



Vaasan yliopisto
UNIVERSITY OF VAASA

Janita Virta

The Impact of Availability Bias on Stock Returns and Volatility

School of Accounting and Finance
Master's thesis in Finance
Master's Degree Programme in Finance

Vaasa 2025

UNIVERSITY OF VAASA**School of Accounting and Finance**

Author: Janita Virta
Title of the Thesis: The Impact of Availability Bias on Stock Returns and Volatility
Degree: Master of Science in Economics and Business Administration
Programme: Master's Degree Programme in Finance
Supervisor: Nebojsa Dimic
Year: 2025 **Pages:** 73

ABSTRACT:

This thesis investigates how investor attention influenced by cognitive biases, particularly availability bias, impacts stock price behaviour in the short and long term. Traditional finance theories, such as the Efficient Market Hypothesis, assume rational decision-making, yet real-world anomalies challenge this view, highlighting the relevance of behavioural finance. Availability bias, where individuals give undue weight to information that is easily recalled or recently encountered, plays a key role in driving short-term market overreactions and longer-term corrections.

To empirically examine this effect, the study utilizes Google Search Volume Index (GSVI) data as a proxy for investor attention and combines it with stock price and volatility data for a sample of 25 publicly traded companies from 2020 to 2025. High-attention events are identified as significant spikes in search volume, and an event study methodology is employed to evaluate market reactions before and after these spikes. Cumulative Abnormal Returns and volatility measures are calculated over multiple event windows to assess short- and long-term effects.

The findings reveal that investor attention is associated with increased volatility and short-term abnormal returns. This thesis contributes to the empirical understanding of how investor attention, driven by cognitive biases, affects market dynamics, offering insights for investors and policymakers seeking to navigate the complexities of modern financial markets

KEYWORDS: Behavioral Finance, Availability bias, Investment performance, Decision making

VAASAN YLIOPISTO**School of Accounting and Finance**

Tekijä:	Janita Virta		
Tutkielman nimi:	The Impact of Availability Bias on Stock Returns and Volatility		
Tutkinto:	Master of Science in Economics and Business Administration		
Oppiaine:	Master's Degree Programme in Finance		
Työn ohjaaja:	Nebojsa Dimic		
Vuosi:	2025	Sivumäärä:	73

ABSTRACT:

Tämä tutkielma tarkastelee, kuinka sijoittajien huomio, erityisesti saatavuusharhan kaltaisten kognitiivinen vinouma, vaikuttaa osakehintojen käyttäytymiseen sekä lyhyellä että pitkällä aikavälillä. Perinteiset rahoitusteoriat, kuten tehokkaiden markkinoiden hypoteesi, olettavat sijoittajien tekevän rationaalisia päätöksiä. Todelliset markkinapoikkeamat haastavat kuitenkin tämän oletuksen ja korostavat käyttäytymisperusteisen rahoituksen merkitystä. Saatavuusharha tarkoittaa taipumusta painottaa liikaa helposti mieleen tulevaa tai äskettäin havaittua tietoa, ja sillä voi olla merkittävä vaikutus osakekurssien liikkeisiin ja volatilitettiin.

Tutkielmassa hyödynnetään Google-hakujen volyyymi-indexiä sijoittajahuomion mittarina, ja yhdistetään se vuosien 2020–2025 pörssiyritysten osake- ja volatilitetidataan. Korkean huomion tapahtumat määritellään merkittävänä hakumäärien piikkeinä, ja markkinoiden reaktioita ennen ja jälkeen näiden tapahtumien arvioidaan tapahtumatutkimuksen menetelmällä. Kumulatiivisia epänormaaleja tuottoja (CAR) ja volatilitettä mitataan useilla aikajaksoilla, jotta saadaan kattava kuva vaikutuksista.

Tulokset osoittavat, että sijoittajahuomio liittyy kohonneeseen volatilitettiin ja lyhyen aikavälin poikkeaviin tuottoihin. Nämä havainnot syventävät ymmärrystä rahoitusmarkkinoiden käyttäytymiseen liittyvistä tekijöistä ja tarjoavat hyödyllistä tietoa sijoittajille, analyytikoille ja päättäjille, jotka pyrkivät ymmärtämään ja ennakoimaan sijoittajapsykologian vaikutuksia arvopapereiden hinnoitteluun.

KEYWORDS: Behavioral Finance, Availability bias, Investment performance, Decision making

Contents

1	Introduction	7
1.1	Purpose of the Study	8
1.2	Structure of the study	10
2	Traditional Finance	11
2.1	Efficient Market Hypothesis	11
2.2	Rational Choice Theory	13
2.3	Limitations of Traditional Finance	13
3	Behavioral Finance	16
3.1	Development of Behavioral Finance	16
3.2	Key Concepts in Behavioral Finance	19
3.3	Availability Bias	22
3.4	Importance of Behavioral Finance in Modern Market Analysis	25
3.5	Impact of Behavioral Biases on Investing performance	26
4	Literature Review and Hypothesis Development	29
4.1	Overview of Research on Availability Bias	29
4.2	Impact on Market Reactions and Performance	32
4.3	Identification of High-Attention Events Using Data Proxies	34
5	Data and Methodology	38
5.1	Data description	38
5.2	Methodology	42
6	Results and discussion	50
6.1	Correlation results	50
6.2	Illustrative Event Example	57
6.3	Regression results	59
6.4	Limitations of the study	64
7	Conclusions	66
	References	68

Figures

Figure 1. Value Function (Kahneman & Tversky, 1979)	20
Figure 2 - Monster Beverage Corp. GSVI spike	41
Figure 3 - Palo Alto Networks GSVI spike	41
Figure 4 - Analog Devices GSVI spike	41
Figure 5 - Mean Volatility, Cumulative Returns, and CARs (Normalized)	47
Figure 6 - KeyCorp GSVI Spike	57
Figure 7 - KeyCorp Stock History	58

Tables

Table 1 - Key Milestones in the Evolution of Behavioural Finance	18
Table 2 - Sample Overview	39
Table 3 - GSVI Descriptive Statistics	40
Table 4 - Descriptive Statistics of Volatility	45
Table 5 - Descriptive Statistics of Cumulative Return	46
Table 6 - Descriptive Statistics of Cumulative Abnormal Returns	46
Table 7 - Correlations between volatility and cumulative returns	51
Table 8 - Correlation between volatility and CARs	52
Table 9 - correlation between cumulative raw returns and abnormal returns	53
Table 10 - Volatility Heatmap	54
Table 11 - Return Heatmap	55
Table 12 - CARs Heatmap	56
Table 13 - Regression 1 results	59
Table 14 - Regression 2 results	62

1 Introduction

Investor behavior in financial markets is shaped not only by rational analysis but also by emotional responses and cognitive shortcuts. Traditional finance theories assume that individuals make optimal choices by processing all available information logically. However, growing evidence suggests that psychological factors and biases often lead to suboptimal and inconsistent financial decisions (Hirshleifer, 2001; Baker & Nofsinger, 2010). This thesis explores how investor attention, as influenced by cognitive biases and particularly availability bias, affects stock price behavior in the short and long term.

The field of finance has long been dominated by traditional theories rooted in rationality and efficiency. From the Efficient Market Hypothesis (EMH) proposed by Eugene Fama (1970) to the Expected Utility Theory articulated by von Neumann and Morgenstern (1947), traditional finance posits that investors act as rational agents, processing all available information to make optimal decisions. These theories provide a solid framework for understanding investor behavior within the context of expected utility and market efficiency.

However, real-world market anomalies, speculative bubbles, and irrational investor behavior have increasingly challenged these assumptions. The rise of behavioral finance marks a shift toward understanding how cognitive limitations and psychological biases affect financial decision-making (Baker & Nofsinger, 2010). Building on the pioneering work of Kahneman and Tversky (1974, 1979), behavioral finance examines how heuristics such as availability bias, anchoring, and overconfidence systematically influence investor choices and market outcomes.

A central focus of this thesis is availability bias, a cognitive shortcut where individuals assess the likelihood or importance of an event based on how easily examples come to mind (Tversky & Kahneman, 1973). In the context of financial markets, this means that investors may give disproportionate weight to stocks or news that have recently

attracted attention, regardless of their fundamental value. This can lead to short-term overreactions and price volatility, followed by longer-term corrections as attention fades

While availability bias is widely recognized in behavioral research, its empirical effects on stock performance and volatility remain an evolving area of study. This thesis aims to address specific gaps in the literature by analyzing high-attention events and their relationship with abnormal returns and price fluctuations. This thesis examines a comprehensive exploration of traditional finance and behavioral finance to explore the complexities of financial decision-making. Through theoretical frameworks and empirical studies, this paper aims to deepen the understanding the interaction between human behavior and financial markets, identifying the factors that influence investor choices and affect investment performance.

1.1 Purpose of the Study

The purpose of this study is to explore the impact of availability bias on stock market volatility, short- and long-term performance. This thesis aims to bridge the gap between behavioral finance theory and empirical evidence by examining how cognitive shortcut called availability bias, influence investment decision-making and market dynamics. Despite the growing recognition of behavioral biases in financial decision-making, the integration of behavioral insights into traditional finance remains an ongoing study. Understanding how heuristic biases influence investment performance is crucial for comprehending financial markets and investor behavior. By combining findings from past studies and theoretical frameworks, researchers aim to bridge the gap between theory and practice, offering insights that can inform investment strategies and enhance investor outcomes (Baker & Ricciardi, 2014).

By analyzing high-attention events and their correlation with stock price movements, this study seeks to provide insights into the short-term overreactions and long-term corrections driven by investor attention. The findings aim to contribute to a deeper understanding of behavioral biases in financial markets and offer valuable implications for both

academics and practitioners. Specifically, this study provides insights that can inform investment strategies, enhance investor outcomes, and guide policymakers in understanding the effects of investor sentiment on asset prices. The study is grounded in an event study framework, analyzing stock returns and volatility before and after attention spikes. Two main hypotheses guide the analysis:

H1a: Heightened investor attention leads to increased short-term stock returns.

This hypothesis is based on research indicating that heightened investor attention can drive temporary mispricing due to overreaction (Barber & Odean, 2008; Da et al., 2011).

H1b: Heightened investor attention predicts a reversal in stock returns over longer time horizons.

This hypothesis is based on research suggesting that market efficiency gradually reasserts itself, correcting the temporary mispricing caused by overreaction (Barber & Odean, 2008; Da et al., 2011).

H2: Increased investor attention, as measured by Google Search Volume Index (GSVI), is positively associated with heightened stock price volatility prior to the attention spike.

This hypothesis is grounded in prior research suggesting that rising investor attention can amplify market volatility through increased trading activity and disagreement among market participants (Barber & Odean, 2008; Da, Engelberg, & Gao, 2011; Andrei & Hasler, 2015). Attention-driven trading may begin prior to a measurable attention spike (e.g., in Google Trends), contributing to elevated volatility in the lead-up to observable events.

1.2 Structure of the study

Chapter 1 introduces the purpose and motivation of the thesis, identifying the research gap and outlining the hypotheses. Chapters 2 and 3 lay the theoretical foundation of the study. Chapter 2 discusses traditional finance, emphasizing models such as the Efficient Market Hypothesis and highlighting their limitations. Chapter 3 turns to behavioral finance, providing an overview of key cognitive biases and heuristics, with a specific focus on availability bias. Chapter 4 presents a review of the relevant literature. Chapter 5 details the methodological framework and data used in the empirical analysis. Chapter 6 reports the empirical findings, interpreting the results and discussing their limitations, while also presenting an event example. Finally, Chapter 7 concludes the thesis by summarizing the key insights, offering implications for investors and policymakers, and proposing directions for future research.

2 Traditional Finance

Traditional finance theory, the foundation of modern financial thought, is grounded in the belief that investors have all the required information, act analytically and rationally and are presumed to be risk averse while expecting compensation to their risks (Baker & Ricciardi, 2014). These principles allow theorists to develop models of crucial financial choices, such as asset pricing and portfolio composition. The traditional approach in finance is based on classical decision theory, assuming rational decision makers evaluate all potential outcomes to find the option with the highest expected utility (Baker & Ricciardi, 2014). Additionally, traditional finance assumes that markets are efficient, a concept famously articulated by Fama (1970).

Numerous theories and models have evolved from these traditional finance principles and are essential in understanding investor behavior. Concepts like the classical decision theory, Efficient Market's Hypothesis, rationality and utility theory, different asset pricing models and Random Walk all are well known theories based on the assumption investors act rationally (Baker & Ricciardi, 2014). However, despite the robustness of these models, real-world observations often reveal deviations from the predictions of traditional finance theories. This chapter aims to highlight the foundational concepts of traditional finance while acknowledging the limitations that have led to the emergence of behavioral finance as a complementary perspective.

2.1 Efficient Market Hypothesis

Efficient Market Hypothesis (EMH) became known by Eugene Fama (1970) who introduced the term "market efficiency". According to Fama (1970), market efficiency implies that stock prices fully incorporate all available information, providing precise indications for resource distribution offering firms accurate signals for resource allocation and investment decisions. Investors are also able to allocate their capital across various options under the assumption of right prices (Fama, 1970). Due to this "efficacy" investors

cannot beat the market because all information is included to stock prices and thus, they fully reflect all information available (Fama, 1970).

The influencing survey article "Efficient Capital Markets" (Fama, 1970) contributed to the acceptance of the efficient market hypothesis. Fama categorizes efficiency into three levels based on the relevant information subsets. The first, weak form, information reflects only historical prices. Semi-strong form includes publicly available information. In the last strong form investors have monopolistic access to any relevant information (Fama, 1970).

EMH can also be built on three arguments according to Shleifer (2000). The first assumption is that investors are rational and value securities according so. If the investors deviate from the first assumption and act irrationally, their trades are considered to be random eliminating any effect on prices by canceling each other out. The third assumption is that irrational investors actions are eliminated by rational arbitragers (Shleifer, 2000).

According to EMH economists believe that that individual stock and the whole stock market would reflect information as it arises without a delay (Malkiel, 2019). This leads to both technical analysis and fundamental analysis to be ineffective when it comes to investors seeking aid in choosing "undervalued" securities (Malkiel, 2019). Studying past stock prices in order to foresee future prices or evaluating financial metrics like asset values and business earnings would not, at least with comparable risk, allow an investor to achieve returns higher than those that could be obtained by holding a randomly chosen portfolio of individual stocks (Malkiel, 2019). This is one of the reasons why the term random walk is often associated with the efficient market theory.

Despite its widespread acceptance, EMH has faced criticism and challenges, particularly in explaining market anomalies and investor behavior that deviates from rationality. These limitations have paved the way for alternative theories, such as behavioral finance, which will be discussed in subsequent chapters.

2.2 Rational Choice Theory

Rational choice theory serves as the basis for decision-making in economics, emphasizing logical assessments of potential outcomes to determine optimal choices, forming the foundation of traditional finance, where decisions are made by maximizing expected utility (Baker & Ricciardi, 2014). Von Neumann and Morgenstern (1947) introduced the theory of expected utility, which assumes individuals prioritize higher expected outcomes and make logical choices under uncertainty. Utility functions rank options for comparison within personal preferences, facilitating the calculation of expected utility by weighting outcomes with their probabilities (Von Neumann & Morgenstern, 1947).

