Advertising's Financial Market Outcomes

Thesis submitted to the Adelaide Business School, Faculty of the Professions, The University of Adelaide, in fulfilment of the requirements for the degree of Doctor of Philosophy.

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January 2021

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I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

Signed: Date: 18/01/2021

Acknowledgements

Words can hardly express the extent of my obligations to Professor Ralf Zurbruegg for his support and guidance throughout my Ph.D. at University of Adelaide. As my principal supervisor, he not only tremendously improved my understanding of finance and what it means to be a researcher but also changed my life. I could not complete this study without his great help. Thank you so much.

I am also thankful to my co-supervisors Professor Arvid Hoffmann and Dr. Chee Cheong, for their valuable suggestions and comments. On top of being excellent scholars, they proved to be fantastic people. Thank you for your generous assistance.

I would like to pay my special regards to all staffs in Adelaide Campus Children's Center. I am the primary carer for my son and most of his time is spent in the Children's Center. Without their help I cannot focus on my research. Thank you for your endless kindness.

Abstract

Using an adjusted Glosten-Milgrom model, I show that, theoretically, advertising can increase information asymmetry in the financial markets. Using high frequency intra-day tick data surrounding Super Bowl Commercials, I then show, empirically, that advertising positively affects informed trading and reduces information efficiency. Moreover, it has a negative impact on stock liquidity. Advertising changes the buy-sell imbalance of different trade size groups, generating more large sell orders, which indicates that institutional investors are net sellers. I also find that there is a decline in cumulative abnormal returns after the advertising event, which is correlated with the rise in informed trading.

Synopsis

Advertising disseminates product or firm information to audiences (Nelson, 1974), and therefore is believed to reduce information asymmetry in the product markets (Kirmani and Rao, 2000). Considering these audiences can also include financial market investors, one would expect that product market advertising has the potential to play an important role in reducing information asymmetry among investors and improving information efficiency in the financial markets.

The impact that advertising has on the financial markets is not, however, clear-cut. The information contained in advertising may be biased and incomplete, as advertising is not designed to portray firms objectively (Lou, 2014). Moreover, individual investors are more likely to be affected by advertising, and most of them are unsophisticated or uninformed (Barber and Odean, 2007; Fehle et al., 2005; Joseph and Wintoki, 2013; Lou, 2014). Furthermore, advertising can capture investors' attention and lead to more attention-driven trading, which inflates short-run stock prices that are then often followed by lower future returns (Gervais et al., 2001; Barber and Odean, 2007).

As advertising may induce increased individual (retail) investor participation in the market (Barber and Odean, 2007; Fehle et al., 2005; Joseph and Wintoki, 2013; Lou, 2014), it it may benefit informed investors at the cost of uninformed individual investors. This suggests advertising may increase information asymmetry in the financial markets. Advertising does not directly contain price-based information on firm value (Joseph and Wintoki, 2013) but it can directly affect stock prices through attention-driven trading (Barber and Odean, 2007; Gervais et al., 2001). Advertising's short-run stock return effect may reduce the stock price efficiency or informativeness when stock prices deviate from what the fundamentals suggest they should be.

Whether advertising has an impact on the information environment surrounding firms in the financial markets is unclear. In order to answer this, I examine information asymmetry and information efficiency in the financial markets, and investigate trading behavior occurring from different kinds of investors, as advertising is broadcast.

Using an adjusted Glosten-Milgrom model, I show that, theoretically, advertising can increase information asymmetry in the financial markets. Based on the results from this theoretical model, I develop the hypothesis that advertising may facilitate informed trading in the financial markets. I use an event study research method to test this hypothesis by tracking changes in informed trading around the event window. Using data on Super Bowl Commercials and high frequency intra-day trading, I show that advertising increases informed trading of stocks whose names are readily identifiable from the content of their adverting.

Furthermore, I investigate whether advertising can improve stocks' information efficiency, measured as the speed with which the market impounds information into prices. Again, using data on Super Bowl Commercials and high frequency intraday trading around game days from 2008 to 2018, I show that firms whose names are readily identifiable from the content of advertising experience a decrease in their information efficiency, accompanied by an increase in informed trading of their stock and a decrease in their cumulative abnormal return around the event window.

Moreover, I study the magnitude and direction of trading from informed institutional investors. I examine the hypothesis that advertising results in more sell orders from institutional investors. By applying t-tests and non-parametric tests to the buy-sell imbalance of large size orders, I find that for firms whose names are recognizable from the content of advertising, there is a reduced buy-sell imbalance for large size orders on the day after the advertising event. This result indicates that institutional investors sell more than they buy after an advertising event.

I also investigate advertising's impact on short-run returns and liquidity. Using the results from t-tests and non-parametric tests, I show advertised firms exhibit a decline in cumulative abnormal returns. Modified Fama-Mecbeth regressions further show that the decrease in cumulative abnormal returns is correlated with increased informed trading. I also find that advertised firms experience a decline in stock liquidity following an advertising event. This result is not consistent with early studies showing that advertising improves stock liquidity due to increased trading from retail investors.

My study provides evidence on the relationship between advertising and firm's financial market information environment, and in particular on the level of informed trading and information efficiency after firm advertising is broadcast. This study also sheds light on the literature investigating the impacts of advertising on short-run abnormal return, stock liquidity, and the trading behavior of institutional investors.

Chapter 1

Introduction

1.1 Objective

My research intends to examine advertising's impact on financial market outcomes. First, I investigate whether advertising can reduce information asymmetry among investors in financial markets, both theoretically and empirically. Second, I examine whether advertising can improve the informational efficiency of advertising firms with respect to their securities in the financial markets. Third, I analyze the influence of advertising on investor trading behavior, with a particular focus on the buy-sell imbalance among institutional investors. Last, I study whether advertising increases firms' short run stock returns and improves firms' short run stock liquidity.

1.2 Motivation

In the product markets, advertising can benefit the firms by increasing sales, maintaining the consumer loyalty, expand the consumer base, etc. Moreover, advertising can increase the brand presence, enhance the brand awareness, and create a favorable image of the firms, which may also increase the firms' visibility in the financial markets. The increased firms' visibility in the financial markets can attract investors attention, and investors attention can influence their investment decisions (Barber and Odean, 2007). Therefore, advertising can affect firms' stock price directly.

Firm managers are aware of the effect of advertising on stock price when making their advertising decisions. They may use advertising for the purpose of influencing the stock price, and some of them may opportunistically adjust the advertising expense to exploit the temporary return effect to their own benefit when stock price matters the most (Luo, 2008; Lou, 2014).

However, advertising has its side effects in the financial markets, which is little known in the literature. First, in influencing the short-run stock prices, advertising may cause a loss to some investors, especially the retail investors. Advertising influences retail (individual) investors more than it does institutional investors (Barber and Odean, 2007; Fehle et al., 2005; Joshi and Hanssens, 2010a ; Lou, 2014). Individual investors being net buyers of such attention-grabbing stocks (Fehle et al., 2005 ; Lou, 2014), they make their investment decisions in part based on familiarity rather than fundamental value or portfolio theory. They may evaluate the firm values over-optimistically and buy stocks at prices higher than their fundamental value, suffering a loss in trading with more informed investors. Second, if advertising can influence the short-run stock price, it may increase the volatility as well, and then results in the mis-pricing. One important function of the financial markets is to incorporate information into stock price, making the price to reflect information timely and effectively. If advertising can cause the price inefficiency, it may not a good signal in investors' decision making.

Marketing decision makers and investors are increasingly aware of the importance of advertising's side effects in the financial markets, which calls for an evaluation of the short-term effects of advertising on information asymmetry, and information efficiency, and investor response.

Advertising plays an important role in both product markets and financial markets. In product markets, it conveys product information to audiences, (Nelson, 1974), making products better known to consumers and potential consumers. Therefore, advertising is believed to reduce information asymmetry in product markets (Kirmani and Rao, 2000). Given that advertising is public information in product markets, and is also visible in the financial markets, there is potential for it to play an important role in disseminating value-relevant information to broad groups of investors. Some firm managers use advertising as a communication channel to provide new product information and show their financial wellbeing to both current and prospective investors (Chemmanur and Yan, 2009). Therefore, one may think advertising has an impact on the information environment in financial markets. A firm's financial market information environment includes both information asymmetry and information efficiency. Information asymmetry among market participants refers to some investors, possessing firm-specific information related to the fundamental value of the security that is not accessible to uninformed investors. As a type of market failure, information asymmetry can lead to a series of problems in financial markets (Akerlof, 1970), such as adverse selection (Akerlof, 1970; Glosten and Harris, 1988), illiquidity (Stoll, 1989), mispricing (Grossman and Stiglitz, 1980), and higher cost of capital (Easley and O'hara, 2004). Information efficiency is the speed and effectiveness with which information is incorporated into price. According to Malkiel and Fama (1970), a market is efficient if value-related information is reflected in stock prices fully and timely. Incorporating information into prices - termed price efficiency - is a fundamental important function of financial markets. Lower levels of information efficiency can pose problems for investors attempting to value firms correctly and in a timely manner.

However, the information contained in advertising may be biased and incomplete. Advertising is not designed to portray commodities or firms in an objective manner (Lou, 2014), and does not directly contain price-based information on firm value and advertising investment productivity (Joseph and Wintoki, 2013). While researchers and managers focus on advertising's role for investor communication, little is known about advertising's impact on information asymmetry and information efficiency in financial markets.

Whether advertising will reduce information risk and improve information efficiency in financial markets is an empirical question that has been unanswered so far in the literature.

The impact of product market advertising on firm value, stock price, and investors' trading behavior in financial markets has been analyzed extensively in the marketing and finance literature. Advertising can directly affect firm value, especially short-run stock returns, by means of advertising-induced investor behavioral bias. Advertising can capture investors' attention (Fehle et al., 2005, Lou, 2014), and affecting investors' behavior by generating a familiarity bias in in stock picking or by influencing investors to evaluate firms more optimistically (Barber and Odean, 2007). The attention-driven trading that results from advertising can directly inflate short-term stock prices (Gervais et al., 2001; Barber and Odean, 2007). However, advertising's effect on short-run return may not be beneficial for all investors. Prior research find that advertising influences retail (individual) investors more than it does institutional investors (Barber and Odean, 2007; Fehle et al., 2005; Joshi and Hanssens, 2010a ; Lou, 2014). Informed investors typically rely on more information resources, are unlikely to consider stocks purely based on attention grabbing advertising, while uninformed investors often trade stocks for reasons unrelated to stock fundamentals such as attention. However, prior research focuses on advertising's impact on individual investors, neglecting the different reactions and performance between individual investors and institutions after advertising is broadcast. For example, advertising may not inflate stock prices. Moreover, it may induce more large size sell orders from institutional investors, resulting in poor performance of individual investors. Advertising's differing impacts on reactions and performance of individual and institutional investors are not fully understood. The extant literature examining the this issue is sparse.

1.3 Brief Results and Contribution

In Chapter 2, I first briefly describe the original Glosten-Milgrom model. I then extend the Glosten-Milgrom model of dealer markets by regarding advertising as a signal that will result in more buying from retail investors. Using this modified Glosten-Milgrom model, I prove that theoretically, advertising may temporally increase information asymmetry in financial markets.

In Chapter 3, I develop hypotheses based on results from the theoretical model and test them with an event study research method. I exploit Super Bowl Commercials as events of interest in this research. I find that firm's information environments in financial markets are significantly and negatively related to a term that captures advertising events. The post-event Monday experiences a reduced return, lower information efficiency, and increased informed trading, indicating that advertising facilitates informed trading and reduces the informational efficiency of stocks in financial markets. This effect is more pronounced for firms whose names are recognizable from the content of advertising. These firms also experience a significantly decrease in buy-sell imbalance among large size orders, defined as orders larger than \$30,000. This indicates there are more large sell orders after the event, likely submitted by institutional investors. I also find advertised firms exhibit a decline in liquidity after an advertising event. This result is inconsistent with prior studies showing that advertising can improve liquidity. Although advertising might have long-term effects on liquidity, effects which are not linked to improved liquidity directly following advertising events. The results from difference in differences regressions provide further evidence that advertising may exacerbate informed trading and reduce information efficiency, especially for firms with names that are recognizable from the content of advertising.

This research contributes to several strands of the finance and marketing literatures.

First, this research improves our understanding of advertising's financial markets outcomes including information asymmetry and information efficiency. Previous research investigates advertising's impact on information asymmetry in product markets, or the default view that advertising can reduce information asymmetry in financial markets. I show, both theoretically and empirically, that advertising can increase information asymmetry among investors in financial markets. Furthermore, I also find advertising can reduce information efficiency for stocks from advertised firms.

Second, my research adds to the growing literature on advertising-induced trading in financial markets. Prior work focuses largely on the trading patterns of individual investors. My main contribution is to study the different reactions and performance between individual and institutional investors. More specifically, for individual investors, my research investigates the potential risk that they are facing in trading attention-grabbing securities. I find that advertising leads to higher information asymmetry between uninformed and informed investors. This study complements the literature on trading behaviour from different kinds of investors on the background that the cut-off rule does not work.

Third, prior studies typically rely on annual advertising expenditure and focus on the contemporaneous low-frequency financial market outcomes. By using an event study method together with high-frequency intra-day tick data, this paper contributes to the literature on advertising's immediate short-run effect in financial markets. While the event study method helps me to isolate an account for any potential reverse causality and some endogeneity concerns, high frequency data allows me to better capture any potential impact of advertising on investors' reactions and financial markets outcomes, which is pivotal since attention after advertising tends to fade quickly.

Finally, by studying the effect of advertising on information asymmetry and information efficiency in financial markets, this paper sheds light on research of market microstructure theory in the context of marketing activities and their financial market outcomes.

The rest of this thesis is organized as follows. Chapter 2 discusses my theoretical model development. Chapter 3 presents the empirical analyses, including a summary of the research design, description of the sample and its summary statistics, and empirical results. Chapter 4 concludes the thesis.

Chapter 2

Theory

2.1 Introduction

In this chapter I introduce a theoretical model to investigate the relationship between advertising and information asymmetry among informed and uninformed investors in financial markets. First, I briefly introduce the original Glosten-Milgrom model. Following this, I extend the Glosten-Milgrom model of dealer markets by regarding advertising as a signal that result in more buying from retail investors.

In the original Glosten-Milgrom model, there are two kinds of investors trading with market makers. In trading with informed investors, market makers require a compensation to offset their potential losses. The compensation that market makers required is the bid-ask spread (adverse selection component), which is the benchmark measure in this chapter.

Advertising may indicate to investors that firms are financially well-being, or at least less risky. It can be utilized as a signal to influence investors decision making. I modify the Glosten-Milgrom model by regarding advertising as a signal that results in more buy orders from some uninformed investors who do not have access to private information about firm value. They have to evaluate signals to make their investment decisions among available options. In the adjusted Glosten-Milgrom model, I assume that uninformed investors can be divided into two groups: the signal sensitive uninformed investors and the signal insensitive uninformed investors. Advertising, as a signal, can influence signal sensitive uninformed investors to submit buy orders when observing the signal. Market makers adjust their bid-ask spread according to the changed order directions. I compare the bid-ask spread (adverse selection component) in the adjusted Glosten-Milgrom model with the benchmark and then theoretically prove that advertising increases information asymmetry among informed and uninformed investors.

Product market advertising is believed to have an impact on investors' trading behaviour and on their investment decisions in financial markets, especially for retail investors (Barber and Odean, 2007; Fehle et al., 2005). Advertising influences investors' behaviour by attracting their attention (Barber and Odean, 2007; Frieder and Subrahmanyam, 2005), and by disseminating value-relevant information to broad groups of investors (Chemmanur and Yan, 2009). This increase firm visibility, changes the trading price, volume and order imbalance, and also enlarges the investor base, increases stock liquidity (Grullon et al., 2004; Barber and Odean, 2007; Frieder and Subrahmanyam, 2005). Given advertising's impact on investor attention and stock prices, some firm managers may potentially use it not only as a communication channel for providing new product information but also as a means to demonstrate their financially wellbeing to investors or future investors. They may increase advertising expenses prior to IPOs, SEOs, or during other period that stock prices matter most (Chemmanur and Yan, 2009; Fehle et al., 2005; Luo, 2008). However, in doing so, such managers may be unaware of advertising's side effects in the financial markets.

Advertising conveys product information to audiences, (Nelson, 1974),makes products better known to consumers and potential consumers, and is therefore believed to reduce information asymmetry in product markets (Kirmani and Rao, 2000). Considering that a product market advertising is also visible to the financial markets, advertising may affect information asymmetry in the financial markets as well. Grullon et al. (2004) assume that advertising reduces the information asymmetry in financial markets and therefore increases the liquidity of stocks. Chemmanur and Yan (2009) and Luo (2008) claim that advertising can reduce information asymmetry prior to IPOs because advertising may help to signal and provide information about the true value of the firm to investors.

