcements that release information with a neutral or weaker connotation.

Overall, our results provide strong evidence that, after the release of new information with a strong positive or negative connotation, attention is associated with faster information discovery as well as an overreaction effect. The directions of both effects depend on whether the information driving the increase in attention has a positive or negative connotation. High attention to very positive new information generates positive price pressure. In contrast, high attention to very negative new information produces negative price pressure. Moreover, both of these effects partially reverse in subsequent weeks.

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APPENDIX

A. FIRST APPENDIX

List of firms and ticker symbols used in the study

Table A.1. Firms' common names and ticker symbols

Ticker	Common Name	Ticker	Common Name
AAL	American Airlines Group	CNP	CenterPoint Energy
AAPL	Apple	CNX	CNX Resources
ABBV	AbbVie	CNXT	Conexant Systems
ADBE	Adobe Systems	COF	Capital One Financial
ADSK	Autodesk	COH	Cobalt Blue Holdings
AGN	Allergan	COP	ConocoPhillips
AIZ	Assurant	COST	Costco Wholesale
AKAM	Akamai Technologies	CSCO	Cisco Systems
AKS	AK Steel Holding	CTB	Cooper Tire & Rubber Company
ALK	Alaska Air Group	CTL	CenturyLink
ALXN	Alexion Pharmaceuticals	CTSH	Cognizant Technology Solutions
AMAT	Applied Materials	CTXS	Citrix Systems
AMED	Amedisys	CVX	Chevron Corporation
AMGN	Amgen	CZR	Caesars Entertainment
AMZN	Amazon.Com	DGX	Quest Diagnostics
ANF	Abercrombie & Fitch	DIS	The Walt Disney Company
ATVI	Activision	DISCA	Discovery
AVGO	Broadcom	DLPH	Delphi Technologies
AXP	American Express	DLTR	Dollar Tree
BAC	Bank Of America	DLX	Deluxe Corporation
BAX	Baxter International	DOV	Dover Corporation
BBBY	Bed Bath & Beyond	DUK	Duke Energy
BBY	Best Buy	DVN	Devon Energy
BDX	Becton Dickinson	ECL	Ecolab
BLK	Blackrock	EGLT	Eagle Test Systems
BLL	Ball Corporation	EIX	Edison International
BMY	Bristol-Myers Squibb	EKDKQ	Eastman Kodak
BRK.B	Berkshire Hathaway	EMN	Eastman Chemical
BSX	Boston Scientific	ENDP	Endo International
BXP	Boston Properties	EOP	Equity Office
CCL	Carnival Corporation	EQIX	Equinix
CELG	Celgene	ESRX	Express Scripts
CFG	Citizens Financial Group	ETR	Entergy Corporation
CHK	Chesapeake Energy	EXC	Exelon Corporation
CHRW	C.H. Robinson Worldwide	EXPD	Expeditors International
CHTR	Charter Communcations	EXPE	Expedia
CIEN	Ciena Corporation	EXR	Extra Space Storage
CINF	Cincinnati Financial Corporation	FBHS	Fortune Brands Home & Security
CLF	Cleveland-Cliffs	FCPT	Four Corners Property
CLX	The Clorox Company	FCX	Feeport-McMoRan
CMG	Chipotle Mexican Grill	FDC	First Data
CMI	Cummins	FDX	Fedex Corporation