Rational decision-makers select the option with the highest expected utility (Baker & Ricciardi, 2014). Classical decision theory, meanwhile, aims to identify optimal choices, assuming individuals are self-interested and rational, striving to maximize outcomes within constraints (Baker & Ricciardi, 2014). Individuals draw on classical decision theory models when faced with multiple options, evaluating preferences, and assigning probabilities to potential outcomes (Baker & Ricciardi, 2014).

Rational choice theory and the theory of expected utility represent traditional finance perspectives on decision-making, emphasizing logical assessments and utility maximization (Baker & Ricciardi, 2014). However, behavioral finance presents an alternative viewpoint, highlighting how psychological biases and heuristics can influence decision-making processes (Baker & Ricciardi, 2014).

2.3 Limitations of Traditional Finance

Traditional finance theory has long been the cornerstone of modern financial analysis. However, critiques and empirical evidence have indicated substantial limitations

inherent in these frameworks, challenging their efficacy in explaining real-world financial phenomena.

Critics, including Simon (1956), have questioned the assumption of absolute rationality, arguing that decision-making rationality is constrained and dependent on both internal and external circumstances. This challenges the idea that economic and statistical theories can fully explain how organisms behave (Simon, 1956). Expected Utility Theory, assumes that individuals make decisions by maximizing expected utility, but often fall short in describing actual observed behavior, highlighting the need for a more nuanced understanding of human decision-making in finance (Baker & Ricciardi, 2014).

The Efficient Market Hypothesis (EMH), another pillar of traditional finance, faces theoretical paradoxes and empirical challenges (Leković, 2018). EMH posits that asset prices reflect all available information and that it is impossible to consistently achieve above-average returns (Fama, 1970). However, the existence of financial incentives for market participants contradicts EMH's assertion, as it implies that market inefficiencies exist and can be exploited for profit (Leković, 2018). Theoretical inconsistencies arise when considering the paradox of detailed securities analysis coexisting with market efficiency assumptions, suggesting limitations in EMH's explanatory power (Leković, 2018).

Anomalies in financial markets, such as deviations from expected patterns, also pose a significant challenge to EMH (Leković, 2018). These anomalies, ranging from pricing discrepancies to predictable patterns in stock returns, undermine the hypothesis's assumption of market efficiency (Leković, 2018). Despite efforts to explain or eliminate anomalies, many persist and contribute to the ongoing debate about EMH's validity. Challenges in testing EMH arise from the necessity to consider corresponding equilibrium models and asset valuation frameworks, complicating the interpretation of empirical results (Malkiel, 2019).

Market anomalies often exhibit a transient nature, disappearing once they become public knowledge and investors adjust their strategies accordingly (Malkiel, 2019). This phenomenon suggests that experienced investors exploit anomalies for profit, leading to their eventual elimination from the market. Pricing irregularities and predictable patterns in stock returns may emerge over time due to collective investor judgment and market imperfections, challenging the notion of perfect market efficiency (Malkiel, 2019).

Empirical research has revealed persistent behavioral biases among individuals that traditional models fail to adequately explain (Baker & Ricciardi, 2014). People exhibit cognitive biases and irrational behaviors that diverge from the assumptions of rational decision-making embedded in traditional finance theories (Baker and Ricciardi, 2014). Rather, research suggests using psychological theories of perception and cognition to examine behavior, which may be more in alignment with how organisms behave in real life and how people allocate time to individual needs without a general utility function (Simon, 1956).

In conclusion, traditional finance theories face limitations in explaining real-world financial phenomena. The reliance on rational decision-making assumptions and market efficiency hypotheses overlooks the complexities of human behavior and the dynamic nature of financial markets. As empirical research continues to uncover anomalies and deviations from traditional models, the need for a more comprehensive understanding of finance becomes increasingly evident.

3 Behavioral Finance

Behavioral finance is relatively new but fast-developing field that combines traditional economics with behavioral and cognitive psychology to explain why people make certain financial decisions (Baker & Nofsinger, 2010). Unlike traditional finance theories, which assume that investors are rational, and markets are efficient, behavioral finance acknowledges that human behavior in financial markets is often far from rational and thus challenging the long-standing assumptions of traditional finance (Baker & Nofsinger, 2010).

The emergence of behavioral finance is the result of a growing realization that traditional economic theories fall short in explaining real-world observations (Shah et al., 2018). Empirical evidence shows that investors are influenced by emotions, mental shortcuts, and systematic errors in judgment—collectively referred to as heuristics and biases. These psychological tendencies form the core of behavioral finance (Shah et al., 2018).

According to Kahneman and Riepe (1998), understanding the decision-making processes behind investments is crucial, as these decisions have long-term emotional and financial consequences. Therefore, this chapter explores key theories and concepts that illustrate how behavioral biases affect investor decisions and performance.

3.1 Development of Behavioral Finance

Behavioral finance began gaining traction in the late 20th century, as traditional theories such as the Efficient Market Hypothesis (EMH) and Rational Choice Theory struggled to account for real-world market behavior. Financial crises, bubbles, and persistent anomalies exposed the limits of assuming that investors always act rationally and in their best interest. These limitations created an opportunity for the integration of psychological insights and helped establish behavioral finance as a distinct paradigm.

A foundational contribution came from psychologists Daniel Kahneman and Amos Tversky, who studied decision-making under uncertainty. Their work revealed that individuals rely on heuristics, or mental shortcuts, that often lead to systematic judgment errors. Their Prospect Theory (1979) was a key turning point. Unlike traditional models that assume investors evaluate all outcomes rationally, prospect theory showed that people view gains and losses asymmetrically, with losses having a stronger psychological impact, known as loss aversion. This helped explain behaviors such as holding losing stocks too long or selling winners too quickly.

In their seminal paper "Judgment under Uncertainty: Heuristics and Biases" (1974), Kahneman and Tversky introduced the idea of cognitive biases, such as availability, anchoring, and representativeness heuristics. These biases illustrate how individuals often rely on readily accessible information, anchor their decisions based on initial values, or judge probabilities based on stereotypical patterns, leading to predictable errors in decision-making. Their research laid the groundwork for integrating psychological factors into economic theories, directly challenging the traditional finance view of rational decision-makers.

Another key figure in the development of behavioral finance was Richard Thaler, who built on the insights of Kahneman and Tversky and applied them to economic and financial contexts. Thaler (1985) introduced the concept of mental accounting, where people treat money differently depending on subjective mental labels, affecting their spending and investment behavior. For example, treating a tax refund as "free money" even though it's economically equivalent to regular income. Thaler (1980) also developed the idea of the endowment effect, where individuals place a higher value on items they own compared to identical items they do not own. This finding contradicts the assumption of rational asset valuation in traditional finance and highlights the role of emotional attachment in investment decisions. Thaler's extensive work in applying psychological insights to financial behavior culminated in the Nobel Prize in Economics (2017), solidifying his contributions to the field.

The shortcomings of traditional finance became increasingly clear through the identification of persistent market anomalies. For example, the Equity Premium Puzzle (Mehra & Prescott, 1985) showed that stocks consistently outperform bonds by more than models predict, suggesting that investors may be more risk-averse than assumed. The January Effect and the Momentum Effect (Jegadeesh & Titman, 1993) point to calendar-driven and trend-following investor behavior that contradicts with market efficiency and points to the influence of herding behavior, where investors follow recent trends rather than focusing on fundamentals. These patterns suggest that psychological forces like herding, overconfidence, and availability bias play a key role in markets.

The term "behavioral finance" gained prominence in the 1980s and 1990s as researchers such as Thaler, Robert Shiller, and Eugene Fama began incorporating psychological insights into financial theories. The field was further legitimized with Nobel Prizes awarded to Kahneman (2002) and Thaler (2017). Their contributions helped solidify the importance of understanding how biases affect both investor behavior and market outcomes. The following section delves deeper into the key concepts that define behavioral finance, exploring specific biases and heuristics that influence financial decisions.

Table 1 - Key Milestones in the Evolution of Behavioural Finance

Year	Milestone
1974	Kahneman and Tversky publish "Judgment under Uncertainty: Heuristics and Biases," introducing the concept of cognitive heuristics such as availability, anchoring, and representativeness.
1979	Kahneman and Tversky introduce Prospect Theory, challenging traditional economic models by showing that people value gains and losses differently, leading to behaviors like loss aversion.
1985	Mehra and Prescott identify the Equity Premium Puzzle, highlighting an anomaly in traditional finance theories that suggests higher-than-expected returns for stocks compared to bonds.
1993	Jegadeesh and Titman publish their study on the Momentum Effect, demonstrating that stocks with strong past performance continue to outperform, contradicting the Efficient Market Hypothesis.
2002	Daniel Kahneman receives the Nobel Prize in Economics for his contributions to behavioral finance, particularly for his work on Prospect Theory and cognitive biases.
2017	Richard Thaler is awarded the Nobel Prize in Economics for his pioneering work in behavioral economics, including his research on mental accounting and the endowment effect.

3.2 Key Concepts in Behavioral Finance

Behavioral finance builds on foundational theories that challenge the traditional assumptions of rational decision-making. These theories explore how individuals evaluate potential gains and losses, often relative to a subjective reference point, and how they mentally organize and treat money in ways that deviate from classical economic models. Two of the most influential theories in this field are prospect theory (Kahneman & Tversky, 1979) and mental accounting (Thaler, 1985).

Prospect theory introduces key concepts such as loss aversion, framing effects, and the tendency for individuals to exhibit risk-averse or risk-seeking behavior depending on how decisions are presented. Mental accounting further expands on this by describing how people categorize financial resources into mental "accounts," leading to decisions influenced by psychological factors rather than purely economic reasoning. These theories are briefly introduced in this chapter to provide a foundation for understanding the key concepts of behavioral finance.

Prospect theory, introduced by Kahneman and Tversky in 1979, challenges the assumption of investor rationality. Their groundbreaking work reveals evidence that investors are not entirely rational and do not consistently adhere to rational decision-making processes, especially in experiments where information is incomplete, challenging conventional ideas of rational calculation. Kahneman and Tversky (1979) explained that investors focus is based on potential gains and losses rather than on final outcomes. People perceive probabilities, both objectively and subjectively, which influences how individuals weigh decisions and evaluate risk and people are risk-averse when involving sure gains but often become risk-seeking when facing sure losses (Kahneman & Tversky, 1979).

According to Kahneman and Tversky (1979) prospect theory breaks down the decision-making process into two key phases: editing and evaluation. During the editing phase, investors simplify their options by organizing information to establish a decision reference point (Kahneman & Tversky, 1979). In the evaluation phase, decision-makers assess

the value of each edited prospect and choose a course of action based on their evaluations (Kahneman & Tversky, 1979).

Kahneman and Tversky (1979) introduced a value function in prospect theory, which is concave for gains, indicating risk aversion, and convex for losses. This function assigns value to gains and losses relative to a reference point, rather than final assets. Typically, it's steeper for losses than gains, reflecting loss aversion. The S-shaped curve of the value function suggests tendencies towards risk aversion with gains and risk seeking with losses. Additionally, people tend to undervalue outcomes that are merely probable compared to those obtained with certainty under prospect theory (Kahneman & Tversky, 1979).

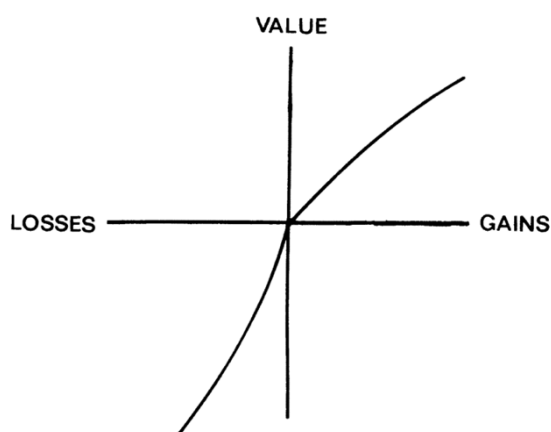


FIGURE 3.—A hypothetical value function.

Figure 1. Value Function (Kahneman & Tversky, 1979)

Mental accounting, introduced by Thaler (1985), describes how individuals categorize and treat money differently depending on its source or intended use. For example, people might treat a tax refund as "free money" and spend it more frivolously compared to their regular income. This concept challenges the traditional view that money is fungible and should be treated the same regardless of its source. Mental accounting can lead to suboptimal financial decisions, such as overspending or under-saving, as individuals

mentally allocate funds into different "accounts" that influence their spending and saving behavior (Thaler, 1985).

As behavioral finance developed, numerous heuristics and cognitive biases were identified, shedding light on the systematic errors in human judgment that influence financial decision-making. Among the most studied are the availability bias, where decisions are influenced by the ease with which similar instances or information come to mind (Tversky & Kahneman, 1974), and the representativeness heuristic, where individuals judge probabilities based on perceived similarity or stereotypes, rather than objective data. Another prominent bias is anchoring, where decisions are overly influenced by an initial reference point (the "anchor"), even when it is irrelevant. Overconfidence bias further impacts investor behavior, as individuals overestimate their ability to predict outcomes, often leading to excessive trading and suboptimal portfolio management (Barber & Odean, 2000).

On a market level, these biases give rise to behaviors such as herding, where investors mimic the actions of others during periods of uncertainty, often amplifying market trends. This collective behavior plays a significant role in market anomalies, such as the momentum effect (Jegadeesh & Titman, 1993), where stocks that perform well in the short term tend to continue their upward trajectory, challenging the Efficient Market Hypothesis. Similarly, the January effect demonstrates how psychological factors drive seasonal deviations in stock performance, often linked to tax-loss selling and investor sentiment.

These cognitive biases and market-level implications have also been used to explain significant real-world market events. For instance, speculative bubbles, such as the Dot-com bubble, are often driven by a combination of availability bias, herd behavior, and overconfidence, leading to excessive valuation of assets far beyond their intrinsic worth. Furthermore, phenomena like overreaction and underreaction underscore the critical role of behavioral biases in shaping market outcomes.

These key concepts are central to understanding the principles of behavioral finance and highlight its importance in explaining real-life financial phenomena. While behavioral finance offers a broad framework to analyze cognitive biases and market anomalies, this thesis narrows its focus to a specific bias—availability bias—to explore its role in driving stock market volatility and long-term performance. This is examined in depth in the following chapter.

3.3 Availability Bias

The concept of heuristics, introduced by Tversky and Kahneman (1974), has been central in understanding how individuals make decisions under uncertainty. Heuristics are cognitive shortcuts that individuals rely on to simplify complex decision-making processes. Often described as rules of thumb, heuristics are useful in situations with time pressure or limited information (Kahneman & Tversky, 1974). As adaptive mechanisms, heuristics allow for quick judgments and problem-solving without excessive cognitive effort, enabling efficient decision-making in everyday life (Gigerenzer & Goldstein, 1996).

Although heuristics simplify complex problems, Tversky and Kahneman's (1974) research revealed that reliance on these mental shortcuts often leads to systematic errors in judgment. Their experiments demonstrated that using intuition for statistical inference can result in outcomes that deviate from probabilistic principles, leading to predictable cognitive biases. These biases, such as availability bias, distort judgment and contribute to suboptimal decision-making, which this thesis explores in the context of financial markets.