However, most advertising portrays the underlying product or firms in a way that neither comprehensive nor objective (Lou, 2014). The information contained in advertising may be biased and incomplete as advertising is not designed to portray a commodity or firm in an objective manner (Lou, 2014), and it does not directly contain price-based information on firm value and advertising investment productivity (Joseph and Wintoki, 2013). Advertising affects investor's trading via familiarity bias. It biases some investors' decisions in favor of familiarity rather than fundamental values. Besides, advertising influences retail (individual) investors more than it does institutional investors (Barber and Odean, 2007; Fehle et al., 2005; Joshi and Hanssens, 2010a ; Lou, 2014), as institutional investors already have informational advantages and their investment decisions are unlikely to be affected by advertising. Individual investors do not have access to private information about firm values, so their investment decisions are more likely affected by brand awareness, familiarity and attention. Such individual investors are likely to be uninformed (Grullon et al., 2004), and be net buyers of attention grabbing stocks (Fehle et al., 2005 Lou, 2014). Moreover, advertising can increase short run stock returns, but this is a temporary effect, which is followed by lower future returns (Lou, 2014). This effect is also called price overreaction or price overshooting. This suggests that investors influenced by advertising may be misguided and buy securities at a price higher than the fundamental value and hence that they might suffer losses trading such attention grabbing securities.

The mechanism by which advertising affects the information asymmetry can be briefly illustrated as follows. After a company increase its advertising exposure, there will be more individual investors trading in its stock. These individual investors are net buyers of securities from heavily advertised firms. They make investment decisions based on familiarity rather than fundamental firm values or portfolio theories. They may evaluate firm values over-optimistically and buy stocks at prices higher than their fundamental values, suffering losses in trading with more informed investors. Informed investors who have private access to value-related information will buy when stock prices are lower than their fundamental values and sell otherwise. They trade more aggressively when the market is more liquid.

As a consequence, advertising may mislead uninformed retail investors, widen the information gap between informed and uninformed investors, and leads to higher information asymmetry in financial markets. Information asymmetry among market participants refers to some investors, possessing firm-specific information related to the fundamental value of the security, who build positions on private information that is not accessible to uninformed investors. As a type of market failure, information asymmetry can lead to a series of problems in the financial markets (Akerlof, 1970), such as adverse selection (Akerlof, 1970; Glosten and Harris, 1988), illiquidity (Stoll, 1989), mispricing (Grossman and Stiglitz, 1980), and higher cost of capital (Easley and O'hara, 2004).

The extant literature examining the above issue is sparse. The relationship between advertising and information asymmetry is unclear and there is limited research examining the magnitude and direction of the impact that advertising can have on information asymmetry in the financial markets.

2.2 The Original Glosten-Milgrom Model

In this section, I briefly describe the original Glosten-Milgrom model and discuss a micro-marketstructure measure of information asymmetry.

In financial markets, information asymmetry among informed and uninformed investors can be measured by the adverse selection cost of the bid-ask spread. Glosten and Milgrom (1985) find that bid-ask spreads consist of 3 primary components: adverse selection cost, order processing cost and inventory cost. They present an econometric model to estimate the adverse selection component of the bid-ask spread and this model is widely used in research on information asymmetry and liquidity.

The bid-ask spread is the difference between the ask and bid prices of a security in the market and can be considered a measure of the supply and demand for a particular asset. The ask price is the lowest sell price that sellers are willing to accept and bid price is the highest buy price that buyers are willing to pay. The bid-ask spread is required from liquidity suppliers to cover their potential costs and risks. Some of the key elements to the bid-ask spread include information asymmetry, the cost of executing orders and maintaining a presence in the market, and the risk of variations in the value of their positions(Glosten and Milgrom, 1985). Accordingly, the bid-ask spread can be decomposed into three components: adverse selection cost, order processing cost, and inventory cost (Glosten and Milgrom, 1985). The adverse selection cost is a compensation required by dealers to offset their potential losses on trades with informed investors (Foucault et al., 2013).

The Glosten-Milgrom model analyzes the bid-ask spread from market makers facing both privately informed and uninformed traders. In particular, this model is employed to analyze information asymmetry among investors by decomposing the bid-ask spread and calculating the adverse selection component.

2.2.1 Assumptions

In analyzing information asymmetry in the financial markets, the assumptions for the Glosten-Milgrom model can be described as follows:

1. No other costs: There are no order processing costs or inventory costs so that the bid-ask spread equals the adverse selection cost.
2. Security values: A security's future value (transaction price in the next trade) has a binary distribution. It can take $v = V^H$ or $v = V^L$, where V^H denotes the transaction price going up and V^L denotes the

transaction price going down.

3. Trade size: The trade size is normalized to one. An investor has only one single trading opportunity. Therefore, the probability that an order comes from an informed (or uninformed) investors is equal to the proportion of informed (or uninformed) investors in the market.

4. Market participants:

   - Informed investors, have private information about future firm values. They will buy a security if the price goes up ($v = V^H$) and sell a security if the price goes down ($v = V^L$). Orders are placed by informed investors with probability π, which equals the proportion of informed investors among all investors.

   - Uninformed investors do not have access to information about future firm values. They place random orders, buys and sells each with probability 50%. Orders are placed by uninformed investors with probability $1-\pi$, which equals the proportion of uninformed investors among all investors.

5. Market makers:

   - Market makers include liquidity suppliers and include a pool of traders who may be individuals need cash, or fund managers who have to invest a recent cash flow or re-balance the portfolio. They are liquidity suppliers in the financial markets.

   - Orders convey information and order direction is the sole source of new information for market makers, based upon on which market makers revise their estimates of the values of securities.

Before observing the $(t+1)^{th}$ order, the market makers estimate of the security's value is

$$\mu_t = \theta_t v^H + (1-\theta_t)v^L,$$

where θ_t and $(1-\theta_t)$ are the probabilities that market makers assign to the occurrence of high (v^H), and low (v^L) values respectively.

- Market makers require a larger bid-ask spread to compensate for their potential losses on trades with more informed investors.

6. Market clearing condition: The market is in equilibrium when market makers make zero expected profits.

2.2.2 The Determinants of the Bid-ask Spread

The or bid-ask spread can be computed by looking at the market clearing condition. By setting the market maker's expected profit with all investors equal to zero and solving the subsequence equation, one can compute the bid and ask prices and therefore also the adverse selection component of the bid-ask spread.

The market maker's expected profit from trading with informed investors at the ask price a_t is given by:

$$\theta_{t-1}\pi \cdot (a_t - v^H),$$

where π is the proportion of informed traders, θ_{t-1} is the market makers' belief about the value of the security, and v^H is a security's higher value.

The market maker's expected profit from trading with uninformed investors at the ask price a_t is given by:

$$\frac{1}{2}(1-\pi) \cdot (a_t - \mu_{t-1}),$$

where π is the proportion of informed traders, θ_{t-1} is market maker's belief about the value of the security, and μ_{t-1} is the mid quote.

The market equilibrium condition at the ask price a_t becomes:

$$\theta_{t-1}\pi \cdot (a_t - v^H) + \frac{1}{2}(1-\pi) \cdot (a_t - \mu_{t-1}) = 0,$$

where π is the proportion of informed traders, θ_{t-1} is market maker's belief about the value of the security, and v^H is a security's higher value.

Solving this equation, we get the competitive ask price at time t:

$$\begin{aligned} a_t &= \mu_{t-1} + \frac{\pi\theta_{t-1}}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)}(v^H - \mu_{t-1}) \\ &= \mu_{t-1} + \frac{\pi\theta_{t-1}(1-\theta_{t-1})}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)}(v^H - v^L). \end{aligned}$$

where π is the proportion of informed traders, θ_{t-1} is market maker's belief about the value of the security, and $v^H - v^L$ is volatility of security's value.

By the same method, we can also compute the competitive bid price at time t.

The market markers expected profit from trading with informed investors at the bid price b_t is given by:

$$(1-\theta_{t-1})\pi \cdot (v^L - b_t).$$

The market markers expected profit from trading with uninformed investors at the bid price b_t is given by:

$$\frac{1}{2}(1-\pi) \cdot (\mu_{t-1} - b_t).$$

The market equilibrium condition at the bid price b_t therefore becomes:

$$(1-\theta_{t-1})\pi \cdot (v^L - b_t) + \frac{1}{2}(1-\pi) \cdot (\mu_{t-1} - b_t) = 0.$$

Solving this equation, we get the competitive bid price at time t:

$$\begin{aligned}
b_t &= \mu_{t-1} - \frac{\pi(1-\theta_{t-1})}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)}(\mu_{t-1} - v^L) \\
&= \mu_{t-1} - \frac{\pi\theta_{t-1}(1-\theta_{t-1})}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)}(v^H - v^L)
\end{aligned}$$

Therefore, the bid-ask spread (adverse selection component) at time t is:

$$\begin{aligned}
S_t &\equiv a_t - b_t \\
&= \pi\theta_{t-1}(1-\theta_{t-1})\left(\frac{1}{\pi\theta_{t-1} + (1-\pi)\frac{1}{2}} + \frac{1}{\pi(1-\theta_{t-1}) + (1-\pi)\frac{1}{2}}\right)(v^H - v^L),
\end{aligned} \tag{2.1}$$

where π is the proportion of informed traders, θ_{t-1} is market maker's belief about the value of the security, and $v^H - v^L$ is the volatility of security's value. The bid-ask spread is an increasing function of π and $v^H - v^L$, which means that the spread is larger when there are more informed investors or greater volatility in the security's value. With other conditions unchanged, the spread is greatest when $\theta_{t-1} = \frac{1}{2}$, which means market makers are perfectly uncertain about the markets direction (when $\theta_{t-1} = 1$, market makers are very confident the security's price will go up; when $\theta_{t-1} = 0$, market makers are very confident the security's price will go down).

This function is also the benchmark measure of bid-ask spread with informed trading in this chapter.

2.3 The Adjusted Glosten-Milgrom Model

I modify the Glosten-Milgrom model to investigate the impact of advertising's short-run effect on information asymmetry in financial markets. In the modified model, advertising is regarded as a signal that can affect the behavior of some uninformed investors and then in turn affect informed trading. First, I illustrate the assumptions about advertising's short-run price impact and investors behavior. Second, I introduce a simplified two-step model to illustrate how advertising can affect informed trading in two time periods. Last, I extend the simplified two-step model into three steps, which align closely with reality.

2.3.1 Assumptions

1. Short-run price impact: I assume advertising has a positive short-run price impact in financial markets. Increased advertising can inflate short-run stock prices.

2. Informed investors: Informed investors are not only aware of advertising's effect but also the expected response from other investors. They submit buy orders using the private information about the price going up and submit sell orders after that. The probability that an order comes from informed investors is π, which is equal to the proportion of informed investors.

3. Uninformed investors: Uninformed investors do not have access to private information about the value of securities. In the presence of uncertainty, some of them will evaluate signals to make their investment decisions among available options. I divide the uninformed investors into two groups, the signal sensitive uninformed investors and the signal insensitive uninformed investors. I assume that advertising can affect signal sensitive uninformed investors such that they will submit buy orders when observing advertising and submit random orders otherwise. Signal insensitive uninformed investors submit random orders (50% buy orders and 50% sell orders). The probability that an order comes from signal sensitive uninformed investors is $(1-\pi)\delta$, while that from signal insensitive uninformed investors is $(1-\pi)(1-\delta)$. The $(1-\pi)$ is equal to the proportion of uninformed investors, and δ is equal to the proportion of signal sensitive uninformed investors among all uninformed investors.

2.3.2 A Two-Step Model

To show how advertising affects information asymmetry in financial markets, I introduce a simplified two-step model first. I assume there are two time periods and advertising is visible in the second one. Then, I compute the adverse selection component of the bid-ask spread in this two-step model by the market clear conditions and then compare it with that in the benchmark model. Advertising will increase information asymmetry among informed and uninformed investors if the adverse selection component of the bid-ask spread is greater than that in the benchmark model.

At time $t-1$, there is no advertising or private information in financial markets. In the absence of informed trading, the order flow is balanced, with 50 percent buy and 50 percent sell orders. Uninformed investors are equally likely to buy a security as they are to sell it. The informed investors do not trade as the price will not change in the next period. The dealers are perfectly uncertain about the direction of the market, which means $\theta_{t-1} = \frac{1}{2}$.

At time t, advertising is observed by investors. Informed investors have private information that the price will go up in the next step. Signal sensitive uninformed investors' portfolio decision making is affected by the signal. Signal insensitive uninformed investors are not affected by the signal. Thus, the informed investors and signal sensitive uninformed investors in the market will submit buy orders while signal insensitive uninformed investors submit random orders. Market makers receive more buy orders and based on that they revise their value estimation. Through this channel, advertising can affect the parameter θ_t, which is the probability that dealers assign to the occurrence that future price going up ($v = v^H$). I later prove that $\theta_t > \frac{1}{2}$.

Transaction	Trader identity	Joint probability	Conditional value
Buyers at a_t	Informed	$\pi\theta_{t-1}$	$v = v^H$
	Informed	0	$v = v^L$
	Signal insensitive uninformed	$\frac{1}{2}(1-\pi)(1-\delta)$	μ_{t-1}
	Signal sensitive uninformed	$(1-\pi)\delta\theta_{t-1}$	μ_{t-1}
	Signal sensitive uninformed	$(1-\pi)\delta(1-\theta_{t-1})$	μ_{t-1}
Sellers at b_t	informed	0	$v = v^H$
	informed	$\pi(1-\theta_{t-1})$	$v = v^L$
	Signal insensitive uninformed	$\frac{1}{2}(1-\pi)(1-\delta)$	μ_{t-1}
	Signal sensitive uninformed	0	μ_{t-1}
	Signal sensitive uninformed	0	μ_{t-1}

Market makers' expected net profit from the transaction at the ask price a_t is:

$$\pi\theta_{t-1}(a_t - v^H) + \frac{1}{2}(1-\pi)(1-\delta)(a_t - \mu_{t-1}) + (1-\pi)\delta(a_t - \mu_{t-1}).$$

Market makers' expected net profit from the transaction at the bid price b_t

is:

$$\pi(1-\theta_{t-1})(v^L - b_t) + \frac{1}{2}(1-\pi)(1-\delta)(\mu_{t-1} - b_t).$$

As the market is assumed to be competitive, the bid and ask prices will be such that the dealer's expected net profit equals zero. I let these formulas equal zero and solve the subsequent equations, where the bid and ask prices can be calculated as follows:

$$\begin{aligned} a_t &= \frac{\frac{1}{2}(1-\pi)(1+\delta)\mu_{t-1} + \pi\theta_{t-1}v^H}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)} \\ &= \mu_{t-1} + \frac{\pi\theta_{t-1}(v^H - \mu_{t-1})}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)} \\ &= \mu_{t-1} + \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)}. \end{aligned}$$

$$\begin{aligned} b_t &= \frac{\frac{1}{2}(1-\pi)(1-\delta)\mu_{t-1} + \pi(1-\theta_{t-1})v^L}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)} \\ &= \mu_{t-1} - \frac{\pi(1-\theta_{t-1})(\mu_{t-1} - v^L)}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)} \\ &= \mu_{t-1} - \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)}. \end{aligned}$$

Given that advertising will result in more buy orders from both informed investors and signal sensitive uninformed investors, the adverse selection component in the bid-ask spread with more buy orders at time t is:

$$\begin{aligned}
S_t &= a_t - b_t \\
&= \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)} + \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)} \\
&= \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{[\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)][\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)]}
\end{aligned} \tag{2.2}$$

In this two-step model, θ_{t-1} is assumed to be equal to $\frac{1}{2}$, so that equation (2.2) equals:

$$\begin{aligned}
S_t &= \pi(v^H - v^L) \cdot \frac{1}{[\pi + (1-\pi)(1-\delta)][\pi + (1-\pi)(1+\delta)]} \\
&= \pi(v^H - v^L) \cdot \frac{1}{[1 + \delta(\pi - 1)][1 - \delta(\pi - 1)]} \\
&= \pi(v^H - v^L) \cdot \frac{1}{1 - [\delta(\pi - 1)]^2}
\end{aligned}$$

It is obvious that $1 - [\delta(\pi - 1)]^2 < 1$, so we have:

$$S_t > \pi(v^H - v^L).$$

In the benchmark model, I let $\theta_{t-1} = \frac{1}{2}$, such that the adverse selection component in the bid-ask spread is:

$$S_t^{'} = \pi(v^H - v^L).$$

This two-step model therefore proves that advertising can increase information asymmetry in financial markets .

2.3.3 The Three-Step Model

In this part, I extend the two-step model into three steps, which is closer to the reality. There are three time periods in this model, and I denote them as $t-2$, $t-1$, and t. Advertising is visible in the second time period. I compute the adverse selection component of the bid-ask spread in this three-step model using the market clearing condition and then compare that result with benchmark model. Advertising increases information asymmetry among informed and uninformed investors if the adverse selection component of the bid-ask spread is greater than that in the benchmark model.

At time $t-2$, there is no advertising or private information in financial markets. In the absence of informed trading, the order flow is balanced, with 50 percent buy and 50 percent sell orders. Dealers are perfectly uncertain about the direction of the market, which means $\theta_{t-2} = \frac{1}{2}$.

