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Literature Review of Salience and Financial Markets

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ABSTRACT:

The purpose of this thesis is to examine the effect of salience on financial markets. More practically, this thesis examines how the salient information affects investment decisions on financial markets. Examples of salient information are extreme returns or news coverage. Furthermore, the purpose is to find out whether positive or negative information has a significantly larger impact on investors impacted by saliency. In the textbook, the markets are defined as efficient, and investors behave rationally and subsequently always maximize their utility in all circumstances.

This thesis finds the answer to the research question supported by the hypotheses. It does so by covering the theoretical background of the topic and investigating relevant previous literature discussing the topic.

KEYWORDS: Behavioral Finance, Salience Theory, Salience Effect

Contents

1 Introduction

In financial markets, investors constantly make investment-decisions under uncertainty. Well-known traditional financial theories, such as the Efficient Market Hypothesis ("EMH") by Fama (1970) and Modern Portfolio Theory ("MPT") by Markowitz (1952) suggest that investors are always rational and make decisions based on available information to maximize their utility. That is how markets are defined in the textbooks. However, in the financial markets investors often deviate from rational behavior and are influenced by psychological factors like cognitive biases. One such is salience, which plays a remarkable role on investors decision-making.

In its simplicity a stimulus is salient when attracting decision-makers attention automatically and involuntarily (Bordalo et al. 2022). For example, information that stands out of the mass due to its unique characteristics. Even though these would not be relevant in the broader context (Bordalo et al. 2022). This thesis concentrates mostly on the effects of salience on decision-making in the financial markets. Where striking or recent events, such as enormous market "crashes", earning announcements or sensational media coverage grabs investors' attention. Salient factors often overshadow the more relevant information, for instance consumer attention is attracted to laptop design over the quality of the laptop (Bordalo et al. 2022).

According to Black (1986) investors trade on noise as if it would be information. The huge number of individual investors are the cornerstone of the financial system (Black, 1986). They make it possible, but also imperfect. For instance, year 2021 extremely shorted and dying company GameStop stock surged more than 700% in one week (Long et al. 2023). This happened because investors followed the speculative involvement of individual investors. These extreme events threat the idea of efficient markets and rationally behaving investors.

Salience effect is mostly pronounced in volatile and uncertain market conditions. (i.e. in circumstances with limits of arbitrage) (Shleifer & Vishny, 1997). Arbitrageurs are the ones who tries to keep market efficient, but they are also risk averse. Thus, inefficiencies are witnessed in financial markets.

1.1 Purpose of the study

The purpose of this thesis is to examine salience in the financial markets. For example, how does salient information, such as extreme returns or news coverage affect the investment decisions of investors in the financial markets. Humans reacts differently to various type of information. In history we have seen stocks skyrocketing but also stocks crashing. One example is the case GameStop mentioned above, where the striking price of the stock attract investors attention. Hence, the first hypothesis is:

H1: Positive salient information (e.g. extreme positive returns or favorable news) lead to higher buying activity than negative salient events tend to lead to selling activity.

In addition, it is important to understand where salient information has the greatest impact. Today we have thousands type of different assets. We do not only have different type of assets we also have various type of investors. And these investors make investment decisions based on different type of information. Hence, the second hypothesis is:

H2: Risky assets are significantly more impacted by salient information than less risky assets.

The hypotheses are based on existing literature, which are examined in chapter four. The motivation behind this study is to understand how salient information affects decision-making, and in which situations it is pronounced the most. The topic is very timely, because of the growing role of social media as an information distributor, and thus it is fine to expect that cases like GameStop will not be the last one of its kind.

1.2 Structure of the thesis

Structure of the thesis is as follows: first is the introduction, followed by the purpose of the thesis and the structure of the thesis. Chapter two and three introduces the theoretical part of the thesis, such as the EMH, noise traders, and a few explanatory behavioral finance theories, (i.e. salience effect.). Chapter four covers the literature review of related research concerning the topic. Lastly, chapter five concludes the findings.

2 Theoretical background

In a broad view, it is necessary to understand the structure of financial markets, to become a successful investor. In the textbook, investors are typically described to behave rationally, and markets are described to be efficient. In practice, "noise traders" are trading, even it would be better for them not to trade. In addition, arbitrageurs face their own challenges in the market, thus, they cannot always keep the markets efficient.