One of the key heuristics identified by Tversky and Kahneman is the availability heuristic, which refers to the tendency of individuals to assess the likelihood of events based on how easily examples come to mind. This can result in overestimating the importance or frequency of recent or vivid information, while neglecting less prominent but potentially

more relevant data. As a result, availability bias can distort perceptions of probability and influence decision-making in various domains, including finance.

In financial markets, availability bias significantly affects investor behavior and market dynamics. Shiller (2000) highlights how waves of public attention or inattention significantly impact how investors allocate their focus across different investment categories. This concept aligns closely with the availability heuristic, as it demonstrates how shifts in public discourse and media emphasis can alter investor behavior. Shiller's insights provide a broader framework for understanding how availability bias operates on a macro level, influencing not just individual investors but the collective behavior of markets.

Shiller's work emphasizes that market trends are often driven by collective psychological forces rather than purely rational evaluations of fundamental data. For instance, during speculative bubbles, investors disproportionately focus on vivid narratives or highly publicized trends, driving up asset prices far beyond their intrinsic value. Shiller argues that these attention-driven dynamics contribute to market anomalies, such as excessive volatility and the persistence of speculative trends, which cannot be explained by traditional finance theories like the Efficient Market Hypothesis.

The availability heuristic is particularly evident in how media and social discourse amplify certain investment narratives. Shiller points out that attention tends to cluster around specific sectors, asset classes, or themes during periods of heightened public interest. This behavior reflects the cognitive tendency of investors to rely on readily available information, leading to herding behavior and the reinforcement of market trends. Such patterns are not only confined to periods of speculative excess but also occur during market downturns, where negative narratives dominate public attention, driving sell-offs and further volatility.

Similarly, Barber and Odean (2008) provide empirical evidence in their study how availability bias influences investor decisions. They find that individual investors tend to focus

disproportionately on stocks that have recently attracted attention, often driven by external factors such as media coverage, extraordinary one-day returns, or spikes in trading volume. These attention-grabbing events capture investors' focus, leading to decisions influenced more by salience than by a thorough evaluation of fundamentals.

The study reveals that investors are more likely to purchase rather than sell stocks that have recently been in the spotlight. For instance, stocks with exceptional one-day returns often draw substantial interest, prompting buying activity that is not necessarily justified by underlying value. Similarly, media coverage amplifies this effect, as it makes certain stocks more visible and readily accessible in investors' minds. The researchers emphasize that this behavior disrupts decision-making processes, leading to purchases based on perceived attention rather than rational analysis. Moreover, the study highlights that on days with high attention levels, individual investors are disproportionately net purchasers. This trend creates noticeable biases in trading patterns, as investors react to highly salient information rather than balancing it against less prominent but potentially more critical data. Barber and Odean's findings underscore the role of availability bias in driving these behaviors, demonstrating its profound impact on trading activity and market outcomes.

Andrei and Hasler (2015) further support the idea that investor attention plays a central role in market fluctuations. Their rational inattention model suggests that attention is an endogenous factor that shapes market outcomes. When investors allocate limited cognitive resources to certain assets or information, it increases belief dispersion and trading activity, contributing to higher volatility. This perspective shifts attention from being a passive response to becoming an active driver of financial dynamics.

The Subrahmanyam (2008) focuses in his paper on the broader theme of limited investor attention. According to Subrahmanyam investors tend to focus disproportionately on salient, recent, or vivid information, often neglecting less prominent but potentially more important data. The paper also finds that cognitive limitations, such as availability bias,

can cause mispricing in financial markets, leading to phenomena like overreaction to news or short-term price volatility. Subrahmanyam highlights studies showing that subtle disclosures or less prominent financial information are often overlooked by investors, impacting asset pricing and return predictability.

Hirshleifer and Teoh (2003) provide additional insights into availability bias in the context of financial reporting. They note that investors tend to focus on information that is prominent, vivid, or presented in a way that makes it readily accessible (Hirshleifer & Teoh, 2003). For example, disclosures in footnotes may be less attended to than items prominently displayed in the main financial statements (Hirshleifer & Teoh, 2003). When investors have limited attention, they are more likely to weigh certain pieces of information over others, not necessarily because of their economic importance but due to their presentation. This can result in biased decision-making, leading to mispricing in the markets (Hirshleifer & Teoh, 2003). The availability bias affects how investors process financial reports, leading to underreaction or overreaction depending on how information is disclosed (Hirshleifer & Teoh, 2003). Misjudgments can occur when attention is disproportionately directed toward more accessible or salient stimuli, irrespective of their actual relevance (Hirshleifer & Teoh, 2003).

Together, these studies underscore the significant role of availability bias in shaping investor behavior and market dynamics. By influencing how investors process and react to information, availability bias leads to temporary market inefficiencies, such as price distortions and excessive volatility. These insights form the foundation for understanding how availability bias impacts stock market performance, as explored in this thesis.

3.4 Importance of Behavioral Finance in Modern Market Analysis

Limitations in explaining phenomena like trading patterns, portfolio choices, and stock return variations beyond risk factors (Subrahmanyam, 2008). The reliance of traditional finance on rational economic theories may not accurately reflect how people behave in

financial markets, resulting in a restricted understanding of financial phenomena (Subrahmanyam, 2008). Notably, traditional theories often fail to satisfactorily account for heuristic patterns, which typically undermine investor portfolio performance (Subrahmanyam, 2008).

Individuals frequently experience behavioral biases, and the conventional models provided by traditional finance fail to offer adequate explanations (Baker & Ricciardi, 2014). Put differently, the theories in traditional finance struggle to explain the actions observed in real-world scenarios (Baker & Ricciardi, 2014). From a behavioral perspective, these normative frameworks do not work due to human irrationality or reliance on inaccurate information (Baker & Ricciardi, 2014). Traditional finance theory is normative as it prescribes how investors should make decisions (Baker & Ricciardi, 2014).

Conversely, the behavioral finance approach seeks to understand the underlying reasons for the decisions that investors actually make (Baker & Ricciardi, 2014). Behavioral finance provides a broader perspective on the underlying motives driving individual investors' trading activities, their methods for selecting portfolios, and their approaches to evaluating performance, emphasizing the importance of understanding investment behavior (Subrahmanyam, 2008). Behavioral finance has emerged as a dynamic field challenging traditional finance paradigm, especially in understanding stock returns and trading behavior (Subrahmanyam, 2008).

3.5 Impact of Behavioral Biases on Investing performance

Investors navigate a diverse decision-making process that covers both quantitative and qualitative factors, shaped by the attributes of the financial instrument or service (Baker & Ricciardi, 2014). When it comes to financial planning and investment management, individuals, financial professionals, and traders explore mental processes and emotional biases (Baker & Ricciardi, 2014). These are the subjects of investor behavior analysis. Biases often lead to flawed, misguided, or irrational investment choices (Baker &

Ricciardi, 2014). Recognizing and comprehending various biases and behavioral tendencies can empower individuals to make prudent financial decisions, which serve as the cornerstone of successful investing (Otuteye & Siddiquee, 2015).

While heuristic biases serve as tools for investors aiming to minimize the risk of loss in ambiguous circumstances, their use often reduces mental effort in the decision-making process, leading to errors in judgment and contributing to market inefficiency (Shah et al., 2018). Financial economists have long contended that these mental shortcuts significantly shape financial decision-making and predictions of financial indicators like earnings or profits, consequently affecting how financial markets operate (Shah et al., 2018).

Numerous studies highlight these tendencies observed in both individual investors and financial professionals, shedding light on the broader impact of these biases on market behavior and efficiency. By examining various aspects of market dynamics, including reactions to unexpected news events, the extremity of forecasts made by analysts, and the responses to earnings information, studies collectively underscore the pervasive influence of mental shortcuts in financial markets (Abarbanell and Bernard, 1992; Debondt and Thaler, 1985).

For instance, overconfidence bias can lead investors to overestimate their ability to predict market movements, resulting in excessive trading and suboptimal portfolio performance (Barber & Odean, 2000). Herding behavior, driven by the fear of missing out, can cause investors to follow the crowd, often leading to market bubbles and subsequent crashes (Shiller, 2000). Loss aversion, a key concept in prospect theory, explains why investors might hold onto losing stocks for too long, hoping to avoid realizing a loss, which can further exacerbate poor investment performance (Kahneman & Tversky, 1979)

Understanding how heuristic biases impact investing performance is crucial for comprehending financial markets and investor behavior. This chapter reviews existing literature

to uncover how these biases influence decision-making processes and shape investment outcomes. By combining findings from past studies, this chapter aims to deepen the understanding of the role of heuristic biases in investment performance. This understanding can provide valuable insights for investors, financial professionals, and policymakers, helping them navigate the complexities of financial markets and enhance investment decision-making processes.

The exploration of behavioral finance highlights how cognitive biases like availability bias shape investor behavior and market outcomes. The following chapter delves deeper into the existing literature, examining empirical studies that have investigated the impact of these biases. This review will provide the foundation for developing the hypothesis and research design of this thesis.

4 Literature Review and Hypothesis Development

By grounding the study in prior research, this chapter aims to integrate both the theoretical foundations and empirical context necessary to understand the behavioral and cognitive mechanisms driving financial decision-making and market dynamics. The chapter begins with an exploration of availability bias, specifically discussing the origins of the availability heuristic and its role in influencing human judgment. It examines how salience, recency, and ease of recall shape perceptions of frequency and probability. This section reviews seminal experiments and more recent studies, delving into the cognitive and neuropsychological mechanisms underlying this bias.

Next, the chapter examines the impact of availability bias on financial markets. Behavioral finance research demonstrates that availability bias contributes to market anomalies, such as overreaction to news or high-attention events, mispricing of assets, and forecasting errors. This section integrates studies showing how cognitive biases influence both individual investor behavior and aggregate market outcomes.

Finally, the chapter addresses the identification of high-attention events, which are central to understanding the manifestations of availability bias in financial settings. It discusses how various proxies, such as Google Trends data, trading volume, and media coverage, have been used to capture investor attention and link it to market reactions. These data-driven approaches provide valuable tools for identifying and quantifying the effects of availability bias on financial performance.

4.1 Overview of Research on Availability Bias

Behavioral biases, such as the availability heuristic, play a significant role in shaping market reactions and investment performance. The availability heuristic describes the tendency of individuals to assess the likelihood of events based on how easily similar instances come to mind (Tversky and Kahneman, 1973). This bias leads individual to place

undue weight on recent or prominent information, often at the expense of a more comprehensive analysis. Numerous studies have explored the implications of this phenomenon in financial markets, providing insights into how it affects decision-making and market outcomes.

Tversky and Kahneman (1973) first introduced the availability heuristic as part of their broader exploration of cognitive biases. They demonstrated through a series of experiments how ease of recall drives judgments rather than actual statistical frequency. This tendency is particularly pronounced when the recalled information is vivid or emotionally charged, leading to distorted perceptions of likelihood. For instance, participants were asked whether certain letters appeared more frequently in the first or third position of English words. Despite objective data showing that "K" is more frequent in the third position, participants overwhelmingly judged it to be more common as the first letter, as words starting with "K" (e.g., "kite") were easier to recall than those with "K" in the third position (e.g., "bake"). This distortion illustrates the heuristic's tendency to prioritize salience over statistical accuracy.

The effect of salience was further demonstrated in another experiment where participants judged the relative frequency of names on lists containing both famous and less famous individuals. Participants consistently overestimated the frequency of the gender associated with famous names, such as judging a list containing 19 famous women and 20 less famous men to have more women. This highlights how the memorability of vivid, prominent stimuli amplifies availability and distorts frequency judgments. Similarly, word-pair studies showed that strongly associated pairs (e.g., "knife-fork") were perceived as occurring more frequently than unrelated pairs (e.g., "lamp-fork"), even when both appeared with equal frequency. These findings are particularly relevant to financial decision-making, where associations (e.g., between inflation and stock prices) may be exaggerated due to their salience, leading to errors in judgment.

Daniel et al. (2002) extended this understanding by incorporating availability bias into financial decision-making models. They demonstrated how investors and analysts often fail to discount manipulated or biased signals, giving undue weight to readily available information. This cognitive shortcut, while efficient, can lead to distorted market prices as flawed but salient information is prioritized over more reliable but less accessible data.

Similarly, Ganzach (2000) explored the role of availability bias in analysts' risk-return assessments for unfamiliar stocks. He found that analysts often rely on global attitudes, such as perceiving "good" stocks as high-return and low-risk, instead of conducting thorough evaluations. This reliance on readily available attributes simplifies complex decision-making but can result in biased assessments and misinformed recommendations.

Availability heuristic is also evident in economic forecasting, particularly in the form of recency bias. Lee et al. (2005) analyzed survey data from professional forecasters and observed a pronounced recency bias, a specific form of availability bias, in growth predictions. Forecasters were found to overweight current economic conditions when projecting long-term growth, resulting in overly optimistic predictions during expansions and excessively pessimistic ones during contractions. This pattern of biased forecasting illustrates the heuristic's impact on macroeconomic decision-making and its potential to misinform long-term investment strategies.

In addition to these cognitive and behavioral insights, neuropsychological studies have provided evidence of the biological underpinnings of availability bias. For example, De Martino et al. (2006) used fMRI to show how emotional salience amplifies cognitive biases, linking increased activity in the amygdala—a region associated with emotional processing—to vivid, emotionally charged information that is more easily recalled. The study also showed that individuals with higher cognitive control (reflected in greater prefrontal cortex activity) are better able to mitigate these biases, underscoring the interplay between emotional processing and rational decision-making.

Taken together, these findings highlight the pervasive influence of availability bias on decision-making, demonstrating how cognitive shortcuts driven by salience and recallability distort judgments in financial and economic contexts. The heuristic simplifies complex decision-making processes but introduces systematic biases that influence behavior at both individual and market levels. Understanding the mechanisms of availability bias provides a foundation for exploring its broader impact, particularly in financial markets. The following section will examine how availability bias contributes to market-level phenomena, such as overreaction to high-attention events and subsequent performance implications.

4.2 Impact on Market Reactions and Performance

Behavioral finance research has extended Tversky and Kahneman's foundational work, linking availability bias to broader market phenomena such as overreaction, speculative bubbles, and herding behavior. Shiller (2000, 2020) emphasized that media amplification of salient events can exacerbate volatility, as collective memory magnifies the perceived likelihood of similar occurrences in the future. By analyzing historical market patterns and media narratives, Shiller (2000) demonstrated that waves of public attention or inattention influence investors' focus on specific investment categories, such as stocks versus bonds or domestic versus foreign assets. Heightened public attention often correlates with speculative bubbles, while neglect results in mispriced assets and underinvestment in less visible markets. This cyclical nature of attention underscores the significant role of availability bias in asset allocation and market dynamics.

The availability heuristic has been directly linked to overreaction in financial markets, particularly during high-attention events like earnings announcements, geopolitical crises, or corporate scandals. Barber and Odean (2007, 2008) explored how individual investors disproportionately trade stocks featured in recent news stories. Using retail brokerage data, they found that investors are drawn to stocks with high trading volumes, extreme price movements, or significant media coverage. This focus on high-attention

stocks, driven by the availability of vivid information, often leads to suboptimal investment decisions. For instance, these stocks tend to underperform in the long term, as initial overreaction subsides and fundamentals regain prominence. The findings highlight how availability bias distorts stock selection and emphasizes the need to mitigate attention-driven biases in investment strategies.