At time $t-1$, advertising has not yet been observed by investors. However, informed investors have private information about the upcoming advertising and its impact on short run stock prices. They submit buy orders while uninformed investors (both signal sensitive and signal insensitive uninformed investors) submit random orders. Market makers receive more buy orders from informed investors, based on which they revise their value estimates. In this way, advertising can affect the parameter θ_{t-1}, which is the probability that dealers assign to future prices going up ($v = v^H$). I prove that $\theta_{t-1} > \frac{1}{2}$ later. Stock prices go up at this point in time as there are more buy orders than sell orders.

As advertising only has an effect on informed investors' trading, the bid-ask spread at time $t-1$ is equal to the benchmark model:

$$\begin{aligned} S_{t-1} &\equiv a_{t-1} - b_{t-1} \\ &= \pi\theta_{t-2}(1-\theta_{t-2})\left(\frac{1}{\pi\theta_{t-2} + (1-\pi)\frac{1}{2}} + \frac{1}{\pi(1-\theta_{t-2}) + (1-\pi)\frac{1}{2}}\right)(v^H - v^L), \end{aligned} \tag{2.3}$$

where $\theta_{t-2} = \frac{1}{2}$, so the bid-ask spread at time $t-1$ equals to:

$$S_{t-1} = \pi(v^H - v^L).$$

At time t, advertising is observed by signal sensitive uninformed investors and they submit buy orders while signal insensitive uninformed investors submit random orders. The informed investors continue buying as they are aware of advertising's short-run price impact.

Transaction	Trader identity	Joint probability	Conditional value
Buyers at a_t	Informed	$\pi\theta_{t-1}$	$v = v^H$
	Informed	0	$v = v^L$
	Signal insensitive uninformed	$\frac{1}{2}(1-\pi)(1-\delta)$	μ_{t-1}
	Signal sensitive uninformed	$(1-\pi)\delta\theta_{t-1}$	μ_{t-1}
	Signal sensitive uninformed	$(1-\pi)\delta(1-\theta_{t-1})$	μ_{t-1}
Sellers at b_t	Informed	0	$v = v^H$
	Informed	$\pi(1-\theta_{t-1})$	$v = v^L$
	Signal insensitive uninformed	$\frac{1}{2}(1-\pi)(1-\delta)$	μ_{t-1}
	Signal sensitive uninformed	0	μ_{t-1}
	Signal sensitive uninformed	0	μ_{t-1}

Market makers' expected net profit from the transaction at the ask price a_t is:

$$\pi\theta_{t-1}(a_t - v^H) + \frac{1}{2}(1-\pi)(1-\delta)(a_t - \mu_{t-1}) + (1-\pi)\delta(a_t - \mu_{t-1}).$$

Market makers' expected net profit from the transaction at the bid price b_t is:

$$\pi(1-\theta_{t-1})(v^L - b_t) + \frac{1}{2}(1-\pi)(1-\delta)(\mu_{t-1} - b_t).$$

As the market is assumed to be competitive, the bid and ask prices will be such that the dealer's expected net profit is zero. I let these formulas equal zero and solve the subsequent equations where the bid and ask prices can be calculated as follows:

$$\begin{aligned} a_t &= \frac{\frac{1}{2}(1-\pi)(1+\delta)\mu_{t-1} + \pi\theta_{t-1}v^H}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)} \\ &= \mu_{t-1} + \frac{\pi\theta_{t-1}(v^H - \mu_{t-1})}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)} \\ &= \mu_{t-1} + \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)}. \end{aligned}$$

$$\begin{aligned} b_t &= \frac{\frac{1}{2}(1-\pi)(1-\delta)\mu_{t-1} + \pi(1-\theta_{t-1})v^L}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)} \\ &= \mu_{t-1} - \frac{\pi(1-\theta_{t-1})(\mu_{t-1} - v^L)}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)} \\ &= \mu_{t-1} - \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)}. \end{aligned}$$

The adverse selection component in the bid-ask spread with more buy orders from both informed investors and signal sensitive uninformed investors at time t is:

$$\begin{aligned} S_t &\equiv a_t - b_t \\ &= \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)} + \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)} \\ &= \frac{\pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L)}{[\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)][\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)]} \end{aligned} \quad (2.4)$$

According to the original Glosten-Milgrom model, if advertising does not induce more buy orders from retail investors (when the informed investors are still buying), the bid-ask spread should be:

$$
\begin{aligned}
S_t^{'} &\equiv a_t^{'} - b_t^{'} \\
&= \pi\theta_{t-1}(1-\theta_{t-1})(\frac{1}{\pi\theta_{t-1} + (1-\pi)\frac{1}{2}} + \frac{1}{\pi(1-\theta_{t-1}) + (1-\pi)\frac{1}{2}})(v^H - v^L).
\end{aligned}
$$

Taking the difference between the bid-ask spread in this three-step model and that in the original Glosten-Milgrom model, we have:

$$
\begin{aligned}
S_t - S_t^{'} =& \pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L) \\
&\cdot \{\frac{1}{[\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)][\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)]} \\
&- \frac{1}{[\pi\theta_{t-1} + \frac{1}{2}(1-\pi)][\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)]}\} \\
=& \pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L) \\
&\cdot \{\frac{1}{[\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)][\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)]} \\
&\cdot \frac{1}{[\pi\theta_{t-1} + \frac{1}{2}(1-\pi)][\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)]}\} \cdot X,
\end{aligned}
$$

where

$$
\begin{aligned}
X =& [\pi\theta_{t-1} + \frac{1}{2}(1-\pi)][\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)] \\
&- [\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)][\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)].
\end{aligned}
$$

The value of the parameters π, θ_{t-1}, and δ is less than 1, so whether $S_t - S_t^{'}$

is greater than zero depends on the sign of X.

$$
\begin{aligned}
X =&[\pi\theta_{t-1} + \frac{1}{2}(1-\pi)][\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)]\\
&- [\pi(1-\theta_{t-1}) + \frac{1}{2}(1-\pi)(1-\delta)][\pi\theta_{t-1} + \frac{1}{2}(1-\pi)(1+\delta)]\\
=&\pi^2\theta_{t-1}(1-\theta_{t-1}) + \frac{1}{2}\pi(1-\pi)\theta_{t-1} + \frac{1}{2}\pi(1-\pi)(1-\theta_{t-1})\\
&+ \frac{1}{4}(1-\pi)^2 - \pi^2\theta_{t-1}(1-\theta_{t-1}) - \frac{1}{2}\pi(1-\pi)(1-\theta_{t-1})(1+\delta)\\
&- \frac{1}{2}\pi(1-\pi)\theta_{t-1}(1-\delta) - 4(1-\pi)^2(1-\delta^2)\\
=&\frac{1}{2}\pi(1-\pi) + \frac{1}{4}(1-\pi)^2\delta^2 - \frac{1}{2}\pi(1-\pi)[\theta_{t-1}(1-\delta) + (1-\theta_{t-1})(1+\delta)]\\
=&\frac{1}{4}(1-\pi)^2\delta^2 + \frac{1}{2}\pi(1-\pi)[1-\theta_{t-1}(1-\delta) - (1-\theta_{t-1})(1+\delta)]\\
=&\frac{1}{4}(1-\pi)^2\delta^2 + \frac{1}{2}\pi(1-\pi)\delta(2\theta_{t-1}-1).
\end{aligned}
$$

When $2\theta_{t-1} - 1 > 0(\theta_{t-1} > \frac{1}{2})$, we get $S_t - S_t^{'} > 0$.

In this adjusted Golsten-Milgrom model, the results depend on the value of the parameter θ_{t-1}, which is the dealer's belief about the future value of the security. The value of θ_{t-1} varies over time, as the market maker changes his value estimate.

Define θ_{t-1}^{+} as the probability that market makers assign to the occurrence that prices go up ($v = v^H$) in the wake of a buy order at time $t-1$. Define θ_{t-1}^{-} as the probability that market makers assign the occurrence that prices go up ($v = v^H$) after they receive a sell order. Using Bayes' Theorem, let A be the event ($v = v^H$) and B be the arrival of a buy order. Then we get:

The probability of the price going up is $\Pr(A) = \theta_{t-2}$.

The probability of a buy order is $\Pr(B) = \pi\theta_{t-2} + \frac{1}{2}(1-\pi)$.

The probability of a buy order conditional on the price going up is $\Pr(B|A) = \pi + \frac{1}{2}(1-\pi)$.

Using Bayes' Theorem,

$$\begin{aligned}
\theta_{t-1}^{+} &= \Pr(A|B) \\
&= \frac{\Pr(B|A)Pr(A)}{\Pr(B)} \\
&= \frac{\theta_{t-2}[\frac{1}{2}(1-\pi)]}{\pi\theta_{t-2} + \frac{1}{2}(1-\pi)},
\end{aligned}$$

$$\begin{aligned}
\theta_{t-1}^{-} &= \Pr(A|\overline{B}) \\
&= \frac{\Pr(\overline{B}|A)Pr(A)}{\Pr(\overline{B})} \\
&= \frac{\theta_{t-2}[\frac{1}{2}(1-\pi)]}{\pi(1-\theta_{t-2}) + \frac{1}{2}(1-\pi)}.
\end{aligned}$$

Rewriting these two equations in terms of an odds ratio yields a linear first order difference equation:

$$\frac{\theta_{t-1}^{+}}{1-\theta_{t-1}^{+}} = \frac{1+\pi}{1-\pi} \cdot \frac{\theta_{t-2}}{1-\theta_{t-2}},$$

and:

$$\frac{\theta^{-}_{t-1}}{1-\theta^{-}_{t-1}} = \frac{1-\pi}{1+\pi} \cdot \frac{\theta_{t-2}}{1-\theta_{t-2}}.$$

If we define x_{t-1} as the cumulative difference between buy and sell orders up to time $t-1$, then the odds ratio can be expressed as a function of the aggregated order imbalance x_{t-1}:

$$\frac{\theta_{t-1}}{1-\theta_{t-1}} = \frac{\theta_0}{1-\theta_0}(\frac{1+\pi}{1-\pi})^{x_{t-1}},$$

where

$$x_{t-1} = \sum_{\tau=1}^{t-1} d_\tau.$$

Rearranging this equation, we get:

$$\frac{1}{1-\theta_{t-1}} = \frac{\theta_0}{1-\theta_0}(\frac{1+\pi}{1-\pi})^{x_{t-1}} + 1,$$

then:

$$\theta_{t-1} = 1 - \frac{1}{\frac{\theta_0}{1-\theta_0}(\frac{1+\pi}{1-\pi})^{x_{t-1}} + 1}.$$

Taking the first order derivative with respect to x_{t-1};

$$\frac{\mathrm{d}\theta_{t-1}}{\mathrm{d}x_{t-1}} = \frac{1}{[\frac{\theta_0}{1-\theta_0}(\frac{1+\pi}{1-\pi})^{x_{t-1}} + 1]^2} \cdot \frac{\theta_0}{1-\theta_0}(\frac{1+\pi}{1-\pi})^{x_{t-1}} \cdot \ln(\frac{1+\pi}{1-\pi}).$$

As $\frac{1+\pi}{1-\pi} > 1$, $\ln(\frac{1+\pi}{1-\pi}) > 0$. Therefore $\frac{d\theta_{t-1}}{dx_{t-1}} > 0$, and θ_{t-1} is an increasing function of aggregated order imbalance.

In this three-step model, at the beginning $T = t - 2$, there are no informed trades happening and the orders are balanced, $\theta_0 = \theta_{t-2} = \frac{1}{2}$. At time $t - 1$, informed investors have private information about advertising and submit buy orders while the uninformed investors submit random orders, so the order imbalance $x_{t-1} > 0$.

As θ_{t-1} is an increasing function of x_{t-1}, we get: $\theta_{t-1} > \theta_{t-2} = \theta_0 = \frac{1}{2}$.

The value of θ_{t-1} is very important in proving $S_t - S_t^{'} > 0$. Now that we have $\theta_{t-1} > \frac{1}{2}$, $S_t - S_t^{'} > 0$ is therefore proved, which means advertising results in a larger adverse selection component in the bid-ask spread (more information asymmetry in financial markets).

The impact of advertising on the adverse selection component in the bid-ask spread can also be illustrated by the first order conditions. This is done by taking the first order derivative of the bid-ask spread with respect to the number of buy orders from signal sensitive uninformed investors at time $T = t$. If the first order derivative is greater than zero, a firm with more retail buy orders has a wider bid-ask spread.

$$
\begin{aligned}
\frac{\partial S_t}{\partial \delta} =& \pi\theta_{t-1}(1-\theta_{t-1})(v^H - v^L) \\
& \cdot \{\frac{\partial[\frac{1}{\pi\theta_{t-1}+\frac{1}{2}(1-\pi)(1+\delta)}]}{\partial \delta} + \frac{\partial[\frac{1}{\pi(1-\theta_{t-1})+\frac{1}{2}(1-\pi)(1-\delta)}]}{\partial \delta}\},
\end{aligned}
$$

where

$$
\begin{aligned}
& \frac{\partial[\frac{1}{\pi\theta_{t-1}+\frac{1}{2}(1-\pi)(1+\delta)}]}{\partial \delta} + \frac{\partial[\frac{1}{\pi(1-\theta_{t-1})+\frac{1}{2}(1-\pi)(1-\delta)}]}{\partial \delta} \\
&= \frac{-\frac{1}{2}(1-\pi)}{[\pi\theta_{t-1}+\frac{1}{2}(1-\pi)(1+\delta)]^2} + \frac{\frac{1}{2}(1-\pi)}{[\pi(1-\theta_{t-1})+\frac{1}{2}(1-\pi)(1+\delta)]^2} \\
&= \frac{1}{2}(1-\pi)\frac{1}{[\pi\theta_{t-1}+\frac{1}{2}(1-\pi)(1+\delta)]^2[\pi(1-\theta_{t-1})+\frac{1}{2}(1-\pi)(1+\delta)]^2} \cdot Y,
\end{aligned}
$$

where

$$
\begin{aligned}
Y =& [\pi\theta_{t-1}+\frac{1}{2}(1-\pi)(1+\delta)]^2 - [\pi(1-\theta_{t-1})+\frac{1}{2}(1-\pi)(1+\delta)]^2 \\
=& \pi^2\theta_{t-1}^2 + \pi(1-\pi)(1+\delta)\theta_{t-1} + \frac{1}{4}(1-\pi)^2(1+\delta)^2 \\
& - \pi^2(1-\theta_{t-1})^2 - \pi(1-\pi)(1-\theta_{t-1})(1-\delta) - \frac{1}{4}(1-\pi)^2(1-\delta)^2 \\
=& \pi^2(2\theta_{t-1}-1) + \pi(1-\pi)(2\delta+\theta_{t-1}-\theta_{t-1}\delta) + \frac{1}{4}(1-\pi)^2(4\delta) \\
=& \pi^2(2\theta_{t-1}-1) + \pi(1-\pi)[2\delta+\theta_{t-1}(1-\delta)] + (1-\pi)^2\delta
\end{aligned}
$$

It is obvious that $\frac{\partial S_t}{\partial \delta} > 0$ when $\theta_{t-1} > \frac{1}{2}$. This indicates that the bid-ask spread will increase when there are more buy orders from retail investors.

2.4 Conclusion

In the original Glosten-Milgrom model, there are two kinds of investors. Informed investors who have private information about the market's direction, and submit buy orders when the price is going up and sell orders when the price is going down, and the uninformed investors who always submit random orders. Market makers include a pool of traders who may be individuals needing cash or fund managers who need to re-balance their portfolios. Their only source of new information is order direction, based on which they revise their estimates of securities' values. In trading with informed investors, market makers require compensation to offset their potential losses. As there are no order processing and inventory costs in this model, the compensation that market makers require is equal to the bid-ask spread. The bid-ask spread (adverse selection component) from the original Glosten-Milgrom model is the benchmark measure in this chapter.

In the adjusted Glosten-Milgrom model, I assume that advertising will temporarily inflate stock prices and that informed investors are aware of advertising's short run price impact. I further assume that the uninformed investors can be divided into two groups: namely the signal sensitive uninformed investors and the signal insensitive uninformed investors. The signal sensitive uninformed investors submit buy orders when they observe advertising and submit random orders otherwise. The signal insensitive uninformed investors submit random orders no matter whether they observe advertising or not.

The two-step model is a special case, where informed investors do not build their positions before advertising is observed by uninformed investors. Market makers receive more buy orders from both informed and signal sensitive uninformed investors after advertising is visible. Based on this order direction imbalance, market makers revise their value estimates and change the bid-ask spread. The bid-ask spread in the two-step model is greater than that in the original Glosten-Milgrom two-step model, which is the benchmark measure in this chapter. Therefore, advertising increases information asymmetry between informed and uninformed investors in this model.