2.1 Efficient Market Hypothesis

Efficient Market Hypothesis ("EMH") is one of the mostly accepted traditional financial theories. EMH expect that stock market are efficient (Fama, 1970). More specifically, asset prices fully reflect all available information at any given time. Thus, in an efficient market it is impossible for investors to consistently achieve higher returns than the average market return without taking any additional risk. That is explained by the fact that all the available information is already reflected to the asset prices (Fama, 1970). As stated by Fama, (1970) there are three forms of market efficiency, weak, semi-strong and strong efficiency.

Weak form efficiency assume that current stock prices incorporate all past trading information like volume and historical prices (Fama, 1970). Thus, it is not possible to predict future asset prices, because all price patterns and movements are reflected in current prices. Weak form efficiency implies that it is not possible to consistently achieve profits through technical analysis (Fama, 1970).

By adding all new public information such as company announcements, economic reports or political events to the weak form efficiency we have the terms of semi-strong efficiency. Semi-strong efficiency suggest that asset prices adjust immediately to new information (Fama, 1970). Herewith no investor could achieve consistently profits by trading on public information, for example on fundamental analysis. The strong form efficiency assumes that all information both public and private is fully reflected on asset prices. Accordingly, even investors with private and exclusive information are not capable to gain superior returns (Fama, 1970).

2.2 Modern Portfolio Theory

Modern portfolio theory (“MPT”) introduces concept of selecting and investment portfolio based on tradeoff between expected return and risk. Theory suggest that investors should try to maximize returns with as little as possible risk through diversification (Markowitz, 1952). That study reveals the Expected Return-Variance (E-V) Rule, this allows investors to find a balance by building a portfolio that maximizes the expected profits they can get for a level of risk they are comfortable with.

According to Markowitz, (1952) the portfolios that follow above-mentioned guidelines are called “efficient portfolios”. Efficient frontier is a visual representation about these efficient portfolios. Usually, it is a curve on a graph where the horizontal axis represents the risk, and the vertical axis represents the expected return. By choosing portfolios on this frontier, investor know that they are making most of their desired risk level.

Markowitz (1952) states that diversification reduces risk more effectively than concentrating on single securities. He found out that constructing a portfolio based on assets that has low or negative correlations can reduce portfolio risk. For example, a portfolio combined across different sectors, bonds and real estate typically has lower risk than portfolios that concentrates only to one sector.

2.3 Limits Of arbitrage

“The simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices” as defined in study by Sharpe & Alexander, (1990). In theory arbitrage is defined as a risk-free, capital-free mechanism that ensures market efficiency by correcting mispricing. However, in real world case arbitrage involves risk, requires significant amount of capital, especially when prices deviate further from their fundamental values (Shleifer & Vishny, 1997).

Shleifer & Vishny, (1997) illustrates the mechanics of arbitrage. They stress the role of arbitrage in financial markets when capital allocation depends on past performance rather than the expected future returns. They assume that there are three types of market participants. Noise traders who trade on noise and not on fundamentals. Then there are arbitrageurs, who are very highly specialized traders (Shleifer & Vishny, 1997). Arbitrageurs exploit the mispricing caused by noise traders and they aim to bring the prices back to its intrinsic values. Third participants are investors, they do not directly trade themselves, but they allocate capital to arbitrageurs based on their past performance (Shleifer & Vishny, 1997). In the model noise traders introduce mispricing through their biased demand for an asset, while arbitrageurs try to correct the mispricing. The challenge arises if arbitrageurs’ recent performance has been bad. Causing investors to withdraw their money, hence reducing the arbitrageur’s capacity to correct the prices and earn higher returns. Thus, leading to higher volatility and less efficient markets. (Shleifer & Vishny, 1997).

They also find that arbitrageurs face both systematic and idiosyncratic risk. These risks influence which markets attract arbitrageurs. Typically favoring bond markets or foreign exchange markets. Conversely stock markets are less attractive due to their higher idiosyncratic risk and volatility. I.e. professional arbitrageurs may avoid extremely volatile arbitrage position, although such conditions offer attractive returns (Shleifer & Vishny, 1997).

2.4 Noise traders

Noise, defined by random, non-informative variations in financial markets, economic models and as a macroeconomic phenomenon (Black, 1986). Noise is essential for liquid stock markets. The ones with information or insight of an individual stock would not be able to trade without the noise traders. Noise traders are those who trade on noise as if it were information (Black, 1986). He notes that from an objective view it would be better not to trade as a noise trader, but they will trade anyway. For example, as a group the noise traders lose money, and as a group information traders make money. The mix of noise and information in prices reduces the market efficiency and makes it more difficult for information traders to gain profits. Black (1986) stress how the noise drives reliance on heuristics and irrational behavior, impacting decision-making and interpreting data.