Chiodo et al. (2003) constructed a belief-formation model illustrating how media coverage influences investor perceptions. Their research showed that stocks receiving significant attention often experience short-term overreactions due to the increased salience of recent news. However, these overreactions typically correct over time as market participants reassess fundamental value. This dual effect of availability bias—driving immediate responses but enabling longer-term corrections—illustrates both its risks and its potential as a learning mechanism for investors.

Similarly, Hirshleifer et al. (2011) analyzed the impact of salient events, such as corporate scandals and economic crises, on market reactions. They documented that vivid and easily recalled events anchor investor expectations, leading to exaggerated responses. This anchoring effect often causes market participants to neglect more fundamental drivers of value, such as cash flows or earnings projections, thereby contributing to market inefficiencies.

Taken together, these studies illustrate how availability bias shapes market behavior. By focusing on vivid and prominent information, investors and analysts often overreact to high-attention events, creating temporary distortions in prices. Over time, markets tend to correct these mispricings, but not before creating inefficiencies that can significantly impact short-term performance. Understanding these dynamics is essential for developing strategies to mitigate the effects of availability bias and enhance decision-making in financial markets.

4.3 Identification of High-Attention Events Using Data Proxies

A consistent theme across studies that leverage Google Trends is the use of search volume data as a proxy for investor attention. This methodology aligns well with the focus of this thesis, which seeks to identify high-attention events and analyze their impact on stock volatility and performance. By tracking changes in search volume for specific financial terms, these studies provide a framework for capturing shifts in collective investor behavior.

Several studies provide a robust framework for utilizing Google search volume as an indicator of high-attention events. Preis et al. (2013) demonstrate that spikes in Google search volume reflect heightened investor concern, often preceding market movements. They hypothesized that changes in search volume for financially relevant terms could reflect investor concerns and anticipate market trends, offering insights into the decision-making processes of market participants

To test this, Preis et al. (2013) tracked search volume for 98 financial terms from 2004 to 2011, with a particular focus on the term "debt," strongly associated with the 2008 financial crisis due to its ability to reflect investor sentiment. Weekly changes in search volume were measured, and a trading strategy was developed to respond to increases, which indicated market concern, or decreases, which suggested optimism. The performance of this strategy was compared to a buy-and-hold strategy and random investment strategies, with portfolio value changes and cumulative returns calculated to assess its effectiveness.

The results showed that the Google Trends strategy significantly outperformed both the buy-and-hold strategy and random strategies. Increases in search volume often preceded market declines, reflecting investor concern before major sell-offs, while decreases in search volume were associated with market rebounds. These findings provide evidence of availability bias causing short-term overreaction, aligning with the hypothesis that heightened attention on accessible information drives volatility. Spikes in Google

search volume indicated increased investor focus on prominent terms, leading to price fluctuations.

The study underscores that search volume data can be leveraged to create profitable trading strategies. It shows that increases in search activity, based on easily accessible and prominent information, are associated with short-term overreactions in stock prices. Although traders can exploit these patterns for positive outcomes, the broader implications of availability bias, such as increased volatility and eventual price corrections, support the hypothesis that availability bias influences long-term market returns.

Expanding on these insights, Da et al. (2011) examined the relationship between search volume using Google Trends data and stock price dynamics, finding that increased search volume correlates with short-term price spikes, followed by a reversion. This aligns with the premise that availability bias can cause temporary price distortions due to investors overreacting to easily accessible information. Da et. al. (2015) refined this analysis by distinguishing between general search volume and sentiment-based searches (e.g., "recession" vs. neutral search terms). Their findings indicate that negative sentiment searches have stronger predictive power for stock returns compared to neutral searches, suggesting that investor fear and uncertainty amplify availability-driven market effects.

Further extending the use of Google Trends, Bank et. al., (2011) analyzed the German stock market, using search volumes for company names instead of ticker symbols to better capture public attention. Their findings showed that increased search volume significantly improves stock liquidity and boosts short-term returns, particularly for smaller firms. They further demonstrated that spikes in search volume are indicative of elevated investor activity, reinforcing the idea that availability bias leads to increased trading based on prominent information. The study also highlights the importance of considering firm name searches over ticker symbols, refining the methodology for measuring investor attention.

While Google Trends provides a reliable proxy for investor attention, several studies explore alternative measures, including news coverage, media sentiment, and Wikipedia searches. Tetlock (2007) introduced news sentiment analysis as a measure of investor sentiment, demonstrating that negative media coverage predicts stock market declines. His study found that spikes in negative sentiment words in financial news are followed by lower stock returns, reinforcing the idea that availability bias amplifies market reactions when investors focus on vivid, negative narratives.

Similarly, Vlastakis and Markellos (2012) examined the relationship between information demand and stock market volatility, demonstrating a strong relationship between Google search volume and stock market fluctuations, and highlighting that investors search for financial terms more frequently during times of uncertainty. This further supports the link between availability bias and market volatility, as investors tend to fixate on salient financial risks, driving fluctuations in trading behavior.

Another extension of search volume in investor decision-making, Drake et. al., (2012) found that Google search volume predicts investor reactions to earnings announcements. Their findings showed that higher search activity precedes abnormal stock returns and trading volume, reinforcing the idea that availability bias manifests before price movements occur.

The studies collectively demonstrate that Google Trends data serves as an effective tool for identifying high-attention periods in financial markets. Across various papers, researchers have established procedures for detecting spikes in investor attention by analyzing search volume thresholds, often defined relative to historical norms or percentage changes. These spikes are typically linked with behavioral changes observable through trading volume, abnormal returns, or changes in liquidity. As such, the literature provides strong empirical justification for using search activity to capture shifts in investor focus prior to actual market movements.

For instance, studies by Preis et al. (2013), Da et al. (2011), and Bank et al. (2011) show how changes in search volume can reveal periods of heightened attention that correspond with short-term price overreactions or shifts in volatility. These results support the notion that availability bias can be detected before it fully materializes in prices. Similarly, alternative proxies such as news sentiment (Tetlock, 2007), information demand (Vlastakis & Markellos, 2012), and Wikipedia searches (Drake et al., 2012) further strengthen the understanding of how investor attention precedes and amplifies market responses.

Taken together, these studies offer a methodological foundation for the approach used in this thesis. While the next chapter will outline the specific procedures adopted in the current research, the existing literature clearly supports the relevance and applicability of attention-based data in capturing behavioral dynamics in financial markets. By drawing on these prior findings, this thesis builds upon an established empirical tradition to explore how availability bias influences stock price behavior in both the short and long term.

5 Data and Methodology

This chapter outlines the methodology used in the empirical portion of this thesis. It begins with a detailed explanation of the data collection process, including the selection criteria and justification for the dataset. The study leverages Google Trends data as a proxy for investor attention and integrates stock market data to capture market reactions to information availability. Following this, the methodology used to measure market responses is introduced. The analysis employs event study techniques to quantify price movements and volatility shifts surrounding high-attention periods. Finally, statistical methods used to evaluate the significance of the findings are presented, including the calculation of Cumulative Abnormal Returns (CARs) and pre- and post-event volatility measures. This methodological framework is designed to test the link between cognitive attention mechanisms and financial market dynamics in both the short and long term.

5.1 Data description

The empirical analysis is based on two primary data sources: Google Trends Search Volume Index (GSVI), which proxies investor attention, and historical stock price data retrieved from Yahoo Finance. The study covers the time period from 2020 to 2025, during which data was collected for a broad cross-section of publicly traded companies. This five-year span was selected to ensure coverage of different market conditions, including both high-volatility and relatively stable periods.

The GSVI provides a normalized “interest over time” metric, ranging from 0 to 100, where 100 represents peak search popularity and 0 indicates no measurable interest. This relative measure of search volume is used to identify high-attention events, defined as spikes in search interest that exceed 45% above a 30-day rolling average. When multiple peaks were observed within a short timeframe, the most prominent and isolated spike was selected for consistency.

A total of 50 companies were initially sampled across diverse industries using random selection to avoid sectoral bias. Of these, 25 companies exhibited qualifying GSVI spikes and were included in the final analysis. For each identified event, corresponding stock data, including daily prices, returns, volatility measures, and market index data (S&P 500), was compiled to evaluate market behavior around the event dates.

Table 2 - Sample Overview

Company Name	Industry	Marke Cap	GSVI Date	Peak	Aver.
C1 Tesla Inc.	Consumer Discretionary	20,98	21.04.2024	100	86,33
C2 AMC Entertainment	Entertainment	16,45	28.01.2021	100	35,33
C3 Fox Corporation	Communication Services	16,51	14.05.2023	100	35,33
C4 Palantir Technologies	Information Technology	18,99	06.02.2024	100	47,33
C5 KeyCorp	Financials	16,76	11.08.2024	100	49,00
C6 Humana Inc.	Health Care	17,84	29.01.2023	100	38,33
C7 Monster Beverage	Consumer Staples	17,91	24.12.2023	100	50,33
C8 Palo Alto Networks	Information Technology	18,59	25.02.2024	100	84,67
C9 Best Buy Co., Inc.	Consumer Discretionary	16,64	24.11.2024	43	29,67
C10 CoStar Group Inc.	Real Estate	17,41	05.04.2020	15	8,33
C11 Pool Corporation	Consumer Discretionary	16,37	10.11.2024	100	48,33
C12 Autodesk, Inc.	Information Technology	17,96	25.08.2024	70	48,33
C13 Garmin Ltd.	Consumer Discretionary	16,95	26.07.2020	100	81,00
C14 Intel Corporation	Information Technology	18,28	28.07.2024	77	51,33
C15 Iron Mountain Inc.	Real Estate	16,83	23.04.2023	100	50,33
C16 Atwood Oceanics, Inc.	Oil & Gas	17,55	10.01.2021	100	72,00
C17 Analog Devices, Inc.	Information Technology	17,82	12.07.2020	100	56,33
C18 Lululemon Athletica Inc.	Consumer Discretionary	17,82	22.11.2020	47	29,33
C19 Albemarle Corporation	Materials	16,57	10.01.2021	100	72,00
C20 Meta Platforms, Inc.	Technology	19,57	25.12.2022	85	57,00
C21 Amcor plc	Materials	16,87	17.11.2024	100	63,67
C22 Tyson Foods, Inc.	Consumer Staples	16,83	10.11.2024	100	43,67
C23 Wynn Resorts, Ltd.	Consumer Discretionary	16,05	23.01.2022	58	43,33
C24 Genuine Parts Company	Consumer Discretionary	16,49	13.12.2020	54	49,00
C25 Deere & Company	Industrials	18,67	31.07.2022	85	61,33

Table 2 above summarizes the 25 firms included in the final sample, along with their respective industry sectors, log market capitalizations, and key GSVI metrics. The

“Average” column reflects each firm’s three-week average GSVI value, calculated over the period leading up to and including the date of the peak. This measure captures the typical level of investor attention during the buildup to a high-attention event, highlighting the contrast between baseline interest and the spike.

Table 3 - GSVI Descriptive Statistics

GSVI	
Mean	85,36
Median	100
Mode	100
Standard Deviation	23,878
Kurtosis	1,889
Skewness	-1,617
Range	85
Minimum	15
Maximum	100
Count	25

Table 3 presents descriptive statistics for GSVI peak values across the sample. The maximum peak value is 100 for most firms. The distribution shows moderate variation in the intensity of attention spikes, with a mean peak of 85,36 and a standard deviation of 23,88, reflecting differences in how prominently each firm featured in investor search activity.

To visually illustrate the nature of high-attention events in the sample, Figures 2 through 4 present Google Trends data for three selected companies: Monster Beverage Corp., Palo Alto Networks, and Analog Devices. These Figures highlight distinct peaks in search interest, corresponding with the GSVI spike dates reported in Table 2. The sharp increases in investor attention for these firms were driven by different types of events, ranging from earnings announcements and partnerships to mergers and acquisitions. These peaks were used as event anchors for return and volatility analysis in the empirical section of this thesis.

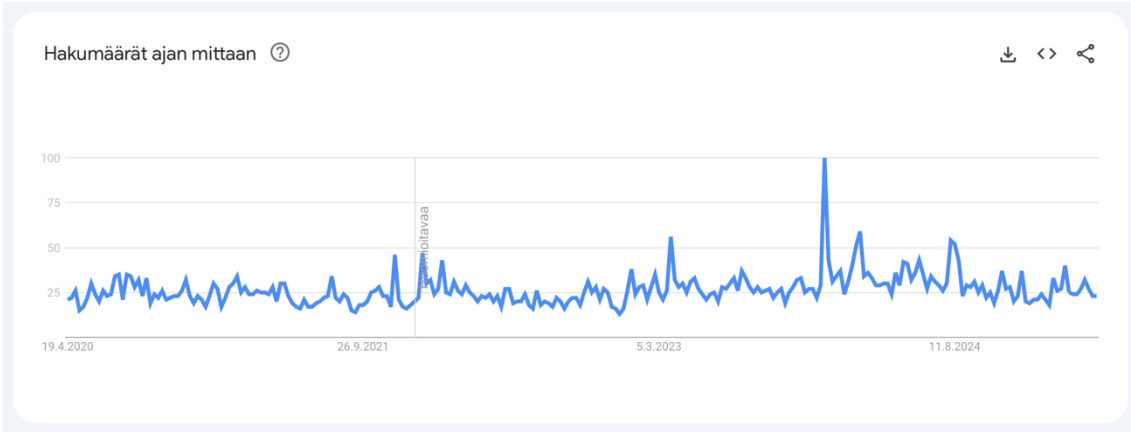


Figure 2 - Monster Beverage Corp. GSVI spike

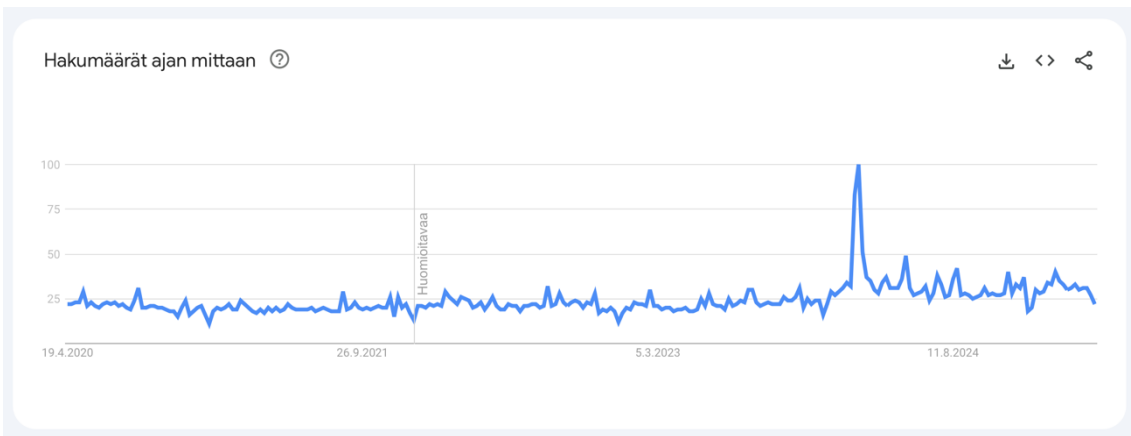


Figure 3 - Palo Alto Networks GSVI spike

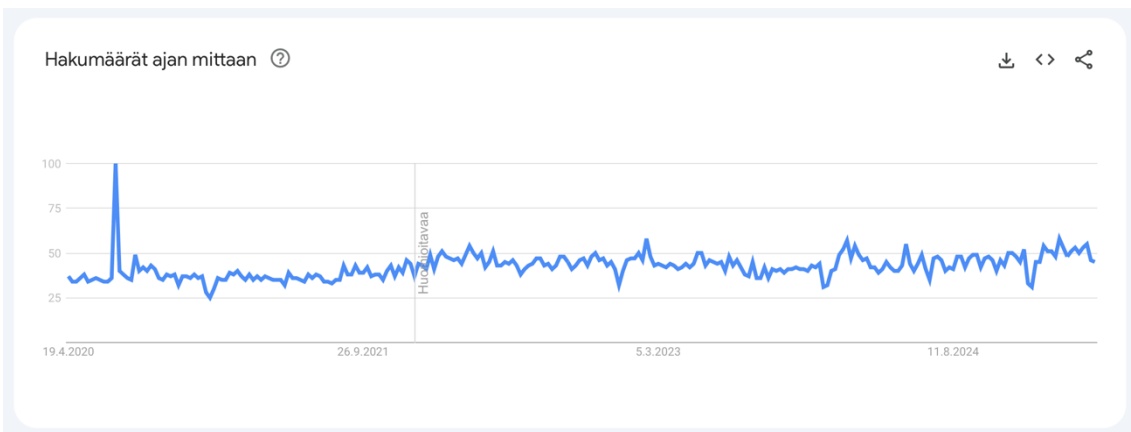


Figure 4 - Analog Devices GSVI spike

5.2 Methodology

To capture both short- and long-term market responses, the study applies event windows of 7, 30, and 90 days before and after the peak in GSVI. This structured dataset forms the basis for analyzing the impact of investor attention on abnormal returns and volatility in the stock market.