The three-step model, where there are three kinds of investors and three time periods, align more closely with reality. Informed investors have private information not only about the time that advertising will be observed but also about the short run price effect of advertising. They submit buy orders before advertising is observed. After that, both informed investors and signal sensitive uninformed investors submit buy orders. Based on this imbalanced order direction, market makers revise their value estimates and change the bid-ask spread. The bid-ask spread in the three-step model is greater than that in the original Glosten-Milgrom model. Moreover, the bid-ask spread is positively related to the proportion of signal sensitive uninformed investors who submit buy orders when observing advertising. In conclusion, theoretically, advertising may temporally increase information asymmetry in the financial markets.

In this chapter, I assume advertising only has a short run price impact. If I extend the three-step model into one with more periods, in step 4, signal sensitive uninformed investors may continue buying but the informed investors may become net sellers as advertising's short run price effect dissipates and prices go down. After that, the signal sensitive uninformed investors will trade like other uninformed investors, submitting random orders (50% buy orders and 50% sell orders). In that case, information asymmetry may decrease and the bid-ask spread might return back to its normal level.

Chapter 3

Advertising's Financial Market outcomes

3.1 Abstract

Using Super Bowl Commercials as events and by looking at high frequency intra-day tick data, I investigate a number of advertising's short-run effects in the financial markets, including the level of information asymmetry among investors, information efficiency, buy sell imbalance, stock returns, and stock liquidity. Based on different information asymmetry and information efficiency measures, I show that advertising positively affects the informed trading and reduces information efficiency. Moreover, it has negative impact on stock liquidity. Advertising changes the buy sell imbalance of different trade size groups, generating more large sell orders, which may indicate that institutional investors are net sellers. Advertised firms exhibit a decline in cumulative abnormal returns, which is correlated to the increased informed trading.

3.2 Introduction

3.2.1 Objective

My research intends to investigate advertising's impact on financial market outcomes at the micro marketstructure level, and especially advertising's impact on information asymmetry, information efficiency, liquidity, buy-sell imbalance, and stock returns.

3.2.2 Motivation

In the product markets, advertising can benefit the firms by increasing sales, maintaining the consumer loyalty, expand the consumer base, etc. Moreover, advertising can increase the brand presence, enhance the brand awareness, and create a favorable image of the firms, which may also increase the firms' visibility in the financial markets. The increased firms' visibility in the financial markets can attract investors attention, and investors attention can influence their investment decisions (Barber and Odean, 2007). Therefore, advertising can affect firms' stock price directly.

Firm managers are aware of the effect of advertising on stock price when making their advertising decisions. They may use advertising for the purpose of influencing the stock price, and some of them may opportunistically adjust the advertising expense to exploit the temporary return effect to their own benefit when stock price matters the most (Luo, 2008; Lou, 2014).

However, advertising has its side effects in the financial markets, which is little known in the literature. First, in influencing the short-run stock prices, advertising may cause a loss to some investors, especially the retail investors. Advertising influences retail (individual) investors more than it does institutional investors (Barber and Odean, 2007; Fehle et al., 2005; Joshi and Hanssens, 2010a ; Lou, 2014). Individual investors being net buyers of such attention-grabbing stocks (Fehle et al., 2005 ; Lou, 2014), they make their investment decisions in part based on familiarity rather than fundamental value or portfolio theory. They may evaluate the firm values over-optimistically and buy stocks at prices higher than their fundamental value, suffering a loss in trading with more informed investors. Second, if advertising can influence the short-run stock price, it may increase the volatility as well, and then results in the mis-pricing. One important function of the financial markets is to incorporate information into stock price, making the price to reflect information timely and effectively. If advertising can cause the price inefficiency, it may not a good signal in investors' decision making.

Marketing decision makers and investors are increasingly aware of the importance of advertising's side effects in the financial markets, which calls for an evaluation of the short-term effects of advertising on information asymmetry, and information efficiency, and investor response.

Advertising plays an important role in disseminating value-relevant information to broad groups of investors. So, firm managers may use advertising as an potential communication channel providing new product information and showing their financial wellbeing to investors or future investors (Chemmanur and Yan, 2009). For this reason, one may expect advertising to ease information asymmetry among investors by providing forecasts of the potential future revenue increases. However, the information contained in advertising may be biased and incomplete as advertising is not designed to portray firms objectively (Lou, 2014), and does not directly contain price-based information on firm value and advertising investment productivity (Joseph and Wintoki, 2013). While researchers and managers focus on advertising's role for investor communication, little is known about advertising's impact on firms' information environment including information asymmetry and information efficiency in financial markets. More information asymmetry increases the risks faced by uninformed investors. Institutional investors have more information about firm values than others, while retail investors can only rely on public information and other sources such as advertising when there is uncertainty in the market. These uninformed retail investors risk suffering losses when trading with more informed investors. Information efficiency measures the speed with which the market impounds information into prices. A lower level of information efficiency can pose problems for investors attempting to value firms correctly and in a timely manner. Given the importance of these questions, whether advertising will reduce information asymmetry and improve information efficiency in financial markets is an empirical question that has been left unanswered so far in the literature.

The impact of product market advertising on firm value, stock prices, and investors' trading in financial markets has been analyzed extensively in the marketing and finance literature. Beside being able to impact firm values by increasing their profitability through future sales, advertising can also directly affect firm value by means of advertising-induced investor behavior bias. Advertising affects investors' trading behavior by grabbing their attention (Barber and Odean, 2007). Advertising can improve a firm's image and increase firm visibility, therefore capture investors' attention (Fehle et al., 2005, Lou, 2014). Attention affects investment decision making by generating a familiarity bias which renders investors more likely to evaluate firms more optimistically (Barber and Odean, 2007). Increased investor attention from advertising is strong enough to inflate short-term stock prices (Gervais et al., 2001; Barber and Odean, 2007). If managers are aware of advertising leading to a short-term attention effect that in turn influences short-run stock prices, they may wrongly believe that advertising is beneficial for all investors in improving their investment decision making.

Advertising influences retail (individual) investors more than it does institutional investors (Barber and Odean, 2007; Fehle et al., 2005; Joshi and Hanssens, 2010a ; Lou, 2014). With more information resources, informed investors are unlikely to consider advertising induced attention grabbing stocks, while uninformed investors often trade stocks for reasons unrelated to stock fundamentals such as attention. However, prior research focuses on advertising's impact on individual investors, neglecting the differing reactions and performance between individual and institutional investors after advertising is broadcast. Since advertising is a tool to attract investor attention, some managers may use it to artificially boost stock prices in the short run without consideration for the side effects of their manipulations. Moreover, advertising may induce more large size sell orders from institutional investors, resulting in poor investment performance for individual investors. If individual investors are unaware of the potential problems of attention-driven trading, they may be falsely led to bid up the stock price and suffer a loss, while professional investors are less likely to involve in attention-driven trading. Furthermore, early studies that analyze the trading of individual investors rely on the cut-off rule to identify whether orders are from individual investors or not. However, after 1998, the cut-off rule does not work since institutional investors use order-splitting techniques to break up their trades into smaller orders. Kyle (1985) finds that informed investors conceal their trades into noise trades to avoid the liquidity shortages. The use of computerized algorithms can not only disguise institutional trades but also improve the timing of their trades. It allows informed investors to trade more when uninformed investors' trading surges and take advantage of uninformed investors by anticipating their trading. Advertising's differential impact on the performance of individual and institutional investors are not yet fully understood. In particular, little is known about periods where new trading methods are widely accepted. The extant literature examining the above issue is sparse.

3.2.3 Brief Results

I find that a firm's information environment in the financial markets is significantly and negatively related to a term that captures advertising events. Both the day-by-day panel data regressions and cross-sectional data estimations indicate that my results are robust, advertising facilitates informed trading and reduces the informational efficiency in the financial markets.

I find that the post-advertising event Monday is associated with reduced returns, lower information efficiency, and increased informed trading. This effect is more pronounced for firms whose names are recognizable from the content of advertising. These firms also experience a significant decrease in buy-sell order balance among large size orders where large orders are defined as those exceeding $30,000. This indicates that there is a greater number of large sell orders after the advertising events, and I argue these are likely to be submitted by institutional investors. The results from difference in differences regressions suggest advertised firms experience a drop in liquidity after an advertising event. These results are inconsistent with prior research shows advertising can improve liquidity. Although advertising might have other long-term effects on liquidity, this may not necessarily be linked to the impacts on liquidity directly following advertising events. The results from difference in differences regressions provide further evidence that advertising may exacerbate informed trading and reduce information efficiency, especially for firms whose names are recognizable from the content of advertising.

3.2.4 Contribution

This research contributes to several strands of the finance and marketing literatures.

First, my research adds to the growing literature on behavioral finance, in particular, the advertising-induced trading in financial markets. Prior work focuses largely on the trading patterns of individual investors. My main contribution is to study the different reactions and performance of individual versus institutional investors. More specifically, for individual investors, my research investigates the potential risks they facing in trading attention-grabbing securities. I find that advertising leads to higher information asymmetry between uninformed and informed investors.

Second, previous research which analyzes trading from individual investors relies on the cut-off rule to identify orders from individual investors. However, after 1998, the cut-off rule does not work since institutional investors use order-splitting techniques to break up their large orders into some smaller ones. The use of computerized algorithms can not only disguise institutional trades but also improve the timing of their trades. This study extends the literature on trading behaviour from different kinds of investors by taking consideration that the cut-off rule does not work.

Third, prior studies typically rely on annual advertising expenditure and focus on the contemporaneous low-frequency financial market outcomes. By using an event study method together with high-frequency intra-day tick data, this paper contributes to the literature on advertising's immediate short-run effects in the financial markets. Early studies exploit attention-grabbing events to investigate investors' trading patterns and financial markets reactions. This research is subject to the criticism that the events of interest may be relevant to value-related information. While the event study method helps me to isolate any reverse causality problem and some endogeneity concerns, high frequency data allows me to better capture any potential impact of advertising on investors' reaction and financial market outcomes, since investor attention after advertising fades quickly.

Finally, by studying the effect of advertising on information risk and information efficiency in financial markets, this paper sheds light on research of market microstructure theory in the context of marketing activities and their financial market outcomes.

3.3 Literature Review

In this section, I first review the literature on advertising's impact on short-run stock returns. Second, I provide a brief overview of attention-driven trading. Third, I give an overview of investors' trading patterns, discussed in conjunction with advertising induced trading. Finally, I discuss the information asymmetry and information efficiency, for they can potentially explain the impact of advertising on financial market outcomes.

The impact of product market advertising on firm value and stock price has been analyzed extensively in the marketing and financial literature. Prior research has found that attention created by advertising influence investors' portfolio choices, and that in this way, advertising can directly affect firm values beyond the indirect effect of lifting profitability by increasing future sales (Frieder and Subrahmanyam, 2005; Grullon et al., 2004; Joshi and Hanssens, 2010b). Advertising, at least in the short run, can boost a firm's stock price (Lou, 2014; Ruenzi et al., 2017). As investors are not necessarily marketing experts, they may wrongly evaluate the impacts of marketing activities on stock prices. For example, as argued by Lou (2014), increased advertising expenditure is associated with an increase in abnormal stock returns, but often followed by lower future returns. Fehle et al. (2005) investigate price reactions and investors' trading activities for firms employing TV advertisements during Super Bowl Games and find significant positive abnormal returns for advertised firms. Being aware of such an effect, firm managers may use advertising to influence their short run stock prices. Moreover, they may opportunistically adjust their advertising expenses to exploit the temporary return effect for their own benefit when stock prices matter most (Luo, 2008; Lou, 2014).

However, whether advertising inflates the short run stock prices or not cannot be determined at present. Madsen and Niessner (2014) document that if firm's recent stock price movement have been increases, advertising may trigger downward price pressure. Focke et al. (2018) find that advertising does not significantly affect short-run stock returns and that previous results of the positive impact of advertising on stock returns may be resulting from the reverse causality. Moreover, results about advertising and short-run returns from prior study are subject to severe endogeneity problems: It is possible that firms with better sales revenue and profits will increase their advertising expenditure in the next year, and these firms are also likely to experience increases in their stock returns in the future.

Advertising's short-run stock return impact, if any, is believed to go through the mechanism of attention-driven trading. Heavily advertised securities appear to be more attractive investment options because advertising has a significant impact on investors' attention (Focke et al., 2018). Advertising can grab investors' attention by creating a favorable image of the firm and increasing firm visibility to current and potential future investors. (Fehle et al., 2005, Lou, 2014). Attention is a scare resource for investors (Kahneman, 1973). Attention affects investor behavior by generating a familiarity bias in which stock investors pick or by rendering investors to evaluate familiar firms more optimistically when making investment decisions (Barber and Odean, 2007). Attention gabbing securities have more trading activity from both individual and institutional investors, have better liquidity (Grullon et al., 2004), and higher abnormal returns (Gervais et al., 2001; Da et al., 2011). However, these studies assume both individual and institutional investors behave similarly in relation to such advertising-induced attention grabbing securities, and this may be inconsistent with the literature on informed investors' trading patterns in the market microstructure area.

Previous research finds that advertising influences retail (individual) investors more than it does institutional investors (Barber and Odean, 2007; Fehle et al., 2005; Joshi and Hanssens, 2010a ; Lou, 2014). After a company increases its advertising exposure, there will be more individual investors trading in its stock. Individual investors being net buyers of such attention-grabbing stocks (Fehle et al., 2005 ; Lou, 2014), they make their investment decisions in part based on familiarity rather than fundamental value or portfolio theory. They may evaluate the firm values over-optimistically and buy stocks at prices higher than their fundamental value. Odean (1999) finds that individual investors often buy stocks that under-perform those they sell, holding on loser stocks rather than winners. Furthermore, such attention-driven trading can be bad for unsophisticated investors if they are attracted to trade more frequently (Peress and Schmidt, 2019). High trading levels result in poor performance of individual investors (Barber and Odean, 2000). Their performance may actually be improved by stopping such attention-driven trading (Peress and Schmidt, 2019). Early studies that analyze the link between advertising and financial markets focus on the reactions and trading pattern of individual investors. Research about advertising and institutional investors' reactions is sparse and the results are mixed. While Grullon et al. (2004) argue advertising results in a larger number of both individual and institutional investors, Frieder and Subrahmanyam (2005) find a negative relationship between institutional holdings and brand visibility.

Grullon et al. (2004) find both individual and institutional investors behave similarly toward advertised firm's securities. Based on Bloomberg search activity, Focke et al. (2018) find that institutional investors such as Bloomberg users are also affected by advertising. Prior research about advertising and institutional investors trading is mixed. Moreover, much of this research relies on the cut-off rule method to identify trades come from institutional investors rather than individual investors. However, the cut-off rule has not worked since early 2000's because the use of computerized trading algorithms has enable institution investors to break trades up into some smaller orders (Campbell et al., 2009), implying therefore that small trade size is not a reliable proxy for the trades of individual investors.

Besides using advertising to influence short-run stock prices, firm managers may use advertising as a communication channel to provide new product information and show that their firms are financially sound to investors or potential future investors for the purpose of improve the information environment surrounding their firms in the financial markets. Advertising conveys product information to consumers (Nelson, 1974) and is regarded as public information in markets. We have good reasons to believe advertising will reduce information asymmetry in the product markets (Kirmani and Rao, 2000). Fehle et al. (2005) find firms benefit from advertising campaigns during the Super Bowl. The results suggest that Super Bowl Commercial advertising is beneficial communication channel for investors. Considering product market advertising is also visible to investors in the financial markets, and that it plays an important role in grabbing investor attention, advertising may affect the information environment in financial markets as well. Markets not only provide liquidity and price discovery, they are also affected by information asymmetry and information efficiency. Information asymmetry among market participants refers to some investors, possessing private firm-specific information related to the fundamental value of the security that is not accessible to uninformed investors. As a kind of market failure, information asymmetry can potentially lead to a breakdown in the functioning of the financial markets (Akerlof, 1970). A rise in information asymmetry will result in illiquidity, and adverse selection. Grullon et al. (2004) assume advertising may reduce the level of information asymmetry in financial markets and therefore increase the liquidity of stocks. Grullon et al. (2004) also find that securities from firms with greater advertising have better liquidity measured by bid-ask spreads, price impacts, and depth. They assume that increased advertising by a firm will decrease adverse selection costs and thereby improve market liquidity. However, they regard it as a given, providing neither theoretical nor empirical evidence that increased advertising reduces asymmetric information (adverse selection costs) and increase stock liquidity. Moreover, they say little about whether stock liquidity will decrease if advertising increases information asymmetry. Chemmanur and Yan (2009) and Luo (2008) claim that advertising can reduce information asymmetry prior to IPOs because advertising can help signal or provide information about the true value of the firm to investors. However, advertising may also increase information asymmetry in financial markets. Using insider gains as a proxy of information asymmetry, Joseph and Wintoki (2013) document that information asymmetry is greater for firms with more advertising investments because advertising investments constitute a significant fraction of firm expenditures and insiders have information advantage with regard to firm investment plans and their productivity. However, in examining advertising's impact on information asymmetry in the financial markets, the authors only regard advertising as investment while ignoring advertising's potential financial market impact. Rinallo and Basuroy (2009) exploit media coverage as a measure of information asymmetry to examine the relationship between advertising spending and information asymmetry in the fashion industry. They find that marketing might affect information asymmetry. However, their study only focuses on one specific industry and their measure of information asymmetry is a lower frequency measure. Questions around advertising's impact on information asymmetry and informed trading remain largely unanswered and there is a pressing need for more research on this.