According to Black (1986) noise is an essential part of economics and financial markets and its effect extend far beyond them. Noise is not only a part of stock markets, but it also plays significant role in macroeconomic phenomena. More detailed, noise arises from uncertainty in future supply and demand changes between different sectors, which leads to mismatches (Black, 1986). This imbalance explains booms and recessions, when many sectors experience a good balance between supply and demand the economy is booming. Conversely, significant mismatches lead to downturns. In addition, Black argues that inflation is driven by arbitrary expectations that do not follow rational rules. In other words, the level of inflation is determined by what people believe inflation will be.

Black (1986) brings to light few examples of noise's impact. A stock is added to S&P 500 index, which leads investors to buy the stock due to that. Following a rise on the stock price, even though the event does not include real fundamental value. The price will rise results from noise, even though the information traders are pushing the price towards its intrinsic value. Additionally, firm with two classes of common stock issues more of one class, the price of the issued stock will decline relative to the class of stock not issued (Black 1986). Hence, trading on noise puts noise into prices, thus the prices are reflected by information traders' information and by noise traders' noise (Black, 1986). Furthermore, it comes more profitable for information traders when there is more of noise in the markets. Noteworthy, to eliminate the increased noise information traders are forced to take bigger positions, thus leading to higher risk. Black notes that information traders cannot even be certain that they trade on information and not on noise.

2.5 Prospect Theory ("PT")

Prospect theory explains people's decision-making under risk. Usually, people's behavior changes under risk and behavior becomes irrational (Kahneman & Tversky, 1979). Prospect theory gives a descriptive model of decision-making under risk. It is an alternative theory to the traditional Expected utility theory ("EUT") (Kahneman & Tversky, 1979). (EUT) assumes that people make rational choices to maximize their utility. According to Shiller (1998) prospect theory has had more impact than any other behavioral theory on economic research.

(PT) asserts that decision-making is made through two-stage process. These two phases are first the editing phase and following the evaluation phase. The function of the editing phase is to organize and reformulate the options so that subsequent evaluation and choice is simpler (Kahneman & Tversky, 1979).

Kahneman & Tversky, (1979) found out that people evaluate potential gains and losses relative to a reference point rather than financial outcomes. That contrasts with the assumptions of expected utility theory. The reference point is usually seen as the current situation and the outcomes, potential gains and losses are perceived from this point. Loss aversion, decision weights, certainty effect and isolation effect are the main principles of prospect theory.

Decision weights give a reason for example why people buy lottery tickets. People tend to overweight extremely small probabilities such as in lottery. On the other hand, people tend to underweight high probabilities. This can lead to risk-aversion in situation there is high chance of success (Kahneman & Tversky, 1979). Situation where people often disregard components shared by all options and focus on what makes each option unique is explained by “isolation effect”. And the last one is certainty effect that define how people tend to overweight the certain outcomes, preferring them over outcomes that are merely probable. Even if the probable outcome could lead to higher utility (Kahneman & Tversky, 1979).

3 Related theories

Behind every trade there is a human, who does not usually behave rationally. The behavior of humans differs due to circumstances. There are various things that attract our mind, even while we do not recognize it. There are several different ways to describe the term "behavioral finance". The definition is usually based on the professional background of the scholar. Behavior and psychology have notable impact on portfolio managers assess risk and make decisions. More specific, through concept of framing how information is presented (Statman, 1995). Behavioral finance tries to incorporate human psychology and systematic departures from rationality to financial models (Barber & Odean, 1999).

3.1 Salience effect

According to the expected utility theory people makes best rational choices to maximize their utility (Kahneman & Tversky, 1979). In other words, it states that goal-relevant stimuli are top of mind. But due to decision-makers ("DMs") cognitive limitations attention is also drawn in a bottom-up fashion (automatically and involuntary). Attention is drawn to stimuli that are salient due to their contrast, surprise and prominence (Bordalo et al. 2022). Salience plays significant role in decision-making because salient information and stimuli are everywhere. Salience can be divided into three parts.