To capture total stock performance over specific time intervals surrounding high-attention events, daily simple returns were first computed using the formula:

$$r_t = \frac{P_t}{P_{t-1}} - 1 \quad (1)$$

where P_t and P_{t-1} represent the closing prices of the stock on day t and $t - 1$, respectively.

Cumulative return over an event window $t-90$, $t-30$, $t-7$, $t+7$, $t+30$, and $t+90$ were then derived using the compound return formula:

$$\text{Cumulative Return} = \prod_{t=t_1}^{t_2} (1 + r_t) - 1 \quad (2)$$

This formula was applied across all six event windows. The cumulative return captures the total gain or loss a stock experienced in each interval.

To isolate firm-specific performance from general market movements, abnormal returns (ARs) were calculated using a market model. Each firm's returns were regressed against the returns of the S&P 500 index over a 180-day estimation window prior to the event, using logarithmic returns to ensure consistency in percentage change measurement. This approach accounts for the influence of overall market trends and enables a clearer interpretation of whether investor attention leads to statistically significant deviations in

stock performance beyond what would be expected from general market movements alone. A market model regression was estimated for each firm over the 180-day pre-event window:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it} \quad (3)$$

Where:

- r_{it} is the log return of stock i at time t , calculated as

$$r_{it} = \ln\left(\frac{P_{it}}{P_{it-1}}\right) \quad (4)$$

with P_{it} being the closing price of stock i at time t

- r_{mt} is the log return of the market index (S&P 500), calculated similarly

$$r_{mt} = \ln\left(\frac{M_t}{M_{t-1}}\right) \quad (5)$$

with α_i being the constant from the regression or the average excess return not explained by the market and β_i being the slope coefficient from the regression or the sensitivity of the stock's returns to market returns

- ϵ_{it} is the error term, capturing the portion of return unexplained by market movements.

Expected market returns were then calculated as:

$$\hat{r}_{it} = \alpha_i + \beta_i r_{mt} \quad (6)$$

Abnormal returns were computed as the difference between actual and expected returns:

$$AR_{it} = r_{it} - \hat{r}_{it} \quad (7)$$

These were aggregated across each event window to derive cumulative abnormal returns (CARs):

$$CAR_{i,[t_1,t_2]} = \sum_{t=t_1}^{t_2} AR_{it} \quad (8)$$

CARs quantify the total deviation from expected market behavior due to investor attention spikes and serve as a key metric in evaluating market overreaction or underreaction. Volatility was measured as the standard deviation of daily log returns over each event window. This measure captures the degree of price fluctuation and is defined as:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{t=1}^n (r_t - \bar{r})^2} \quad (9)$$

Where \bar{r} is the mean return over the event window, and n is the number of trading days in the window.

Descriptive statistics were computed to summarize the distributional characteristics of these the three core variables: volatility, cumulative returns, and cumulative abnormal returns (CARs) across the six time windows. These measures provide a foundational understanding of how stock price behavior evolves around periods of elevated investor attention. This statistical overview helps to identify patterns such as increased pre-event volatility, asymmetry in return distributions, or the persistence of possible abnormal returns, thereby informing the interpretation of subsequent regression analyses and hypothesis testing.

Table 4 - Descriptive Statistics of Volatility

Volatility						
	t-90	t-30	t-7	t+7	t+30	t+90
Mean	0,0605	0,0576	0,0711	0,0477	0,0430	0,0403
Standard Error	0,0361	0,0327	0,0457	0,0177	0,0188	0,0177
Median	0,0204	0,0234	0,0183	0,0228	0,0191	0,0183
Standard Deviation	0,1807	0,1636	0,2287	0,0884	0,0942	0,0885
Sample Variance	0,0327	0,0268	0,0523	0,0078	0,0089	0,0078
Kurtosis	24,817	24,559	24,073	19,549	23,291	24,134
Skewness	4,9738	4,9380	4,8750	4,2637	4,7633	4,8770
Range	0,9136	0,8300	1,1513	0,4446	0,4773	0,4504
Minimum	0,0129	0,0097	0,0082	0,0053	0,0110	0,0116
Maximum	0,9265	0,8397	1,1595	0,4499	0,4883	0,4620
Sum	1,5126	1,4395	1,7778	1,1916	1,0748	1,0085
Count	25	25	25	25	25	25
Largest(1)	0,9265	0,8397	1,1595	0,4499	0,4883	0,4620
Smallest(1)	0,0129	0,0097	0,0082	0,0053	0,0110	0,0116

Table 4 presents the summary statistics for volatility, measured as the standard deviation of daily returns over each time window. The table indicate that volatility tends to increase in the days leading up to a high-attention event, peaking around t-7. This suggests rising uncertainty or market anticipation prior to news or attention spikes. Post-event windows show a general decline in volatility, consistent with the idea that attention-driven volatility may be temporary. Notably, the sharp drop in both mean and median volatility post-event supports the notion that attention-induced market noise is short-lived. Furthermore, high kurtosis and skewness across all periods suggest the presence of outliers and non-normal return distributions, typical of stocks experiencing abnormal investor attention.

These patterns suggest that models assuming normality may not fully capture stock behavior during high-attention events. Elevated skewness likely reflects asymmetric market reactions to news, while high kurtosis points to fat-tailed distributions and extreme price movements. Together, these traits highlight the irregular and volatile nature of markets influenced by intense investor attention.

Table 5 - Descriptive Statistics of Cumulative Return

Cumulative Return						
	<i>t-90</i>	<i>t-30</i>	<i>t-7</i>	<i>t+7</i>	<i>t+30</i>	<i>t+90</i>
Mean	-0,0210	0,0137	-0,0136	0,0841	0,1001	0,1577
Standard Error	0,0268	0,0415	0,0148	0,0372	0,0388	0,0480
Median	-0,0312	-0,0070	-0,0021	0,0461	0,0603	0,1225
Standard Deviation	0,1341	0,2074	0,0741	0,1861	0,1940	0,2401
Sample Variance	0,0180	0,0430	0,0055	0,0346	0,0376	0,0576
Kurtosis	0,0696	17,8480	2,9762	5,6191	2,7797	1,1121
Skewness	0,3449	3,8288	-0,9560	1,3778	0,8516	0,9118
Range	0,5527	1,1912	0,3852	1,0610	0,9693	1,0218
Minimum	-0,3066	-0,2537	-0,2311	-0,3585	-0,3598	-0,2766
Maximum	0,2461	0,9375	0,1541	0,7024	0,6095	0,7453
Sum	-0,5260	0,3427	-0,3397	2,1024	2,5023	3,9426
Count	25	25	25	25	25	25
Largest(1)	0,2461	0,9375	0,1541	0,7024	0,6095	0,7453
Smallest(1)	-0,3066	-0,2537	-0,2311	-0,3585	-0,3598	-0,2766

Table 5 shows cumulative returns, which reflect the total stock price change over each window. While some firms experienced losses, the average cumulative return across the sample was generally positive, particularly in the longer post-event window (*t+90*).

Table 6 - Descriptive Statistics of Cumulative Abnormal Returns

CARs						
	<i>t-90</i>	<i>t-30</i>	<i>t-7</i>	<i>t+7</i>	<i>t+30</i>	<i>t+90</i>
Mean	-0,0619	-0,0192	-0,0099	0,0623	0,0132	0,0564
Standard Error	0,0273	0,0240	0,0117	0,0300	0,0367	0,0426
Median	-0,0485	-0,0445	-0,0005	0,0249	0,0322	0,0210
Standard Deviation	0,1366	0,1202	0,0587	0,1499	0,1833	0,2130
Sample Variance	0,0187	0,0144	0,0034	0,0225	0,0336	0,0454
Kurtosis	2,9538	13,8208	5,2617	6,9003	10,4495	4,1480
Skewness	0,0179	3,2446	-1,1716	2,2762	-2,2508	-0,5624
Range	0,6968	0,6546	0,3349	0,7788	1,0975	1,1583
Minimum	-0,3727	-0,1664	-0,2058	-0,1785	-0,7065	-0,6139
Maximum	0,3241	0,4882	0,1291	0,6002	0,3910	0,5443
Sum	-1,5465	-0,4802	-0,2482	1,5585	0,3299	1,4089
Count	25	25	25	25	25	25
Largest(1)	0,3241	0,4882	0,1291	0,6002	0,3910	0,5443
Smallest(1)	-0,3727	-0,1664	-0,2058	-0,1785	-0,7065	-0,6139

Table 6 reports the distribution of CARs, capturing firm-specific deviations from market performance. CARs are more volatile than raw cumulative returns, reflecting stock-specific over- or under-reactions to attention. Similar to cumulative returns, CARs show higher mean values in the post-event periods, with the largest values observed at t+90.

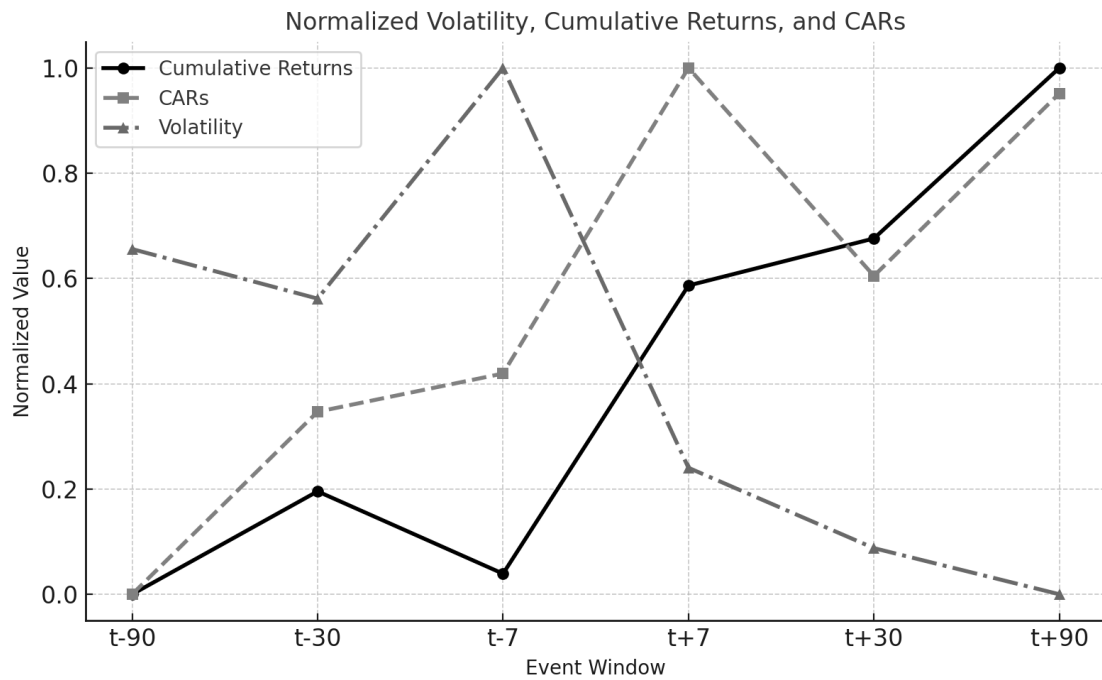


Figure 5 - Mean Volatility, Cumulative Returns, and CARs (Normalized)

Based on the descriptive statistics, Figure 5 visualizes the normalized average values of volatility, cumulative returns, and cumulative abnormal returns across six event windows surrounding high-attention periods. The chart shows that both cumulative returns and CARs tend to increase after the event, while volatility moves in the opposite direction. To empirically test the hypotheses on the relationship between investor attention and stock performance and volatility, two separate regression models are specified. The first model tests whether increased attention affects stock performance in the short and long-term following high-attention events. The second model analyzes whether investor attention contributes to abnormal increases in pre-event volatility. Each model controls for firm-specific characteristics such as size and market beta.

To test does heightened investor attention, proxied by GSVI, lead to significant cumulative abnormal returns, the following cross-sectional regression model is employed:

$$CAR_{i,t} = \alpha + \beta_1 \cdot GSVI_{i,t} + \beta_2 \cdot Volatility_{pre,i,t} + \beta_3 \cdot Size_i + \beta_4 \cdot Beta_i + \varepsilon_{i,t} \quad (10)$$

Where:

$CAR_{i,t}$ cumulative abnormal return for firm i over event window t (t+7, t+30, t+90)

$GSVI_{i,t}$ Google Search Volume Index at the time of the event

$Volatility_{pre,i,t}$ volatility prior to the event (t-30 or t-7)

$Size_i$ log of market capitalization at the time of the peak (firm-level)

β_1 : firm's historical beta relative to market index

$\varepsilon_{i,t}$ error term

This model evaluates whether spikes in investor attention are associated with stock price overreactions or underreactions, controlling for firm size, recent volatility, and systematic risk exposure. The dependent variable $CAR_{i,t}$ is calculated over multiple event windows (t+7, t+30, t+90) to assess both short- and longer-term market reactions.