Advertising affects investors' attention (Focke et al., 2018; Fehle et al., 2005; Lou, 2014; Barber and Odean, 2000), and attention is regarded as one source of changes in the short-horizon financial markets information environment (Vozlyublennaia, 2014). So, we have good reason to believe advertising has an impact on the informational efficiency of stock prices in the financial markets. According to Malkiel and Fama (1970), a market is efficient if information is fully reflected in stock prices. Incorporating information into prices is a fundamentally important function of financial markets (i.e. price discovery). Information efficiency is the speed and effectiveness with which information is incorporated into prices. When the observed stock price accurately reflects more private information, firms are closer to being priced at their intrinsic value. Therefore, increasing information efficiency can reduce information asymmetry, promote efficient investment decisions, and improve (uninformed) investors performance (Edmans et al., 2017). Otherwise, decreased information efficiency may result in more information asymmetry and mispricing (Chordia et al., 2008). In financial markets, information efficiency depends on the information completeness and symmetry, and investors reactions to information releases (Busse and Green, 2002; Edmans et al., 2017; Chordia et al., 2008; Boehmer and Kelley, 2009). Grossman and Stiglitz (1980) document that more information leads to more informative prices and therefore also increases information efficiency. However, the information contained in advertising may be biased and incomplete as advertising is not designed to portray firms objectively (Lou, 2014), and does not directly contain price-relevant information on firm value and advertising investment productivity (Joseph and Wintoki, 2013). So, whether advertising improves information efficiency remains unclear.

3.4 Hypotheses Development

In the last chapter, I develop a theoretical model and prove that advertising can increase the information asymmetry in the financial markets due to the advertising induced attention-driven buying from individual investors. Based on the results from the theoretical model, I propose the central hypothesis in this research is: Advertising has a positive effect on information asymmetry (informed trading) and a negative effect on information efficiency in financial markets.

In investigating advertising's short-run effect on financial markets outcomes, I exploit Super Bowl Commercials as events of interest. The advertising induced attention-driven buying is more likely to happen for firms with names more recognizable from the content of advertising. For the event window, I expect market reactions following Super Bowl Commercial advertising to be more pronounced for firms whose names are recognizable from the content of advertising than for other firms.

I use the event study research method to investigate advertising's impact on financial market outcomes. I first examine advertising's event effect by comparing financial market outcomes and investor reactions in the event window relative to their equivalents in a control period. If advertising can impact investors' trading behavior and change the information asymmetry and information efficiency in the financial markets, there should be a significant difference of financial market outcomes between event window and the control period.

I then study the informed trading and price discovery processes. I assume that, at the begining, advertising leads to a surge in retail buying for the stocks from advertised firms in the financial markets. The reason is that advertising can attract investors' attention and attention can influence investor's portfolio choice, especially for the retail investors. Then, the increased buy orders from retail investors can inflate the stock price and improve stock liquidity. The informed (institutional) investors have information advantage about the advertising induced buying in the financial markets. If the retail investors are the net buyer of the stocks from advertised firms, then the institutional investors will be the net seller. The institutional investors sell the stocks when their prices are higher than the fundamentals. They sell more when the markets are more liquid. Therefore, I expect advertising has an impact on buy-sell imbalance, stock prices, and stock liquidity. Moreover, if the institutional investors are trading with their information advantage about advertising induced attention-driven buying from retail investors, advertising can affect the information asymmetry as well. Advertising leads to more irrational buying from retail investors, which can affect the information efficiency in the financial markets.

I expect more informed trading in the event window relative to the control period. I also hypothesize that advertising changes the buy-sell balance, generating more sell orders from informed investors (institutional investors), which is subsequently accompanied by a decrease in short run returns. Following these arguments, I formally state my hypotheses as follows:

- H1: Super Bowl Game Commercial advertising has no event effect on financial market outcomes and investors' reactions.
- H2: Advertising has a positive impact on stock returns in financial

markets.

- H3: Advertising has a positive impact on stock liquidity in financial markets.
- H4: Advertising changes the buy-sell balance, generating more sell orders from informed investors (institutional investors), which is accompanied by a decrease in short run returns.
- H5: Advertising can increase information asymmetry between informed and uninformed investors in financial markets.
- H6: Advertising can improve the information efficiency of a firm's stock in financial markets.

3.5 Sample and Data

3.5.1 Sample Selection

In this section, I first describe the event data I use, which includes about 162 firm-year events. I then introduce the high-frequency tick data and low-frequency data I use for control variables.

My initial advertising sample is selected from Super Bowl Commercial videos over the 2008-2018 period. Advertising by private firms or foreign companies is excluded. Then, I obtain information about the product and company name for each commercial. The sample is categorized as to whether the advertised firm's name is recognizable from the commercial or not. It is composed of 162 firm-events, where 81 firm names are recognizable from the advertising and 81 firm names are not. I only include observations in my final sample if they have high-frequency intra-day tick data available. This filtering reduces my sample size.

Table 3.1 presents the composition of my sample, which is comprised of 162 firm-events. All firms are categorized as to whether their firm's name was recognizable from the advertising or not.

Table 3.1: Sample Distribution

Year	No. Samples	Recognized	Unrecognized
2008	10	5	5
2009	7	4	3
2010	15	8	7
2011	14	9	5
2012	10	5	5
2013	15	6	9
2014	15	7	8
2015	16	8	8
2016	20	7	13
2017	22	12	10
2019	18	10	8

3.5.2 Data

I compile data from several sources. High frequency trading data are collected from the Thomson Reuters Tick History (TRTH) database. This database offers global intra-day millisecond time-stamped Sales, Quotes, and Market Depth content for more than five million equities from about 250 stock exchanges worldwide since 1996. I collect tick data at the millisecond level including for trade time, trade price, quotes, and trade volume for all 162 firms in my sample (advertised firms). In order to ensure the integrity of the dataset, I exploit a number of filters. I examine all trades executed both on the NYSE and NASDAQ exchange. To account for abnormal trading patterns and procedures around the start and close of each day, I exclude after-market hours trading and all trading activity which happens within the first 15 minutes after the markets open and within the last 15 minutes before the markets close. Hence, only trades and quotes occurring between 9:45 a.m. and 15:45 p.m. are examined. I also delete all transactions where the bid price, ask price, bid size, or ask size is listed as zero. Finally I eliminate all transactions where the transaction price lies outside the bid ask spread or where the transaction price differs from the previous one by more than 10 percent.

My low-frequency data, on total assets, capital, prior year advertising expenses, BM ratio, leverage, institutional ownership, and the number of analysts following a stock, are obtained from the CRSP and COMPUSTAT databases.

3.6 Methodology

In this section, I first describe the event study method. I then introduce the propensity score (PS) matching method used to construct the control or matched samples. I also introduce the data processing which I apply to my trade and size classification. Finally, I define all variables.

3.6.1 Event Study

In this paper I aim to improve our understanding of how advertising affects firm financial market outcomes. To that end, I use an event study methodology. The event study methodology allows me to investigate the investor reactions and financial market outcomes in a quasi-experimental setting, where various information proxies, trade variables, and liquidity measures are tracked around time windows surrounding the focal events. The focal events in this study are Super Bowl Commercials, which absorb the attention of wide audiences including investors and potential investors. Given that most Super Bowl Commercials are pre-announced and typically do not convey new fundamental information, these advertising events should not affect fundamental firm values, allowing me to isolate the effect of advertising on the information environment and investors' reactions within financial markets.

Since the Super Bowl is scheduled on a Sunday in each February, I set the event window to be the post-game Monday each year. I then examine investors behavior and financial markets outcomes on post-event Monday. Brennan et al. (2018) use a window covering the period (-20, -1), while Baruch et al. (2017) use an event window (-5, -1) and control window (-20, -10). I use the (-20, -1) time periods as my pre-event window and (1,20) as my post-event window in this research. The estimation window includes both the pre-event and post-event periods, centered on the post event Monday, allowing me to neutralize any trend in the data. The results are robust if the estimation window only includes the pre-event period.

3.6.2 Propensity Score Matching for the Control Group

I exploit propensity score matching (PSM) to investigate advertising event's impact on financial market outcomes of advertised firms relative to firms that did not run the advertising campaigns during the Super Bowl. The PSM is a statistical matching technique introduced by Rosenbaum and Rubin (1983). This method is regarded as being able to mimic some of the particular aspects of a randomized controlled trial by matching samples on their propensity scores with regard to a number of characteristics other than the treatment. It can therefore reduce treatment assignment bias when estimates of effects are generated by comparing treated and untreated subjects in a matched sample. I select the matched sample from NYSE and NASDAQ listed firms that belong to the same industry and have similar firm size as the treated firms that run advertising campaigns during the Super Bowl. I use 1 to 4 matching and then delete firms whose high-frequency tick data is unavailable from the TRTH database.

3.6.3 Trade Classification

In order to compute the number of buys and sells and therefore also the market micro structure level financial market outcomes, I need to capture the direction of each trade. The Lee and Ready (1991) algorithm is the most common classifier used to identify an order as market buy or market sell. This trade classification algorithm involves two steps. The first step is to compute the midquote of the bid and ask quotes at the same point in time (millisecond level). The second step is to compare the midquote with the transaction price by either quote or tick test. When the transaction price is not equal to the midquote, a trade is classified as buyer-initiated (seller-initiated) if the price is above (below) the midquote, with this called the quote test. When the transaction price is equal to the midquote, a trade is classified as buyer-initiated (seller-initiated) if the transaction price is above (below) the previous price, with this called the tick test.

3.6.4 Size Classification

Prior research relies on the cut-off rule to classify trades are placed by individual or institutional investors. However, the cut-off no longer works since early 2000's because institutional investors use computerized trading algorithms to break up their larger trades into smaller orders (Campbell et al., 2009), this implies that small trade size is not a reliable proxy for individual investors' trading activity. Campbell et al. (2009) present a method to infer daily institutional flows with high frequency intra-day data. They find that orders where trade value is larger than $30,000 or below $2,000 are likely to have the same direction as institutional investors' orders, while orders where trade value is between $2,000 and $30,000 are associated with investors' trading in the opposite direction to institutional flows. I follow the results from Campbell et al. (2009) and classify all trades into 3 bins of different size: below $2,000, between $2,000 and $30,000, and larger than $30,000. Then I compute the buy-sell imbalance for each bin and compare these to infer the trade direction stemming from institutional investors.

3.6.5 Variable Construction

PIN: The probability of informed trading (PIN), which can be computed from direction identified high frequency intra-day trading data, is employed as the measure of information asymmetry. After every trade is classified either as buyer or as seller initiated, PIN is computed according to Easley et al. (2002). PIN utilizes information from the trading process to capture the probability of informed trading in a stock. It is widely used as a proxy of information asymmetry or the private information content reflected in stock prices.

Suppose trades can come from uninformed investors or from informed investors, and that the daily arrival rates of uninformed investors that submit buy and sell orders are denoted ϵ_b and ϵ_s respectively. The arrival rate of informed investors is ϵ_i when an information event occurs. Suppose in one day, no information event occurs with probability $(1-\alpha)$, a good information event occurs with probability $\alpha(1-\delta)$, and a bad information event occurs with probability $\alpha\delta$.

Information	Probability	Buyers	Sellers
Bad news	$(1-\alpha)(1-\delta)$	ϵ_b	$\epsilon_s + \epsilon_i$
Good news	$(1-\alpha)\delta$	$\epsilon_b + \epsilon_i$	ϵ_s
No news	$(1-\alpha)$	ϵ_b	ϵ_s

The likelihood of observing B buy orders and S sell orders conditional on a bad news day is given by:

$$\frac{(\epsilon_b)^B e^{-\epsilon_b}}{B\,!} \cdot \frac{(\epsilon_s + \epsilon_i)^S e^{-(\epsilon_s+\epsilon_i)}}{S\,!}.$$

The likelihood of observing B buy orders and S sell orders conditional on a good news day is given by:

$$\frac{(\epsilon_b + \epsilon_i)^B e^{-(\epsilon_b+\epsilon_i)}}{B!} \cdot \frac{(\epsilon_s)^S e^{-\epsilon_s}}{S!}.$$

The likelihood of observing B buy orders and S sell orders conditional on a no news day is given by:

$$\frac{(\epsilon_b)^B e^{-\epsilon_b}}{B!} \cdot \frac{(\epsilon_s)^S e^{-\epsilon_s}}{S!}.$$

Therefore,let $\theta = \{\epsilon_b, \epsilon_s, \alpha, \delta, \epsilon_i\}$, the unconditional probability of B buy orders and S sell orders in a single trading day is given by:

$$\begin{aligned} Pr(B,S) = (1-\alpha) \cdot & \frac{(\epsilon_b)^B e^{-\epsilon_b}}{B!} \cdot \frac{(\epsilon_s)^S e^{-\epsilon_s}}{S!} \\ + \alpha(1-\delta) \cdot & \frac{(\epsilon_b)^B e^{-\epsilon_b}}{B!} \cdot \frac{(\epsilon_s + \epsilon_i)^S e^{-(\epsilon_s+\epsilon_i)}}{S!} \\ + \alpha\delta \cdot & \frac{(\epsilon_b + \epsilon_i)^B e^{-(\epsilon_b+\epsilon_i)}}{B!} \cdot \frac{(\epsilon_s)^S e^{-\epsilon_s}}{S!} \end{aligned}$$

These parameters can be estimated by the likelihood function maximization:

$$L(\theta|B,S) = \prod_{t=1}^{t=T} Pr(B_t, S_t).$$

Then, PIN for a given stock on a given day can be shown to be:

$$PIN = \frac{\alpha\epsilon_i}{\epsilon_b + \epsilon_s + \alpha\epsilon_i}.$$

AutocorrelFactor: $AutocorrelFactor$ is an information efficiency measure of short-term return predictability. It can be computed by calculating first-order return autocorrelations for each stock-day, at various intra-day frequencies, $k \in \{10sec, 30sec, 60sec\}$, and by taking their absolute values:

$$Autocorrelation_k = |Corr(r_{k,t}, r_{k,t-1})|,$$

where $r_{k,t}$ is the $t-th$ midquote return of length k for a stock-day. To compute the combined autocorrelation measure, $AutocorrelFactor$. I take the first principal component of the absolute autocorrelations at the three frequencies. This variable is computed as in Hendershott and Jones (2005). $AutocorrelFactor$ measures short term return predictability, with larger values indicating greater inefficiency.

StdevFactor: $StdevFactor$ is a standard deviation factor, an information efficiency measure of short-term midquote volatility. It is computed by calculating intra-day midquote return standard deviations for each stock-day, again at various intraday frequencies, $k \in \{10sec, 30sec, 60sec\}$:

$$Stdev_k = \sigma_{k,t}.$$

This is a measure of short-term volatility and a proxy for noise and temporary deviations of prices from their equilibrium values due to trading frictions (O'Hara and Ye, 2011). Larger $StdevFactor$ values indicate greater inefficiency.

Delay: $Delay$ is a measure of the extent to which lagged market returns predict a stock's midquote returns (Hou and Moskowitz, 2005). First, for each stock-day, I estimate a regression of 1-minute midquote returns for stock i, $r_{i,t}$, on the index return, $r_{m,t}$, and ten lags:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \sum_{k=1}^{10} \delta_{i,k} r_{m,t-k} + \epsilon_{it},$$

and then save the R^2 from the above unconstrained regression. Second, I re-estimate the regression constraining the coefficients on the lagged market returns to zero and again save the R^2. Delay is then calculated as 1 minus the ratio of the constrained and unconstrained regression R^2s:

$$Delay = 1 - \frac{R^2_{constrained}}{R^2_{unconstrained}}.$$

Then I normalize the value of $Delay$ to be between 0 and 100. The value of $Delay$ indicates the degree to which incorporation of market-wide information into prices is delayed. Hence, a larger value of $Delay$ indicates greater market inefficiency.

In financial markets, information asymmetry can affect stock returns, liquidity, and investors compositions (e.g., Grullon et al., 2004). Therefore, I compute the time-weighted bid-ask spread and Amihud illiquidity as a liquidity measure and cumulative abnormal returns (CARs) as my return measure. I obtain institutional holdings data from the CRSP database to measure changes of investors compositions.

Different kinds of the bid-ask spread: Bid-ask spread is widely used as a liquidity measure. I use the following three kinds of bid-ask spread to measure the liquidity of a security.

$$QuotedSpread = (Ask - Bid)/midquote,$$

$$EffectiveSpread = 2 \cdot direction \cdot [(price - midquote)/midquote],$$

$$RealizedSpread = 2 \cdot direction \cdot [(price - midquote_{5m})/midquote],$$

where $-midquote_{5m}$ is the midquote five minutes after the trade.