Contrast refers to the phenomenon where a particular attribute of an item becomes more noticeable when compared to other alternatives in choice set. The heightened visibility occurs because the attribute stands out sharply against the average value of attribute in other items (Bordalo et al. 2022). For example, a laptop with better looking design catches more attention than the others. Also, where red dot stands out of green dot field. That is how contrast driven attention can bias decision-making by emphasizing the salient attribute, such as design over the other factors such as price (Bordalo et al. 2022). Study points out that salience has diminishing sensitivity, i.e. a given attribute difference is more salient at lower attribute values. For example, a $100 price difference is more noticeable on price point €400 than it is at $1000 (Bordalo et al. 2022).

People feel often surprised seeing a different price than before. For example, if consumer remember laptop to be around $1000 but then notice a price at $1200. That increase in price attracts consumer attention over the other important factors like quality (Bordalo et al. 2022). Furthermore, Bordalo et al. (2020) presents memory to capture surprise. It is based on three well-established regularities in human recall: frequency, similarity, and interference (Bordalo et al. 2022). When human face particular certain information, our memory tends to bring up experiences that are common and similar. Hence, it interferes with recall of less frequent and less similar ones, which then creates reference point effects.

Decision-making is highly influenced of prominence. Prominence refers to the visibility of certain features of a product. These features draw our attention over the other features. (Bordalo et al. 2022). On ideal situation consumers would take all relevant information into account, even details that are less obvious. However, because of selective memory, highly visible features like a product's design or a prominently advertised discount. This tends to capture consumer attention more effectively (Bordalo et al. 2022).

Furthermore, the Allais paradox is a key example how changing the salience of specific outcomes can change the DMs preferences from risk-seeking to risk-averse behavior (Bordalo et al. 2012). It is depending on the contest whether the lottery's upside or downside determines its attractiveness. Explained further, DMs tend to overweight the outcome if lottery's upside is more salient leading into risk-seeking behavior. This happens because the potential reward dominates attention. Contrary, DMs attention is drawn into the risk if the lottery's downside is more salient and therefore causing risk-averse decisions (Bordalo et al. 2012). Authors state also that decision-making is also affected by the contest how the options are presented (Bordalo et al. 2012).

3.2 Common biases

There are many biases that investors tend to follow. Typically, the importance of the bias depends on the situation, and some biases are more pronounced at certain time. Many of these biases are very closely related to each other, thus, several of them can occur at the same time. In addition, loss aversion and herding are mostly pronounced during high uncertainty. Table. 1 show a list of common biases that is useful to broadly understand human behavior on stock markets. The biases used in Table 1 are loss aversion, herding, overconfidence, overreaction and representativeness.

Table 1. List of common biases.

Bias
Loss aversion
Herding
Overconfidence
Overreaction
Representativeness

For instance, loss aversion plays central role in explaining human behavior under risk. Loss aversion is a critical concept in prospect theory. Humans are more motivated to avoid losses than to seek gains of equivalent value (Kahneman & Tversky, 1979). The study show that value function for losses is steeper than for gains, so the displeasure for losing money is stronger than the pleasure for gaining. One example from their study shows out that perceived difference between losing $100 and losing $200 feels larger than the difference between losing $1,100 and $1,200. Another good example from

(Kahneman & Tversky, 1979) study is symmetric bets. Usually, individuals would find a 50% of losing $100 and 50% of winning $100 unattractive. Essentially the way a choice is framed, either as a gain or loss affects the way we approach risk. That iis almost the same as stated in the study of Bordalo et al. (2012). Bordalo et al. (2012) point out that risk-averse behavior is triggered when the loss of lottery is more salient than its payoff.

Another common human behavior is herding. Herding in financial markets refers to the tendency of investors to follow the actions of others (Christie & Huang, 1995). Herding occurs particularly at the time of market stress and uncertainty. Following the actions of others usually happens at the expense of not trusting your own knowledge and information (Christie & Huang, 1995). The study interpret that this behavior implies that investors decision making is influenced by the collective movements in stock market, which may lead asset prices away from their intrinsic value. According to Bouri et al. (2021) herding is triggered by few instruments like information uncertainty. People may lack of clear information particularly during crises. That causes them to mimic others, if they have greater knowledge and insights.