The independent variables were selected based on the research objectives and existing literature. Investor attention is proxied by Google Trends data for each firm's stock ticker, measured as the average of the peak value and the four preceding weeks surrounding the attention event. In robustness checks, the raw Google Search Volume Index (GSVI) values are also standardized using z-scores. Cumulative Abnormal Returns (CARs) are computed using market model residuals across three post-event windows—t+7, t+30, and t+90—to capture both short- and long-term performance effects. Volatility is calculated as the standard deviation of daily log returns over a 7-day or 30-day pre-event window, allowing analysis of whether pre-event uncertainty predicts post-event returns. Firm size is measured as the natural logarithm of market capitalization at the time of the GSVI peak. Beta, representing the firm's sensitivity to market movements, is obtained from financial databases

To test are increased investor attention is associated with heightened post-event volatility, a second regression model is estimated:

$$Volatility_{i,t} = \alpha + \beta_1 \cdot GSVI_{i,t} + \beta_2 \cdot Size_i + \beta_3 \cdot CAR_{i,t} + \epsilon_{i,t} \quad (11)$$

The dependent variable represents realized volatility in the aftermath of the GSVI peak (e.g., over t+7 or t+30). By including CAR as a control, the model distinguishes the effect of attention on volatility from any impact caused by returns themselves. Firm size is included to account for the typical inverse relationship between size and volatility.

6 Results and discussion

This chapter presents the results of the empirical analysis examining how investor attention, as proxied by Google search volume spikes, influences stock price behavior. Three hypotheses are tested: H1a: Heightened investor attention leads to increased short-term stock returns. H1b: Heightened investor attention predicts a reversal in stock returns over longer time horizons. H2: Increased investor attention is positively associated with heightened stock price volatility prior to the attention spike.

The results focus on relationships between volatility, cumulative returns, and abnormal returns (CARs) across defined event windows, supported by correlation analysis, regressions, and visualizations. The results are discussed in relation to these hypotheses and the behavioral finance literature on availability bias.

6.1 Correlation results

Correlations between volatility, cumulative returns, and CARs were tested in order to explore the dynamics of market behavior around high-attention events. The analysis aims to identify whether pre-event variables, such as volatility and returns, are associated with post-event outcomes, particularly abnormal returns. The following sections interpret the results of correlation analyses in the context of the study's hypotheses. While correlations can highlight meaningful associations between variables, they cannot establish causality. As such, the findings should be understood as indicative of potential relationships rather than definitive evidence of directional effects.

To quantify the linear relationships between variables, Pearson correlation coefficients were calculated using the standard formula:

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \cdot \sigma_Y} \quad (12)$$

where $\text{Cov}(X, Y)$ is the covariance between two variables, and $\sigma_X \cdot \sigma_Y$ are their respective standard deviations. Statistical significance was assessed using t -tests for correlation coefficients:

$$t = \frac{r \cdot \sqrt{n - 2}}{\sqrt{1 - r^2}} \quad (13)$$

The corresponding two-tailed p -value is then derived from the t -distribution as:

$$p = 2 \cdot P(T > |t|), \quad T \sim t(n - 2) \quad (14)$$

where r is the sample correlation and n the number of observations. The p -value indicates the probability of observing such a correlation under the null hypothesis of no linear association. Significance levels are denoted by asterisks in the correlation tables ($p < 0,05$ *, $p < 0,01$ **, $p < 0,001$ ***).

Table 7 - Correlations between volatility and cumulative returns

Panel A	r_t-90	r_t-30	r_t-7	r_t+7	r_t+30	r_t+90
Vol_t-90	0,1479	0,9219 ***	0,4554 *	0,7037 ***	0,5658 **	-0,0012
Vol_t-30	0,1505	0,9071 ***	0,4213	0,7008 ***	0,5555 **	-0,0098
Vol_t-7	0,1611	0,9006 ***	0,3897	0,6955 ***	0,5472 **	-0,0228
Vol_t+7	0,0638	0,8638 ***	0,3161	0,6791 ***	0,5545 **	0,0178
Vol_t+30	0,1005	0,9056 ***	0,3985	0,6997 ***	0,5636 **	-0,0037
Vol_t+90	0,1189	0,9215 ***	0,4363 *	0,6996 ***	0,5689 **	0,0062

Significant at: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A presents the correlation between volatility across different time windows and cumulative raw returns. Notably, pre-event volatility at $t-30$ and $t-7$ shows strong positive correlations with returns shortly after the attention spike (e.g., Vol_t-30 and Return_t+7: 0,7008 ***), suggesting that periods of elevated volatility may precede price increases, potentially driven by speculative investor activity or anticipatory trading.

However, volatility at longer post-event windows (Vol_t+90) is not significantly correlated with long-term returns (Return_t+90), indicating that any initial price effects may not persist. These findings relate primarily to H2, as they provide partial evidence that increased volatility tends to precede investor attention spikes, though the causality cannot be definitively established.

Table 8 - Correlation between volatility and CARs

Panel B	CAR_t-90	CAR_t-30	CAR_t-7	CAR_t+7	CAR_t+30	CAR_t+90
Vol_t-90	0,5768 **	0,8741 ***	0,4717 *	0,7536 ***	-0,8078 ***	-0,6351 **
Vol_t-30	0,5831 **	0,8552 ***	0,4365 *	0,7446 ***	-0,8185 ***	-0,6480 **
Vol_t-7	0,5884 **	0,8430 ***	0,4001	0,7355 ***	-0,8234 ***	-0,6512 **
Vol_t+7	0,3931	0,7669 ***	0,3444	0,7641 ***	-0,7052 ***	-0,5841 **
Vol_t+30	0,4916 *	0,8338 ***	0,4286 *	0,7722 ***	-0,7630 ***	-0,6254 **
Vol_t+90	0,5202 *	0,8615 ***	0,4589 *	0,7665 ***	-0,7752 ***	-0,6151 **

*Significant at: *p < 0.1, **p < 0.05, ***p < 0.01*

Panel B displays the correlation coefficients between volatility at different time windows and CARs. The results indicate strong and statistically significant positive correlations between pre-event volatility (t-90 to t-7) and short-term post-event CARs (e.g., Vol_t-30 and CAR_t+7: 0.7446 ***). This pattern suggests that attention events linked to heightened volatility tend to produce abnormally high short-term returns, supporting the notion that heightened investor attention possibly leads to increased short-term stock returns.

Importantly, these positive short-term relationships reverse over longer horizons, with strong negative correlations emerging between pre-event volatility and long-term CARs (e.g., Vol_t-30 and CAR_t+30: -0.8185 ***). This trend supports H1b, indicating that early price increases are not sustained and may be corrected over time, consistent with return reversal and mispricing correction theories.

Post-event volatility (Vol_t+7 to Vol_t+90) also shows a similar results. It is positively correlated with short-term CARs (t+7), but negatively with CARs at t+30 and t+90. These

findings suggest that volatility spikes are short-lived and possibly tied to overreaction rather than persistent fundamental change.

Table 9 - correlation between cumulative raw returns and abnormal returns

Panel C	CAR_t-90	CAR_t-30	CAR_t-7	CAR_t+7	CAR_t+30	CAR_t+90
r_t-90	0,6165 **	0,2400	0,0952	-0,1567	-0,4401 *	-0,5543 **
r_t-30	0,5676 **	0,9304 ***	0,6551 ***	0,6773 ***	-0,7194 ***	-0,6028 **
r_t-7	0,4224	0,6912 ***	0,9471 ***	0,3557	-0,3111	-0,2947
r_t+7	0,1433	0,6129 **	0,3512	0,9662 ***	-0,2895	-0,1217
r_t+30	-0,0704	0,5010 *	0,3218	0,9072 ***	-0,0450	0,1271
r_t+90	-0,5193 *	-0,0181	-0,0814	0,4194	0,4085	0,6368 **

Significant at: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C displays the relationship between cumulative raw returns and abnormal returns (CARs). The results show that pre-event returns (especially at $t-90$ and $t-30$) are strongly and positively correlated with early CARs (e.g., r_{t-30} and CAR_{t-30} 0,9304 ***), indicating that stocks with recent strong performance often exhibit short-term abnormal returns, possibly due to momentum or attention-driven buying behaviour. This supports H1a, as it suggests heightened attention may amplify recent trends.

Over longer horizons, these correlations turn negative (e.g., r_{t-30} and CAR_{t+90} : -0,6028 **), suggesting that initial gains may be followed by reversals, in line with H1b. This pattern reinforces the view that investor attention can drive short-term overvaluation, which is later corrected as markets revert toward fundamentals. Additionally, r_{t+90} shows a positive correlation with CAR_{t+90} (0,6368 **), indicating that long-term adjustments may align with deeper value factors rather than short-term attention spikes.

To support the interpretation, heatmaps were used to visualize the strength and variation of volatility, returns, and CARs across firms and time windows. Values were normalized to enhance comparability, with darker shades indicating higher intensity.

Table 10 - Volatility Heatmap

Volatility	t-90	t-30	t-7	t+7	t+30	t+90
C1	24,75 %	18,22 %	0,00 %	100,00 %	56,88 %	38,85 %
C2	67,16 %	54,93 %	100,00 %	0,00 %	5,41 %	1,70 %
C3	89,07 %	100,00 %	10,44 %	85,09 %	0,00 %	26,26 %
C4	3,46 %	0,00 %	6,94 %	100,00 %	50,78 %	22,20 %
C5	13,21 %	34,95 %	0,00 %	100,00 %	43,18 %	47,99 %
C6	12,05 %	0,00 %	26,95 %	100,00 %	36,20 %	27,91 %
C7	100,00 %	64,60 %	98,25 %	0,00 %	55,75 %	64,64 %
C8	19,76 %	42,34 %	100,00 %	12,18 %	3,23 %	0,00 %
C9	18,54 %	100,00 %	81,59 %	0,00 %	87,28 %	29,66 %
C10	32,94 %	100,00 %	61,27 %	50,61 %	41,95 %	0,00 %
C11	14,22 %	89,46 %	100,00 %	96,95 %	18,16 %	0,00 %
C12	100,00 %	92,24 %	0,00 %	11,94 %	16,38 %	35,03 %
C13	100,00 %	19,94 %	77,77 %	86,38 %	0,00 %	9,45 %
C14	0,00 %	6,80 %	1,40 %	100,00 %	55,92 %	31,88 %
C15	100,00 %	58,44 %	43,17 %	0,00 %	26,46 %	29,92 %
C16	18,12 %	0,00 %	100,00 %	73,40 %	33,44 %	42,08 %
C17	100,00 %	67,59 %	0,00 %	91,06 %	45,78 %	45,81 %
C18	92,82 %	82,21 %	35,30 %	0,00 %	100,00 %	64,68 %
C19	100,00 %	91,73 %	86,81 %	0,00 %	28,84 %	77,08 %
C20	100,00 %	47,88 %	32,15 %	11,32 %	0,00 %	53,01 %
C21	36,36 %	75,05 %	0,00 %	100,00 %	46,37 %	32,35 %
C22	19,08 %	0,00 %	1,97 %	100,00 %	41,11 %	26,93 %
C23	48,31 %	42,36 %	100,00 %	0,00 %	13,16 %	70,68 %
C24	100,00 %	91,18 %	36,54 %	0,00 %	56,89 %	81,99 %
C25	100,00 %	71,51 %	15,39 %	31,08 %	0,00 %	11,87 %

A general pattern can be observed in the volatility heatmap, where the darkest shades are concentrated in the pre-event periods (t-90 to t-7) and around the event peak (t+7). This suggests that volatility tends to peak before or around the attention. Volatility then decreases noticeably in the post-event windows (t+30 and t+90), indicating that markets tend to stabilize as new information is absorbed and priced in. At the firm level, volatility peaks pre-event for companies like C2, C8, C9, C11, C16, and C23, potentially indicating speculative behaviour or early signals. Others (e.g., C3, C4, C5, C6) exhibit post-event volatility surges, which may reflect delayed market reactions. Firms such as C7 and C17 display consistently high volatility throughout the event window, pointing to prolonged sensitivity to attention-related dynamics. Meanwhile, C14, C21, and C22 show low pre-

event volatility but spike sharply at t+7, suggesting more sudden investor responses. These patterns support H2, indicating that elevated investor attention can coincide with or precede increased volatility, though timing and magnitude vary by firm.

Table 11 - Return Heatmap

Returns	t-90	t-30	t-7	t+7	t+30	t+90
C1	0,00 %	14,46 %	14,93 %	58,71 %	60,79 %	100,00 %
C2	0,00 %	100,00 %	9,00 %	72,69 %	61,90 %	5,33 %
C3	0,00 %	20,53 %	51,33 %	60,69 %	95,32 %	100,00 %
C4	0,00 %	21,16 %	13,72 %	81,08 %	100,00 %	91,64 %
C5	0,91 %	0,00 %	12,91 %	50,41 %	38,74 %	100,00 %
C6	0,00 %	30,46 %	42,57 %	51,98 %	64,59 %	100,00 %
C7	38,79 %	37,68 %	0,00 %	80,43 %	31,60 %	100,00 %
C8	78,48 %	16,25 %	0,00 %	78,84 %	66,66 %	100,00 %
C9	0,00 %	34,10 %	32,87 %	71,99 %	100,00 %	91,02 %
C10	16,19 %	0,00 %	24,81 %	69,65 %	68,89 %	100,00 %
C11	100,00 %	22,67 %	13,89 %	71,95 %	47,10 %	0,00 %
C12	51,78 %	0,95 %	0,00 %	2,20 %	17,85 %	100,00 %
C13	100,00 %	12,08 %	0,00 %	28,30 %	38,32 %	23,06 %
C14	93,46 %	100,00 %	67,30 %	0,33 %	0,00 %	21,64 %
C15	27,01 %	40,84 %	7,23 %	22,75 %	0,00 %	100,00 %
C16	0,00 %	48,06 %	47,61 %	40,11 %	66,72 %	100,00 %
C17	100,00 %	25,64 %	35,07 %	0,00 %	3,14 %	18,77 %
C18	0,00 %	71,57 %	84,99 %	100,00 %	80,69 %	7,30 %
C19	100,00 %	0,00 %	2,12 %	33,10 %	60,18 %	86,49 %
C20	0,00 %	22,01 %	17,13 %	24,27 %	47,73 %	100,00 %
C21	60,79 %	0,00 %	79,79 %	100,00 %	15,91 %	66,85 %
C22	16,82 %	47,14 %	42,42 %	100,00 %	61,64 %	0,00 %
C23	52,61 %	100,00 %	79,25 %	74,84 %	80,66 %	0,00 %
C24	0,00 %	11,90 %	21,99 %	34,40 %	48,83 %	100,00 %
C25	0,00 %	38,88 %	55,19 %	60,25 %	79,84 %	100,00 %

Table 11 presents a heatmap of cumulative returns, where a clear upward trend is visible. The darkest shades cluster predominantly in the post-event windows, particularly from t+30 to t+90. However, there is little evidence of return reversal within this dataset, as prices generally continue to rise in the long term. This suggests that H1b is not clearly supported when considering raw returns alone. This pattern suggests that stock prices tend to increase following periods of heightened investor attention, consistent with the idea of overreaction or delayed positive momentum. Notably, firms such as C1, C3, C4, C5, C6, C7, C8, and C9 exhibit strong cumulative returns from t+7 through t+90, which may reflect optimism or continued investor engagement after the event. In contrast,

firms like C11 and C13 show pronounced spikes before the event, suggesting that prices may have reacted in anticipation of the attention peak—possibly due to early signals or information leakage. Both firms also continue to show elevated returns after the event. Meanwhile, other firms (e.g., C14, C17, and C19) experience peak returns around the event date but show stagnation or a decline in subsequent periods, indicating a short-lived response to attention.