Buy-sell imbalance is a ratio that the excess of buy or sell orders relative to total number of orders for a specific security. It is computed by dividing the order imbalance by the total number of orders for a security in a specific time period:

$$BSratio = (N\_buys - N\_sells)/(N\_buys + N\_sells),$$

where N_buys is the number of buy orders and N_sells is the number of sell orders.

Amihud illiquidity: Amihud (2002) defines the liquidity of stock i in month t as the average ratio of hourly absolute midquote returns to hourly trading dollar volume:

$$ILLIQ_t^i = \frac{1}{Days_t^1} \sum_{d=1}^{Days_t^1} \frac{|R_{td}^i|}{V_{td}^i}$$

where i is stock, d is day, t is month, $Days_t^i$ is the number of observation days, R_{td}^i is the return and V_{td}^i is the trading dollar volume. This measure denotes the price impact scaled by the trade dollar volume. A high value of $ILLIQ$ means the stock is illiquid. This measure is computed from high-frequency tick data over 15 minute intervals and is averaged as a daily measure.

Turnover is measured as the log of daily trading volume, scaled by the number of shares outstanding.

CAR: CAR is cumulative abnormal return that can be exploited to examine stock price reactions to informed trading around Super Bowl advertising events. The market return is defined as the return on the CRSP equal-weighted stock index. The cumulative abnormal return for firm i over period (t_1, t_2) is computed by:

$$CAR_{t_1,t_2}^i = \sum_{t=t_1}^{t_2} e_{it}$$

where $e_{it} = r_{it} - r_{mt}$, and r_{it} and r_{mt} are the stock returns for firm i and the market, respectively.

Table 3.2: Summary Statistics

	Group A			***Group B***		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
Panel 1						
Illiquidity	0.00	0.02	3815	0.00	0.01	3722
PIN	0.24	0.16	3646	0.23	0.16	3538
No.trades	0.02	0.07	3770	0.04	0.11	3677
Trade size	1.51	2.59	3770	1.49	2.69	3677
Trade volume $	83.40	206.09	3770	64.82	136.33	3677
Turnover	0.00	0.02	3495	0.00	0.01	3166
Price	96.64	207.94	3817	56.22	65.60	3722
Panel 2						
Total Asset	70.71	70.12	77	123.31	198.82	70
Capital (size)	456.44	1125.13	77	305.43	1030.14	70
Ad expense	0.06	0.05	70	0.07	0.06	59
BM ratio	0.40	0.54	73	0.30	0.34	68
Leverage	0.07	0.07	77	0.05	0.06	70
No. Analyst	18.11	8.27	70	21.42	8.04	71
Volatility	5.03	13.07	81	2.88	4.94	81
Instown_perc	0.69	0.21	68	0.75	0.21	72

Table3. 2

The table 3.2 shows summary statistics for advertised firms where group A contains firms whose names are recognizable from the content of advertising and group B contains firms whose names are not recognizable from the content of advertising.

Panel 1 reports summary statistics for variables measured daily and panel 2 reports summary statistics for variables measured annually.

3.6.6 Event Effect Around Super Bowl Commercials: T-tests and Non-parametric Tests

I hypothesize that Super Bowl Commercials can increase the level of informed trading and reduce the information efficiency in financial markets, and that this effect is stronger for firms whose names are readily identifiable from the contents of advertising.

I compute PIN and other information efficiency measures during the event window and then make comparisons with other non-event time periods. I also classify the samples into two groups according to whether firm names are recognizable from the content of advertising. Then I make my comparisons separately for each group. As not all of the variables are normally distributed, I use both t-tests and non-parametric tests.

3.6.7 Regression Methodology

Three regressions are employed in this part: an event impact test, a difference in differences analysis, and a price discovery analysis.

3.6.8 Advertising and Information Asymmetry: Event Effect Regressions

First, I apply cross-sectional regressions to my measures of information asymmetry and information efficiency regressed against an event dummy, investor trading characteristics, and other control variables. The purpose of this approach is to test the event impact and examine the relationship between advertising and firms' information environment around the Super Bowl Commercials events. I regress my dependent variables on an event dummy variable which equals one if a firm's name can be recognized from the content of the advertising and zero otherwise. The event's impact is captured by the coefficient of the dependent variable relative to the event dummy.

The regression equation is:

$$\begin{aligned} Y = &\beta_0 + \beta_1 EventDummy + \beta_2 Turnover + \beta_3 Imbalance \\ &+ \beta_4 BMratio + \beta_5 Size + \epsilon \end{aligned}$$

where the event dummy equals one if a firm's name can be recognized from the content of advertising and zero otherwise, turnover is the share turnover, Imbalance is the buy-sell order imbalance, BMratio is the log book-to-market ratio, and Size is the log market capitalization of the advertised firm. The dependent variable in this regression model is one of PIN, $AutocorrelFactor$, $StdevFactor$, or $Delay$.

3.6.9 Difference in Differences Regressions on Information Environment, Returns, and Liquidity

To investigate whether advertising events change financial market outcomes such as information asymmetry, information efficiency, liquidity, and returns, I use the panel data difference in differences regressions with firm and year fixed effects.

In the first group of regressions, the treatment dummy is equal to 1 if advertised firms' names are recognizable from the content of advertising and 0 otherwise. In the second group of regressions, the treatment dummy is equal to 1 for advertised firms and 0 for firms from the matched sample. The time dummy is equal to 1 if the day is the post-event Monday.

The regression model is:

$$y_{it} = \beta_i + \beta_1 time + \beta_2 treated + \beta_3 time * treated + \beta_4 control + \epsilon_{it}.$$

Advertising's impact on financial market outcomes is measured by the coefficients β_1, β_2, and β_3, but especially β_3.

All regressions include firm fixed effects to control for firm specific variations in information asymmetry and my information efficiency measures. I also include year fixed effects in the regressions to control for potential time trends in the changes in information asymmetry and efficiency.

3.6.10 Price Discovery Analysis: Return and Information Asymmetry Resulting from Advertising

To explain changes in short-run stock returns and to investigate the speed with which asymmetric information results from advertising being incorporated into stock prices. I conduct asset pricing tests like those employed by Easley et al. (2002) and Duarte and Young (2009). These tests examine whether the asymmetric information after advertising is priced by markets.

The adjusted Fama and MacBeth (1973) regression is:

$$r_{it+1} = \beta_0 + \beta_1 PIN_{it} + \beta_2 Illiquidity_{it} + \beta_3 BM_{it} + \beta_4 Size_{it} + \epsilon_{it+1},$$

where r_{it+1} is the monthly stock return of firm i in excess of market return at time $t+1$, *Illiquidity* is the Amihud illiquidity measure, BM is the log book-to-market ratio of the firm, and $Size$ is the log market capitalization. The coefficient β_1 measures the speed with which asymmetric information is incorporated into prices by markets. I hypothesize that advertising can increase informed trading, and that this can explain short run fluctuations in stock returns. Hence, I expect a positive coefficient here.

3.7 Results

3.7.1 T-test and Non-parametric Test Results

Table 3.3 illustrates the T-test results for securities' returns, PIN, and my information efficiency metrics within the event window relative to a control period, where group A contains firms whose name is recognizable from the advertising content I study and group B contains other advertised firms.

Table 3.3: T-test Results: Information Environment and Stock Returns

	Group A			Group B		
	Event	Non-event	Difference	Event	Non-event	Difference
Return	-.0113	.005	-.0117 ***	-.0112	.0001	-.0113***
PIN	.2857	.2398	.0458 ***	.1920	.2267	-.0347*
AutocorrelFactor	.2292	-.0313	.2605 **	-.0888	.0302	-.1191
StdevFactor	.2885	.0231	.2654 **	.2610	-.0362	.2522**
Delay	.9450	.9077	.0374 *	.0645	.0775	-.0130

To assess the effect of product market advertising on returns, informed trading, and information efficiency in financial markets, I examine the significance of differences in the event/non-event means, using a two-tailed test. While the abnormal returns decrease during the event window, my information asymmetry measure (PIN) and information efficiency measures (autocorrelation factor, standard deviation factor, and delay) all increase. This implies greater information asymmetry and inefficiency, and lower abnormal returns. A drop in abnormal returns on the post-event Monday indicates that any advertising-induced buyers suffer a loss in trading the stocks of advertised firms. The increase in PIN indicates that there is more informed trading in the financial markets, which is significantly greater for samples from group A. I also find a statistically significant increase in all measures of information efficiency, which suggests a greater inefficiency overall. This effect is also significantly greater for samples from group A. The effect of advertising on financial markets outcomes is more pronounced for stocks from firms with whose names are readily identifiable from the content of the advertising. This means advertising that is more recognizable to investors has a larger impact. The difference is more statistically significant for firms whose names are recognizable from the content of advertising, allowing me to reject the hypotheses that advertising has a positive impact on stock returns and that advertising reduces information asymmetry, and improves information efficiency in the financial markets.

The followed table contains both t-tests and the non-parametric tests for robustness.

T-test and Non-parameter test Results: Information Environment and Stock Returns

	Means			Medians		
	Non-event	Event	p	Non-event	Event	p
Group A						
Return	.0003	-.0116	0.0000	.0005	-.0092	0.0000
PIN	.2419	.2918	0.0119	.1902	.2492	0.0083
AutocorrelFactor	-.0244	.2301	0.0288	-.1926	.0065	0.2334
StdDevFactor	.0279	.3026	0.0366	-.2748	-.2066	0.0647
Delay	.9083	.9233	0.2711	.9534	.9646	0.3424
Group B						
Return	.0001	-.0116	0.0000	.0005	-.0086	0.0000
PIN	.2269	.1923	0.0781	.1804	.1712	0.1553
AutocorrelFactor	.0358	-.1322	0.1930	-.1761	-.3601	0.0770
StdDevFactor	-.0581	.1393	0.0619	-.2884	-.1832	0.0371
Delay	.9046	.9238	0.1843	.9508	.9636	0.2693
Matched Samples						
Return	.0006	-.0081	0.0000	.0004	-.0071	0.0000
PIN	.2587	.2639	0.7397	.1953	.1908	0.5319
AutocorrelFactor	-.0044	.0116	0.8088	-.3178	-.2515	0.8153
StdDevFactor	.0005	-.0511	0.4366	-.3426	-.3106	0.9600
Delay	.9058	.9066	0.9256	.9538	.9465	0.7993

The table 3.4 illustrates t-test for the trading variable metrics in the event window relative to the control period, where group A contains firms whose names are recognizable from the content of advertising and where group B contains other advertised firms. N_trades01 is the number of trades of group01. Val_sum01 is the dollar trading volume of group01. BSratio01 is the buy-sell imbalance of group01. These variables are analogous for the remaining two groups (group 02 and group 03). Group 01 includes all trades whose size is below \$2,000. Group 02 includes all trades whose size is between \$2,000 and \$30,000. Group 03 includes all trades whose size is larger than \$30,000.

Table 3.4 reports the means differences across event and non-event around the Super Bowl Commercials, and the significance of any differences using two-tailed tests. According to Campbell et al. (2009), I classify all trades into 3 bins of different size: below \$2,000 (group01), between \$2,000 and \$30,000 (group02), and larger than \$30,000 (group03).

The difference is more statistically significant for firms from group A, which means the effect of advertising is more pronounced for firms whose names are recognizable from the content of advertising. The buy-sell imbalance for group 03 drops from 0.0116 during the non-event period to -0.1550 on the post-event Monday. This change is not only statistically significant at the 1% level but also economically significant, as the change in buy-sell imbalance on the post-event Monday is greater than ten times (1,423%) its value during the non-event period. This change, along with the increased number of trades

Table 3.4: T-test Results: Trades

	Group A			Group B		
	Event	Non-event	Difference	Event	Non-event	Difference
N_trades01	1878.6	1251.0	627.6 *	1155.2	880.8	274.4
Val_sum01	1853	1175	678 **	1029	845	184
BSratio01	-.0750	-.0101	-.0649 *	-.0947	.0025	-.0971***
N_trades02	4585.9	3418.5	1167.4 **	4962.9	4049.9	913.0*
Val_sum02	38661	29055	9607 **	39750	32808	6942
BSratio02	-.0488	-.0556	.0132 **	-.0598	-.0188	-.0410*
N_trades03	853.7	648.0	205.7	485.1	477.1	8.009
Val_sum03	76028	54430	21588	32843	33531	687
BSratio03	-.1550	.0116	-.1666 ***	-.1165	-.0075	-.1090*

and trading volume, suggests that there are more large size trades on the post-event Monday and that most of them are sell orders.

These results indicate that the effect of advertising on the overall order imbalance is insignificant, however, for trades with size larger than $30,000, the effect of advertising on the volume of sells is greater than the effect of advertising on the volume of buys.

The results in this table allow me to infer the direction of trade from institutional investors. Campbell et al. (2009) document that trades with size below $2,000 or above $30,000 are likely consistent with the direction of institutional orders, while trades sized between $2,000 and $30,000 likely have an opposite direction to the institutional orders.

Thus, it is possible that Super Bowl advertising not only affects individual investors but also institutional investors. There are more institutional investors involved in trading stocks from advertised firms, but they sell significantly more than they buy. I analyze trade volumes and order imbalance and show that the effect of Super Bowl advertising on the volume of sells is greater than it is on the volume of buys for the large size order group. These results indicate that informed or institutional investors strategically time their sell trades to occur on predicted imminent noise trading. The way that informed investor interact with uninformed traders exacerbates the level of informed trading or information asymmetry in the financial markets.

The following table contains both t-tests and non-parametric tests for advertised firms and a matched sample.

T-test and Non-parameter test results: Trades (Group A)

	Means			Medians		
	Non-event	Event	*p*	Non-event	Event	*p*
Group A						
N_trades01	1,278	1,922	0.0689	481.5	844	0.1496
Siz_sum01	121,507	148,303	0.6119	6,773	11,770	0.2206
Val_sum01	1177000	1879422	0.0314	425,146	558,923	0.1436
BS01	-.0099	-.0639	0.1132	-.004	-.0897	0.1182
N_trades02	3,506	4,737	0.0218	2,056	2,505	0.3445
Siz_sum02	784,248	948,673	0.2933	360,879	440,574	0.2783
Val_sum02	2.98e+07	4.00e+07	0.0181	1.77e+07	2.32e+07	0.3811
BS02	-.0059	-.0544	0.0233	-.0054	-.0469	0.0732
N_trades03	670.9	886.1	0.3283	170	161	0.9459
Siz_sum03	706,763	679,560	0.8617	306,554	305,000	0.7812
Val_sum03	5.57e+07	7.80e+07	0.3076	1.61e+07	1.81e+07	0.9367
BS03	.0068	-.1615	0.0026	.0005	-.1353	0.0010

T-test and Non-parameter test results: Trades (Group B)

	Means			Medians		
	Non-event	Event	*p*	Non-event	Event	*p*
Group B						
N_trades01	858.2	1,154	0.1865	352.5	488.5	0.1557
Siz_sum01	38,697	43,119	0.8321	5,836	10,063	0.1724
Val_sum01	827,496	1032567	0.4076	263,789	351,591	0.1409
BS01	.001	-.0814	0.0327	-.0009	-.088	0.0192
N_trades02	4,208	5,155	0.0940	2,781	3,122	0.2384
Siz_sum02	812,419	930,000	0.4757	484,081	566,645	0.2360
Val_sum02	3.36e+07	4.10e+07	0.1937	2.09e+07	2.28e+07	0.2671
BS02	-.0189	-.0614	0.0783	-.0214	-.0554	0.0182
N_trades03	320.8	320.9	0.9994	97	100	0.7106
Siz_sum03	642,683	652,755	0.9571	158,457	177,116	0.8465
Val_sum03	2.34e+07	2.30e+07	0.9430	7564300	7058740	0.8354
BS03	-.0109	-.1007	0.1266	-.0258	-.0801	0.1081

T-test and Non-parameter test results: Trades (Match Samples)

	Means			Medians		
	Non-event	Event	p	Non-event	Event	p
Matched Samples						
N_trades01	382.7	388.6	0.9403	63	76	0.2943
Siz_sum01	43,336	43,914	0.9703	2,093	2,876	0.2506
Val_sum01	450,114	422,375	0.8088	53,601	60,715	0.2502
BS01	-.0170	-.0364	0.5388	-.0072	-.0224	0.8273
N_trades02	654.1	685.9	0.7503	170.5	152	0.9258
Siz_sum02	138,722	141,849	0.9284	29,567	25,018	0.9356
Val_sum02	4440081	4595892	0.8828	783,571	647,776	0.8584
BS02	-.018	-.0395	0.4239	-.0142	-.0211	0.3736
N_trades03	35.99	34.45	0.9239	3	3	0.7872
Siz_sum03	58,427	45,357	0.5486	10,905	10,744	0.8366
Val_sum03	2628325	2268128	0.7780	328,951	343,056	0.9803
BS03	.0199	-.2099	0.0004	.0284	-.3114	0.0006

The table 3.5 illustrates t-tests for my liquidity metrics in the event window relative to the control period, where group A contains firms whose names are recognizable from the content of advertising and group B contains other advertised firms. Illiquidity is the intra-day version of Amihud (2002) illiquidity ratio. Price impact is the Kyle (1985) lamda. Rspread is the realized bid-ask spread. Espread is the effective bid-ask spread. Qspread is the quoted bid-ask spread.