Also, humans are usually overconfident about their own skills (Baker & Nofsinger, 2002). For example, investors are usually overconfident about their abilities to pick winning stocks. They believe their knowledge is more accurate than it really is. Humans also believe that their future predictions are more precise than their experience should validate (Baker & Nofsinger, 2002). Several factors cause overconfidence. One of the factors is called the illusion of knowledge. It refers to have more information available. This does not automatically mean that more information available increases knowledge. In addition, investors tend to interpret new information to confirm what they already know (Baker & Nofsinger, 2002). Another important psychological factor is illusion of control. Investors usually believe they can influence the outcome of uncontrollable event (Baker & Nofsinger, 2002). Key attributes that contribute the illusion of control are choice, outcome sequence, task familiarity, information and active involvement (Presson & Benassi, 1996). Online investors routinely experience these attributes. They actively make choices, experience different outcomes, becomes very familiar with trading and have access to enormous amount of information (Barber & Odean, 2002).

In addition, humans tend to overreact in the financial markets. According to De Bondt & Thaler (1985) overreaction occurs in stock market when investors play too much emphasis on recent dramatic news. After a positive or negative movement investors belief the trend to continue causing prices to overshoot. De Bondt & Thaler (1985) found out that after an overshoot there is usually a reversal in the price of the asset. Which means that stocks that were overbought may decline and those that were oversold tend to rebound. They demonstrated empirical evidence that portfolios of past losers consistently outperformed the stock market and vice-versa. As mentioned by Shiller, (1998) overreaction can also be seen in the behavior of market participants and analyst, who may draw excessive conclusions of past earnings trends to the future. This might lead into excessive share price appreciation, which are corrected by reversal.

Lastly, the brain tends to assume that things with similar characteristics are alike. Representativeness is defined as people making judgements based on these stereotypes. This bias lead investor to buy assets that seem to have desirable features (Shefrin, 2002). For instance, investors often mistake a good company for a good investment. Firms that have rapid sales growth, strong earnings and quality management are seen as good firms. However, Solt & Statman, (1989) states that good investments are stocks that increase in price more than others. Firms with a history of consistent growth are usually seen as good investments. It ignores the fact that very few companies can sustain such as high-level growth. Popularity of these firms increases the stock prices until it becomes overpriced (Baker & Nofsinger, 2002). Investors tends also to overweigh the past stock returns. Stocks that have been performing well (bad) during past few years might be considered as winners (losers). This causes investors to chase the winners and buy stocks that has been performing upwards in price. (Baker & Nofsinger, 2002).

4 Literature Review of Salience and Financial Markets

The exist of salient information and particularly the salience effect has been studied extensively in the literature of finance. Research has been made on traditional assets and about the growing sector of cryptocurrencies. There has been discussion of its effects, because it can be examined in many various ways.

4.1 Generally

The study by Barber & Odean (2008) examines whether investors are more likely to buy attention-grabbing stocks than sell them. They use three observable measures that can be associated with attention-grabbing events. These measures are news, unusual trading volume and extreme returns. They use data is from four sources: a large discount brokerage, a small discount brokerage, a large full-service brokerage and Plexus Group. The latter is a consulting firm that tracks the trades of professionals.

First, Barber & Odean (2008) examine the buy-sell imbalances for stocks that are sorted on the current days abnormal trading volume. They find that investors at the large discount brokerages shows the most attention-driven buying. For example, their buy-sell imbalance among the highest volume decile is 29.5% and the lowest volume decile is 18.15%. They find similar results among the large retail brokerage and small discount brokerage. Conversely, data shows that among the professionals it is the opposite. Professionals buy on low-volume days and sell on high-volume days. Second, they examine the buy-sell imbalance on previous day’s return. Significant buying activity can be seen on the worst-performing stocks among every individual investor group. On each group the buy-sell imbalance declines on average down to zero and then starts increasing again. Each group is a net buyer among the stocks that performed the best on previous day. Noteworthy, the buy-sell imbalance is most positive among the investors at the large discount brokerage. In addition, the authors find that on average the buy-sell imbalance is greater on days with news than without news. And, that the imbalance is bigger during negative days than positive days. That can be explained by disposition effect. This refers to the preference to selling winners and holding losers (Barber & Odean, 2008).

Another study of salience effect is made by Chaudary (2019). The study investigates the influence of salience on long-term and short-term investment decisions of individual investors and institutional investors. Chaudary (2019) made a survey that included 277 active equity investors from Pakistan. 41 percent were individual investors and 59 percent were institutional investors. The study finds that statistically both groups differ significantly from each other. The impact of salience on short-term and long-term decisions is higher for individual investors than it is for institutional investors. Additionally, the study revealed that the impact of salience on short-term investment decisions is approximately 1.5 times greater than its impact on long-term decisions. This indicates that individual investors are more affected by salience compared to professional investors. These findings somehow share the outcome with the study by Barber & Odean (2008).