Table 12 - CARs Heatmap

CARs	t-90	t-30	t-7	t+7	t+30	t+90
C1	0,00 %	37,92 %	36,36 %	78,16 %	69,04 %	100,00 %
C2	78,87 %	91,43 %	63,95 %	100,00 %	0,00 %	7,09 %
C3	0,00 %	13,13 %	44,45 %	56,07 %	81,72 %	100,00 %
C4	0,00 %	37,83 %	45,37 %	96,43 %	100,00 %	96,93 %
C5	0,00 %	59,04 %	55,30 %	86,41 %	63,64 %	100,00 %
C6	0,00 %	24,43 %	41,75 %	42,60 %	64,17 %	100,00 %
C7	2,33 %	14,28 %	33,34 %	100,00 %	0,00 %	51,77 %
C8	94,06 %	19,16 %	0,00 %	79,70 %	45,43 %	100,00 %
C9	10,21 %	0,00 %	61,09 %	94,05 %	100,00 %	64,89 %
C10	56,01 %	0,00 %	34,34 %	100,00 %	77,35 %	72,84 %
C11	100,00 %	37,68 %	31,17 %	88,21 %	39,26 %	0,00 %
C12	0,00 %	8,24 %	68,67 %	72,14 %	60,14 %	100,00 %
C13	100,00 %	12,65 %	11,30 %	56,57 %	28,18 %	0,00 %
C14	17,18 %	41,02 %	73,26 %	4,06 %	100,00 %	0,00 %
C15	0,00 %	50,77 %	57,49 %	88,28 %	16,06 %	100,00 %
C16	0,00 %	44,18 %	40,81 %	42,97 %	66,92 %	100,00 %
C17	100,00 %	74,30 %	62,29 %	14,02 %	0,00 %	15,32 %
C18	7,66 %	66,61 %	85,39 %	100,00 %	77,52 %	0,00 %
C19	0,00 %	42,58 %	41,77 %	100,00 %	78,86 %	47,25 %
C20	0,00 %	31,48 %	25,24 %	33,38 %	56,68 %	100,00 %
C21	75,86 %	0,00 %	89,39 %	100,00 %	20,20 %	84,91 %
C22	27,00 %	46,33 %	36,12 %	100,00 %	62,57 %	0,00 %
C23	0,00 %	11,90 %	21,99 %	34,40 %	48,83 %	100,00 %
C24	0,00 %	27,66 %	49,77 %	48,70 %	72,87 %	100,00 %
C25	0,00 %	23,08 %	51,97 %	55,70 %	76,56 %	100,00 %

Table 12 displays the heatmap of CARs, offering further insight beyond raw return patterns. While the overall pattern resembles of cumulative returns some differences emerge. A general trend can be observed in the concentration of darker shades in the post-event windows, particularly at t+90, where many firms reach their peak CARs. This suggests that attention-driven price reactions often persist and exceed what would be expected based on overall market movement.

However, because most firms do not exhibit a clear reversal in CARs over time, the evidence for H1b is limited in this context. While some individual cases indicate mean reversion, the broader pattern points to sustained abnormal performance following attention spikes, weakening support for a consistent return correction effect.

Notable exceptions include firms like C11, C13, and C17, which show peak CARs prior to the event (e.g., at $t-90$), followed by a drop and later a secondary rise. This may reflect anticipatory trading or influences unrelated to investor attention. Firms such as C2 and C7 display sharp rises followed by quick declines, indicative of short-term overreaction and correction, aligning more closely with behavioral predictions.

6.2 Illustrative Event Example

To illustrate the link between investor attention, corporate events, and market reactions, this section highlights a KeyCorp case. As shown in Figure 6, a GSVI spike on August 12, 2024, coincided with the announcement of a \$2.8 billion investment from the Bank of Nova Scotia (Fitch Ratings, 2024), which also drove a stock price increase (Figure 7). The surge in attention likely reflects availability bias, where prominent, easily called news disproportionately influenced investor focus and market behaviour.

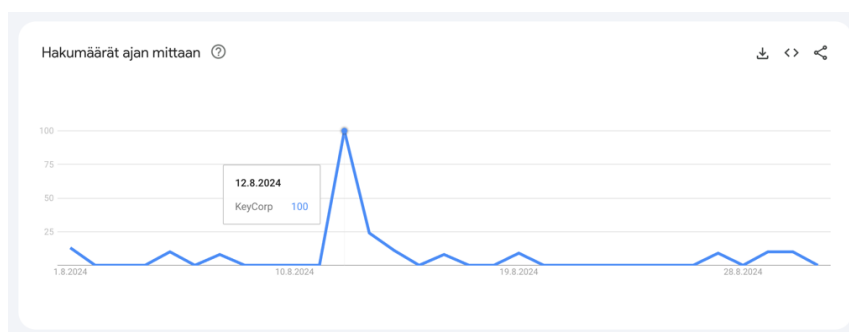


Figure 6 - KeyCorp GSVI Spike



Figure 7 - KeyCorp Stock History

The spikes presented in previous chapter in figures 2, 3, and 4 be attributed to key corporate announcements and media coverage, driven by factors such as market reactions and availability bias. In November 2023, Monster Beverage's (Figure 2) \$500 million share repurchase announcement led to a GSVI peak on December 24, 2023, fueled by media attention and year-end analyses (Nasdaq, 2023). Availability bias likely influenced investors as they revisited the company's financials during the holiday season.

Palo Alto Networks (Figure 3) experienced a GSVI peak on February 25, 2024, following negative earnings forecast and a positive partnership announcement with Nvidia (Nasdaq, 2024; Investopedia, 2024). The spike was likely driven by availability bias, as investors focused on recent developments, possibly overlooking broader market trends. Analog Devices' announcement of acquiring Maxim Integrated in a \$20.9 billion deal on July 13, 2020, generated significant media coverage, resulting in a GSVI peak on July 12, 2020 (Bloomberg, 2020). The heightened attention can be attributed to availability bias, with investors focusing on the large-scale merger.

6.3 Regression results

To examine whether availability-driven investor attention affects abnormal returns across different time horizons, multiple regression models were estimated using cumulative abnormal returns as the dependent variable for three event windows: t+7, t+30, and t+90. For each window, regressions were conducted using two volatility specifications, 7-day and 30-day pre-event, to assess the robustness of results across different measures of uncertainty.

Table 13 - Regression 1 results

CAR Window	t+7	t+7	t+30	t+30	t+90	t+90
Vol Type	t-30	t-7	t-30	t-7	t-30	t-7
R ²	0,7196	0,7143	0,8508	0,8502	0,7079	0,7080
Adj. R ²	0,6635	0,6572	0,8210	0,8202	0,6495	0,6496
Intercept	-0,6049	-0,6115	-0,8755 **	-0,8616 **	-1,4330 **	-1,4205 **
Market Cap	0,0282	0,0286	0,0453 **	0,0443 **	0,0775 **	0,0766 **
Beta	0,1114 *	0,1136 *	0,1222 **	0,1193 **	0,1446 *	0,1421 *
GSVI	-0,0267	-0,0291	-0,0413 *	-0,0373 *	-0,023	-0,0195
Vol	0,5812 ***	0,4099 ***	-1,0271 ***	-0,7299 ***	-0,9082 ***	-0,6457 ***

Significant at: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

All models exhibit strong explanatory power, with R² values ranging from 0,7079 to 0,8508, and adjusted R² between 0,6495 and 0,8210. The highest explanatory value is observed in the t+30 model with 30-day volatility, adjusted R² being 0,8210, suggesting that this intermediate time horizon may best capture investor reactions following attention spikes.

Volatility prior to the event is consistently significant at the 1% level in all models. The negative coefficients (e.g., -1,0271 in the t+30 model with 30-day volatility) indicate that higher pre-event uncertainty is associated with weaker post-event returns. This implies that firms experiencing heightened volatility before the attention peak tend to underperform afterward. This result aligns with behavioral theories that associate

elevated uncertainty with speculative trading or noise, leading to temporary mispricing. The finding lends support to the idea that short-term investor behavior under conditions of heightened risk may result in inefficient price formation. Vlastakis and Markellos (2012), for example, found that Google search volume increases during periods of uncertainty, reinforcing the link between information demand and volatility, and suggesting that investors may fixate on salient or emotionally charged risks, which is a key symptoms of availability bias.

The Google Search Volume Index (GSVI), shows negative coefficients across all models, implying that higher attention levels are associated with lower subsequent returns. However, this relationship is only statistically significant in the t+30 models ($-0,0413$ and $-0,0373$, both $p < 0,05$). The negative coefficient of GSVI in the t+30 model suggests that heightened investor attention is followed by underperformance, consistent with the idea of return reversal. Meanwhile, in the t+7 window, the coefficient is also negative but not significant ($-0,0267$, $p = 0,18$), offering only weak support for short-term price reactions. The insignificance in t+90 ($-0,023$ and $-0,0195$, both $p > 0,4$) may reflect the fading influence of attention over time or the rising role of fundamental information in determining long-run outcomes.

To assess robustness, the models were re-estimated using standardized (z-score) GSVI values as well as a change-based measure of attention, calculated as the week-over-week difference in Google Search Volume. The results did not materially change under either specification. GSVI remained statistically insignificant in the short- and long-term models, suggesting that the observed patterns are not an artifact of scale or specification, but reflect a generally weak relationship between investor attention and abnormal returns.

Control variables behave largely as expected. Firm size, measured as the logarithm of market capitalization, is positively related to CARs and statistically significant in most of the models at the 5% level. This suggests that larger firms may attract more sustained

investor confidence or institutional backing post-event. Market beta is also positively associated with CARs and significant at the 5% or 1% level across all models. While a positive beta-return relationship is somewhat counterintuitive from a risk-adjusted perspective, it may indicate that high-beta firms benefit more from market-wide movements or sentiment-driven momentum during periods of heightened attention.

Taken together, these findings offer partial support for H1: attention induced by availability bias may boost stock prices in the short term. The strongest evidence emerges in the t+30 window, where both attention and volatility exhibit significant effects.

Together, these findings offer partial support for H1. While investor attention does not appear to significantly boost abnormal returns in the immediate aftermath of attention spikes (t+7), the t+30 results indicate that high attention is followed by moderate underperformance, consistent with behavioral theories of overreaction and reversal. The diminishing effect by t+90 underscores that availability-driven attention may have only transient pricing power. These insights contribute to a growing literature highlighting the limits of informational efficiency in the face of psychologically driven investor behavior.

To test the second hypothesis—that investor attention increases volatility before attention spikes—a series of regressions were conducted using pre-event volatility as the dependent variable. The models included Google Search Volume Index (GSVI) as the main explanatory variable of interest, while controlling for firm size (log market capitalization), market beta, and post-event abnormal returns (CARs). Volatility was measured using three different pre-event windows (t-90, t-30, and t-7), and each model was estimated across three CAR windows (t+7, t+30, and t+90), resulting in a total of nine specifications. While all combinations of volatility windows and CAR windows were estimated, the t-30 volatility models showed the strongest overall model fit

(average adjusted R^2 of 0,642), and clearest patterns for CAR and GSVI effects. Therefore, we focus on these models in the main table. The full results are available in Appendix 1.

Table 14 - Regression 2 results

Vol Window	t-30	t-30	t-30
Car Type	t+7	t+30	t+90
R^2	0,6255	0,8388	0,6403
Adj. R^2	0,5506	0,8065	0,5684
Intercept	0,6888	-0,6161 *	-0,7470
Log Market Cap	-0,0362	0,0307	0,0377
Beta	-0,0421	0,1167 **	0,1435 **
GSVI	0,0104	-0,0324	-0,0198
CAR	0,9224 ***	-0,8057 ***	-0,6390 ***

Significant at: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results show that GSVI fails to exhibit a consistent or statistically significant relationship with pre-event volatility. Across all specifications, GSVI coefficients are small in magnitude and lack statistical significance, offering no robust support for Hypothesis 2 (H2), which posited a positive association between investor attention and pre-event volatility.

Although two models (t-30/t+30 and t-30/t+90) yielded marginal significance at the 10% level, the direction of the relationship was negative, contradicting the expected positive association. In other words, higher investor attention appears weakly related to lower, not higher, pre-event volatility, and even this inverse relationship does not hold consistently across models.

By contrast, CARs consistently show a strong and statistically significant positive relationship with pre-event volatility across all specifications ($p < 0,001$). This indicates that firms with higher post-event returns also experienced greater volatility in the period leading up to the attention spike. This aligns with prior literature suggesting that periods

of uncertainty and speculative noise—rather than investor attention per se—can amplify price reactions (Da et al., 2011).

Taken together, the regression results provide no support for the second hypothesis. While CARs strongly and positively predict pre-event, the coefficients for GSVI remain small in magnitude and statistically insignificant across all specifications. These findings are inconsistent with the expectation that heightened investor attention signals elevated uncertainty or speculative activity prior to the event. Instead, attention appears largely disconnected from volatility, undermining support for H2. Contrary to earlier literature on availability bias and attention-driven volatility (e.g., Vlastakis and Markellos, 2012), the results reveal little evidence that investor attention is positively associated with stock price volatility ahead of attention spikes. Rather, pre-event volatility appears to be more closely linked to realized return outcomes than to search-based measures of investor sentiment. This suggests that while volatility may shape subsequent market reactions, it is not directly driven by attention as measured in this study.

Summarizing the results Across the empirical analysis, correlation matrices and heatmaps revealed consistent patterns: pre-event volatility (particularly at $t-30$ and $t-7$) is positively associated with short-term CARs, but negatively associated with longer-term CARs. This is consistent with a return-reversal pattern, where initial overreactions to salient events are subsequently corrected, asupporting H1b.

Regression analysis provides partial support for Hypothesis 1. While GSVI was significantly and negatively associated with CARs in the $t+30$ model, supporting the idea of medium-term return reversal, the lack of significance in the $t+7$ and $t+90$ windows indicates only limited support for attention-driven price dynamics. Specifically, H1a is not supported, as no evidence of a short-term positive price reaction following heightened attention was found.

In contrast, pre-event volatility consistently predicted lower post-event CARs across all models, aligning with behavioural theories of overreaction under uncertainty. This

suggests that investor behaviour in volatile periods may be more sentiment-driven, leading to temporary mispricing that eventually reverses.

Hypothesis 2 was not supported. GSVI did not significantly predict pre-event volatility, regardless of how attention was measured. Instead, post-event CARs strongly and positively predicted earlier volatility, reinforcing the idea that volatility anticipates, rather than results from, attention spikes.

6.4 Limitations of the study

While this thesis provides new insights into the relationship between investor attention and stock performance through the lens of availability bias, several limitations should be acknowledged. While the regression models presented earlier provide some evidence of a relationship between investor attention and stock returns—particularly in the $t+30$ window—the findings raise important questions about causality and model robustness. Notably, the Google Search Volume Index (GSVI) does not exhibit a consistent or strong statistical relationship with abnormal returns across all time horizons. This is especially evident in the $t+90$ window, where the effect of attention appears to dissipate entirely. This inconsistency underscores a core limitation, that correlation does not imply causation. Although a weak negative association exists between GSVI and returns in the medium term, there is insufficient evidence to conclude that GSVI drives return reversals.