Table 3.5: T-test Results: Liquidity

	Group A			Group B		
	Event	Non-event	Difference	Event	Non-event	Difference
Illiquidity	169.5	650.8	-481.2	80.087	101.1	20.98
Price impact	26.356	24.030	2.326	20.590	19.912	0.677
Rspread	-3.356	1.805	-5.161	-3.194	-0.240	-2.954
Espread	2.109	2.432	-3.230	1.6245	1.833	-.208
Qspread	2.084	2.219	-.1355	1.866	2.222	-.356

This table reports my findings for liquidity. I show that all of my liquidity measures do not statistically significantly increase after an advertising event. This is inconsistent with some prior research. For example, Grullon et al. (2004) find that product market advertising results in an increase in trading activity, and increased trading activity lowers adverse select costs and improves liquidity. However, their finding is based on annual advertising expenditures and annualized low frequency liquidity measures. Advertising might have long-run effects on stock liquidity as shown in Grullon et al. (2004). However, in the short-run, advertising might not be linked with improved liquidity. Focke et al. (2018) find that liquidity improves only to a very minimal extent after a small increase in noise trading. Moreover, liquidity could also decrease due to the attention-induced order imbalance. For example, Barber and Odean (2007) find increased inventory holding cost decreases liquidity. As is shown in the above table, most of the liquidity measures for Group A deteriorate, fall which, though not statistically significant, are economically significant. I also show liquidity changes around the Super Bowl advertising events by using the difference in differences models in table 3.10. These indicate that advertised firms experience a drop in liquidity. My results might be explained by advertising induced changes in order imbalance among large size orders, which can potentially offset any improved liquidity due to attention-driven noise trading.

3.7.2 Regression Results

The table 3.6 shows the results of cross-sectional regressions of PIN on an event dummy, investors' trading activity variables, and other control variables. The event day is defined as the post-event Monday.

The purpose of this regression is to test the event effect on PIN and explain the cross-sectional variations in PIN values I computed. The event effect is captured by the event effect dummy which is equal to one if the company is identifiable from the advertising content and zero otherwise.

The coefficient of the event effect dummy on PIN is positive and significant, which means firms whose names are identifiable form the content of advertising have higher PIN levels than other firms.

I find a strong positive relationship between PIN and illiquidity, which suggests that events which are associated with increased information asymmetry or informed trading are also related to reduced stock liquidity. This may potentially be explained by the changed buy-sell imbalance I observe among large size orders following advertising events.

Table 3.6: Regression Results: Corss-sectional Event Effect Regressions

	(1) PIN	(2) PIN
Tradesize	-0.0579^{***}	
	(-3.4190)	
Trade volume		-0.0536^{***}
		(-3.3745)
Illiquidity	3.4982^{**}	3.0786^{*}
	(2.0172)	(1.7179)
Turnover	-0.5410	-0.8667
	(-0.2768)	(-0.4636)
Volitility	-0.0011	-0.0000
	(-0.2174)	(-0.0028)
Ownership concentration	0.6842	0.6495
	(1.4079)	(1.3298)
NO. of analyst	0.0084^{***}	0.0094^{***}
	(3.6715)	(3.6561)
Leverage	0.4907	0.4121
	(1.5263)	(1.3376)
BM ratio	-0.0205	-0.0291
	(-0.4225)	(-0.5984)
Advertising expense	-0.9051	-0.8216
	(-1.6243)	(-1.4923)
Event effect	0.1112^{***}	0.1131^{***}
	(3.1728)	(3.2130)
_cons	0.3281	0.4143
	(1.4353)	(1.6459)
N	84	84
R^2	0.3727	0.3696
adj. R^2	0.2769	0.2732

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Regression Results: Panel Data Event Effect Regressions

	(1) PIN	(2) PIN	(3) PIN
Tradesize	-0.0756^{***}	-0.0769^{***}	-0.0661^{***}
	(-15.1474)	(-11.2754)	(-6.6563)
Turnover	0.9564	2.5574^{***}	-13.2411^{*}
	(1.2515)	(3.1201)	(-1.7432)
Volatility	-0.0022^{**}	-0.0034^{**}	-0.0002
	(-2.0012)	(-2.1720)	(-0.1235)
Illiquidity	-0.4373^{**}	-0.5687^{**}	8.8065^{*}
	(-2.0398)	(-2.3743)	(1.8718)
Ownership concentration	0.5004^{***}	0.4329	0.5530^{***}
	(3.7761)	(1.5532)	(3.1287)
NO. of analyst	0.0062^{***}	0.0089^{***}	0.0034^{***}
	(9.3277)	(9.5671)	(3.1169)
Leverage	0.2703^{***}	0.2500^{**}	0.2476
	(3.0960)	(2.4314)	(1.1342)
BM ratio	0.0257^{***}	0.0428^{***}	0.0008
	(5.0337)	(6.3773)	(0.0886)
Advertising expense	-0.6189^{***}	-0.5549^{**}	-0.4049
	(-4.0903)	(-2.4159)	(-1.5248)
Event effect	0.0603^{***}		
	(6.2764)		
_cons	0.7018^{***}	0.8654^{***}	0.4763^{***}
	(11.5037)	(10.2546)	(4.4706)
N	1027	565	462
R^2	0.2774	0.3601	0.1995
adj. R^2	0.2695	0.3485	0.1817

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7 shows the results from panel data regressions of PIN on my event dummy, investor trading activity variables, and other control variables. The data cover the (t-10, t+10) time period.

The first column of this table reports the results of regressions for all advertised firms. The second column reports the results of regressions for firms whose names are readily identifiable from the content of advertising, and the third column is for other firms.

I run these regressions of PIN on advertising events and other key variables. In column 1, I find a positive and significant impact of advertising events on PIN, suggesting that advertising events precede increase in informed trading and higher information asymmetry. In columns 2 and 3, I repeat the same regression as in column 1 but exclude the event dummy. I find a positive relationship between PIN and turnover, which is measured as daily trading volume over shares outstanding. I find that the explanatory power, as measured by R^2, is higher in the subsample of firms whose names can be recognizable from the content of advertising.

Table 3.8: Regression Results: Information Environment Change for Advertised Firms

	(1) PIN	(2) ACFactor	(3) StdevFactor	(4) Delay
Time				
Treated	-0.0134^{***}	0.3846^{***}	0.0327	0.0036
	(-4.4440)	(13.9667)	(1.4451)	(1.0152)
Time·Treated	0.0101^{***}	0.1817^{***}	0.1970^{***}	0.0265^{***}
	(4.2975)	(10.8119)	(11.6674)	(8.8384)
_cons	0.2607^{***}	0.4662^{***}	0.0691	0.9041^{***}
	(28.9394)	(9.7382)	(1.6149)	(95.8330)
Firm Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
Cluster	*Yes*	*Yes*	*Yes*	*Yes*
N	9975	9976	9976	9569
R^2	0.2746	0.0659	0.1392	0.0054
adj. R^2	0.2731	0.0640	0.1374	0.0033

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows difference in differences regression results for advertised firms relative to a matched sample. The dependent variables are information asymmetry and information efficiency variables including PIN, autocorrelation factor, standard deviation factor, and delay. Time is a dummy variable that is equal to one if the date is after the Super Bowl advertising event, and zero otherwise. Treated is a dummy variable that is equal to one if the firm has run an advertising commercial at the Super Bowl, and zero if the firm belongs to propensity score matched sample. The effect of advertising on information asymmetry and information efficiency can be assessed by the coefficient on Time·Treated. All four of these coefficient estimates are positive and highly statistically significant (at 1% level), showing that Super Bowl commercial advertising exacerbates informed trading and reduces market information efficiency.

Table 3.9: Regression Results: Information Environment Change for (Recognizable) Advertised Firms

	(1) PIN	(2) ACFactor	(3) StdevFactor	(4) Delay
Time				
Treated	0.5659***	−0.1264***	0.1098***	0.0026
	(3.4672)	(−4.5079)	(6.1345)	(0.5342)
Time·Treated	0.4539***	0.2044***	0.0013	0.0171***
	(27.7268)	(2.5136)	(0.0746)	(4.5927)
_cons	−2.0853***	−0.160	−0.2700**	0.9101***
	(−28.9105)	(−0.5659)	(−2.5117)	(53.1650)
Firm Controls	*Yes*	*Yes*	*Yes*	*Yes*
Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year Dummies	*Yes*	*Yes*	*Yes*	*Yes*
Cluster	*Yes*	*Yes*	*Yes*	*Yes*
N	4209	4649	4883	4708
R^2	0.4370	0.0246	0.1915	0.0119
adj. R^2	0.4326	0.0247	0.1884	0.0121

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9 shows the results of panel data difference in differences regressions of my financial market reaction variables on an event dummy and firm-level control variables with firm and year fixed effects. I run these regressions to investigate the difference in differences for advertised firms whose names are recognizable from the content of their advertising relative to other advertised firms whose names are not similarly recognizable. The data cover the (t-30, t+30) time period. The dependent variables again capture information asymmetry and information efficiency, including PIN, autocorrelation factor, standard deviation factor, and delay. Time is a dummy variable that equals one if the date is after the Super Bowl advertising event and zero otherwise. Treated is a dummy variable that equals to one if the firm has run commercial advertising at the Super Bowl and its name is recognizable from content of its advertising and zero if it is not. The effect of advertising on information asymmetry and information efficiency can be assessed by the coefficient on Time·Treated. All three coefficient estimates are positive and highly statistically significant at the 1% level, again showing that Super Bowl advertising exacerbates informed trading and reduces the information efficiency of the market. These results provide evidence that advertising's impact is more pronounced for stocks from firms whose names are identifiable from the content of their advertising.

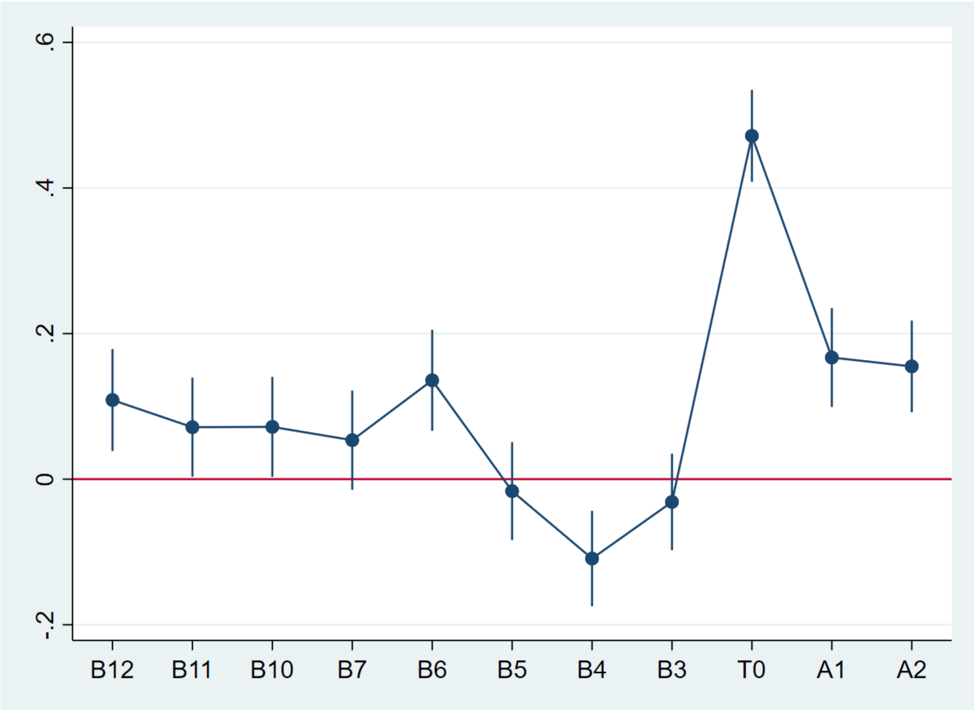

Figure 3.1: Parallel Trend Test: PIN

This graph reports the results of a parallel trend test for my difference in differences regressions, where B3 denotes 3 days before T0 and A1 denotes 1 day after T0. This figure shows informed trading increases significantly on the Monday after a Super Bowl advertising event.

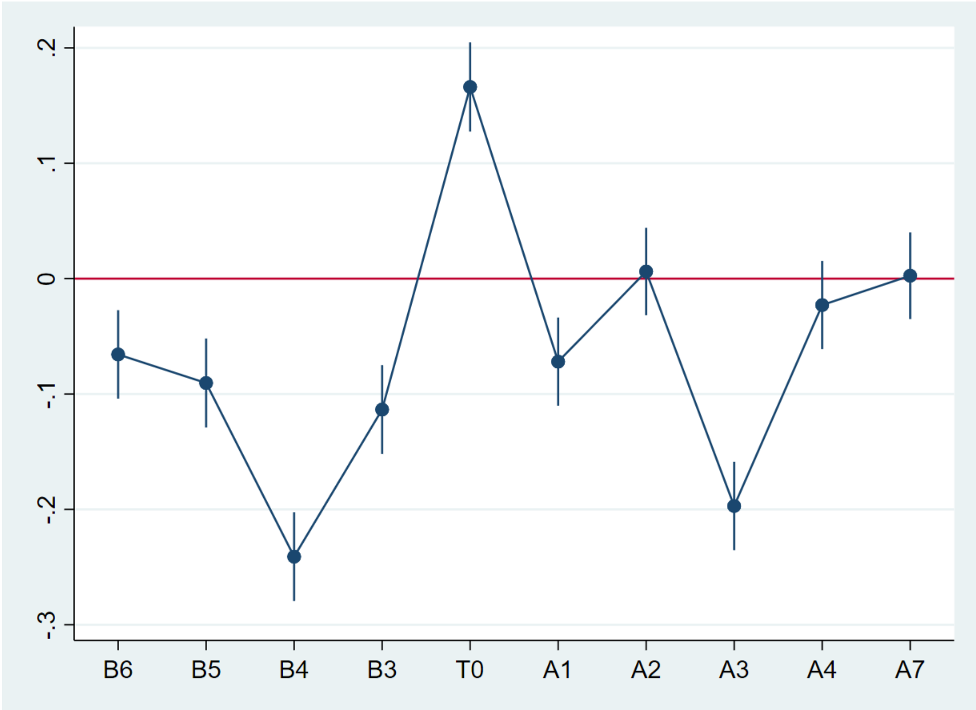

Figure 3.2: Parallel Trend Test: Autocorrelation Factor

This graph reports the results of a parallel trend test for my difference in differences regressions, where B3 denotes 3 days before T0 and A1 denotes 1 day after T0. This figure shows Autocorrelation Factor increases significantly on the Monday after a Super Bowl advertising event, which indicates that the market is more inefficient.

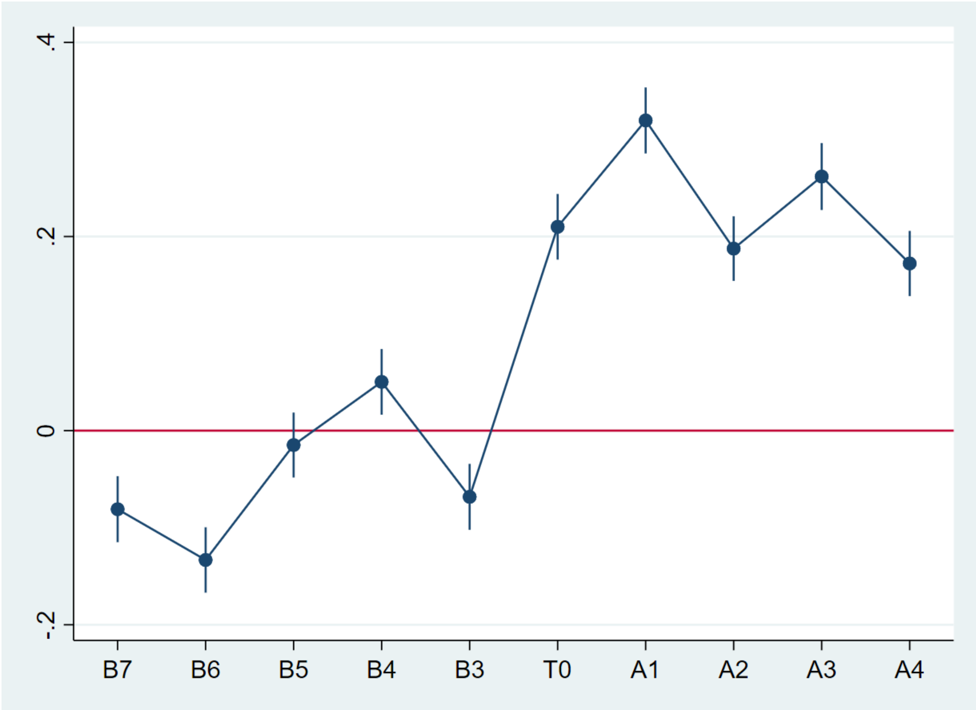

Figure 3.3: Parallel Trend Test: Standard Deviation Factor

This graph reports the results of a parallel trend test from difference in differences regressions, where B3 denotes 3 days before T0 and A1 denotes 1 day after T0. This figure shows Standard Deviation Factor increases significantly on the Monday after a Super Bowl advertising event, which indicates that the market is more inefficient.