Table A.1. Firms' common names and ticker symbols

Ticker	Common Name	Ticker	Common Name
FFIV	F5 Networks	LVLT	Level 3 Communications
FISV	Fiserv	LYB	LyondellBasell
FITB	Fifth Third Bank	MAR	Marriott International
FLS	Flowserve Corporation	MBII	Marrone Bio Innovations
FOXA	21st Century Fox	MCD	McDonald's Corporation
FRT	Federal Realty Investment Trust	MCHP	Microchip Technologies
FSLR	First Solar	MCK	Mckesson Corporation
FTR	Frontier Communications	MDLZ	Mondelez International
GILD	Gilead Sciences	MMM	3M Company
GLW	Corning	MNK	Mallinckrodt
GME	Gamestop Corporation	MNST	Monster Beverage Corporation
GNW	Genworth Financial	MRK	Merck & Co.
GOOG	Alphabet	MRO	Marathon Oil Corporation
GOOGL	Google	MSFT	Microsoft Corporation
GRMN	Garmin	MUR	Murphy Oil Corporation
GWW	W.W. Grainger	MXIM	Maxim Integrated
HBAN	Huntington Bancshares	MYL	Mylan Laboratories
HBI	Hanesbrands	NDAQ	Nasdaq
HES	Hess Corporation	NFLX	Netflix
HLT	Hilton Hotels	NFX	Newfield Explora
HLTH	Nobilis Health	NGVT	Ingevity
HOLX	Hologic	NKE	Nike
HPQ	Hewlett-Packard	NLSN	Nielsen Holding
HRB	H&R Block	NTRS	Northn Trust Corporation
HRL	Hormel Foods Corporation	NVDA	Nvidia Corporation
HSY	The Hershey Company	NVLS	Novellus Systems
IDXX	Idexx Laboratories	NWL	Newell Rubber
IHRT	IHeartMedia	OKE	Oneok
ILMN	Illumina	ORCL	Oracle Corporation
INCY	Incyte Corporation	PAYX	Paychex
INTC	Intel Corpotation	PBCT	People's United Financial
INTU	Intuit	PBI	Pitney Bowes
ISRG	Intuitive Surgical	PCG	PG&E Corporation
IVZ	Invesco	PCLN	Priceline Group
JBHT	J.B. Hunt Transport Services	PDCO	Patterson Companies
JEC	Jacobs Engineering Group	PFE	Pfizer
JNPR	Juniper Networks	PGR	Progressive Corporation
JWN	Nordstrom	PRGO	Perrigo Company
KHC	Kraft Heinz	PRU	Prudential Financial
KMX	CarMax	PSX	Phillips 66
KSS	Kohls Corporation	PTC	PTC
LDOS	Leidos Holdings	PXD	Pioneer Natural Resources
LLL	L3 Technologies	PYPL	Paypal Holdings
LLY	Eli Lilly and Company	QCOM	Qualcomm
LMT	Lockheed Martin	QRVO	Qorvo
LNC	Lincoln National Corporation	REGN	Regeneron Pharmaceuticals
LOW	Lowe's Corporation	RHAT	Red Hat Software
LPX	Loouisiana-Pacific Corporation	RIG	Transocean
LRCX	Lam Research	ROK	Rockwell Automation
LUV	Southwest Airlines	ROST	Ross Stores

Table A.1. Firms' common names and ticker symbols

Ticker	Common Name	Ticker	Common Name
SANM	Sanmina Corporation	TXT	Textron
SBUX	Starbucks Corporation	UNP	Union Pacific Corporation
SCHW	Charles Schwab Corporation	UTX	United Technologies Corporation
SHLD	Sears Holdings	VFC	VF Corporation
SHW	Sherwin-Williams	VIAB	Viacom
SJM	The J.M Smucker Company	VIAV	Viavi Solutions
SLB	Schlumberger	VLO	Valero Energy Corporation
SPGI	S&P Global	VNO	Vornado Realty Trust
SPLS	Staples	VRSK	Verisk Analytics
SRCL	Stericycle	VRSN	Verisign
STT	State Street	VRTS	Veritas Software
STZ	Constellation Brands	VRTX	Vertex Pharmaceuticals
SUNE	SunEdison	WBA	Walgreens Boots Alliance
SWK	Stanley Wks	WFC	Wells Fargo
SWKS	Stanley Black & Decker	WFM	Whole Foods Market
SWN	Southwestern Energy	WFT	Weatherford International
SYF	Synchrony Fincancial	WHR	Whirlpool Corporation
SYK	Stryker Corporation	WLTW	Willis Towers Watson
SYMC	Symantec Corporation	WMB	Williams Companies
SYY	Sysco Corporation	WMT	Walmart
TDG	TransDigm Group	WRK	WestRock
TER	Teradyne	WYNN	Wynn Resorts
TGNA	Tegna	XEC	Cimarex Energy
TIF	Tiffany & Co.	XEL	Xcel Energy
TMO	Thermo Fisher Scientific	XLNX	Xilinx
TRCO	Tribune Media	XOM	Exxon Mobil Corporation
TROW	T. Rowe Price Group	XRX	Xerox Corporation
TRV	The Travelers Companies	XYL	Xylem
TSCO	Tractor Supply Company	YHOO	Yahoo!
TSO	Tesoro Petroleum	ZMH	Zimmer Holdings
TWX	Time Warner	ZTS	Zoetis
TXN	Texas Instruments		