Other limitations are also found that could be further expanded in the future studies. First, the sample size is relatively small. Although an effort was made to include firms from different sectors and with different characteristics, the limited sample reduces the strength of the results and may make it harder to apply the findings more broadly to other markets.

Second, the study does not prove cause and effect. The analysis is based on observed relationships, so it cannot determine whether attention leads to changes in stock returns

and volatility, or whether all of these variables are influenced by something else—such as news or economic conditions. In addition, GSVI data is provided weekly, which may miss short-term changes in attention during the week. The method used to identify high-attention events (based on GSVI spikes) also doesn't explain why attention increased—it could be due to earnings, media coverage, or other reasons not captured here.

Third, while GSVI is a useful tool to measure investor attention, it has its limitations. Since each GSVI value is scaled from 0 to 100 based only on its own search data, the numbers can't be directly compared across companies. This makes the cross-company analysis less reliable and might explain why some regression results were weak or inconsistent. Even though additional tests were done using standardized values and changes in GSVI, this basic issue remains.

Fourth, the study does not account for bigger events in the economy or market, such as central bank decisions or global news, which could affect many stocks at once. The abnormal returns were calculated using a simple model that assumes risk stays constant, which might not hold true during major events. More advanced models, such as those that include more risk factors or allow for changing volatility, could provide deeper insights but were beyond the focus of this thesis. While the results are in line with certain behavioral finance theories, future studies with more data, better attention measures, and more detailed investor behavior would help build even stronger evidence.

Finally, future research could extend the methodology by incorporating a second portfolio based on lower GSVI spikes, for example, events where search interest increased by more than 45%. Comparing this with the original portfolio might reveal whether larger attention spikes lead to different or stronger patterns in returns and volatility. This could also help identify thresholds beyond which investor behavior or market reaction changes more dramatically.

7 Conclusions

This thesis set out to examine the impact of availability bias on stock price behavior and volatility, focusing on how heightened investor attention, proxied by Google Search Volume Index (GSVI), affects short- and long-term market outcomes. By integrating insights from behavioral finance with empirical event study methods, this research contributes to a growing body of literature that challenges the assumptions of rational decision-making and market efficiency within traditional finance theory.

While initial correlation analyses and heatmaps suggested patterns linking investor attention, volatility, and returns, the regression results did not offer consistent statistical support. These limitations affected hypothesis testing outcomes.

Hypothesis 1a (H1a), which proposed a short-term price increase ($t+7$) following spikes in attention, was not supported. The lack of statistical significance in the short-term models undermines the case for immediate investor overreaction. Hypothesis 1b (H1b), which posits a return reversal following attention spikes, received partial support, especially through the significant negative coefficients in the $t+30$ models. This suggests that initial overreactions may be corrected in the medium term, consistent with the idea of attention-driven mispricing and correction. Hypothesis 2 (H2), which anticipated that heightened investor attention would be preceded by elevated volatility, was also not supported. While volatility prior to events was significant, it was not positively associated with GSVI. Instead, pre-event volatility was more closely linked to subsequent abnormal returns, suggesting that attention may follow uncertainty rather than cause it.

From a theoretical standpoint, the results highlight the relevance of behavioral finance in explaining market anomalies and investor behavior. The findings challenge the predictions of the Efficient Market Hypothesis (EMH) by showing that cognitive biases, specifically availability bias, may contribute to mispricing. However, the inconsistencies in the significance of GSVI across models also point to the complexity of measuring investor attention and its effects on market outcomes.

Practically, the study's outcomes can inform investors and financial professionals about the risks associated with attention-driven trading. Recognizing the patterns of short-term overreaction can aid in developing more resilient investment strategies. Investors and market practitioners should be aware of patterns of short-term overreaction and medium-term correction and use caution when interpreting attention-based indicators like GSVI in isolation. The research also underscores the potential value of alternative data sources, such as search volume trends, in augmenting traditional market analysis.

Despite these contributions, the study has certain limitations. The reliance on Google Trends data, while effective in measuring attention, may not fully capture all forms of investor focus, particularly those driven by institutional or algorithmic trading. The sample size, though representative, may limit the generalizability of the results across different markets or economic conditions. Moreover, the study does not control for sentiment polarity in search behavior, which could influence the direction and magnitude of market reactions.

Future research could address these limitations by incorporating sentiment analysis, expanding the dataset to include other markets, or exploring different behavioral biases in tandem with availability bias. Additionally, further exploration into the role of social media platforms and news sentiment could enrich our understanding of how information flow shapes investor behavior and market outcomes.

In conclusion, this thesis reinforces the importance of behavioral insights in understanding market inefficiencies and highlights the need for interdisciplinary approaches in financial research. The complex interplay between investor attention, sentiment, and price dynamics presents a promising area for further exploration. Understanding these mechanisms is vital not only for academic progress but also for developing more informed and resilient investment strategies in an increasingly data-driven financial environment.

References

- Adams, A. (2019, October 8). *Book and book chapter references: No location required*. APA Style Blog. Retrieved December 17, 2019, from <https://apastyle.apa.org/blog/publisher-locations-in-book-references>
- Andrei, D., & Hasler, M. (2015). Investor attention and stock market volatility. *Review of Financial Studies*, 28(1), 33–72. <https://doi.org/10.1093/rfs/hhu059>
- Abarbanell, J., & Bernard, V. L. (1992). Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalies in stock prices. *The Journal of Finance*, 47(3), 1181–1207. <https://doi.org/10.1111/j.1540-6261.1992.tb04010.x>
- Baker, H. K., & Nofsinger, J. R. (2010). Behavioral finance: an overview. *Behavioral finance: Investors, corporations, and markets*, 1-21. <https://doi.org/10.1002/9781118258415.ch1>
- Baker, H. K., & Ricciardi, V. (2014). How biases affect investor behaviour. *The European Financial Review*, 7-10.
- Bank, M., Larch, M., & Peter, G. (2011). Google search volume and its influence on liquidity and returns of German stocks. *Financial markets and portfolio management*, 25, 239-264. <https://doi.org/10.1007/s11408-011-0165-y>
- Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, 55(2), 773–806. <https://doi.org/10.1111/0022-1082.00226>
- Barber, B. M., Lee, Y. T., Liu, Y. J., & Odean, T. (2007). Is the aggregate investor reluctant to realise losses? Evidence from Taiwan. *European Financial Management*, 13(3), 423-447. <https://doi.org/10.1111/j.1468-036X.2007.00402.x>
- Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies*, 21(2), 785-818. <https://doi.org/10.1093/rfs/hhm079>
- Bloomberg. (2020, July 13). *Analog Devices to buy rival Maxim in \$21 billion chip deal*. Bloomberg. <https://www.bloomberg.com/news/articles/2020-07-13/analog-devices-to-buy-rival-maxim-in-21-billion-chip-deal>

- Chiodo, D., Leschied, A. W., Whitehead, P. C., & Hurley, D. (2003). The impact of violence on child outcomes in a child protection sample: implications for intervention. *The University of Western Ontario*.
- Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The journal of finance*, 66(5), 1461-1499. <https://doi.org/10.1111/j.1540-6261.2011.01679.x>
- Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*, 28(1), 1-32. <https://doi.org/10.1093/rfs/hhu072>
- Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, 53(6), 1839–1885. <https://doi.org/10.1111/0022-1082.00077>
- De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3), 793–805. <https://doi.org/10.1111/j.1540-6261.1985.tb05004.x>
- De Martino, B., Kumaran, D., Seymour, B., & Dolan, R. J. (2006). Frames, biases, and rational decision-making in the human brain. *science*, 313(5787), 684-687. <https://doi.org/10.1126/science.1128356>
- Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2012). Investor information demand: Evidence from Google searches around earnings announcements. *Journal of Accounting research*, 50(4), 1001-1040. <https://doi.org/10.1111/j.1475-679X.2012.00450.x>
- Fama, E. F. (1970). Efficient capital markets. *Journal of finance*, 25(2), 383-417. <https://doi.org/10.1111/j.1540-6261.1970.tb00518.x>
- Ganzach, Y. (2000). Judging risk and return of financial assets. *Organizational Behavior and Human Decision Processes*, 83(2), 353–370. <https://doi.org/10.1006/obhd.2000.2914>
- Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, 103(4), 650–669. <https://doi.org/10.1037/0033-295X.103.4.650>
- Hirshleifer, D. (2001). Investor psychology and asset pricing. *The journal of Finance*, 56(4), 1533-1597. <https://doi.org/10.1111/0022-1082.00379>

- Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2011). Investor attention and stock price reactions to accounting information. *Review of Accounting Studies*, 16(3), 615–648. <https://doi.org/10.1007/s11142-010-9143-3>
- Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics*, 36(1-3), 337-386. <https://doi.org/10.1016/j.jacceco.2003.10.002>
- Investopedia. (2024, February 13). *Palo Alto Networks jumps as it teams with Nvidia and others to provide private 5G security*. Investopedia. Retrieved April, 8, 2025, from <https://www.investopedia.com/palo-alto-networks-jumps-as-it-teams-with-nvidia-and-others-to-provide-private-5g-security-8600295>
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1), 65-91. <https://doi.org/10.1111/j.1540-6261.1993.tb04702.x>
- Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In *Handbook of the fundamentals of financial decision making: Part I* (pp. 99-127) https://doi.org/10.1142/9789814417358_0006
- Kahneman, D., & Riepe, M. W. (1998). Aspects of investor psychology. *Journal of portfolio management*, 24(4), 52-+ <https://doi.org/10.3905/jpm.1998.409643>
- Kallir, I., & Sonsino, D. (2009). The neglect of correlation in allocation decisions. *Southern Economic Journal*, 75(4), 1045-1066. <https://doi.org/10.1002/j.2325-8012.2009.tb00946.x>
- Kliger, D., & Kudryavtsev, A. (2010). The availability heuristic and investors' reaction to company-specific events. *The journal of behavioral finance*, 11(1), 50-65. <https://doi.org/10.1080/15427561003591116>
- Lee, K., Kwon, T. H., & Park, H. (2005). Recency bias in economic forecasting: Evidence from professional forecasters. *Journal of Economic Behavior & Organization*, 56(4), 457-473. <https://doi.org/10.1016/j.jebo.2004.03.001>
- Leković, M. (2018). Evidence for and against the validity of efficient market hypothesis. *Economic themes*, 56(3), 369-387. <https://doi.org/10.2478/ethemes-2018-0022>

- Lieder, F., Griffiths, T. L., M. Huys, Q. J., & Goodman, N. D. (2018). The anchoring bias reflects rational use of cognitive resources. *Psychonomic bulletin & review*, 25, 322-349. <https://doi.org/10.3758/s13423-017-1286-8>
- Malkiel, B. G. (2019). *A random walk down Wall Street: The time-tested strategy for successful investing* (12th ed.). W.W. Norton & Company.
- Mehra, R., & Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of monetary Economics*, 15(2), 145-161. [https://doi.org/10.1016/0304-3932\(85\)90061-3](https://doi.org/10.1016/0304-3932(85)90061-3)
- Nasdaq. (2023, November 8). *Monster Beverage (MNST) approves \$500M share repurchase plan*. Nasdaq. Retrieved March 8, 2025, from <https://www.nasdaq.com/articles/monster-beverages-mnst-approves-%24500m-share-repurchase-plan>
- Nasdaq. (2024, February 13). *Palo Alto Networks (PANW) surpasses Q2 earnings and revenue estimates*. Nasdaq. Retrieved March 8, 2025, from <https://www.nasdaq.com/articles/palo-alto-networks-panw-surpasses-q2-earnings-and-revenue-estimates-1>
- Otuteye, E., & Siddiquee, M. (2015). Overcoming cognitive biases: A heuristic for making value investing decisions. *Journal of Behavioral Finance*, 16(2), 140-149. <https://doi.org/10.1080/15427560.2015.1034859>
- Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific reports*, 3(1), 1-6. <https://doi.org/10.1038/srep01883>
- Shah, S. Z. A., Ahmad, M., & Mahmood, F. (2018). Heuristic biases in investment decision-making and perceived market efficiency: A survey at the Pakistan stock exchange. *Qualitative Research in Financial Markets*, 10(1), 85-110. <https://doi.org/10.1108/QRFM-04-2017-0033>
- Shleifer, A. (2000). *Inefficient markets: An introduction to behavioural finance*. Oup Oxford. <https://doi.org/10.1093/0198296125.001.0001>
- Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *The Journal of Psychology and Financial Markets*, 1(1), 49-60. https://doi.org/10.1207/S15327760JPFM0101_05

- Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of economic perspectives*, 17(1), 83-104. <https://doi.org/10.1257/089533003321164967>
- Shiller, R. J. (2020). *Narrative economics: How stories go viral and drive major economic events*. Princeton University Press. <https://doi.org/10.23943/princeton/9780691198830.001.0001>
- Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological review*, 63(2), 129. <https://doi.org/10.1037/h0042769>
- Subrahmanyam, A. (2008). Behavioural finance: A review and synthesis. *European Financial Management*, 14(1), 12-29. <https://doi.org/10.1111/j.1468-036X.2007.00415.x>
- Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of finance*, 62(3), 1139-1168. <https://doi.org/10.1111/j.1540-6261.2007.01232.x>
- Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of economic behavior & organization*, 1(1), 39-60. [https://doi.org/10.1016/0167-2681\(80\)90051-7](https://doi.org/10.1016/0167-2681(80)90051-7)
- Thaler, R. (1985). Mental accounting and consumer choice. *Marketing science*, 4(3), 199-214. <https://doi.org/10.1287/mksc.4.3.199>
- Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, 185(4157), 1124-1131. <https://doi.org/10.1126/science.185.4157.1124>
- Von Neumann, J., & Morgenstern, O. (1947). *Theory of games and economic behavior*, 2nd rev.
- Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance*, 36(6), 1808-1821. <https://doi.org/10.1016/j.jbankfin.2012.02.002>

Appendices

Appendix 1. Regression 2 full results

Vol Window	t-90	t-90	t-90	t-30	t-30	t-30	t-7	t-7	t-7
Car Type	t+7	t+30	t+90	t+7	t+30	t+90	t+7	t+30	t+90
R ²	0,6380	0,8243	0,6243	0,6255	0,8388	0,6403	0,6148	0,8362	0,6373
Adj. R ²	0,5657	0,7892	0,5492	0,5506	0,8065	0,5684	0,5378	0,8035	0,5647
Intercept	0,7498	-0,6826 *	-0,8171	0,6888	-0,6161 *	-0,7470	0,9905	-0,8379 *	-1,0235
Log Market Cap	-0,0396	0,0337	0,0408	-0,0362	0,0307	0,0377	-0,0526	0,0412	0,0511
Beta	-0,0471	0,1305 **	0,1595 **	-0,0421	0,1167 **	0,1435 **	-0,0604	0,1609 **	0,1984 **
GSVI	0,0112	-0,0362	-0,0225	0,0104	-0,0324	-0,0198	0,0208	-0,0389	-0,0212
CAR	1,0302 ***	-0,8790 ***	-0,6922 ***	0,9224 ***	-0,8057 ***	-0,6390 ***	1,2858 ***	-1,1310 ***	-0,8980 ***

ChatGPT, an AI language model developed by OpenAI, was used in this thesis to improve the language.