Table 3.10: Regression Results: Stock Returns and Liquidity

	(1)	(2)
	Abnormal Return	illiquidity
Treated	0.0002	1630.8316***
	(0.2448)	(4.4800)
Time		
Time·Treated	−0.0013***	−306.9281***
	(−3.1663)	(−3.0526)
_cons	0.0003	−870.5551**
	(0.1544)	(−2.1110)
Firm Controls	Yes	Yes
Fixed effects	Yes	Yes
Year Dummies	Yes	Yes
Cluster	Yes	Yes
N	10271	10119
R^2	0.0012	0.1064
adj. R^2	−0.0008	0.1045

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table 3.10 shows the results of panel data difference in differences regression of my financial market reaction variables on event dummy and firm-level control variables with firm and year fixed effects. I run this regression to investigate the difference in differences for firms that run advertising campaigns during the Super Bowl Game relative to firms from a matched sample. The data cover the (t-30, t+30) time period. The dependent variables are cumulative abnormal returns and stock illiquidity. Time is a dummy variable that equals one if the date is after the Super Bowl advertising event and zero otherwise. Treated is a dummy variable that equals one is the firm has run advertising at the Super Bowl and zero if the firm is from a matched sample. The effect of advertising on returns and iliquidity can be assessed by the coefficient on Time·Treated. Both of the coefficient estimates are negative and highly statistically significant at the 1% level, showing that firms which run advertising campaigns during Super Bowl experience reductions in their stock returns. However, the adjusted R^2 for the first regression is negative, indicating an insignificant impact of advertising events on abnormal returns. These firms also exhibit an improved stock liquidity on the post event Monday, but their stock liquidity deteriorates after that. I show this by the parallel trend test for illiquidity.

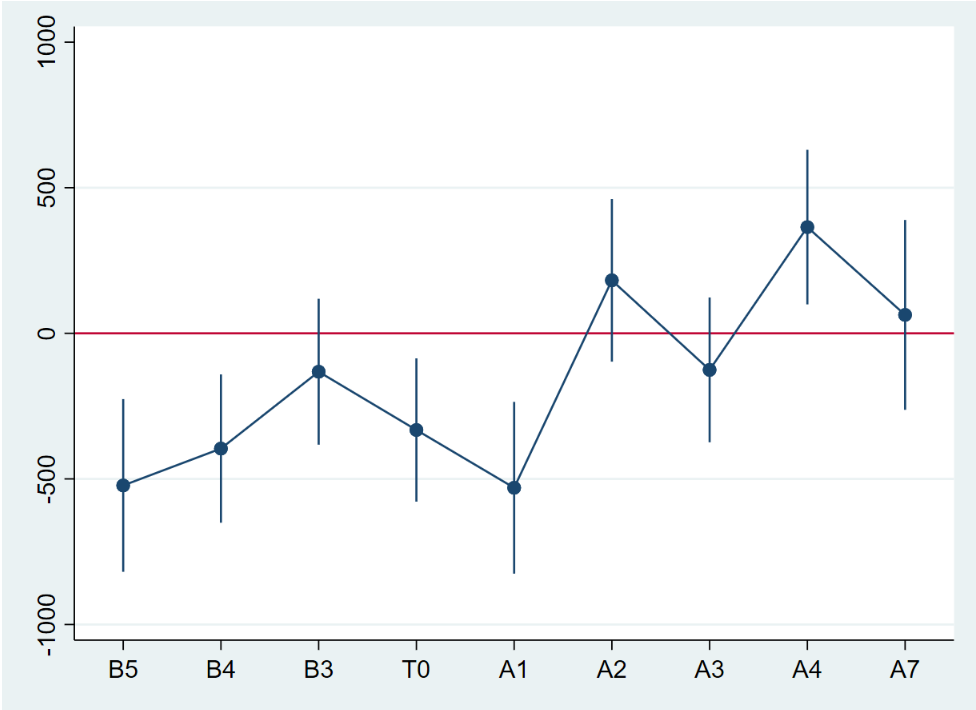

Figure 3.4: Parallel Trend Test: Illiquidity

This graph reports the results of a parallel trend test for my difference in differences regressions, where B3 denotes 3 days before T0 and A1 denotes 1 day after T0. This figure shows that stock illiquidity increases significantly after a Super Bowl advertising event, which indicates that advertised firms' securities experience liquidity problems in the financial markets after the advertising events.

Table 3.11: Regression Results: Fama-Mecbeth Regressions

	(Full Sample)	(Group A)	(Group B)
	CAR	CAR	CAR
PIN	0.4441	-11.7583^{*}	16.2282^{*}
	(0.0833)	(-1.6896)	(1.7986)
Illiquidity	-0.0039^{***}	-0.0031^{***}	-0.0162^{**}
	(-3.4386)	(-2.7163)	(-2.5870)
BM	0.6584	1.0502	0.8399
	(0.8141)	(0.9592)	(0.6821)
Size	-0.1144	0.0798	-0.9370
	(-0.3728)	(0.2198)	(-1.6081)
_cons	0.1710	3.4110	0.3362
	(0.0818)	(1.1483)	(0.1045)
N	237	136	101
R^2	0.0503	0.0855	0.1173
adj. R^2	0.0339	0.0575	0.0805

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table reports modified Fama-Mecbeth regression results. I run these regressions to analyze whether informed trading accounts for the decline in firm stock returns after a Super Bowl advertising event, where group A contains firms whose names are recognizable from the content of their advertising and group B contains other advertised firms. I find a highly negative impact of informed trading on abnormal accumulated returns for firms from group A.

This means advertising's effect is more pronounced for firms whose names are recognizable from the content of their advertising. The effect is statistically significant at the 10% level and the coefficient is also economically significant.

3.8 Conclusion

This paper studies how advertising affects financial market outcomes. I exploit Super Bowl Commercials as notable events to examine how advertising influences the trading behavior of market participants and the consequential market implications , especially for information asymmetry and information efficiency. I find that the post-event Monday is associated with reduced returns, informational inefficiency, and increased informed trading. These effects are more pronounced for firms whose names are recognizable from the content of their advertising. These firms also experience a significant decrease in their buy-sell imbalance for large size orders that are defined as order values greater than $30,000. This indicates there are more large sell orders after an advertising event, likely submitted by institutional investors. The results from difference in differences regressions examining the short run effect of advertising on liquidity indicate that advertised firms experience a decrease in stock liquidity. Although advertising might have long-term effect on liquidity, I show that this is not necessarily linked to improved liquidity directly following an advertising event. The results from difference in differences regressions provide further evidence that advertising may exacerbate informed trading and reduce information efficiency, especially for firms whose names are recognizable from the content of advertising.

These findings might be attributable to advertising induced trading. That is, informed investors may be strategically timing their trades to occur or front-run when they anticipate that their will be more attention-driven noise trading from retail investors. Informed investors might be able to anticipate uninformed traders after an advertising event. With the wide spread use of algorithmic trading technology, they can trade on predicted short-run market changes. The way that informed investors interact with uninformed traders after the Super Bowl might exacerbate information asymmetry among them and reduce market information efficiency.

This research shows empirically that advertising can increase information asymmetry among investors in financial markets, which is in contrast to the prior literature that advertising can reduce information asymmetry in financial markets. There are two reasons may help to explain the difference. First, the information asymmetry in the financial markets is unobservable, so I use the probability of informed trading to proxy it. That measure reflect the information asymmetry among informed and uninformed investors, while some prior studies use information asymmetry to measure the information gap between insiders and investors. Advertising can at least make the firms' name better known for investors and therefore reduce the information asymmetry between insiders and investors. However, it may also mislead some uninformed investors to bid up the stock prices and suffer a loss in trading with more informed investors, which means that advertising increase the information asymmetry between informed investors and uninformed investors. Second, in this study I use the high-frequency intra-day trading data to investigate the information asymmetry and information efficiency at the micro level, while most of the prior research rely on the low frequency data.

My findings have important implications for the literature on financial market effects of marketing endeavor's. In particular, my findings confirm that advertising may not inflate short-run stock prices and improve liquidity. Moreover, my results uncover the potential risks in trading the attention-grabbing securities. This means some uninformed retail investors may suffer losses when trading stocks of the advertised firms.

While advertising is widely regarded as some kind of public information, I find advertising does not help to make financial markets more informationally efficient. Moreover, advertising events appear to be associated with short-run market inefficiency.

My findings also shed light on the literature which relies on using high-frequency data to analyze advertising's short-run financial market impacts. I add to this body of work since advertising's impacts are supposedly mainly short-term, and high frequency data allows me to better capture any potential impacts.

My results highlight the importance of interactions among institutional and individual investors after advertising events. The increased large sell orders I document appear at the same time as informed trading increases and information efficiency decreases. This suggests such interactions could be important. I look forward to reading more studies which focus on this area.

Chapter 4

Conclusion

4.1 Summary

This study examines the impact of advertising on firm financial market outcomes. In particular, I focus on outcomes related to firms' information environment, including information asymmetry and information efficiency, and on the trading behavior of different market participants, as well as for firms' short-run stock returns and liquidity.

Using an adjusted Glosten-Milgrom model, I show that theoretically, advertising can increase information asymmetry in financial markets.

Based on the results from this theoretical model, I develop the hypothesis that advertising may facilitate informed trading in financial markets. I use an event study research method to track the changes in informed trading around the event windows. Using data on Super Bowl Commercials and high frequency intra-day trading data, I show that advertising increases informed trading of stocks whose names are readily identifiable from the contents of their adverting.

This research shows theoretically and empirically that advertising can increase information asymmetry among investors in financial markets, which is in contrast to the prior literature that advertising can reduce information asymmetry in financial markets. There are two reasons may help to explain the difference. First, the information asymmetry in the financial markets is unobservable, so I use the probability of informed trading to proxy it. That measure reflect the information asymmetry among informed and uninformed investors, while some prior studies use information asymmetry to measure the information gap between insiders and investors. Advertising can at least make the firms' name better known for investors and therefore reduce the information asymmetry between insiders and investors. However, it may also mislead some uninformed investors to bid up the stock prices and suffer a loss in trading with more informed investors, which means that advertising increase the information asymmetry between informed investors and uninformed investors. Second, in this study I use the high-frequency intra-day trading data to investigate the information asymmetry and information efficiency at the micro level, while most of the prior research rely on the low frequency data.

Furthermore, I investigate whether advertising can improve stocks' information efficiency, which measures the speed with which the market impounds information into prices. Analyses of Super Bowl Commercials paired with the high frequency intraday trading data around game days between 2008 and 2018 reveal that advertised firms whose names are readily identifiable from the contents of their advertising experience decreased information efficiency of the market, accompanied by an increase in informed trading and a decrease in cumulative abnormal returns around the advertising event windows. These results are robust for different proxies of information efficiency.

Moreover, I study the magnitude and direction of trading from informed investors, the institutional investors. I examine the hypothesis that advertising will result in more sell orders from institutional investors. Using the t-tests and non-parameter tests applied to the buy-sell imbalance of large size orders, I find that there is a reduced buy-sell imbalance for large size orders on the day after an advertising event for firms whose names are recognizable from the content of advertising. This result indicates institutional investors sell more than they buy after an advertising event.

I also investigate advertising's impact on short-run returns and stock liquidity. Using results from t-tests and non-parametric tests, I show that advertised firms exhibit declining cumulative abnormal returns. Modified Fama-Mecbeth regressions suggest that the lower cumulative abnormal returns are correlated with increased informed trading. I also find stocks liquidity decreases after advertising events. This result in contrast with early studies suggesting that advertising improves stock liquidity because of the increased retail investor's trading activity.

My study provides evidence on the relationship between firm advertising and financial markets information environment, and in particular on informed trading and the level of information efficiency after advertising is broadcast. I also shed light on the literature examining advertising's impact on short-run abnormal returns, stock liquidity, and institutional investors' behavior.

4.2 Limitation

This research also has some limitations owing to the limited time to conduct it and restricted access to databases.

In the theoretical section, I only use a modified Golsten-Milgrom model to illustrate how advertising changes the information asymmetry among investors in financial markets. However, recently, the PIN model has become more widely used and accepted than the Glosten-Milgrom model. If I use both the PIN model and Glosten-Milgrom model, the results will be more robust. In the modified Glosten-Milgrom model, I show that advertising can increase information asymmetry with both a two-step and three-step model. However, I don't illustrate how information asymmetry goes back to a normal level in the long-run, and this is also important to complete the story about changes in information asymmetry resulting from advertising.

The main research method used in empirics is the event study method. This is a compromise since I do not have access to an appropriate advertising database. The event study method allows me to investigate investors' reactions and financial market outcomes in a quasi-experimental setting, in which various information proxies, trade variables, and liquidity measures are tracked around a time window surrounding the focal advertising events. However, the empirical analyses related to the event study method are limited. I can only rely on t-tests and difference in differences models to test the event effect. Another limitation resulting from the event study method is sample size. My initial advertising sample is selected from advertising video of Super Bowl Commercials over the 2008 to 2018 period. It is composed of 162 firm-events, where 81 firms have recognizable advertisement and other 81 firms cannot be readily identified from their advertising. The sample size becomes very small. It would be nice to add some analyses with larger data sets (that are potentially more noisy) to rule out that the findings are not an artifact of the particular sports event/sample. Moreover, as my sample size is limited, I cannot do further analyses about firms from different industries.

The events of interest in this research is the Super Bowl Commercial. The Super Bowl is on Sunday, which undermines the importance of using high frequency data as there are possibilities of other compounding events over the weekend.

This study also has some endogeneity problems. For example, firms who choose to advertise on Super Bowl also attach great importance to firm images during other times, which could attract both institutional and retail investors. The using of matched sample from the propensity score matching (PSM) is a solution to this problem, however, it still has some selection bias. That is, the PSM can only match advertising firms and non-advertising firms on observed variables. PSM can only mitigate selection bias due to observables. When advertising firms and non-advertising firms make their advertising decisions based on factors that are not observable or not included into the analysis, there are still differences between two groups of firms.

I show that advertising events are correlated with reduced abnormal returns, and also find that advertising events do not have significant impacts on short term stock liquidity, both findings which depart from prior studies. However, I do not investigate these questions any further here.

4.3 Future Directions

With regards to future research, it would be promising if this thesis could be extended into the following directions:

Previous research about attention and stock returns has the endogeneity problems because the attention-grabbing events often relate to the price fundamentals of the firm (Focke et al., 2018; Peress and Schmidt, 2019). The Google trend and the Blomberg search intensity measures are two commonly used measures of attention (Focke et al., 2018), however, both of them are correlated with information about firm values. Advertising does not directly contain value-based information but can capture audiences' attention (Lou, 2014). So it would be very useful to exploit advertising as an instrument when conducting 2SLS regressions to examine how attention affects stock returns.

While Grullon et al. (2004) document advertising can increase stock liquidity due to the increased noise trading, Focke et al. (2018) find advertising does not have significant impact on stock liquidity. This inconsistency stems from the difference in the frequency and measurement of liquidity. I find advertising events do not significantly affect stock liquidity on the post-event Monday, however, advertised firms exhibit a decline in liquidity over the next few days. In examining advertising's impact on stock liquidity, I do not go far enough, as the event study method has limitations in studying the long-run effects. The daily advertising intensity data is available in the Kantar database. By combining it with high frequency tick data, one can trace daily changes of stock liquidity resulting from advertising. This could give us better understanding about advertising's stock liquidity effect in both the short-run and long-run.

Advertising's financial market effects vary from different industries (Joshi and Hanssens, 2010a). For example, advertising's spillover effects in the financial markets are more likely to happen in the business to consumer industries than the business to business industries. With daily advertising intensity data, there should also be more samples available from a number of different industries. Investigating of advertising's impact on financial markets for different industries is a potentially desirable future research direction.

Advertising affects individual investors more than it does institutional investors (Barber and Odean, 2000; Fehle et al., 2005; Joshi and Hanssens, 2010a). Individual investors are the net buyer of stocks from heavily advertised firms (Barber and Odean, 2007), and institutional investors are net sellers. There is a possibility that cannot be ruled out that institutional investors might leave such heavily advertised firms. In-depth exploration of how institutional investors behave before and after firms increase or decrease their advertising expenditure would be very helpful.

The wide use of algorithmic trading is changing the mechanisms by which information and signals affect the markets (Peress and Schmidt, 2019). Machine learning and deep learning are becoming more important in the financial markets. Artificial intelligence plays a more important role in asset pricing. I expect there will be more work on advertising's financial market outcomes under the umbrella of new trading technologies.

Finally, in response to the concerns about advertising's side effects in the financial markets, I study advertising's impact on information risk, information efficiency, cumulative abnormal returns, and liquidity. Advertising might affect stock price crash risk and liquidity risk as well, so it would be helpful to further explore advertising's side effects in the financial markets.

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