Ramos et al. (2020) research reinforce the knowledge of salience. Study seeks to get answer whether web searches for market information is more predictive power than those for firm-specific information. To answer this question, they use three proxies': first, firm's data on EURO STOXX 50 Index, second, Google Search Volume Index (GSVI), which is calculated as *Actual Number of Searches/ Average Number of Searches.* Value of GSVI stands for the rise or fall in the web searches. And third, they measure the stock market activity in terms such as volatility, volume and returns. The results are as following. Trading volume increased for the most traded stocks in week 0 (3.07%) and continued growing week 1 (6.5%) but declined in week 2-4. Returns peaked on week -2 but decreased after portfolio formation. To conclude, the above-mentioned portfolio approach suggest that web search queries might be related to stock market activity. Furthermore, study find that web search queries are great indicator of trading volume and volatility. Large increases (decreases) in search queries have a proportionally larger impact than do smaller increases (decreases). Lastly, they find that when the firm prices break through or approach 52-week highs or lows, web attention has a significant predictive effect on trading volume and volatility. Whereas, at the market level, web attention had a stronger effect during 52-week highs compared to lows. This reinforces the notion that prominent price levels engage investor attention and impact market behavior.

Palomino et al. (2009) study aligns with the previous one. It attempts to analyze whether market reactions stem from rational expectation or overreaction driven by investor sentiment and the visibility (salience) of the information. It examines the stock market reactions of British soccer clubs listed on the stock market. They use two kinds of salience. First, fixed-odds betting made by professionals, which gives insight of professionals though about the condition and possibilities to win the match. That kind of information is short-lived information that evaporates in few days after the match and is only available on sport-websites. Second type of information is match-results that are public and easily accessed to everyone.

The study by Palomino et al. (2009) find that stock prices react to the information of the game results. A win causes a positive abnormal return of 53 basis points on day 1 and a positive abnormal return of 88 basis points over the first three days (statistically significant at the 1% level). On the contrary a loss is followed by a significantly negative abnormal return of 28 basis points on the first day after the game (significant at the 5% level). In addition, a negative average return of 101 basis points inside three days of the match (significant at the 1% level) That result suggest that markets proceed good news faster than negative ones (See Table 2). After a win 60% of abnormal returns are seen in first day, whereas only 28% of abnormal return is seen in the first three days. To sum up, investors react strongly to information contained in game results, and stock prices react faster on positive news than negative news.

According to Palomino et al. (2009) firms with institutional owners are not associated with stronger market returns. Although smaller clubs with individual owners experience stronger market reactions to game results. They suggest that investors overreact to a win if it was expected, due to the positive sentiment. However, investors sentiment is less influenced if their team lose because of fans loyalty. Study finds that match results have influence on stock prices, whereas bedding odds does not have any prominent influence. This might be because of investors might think the same way as professionals who are behind these odds, and they interpret odds differently. Along with trading volume, no abnormal findings occur. Next, they find out whether betting odds can predict returns or not? When a team is strongly predicted to win, the stock performs 68 basis points abnormal return within 3 days. This suggest that betting odds give valuable information for investors. In addition, abnormal returns only emerge when a team is most likely to win. Not in a situation where the team is weakly likely to win or strongly expected to lose. This indicates that investor sentiment plays bigger role how stock market reacts, rather than salience information.

Table 2. Stock market reaction on game results.

	AAR(1)	**A(C)AR(3)**
Win	52.72 BPS	88.26 BPS
Draw	-8.15 BPS	-32.54 BPS
Loss	-27.95 BPS	-100.81 BPS

Table 2. presents Palomino et al. (2009) findings on the average abnormal (cumulative) returns (A(C)ARs) in basis points (BPS) one day and three days after the British soccer game results.

Cosemans & Frehen (2021) and Cakici & Zaremba (2022) finds similar results as Barber & Odean (2008). Both studies align with the fact that investors are attracted to salient payoffs, i.e. investors are interested in stocks with salient upsides. The interest and excess demand for these stocks lead into overvaluation and therefore lower future returns and vice versa. Cosemans & Frehen concentrated only on U.S. stocks and collected data on firms listed on the NYSE, Amex and Nasdaq. Cosemans & Frehen use data from 1926 to 2015. Whereas Cakici & Zaremba (2022) collected data on 49 countries, including 23 developed countries and 26 emerging countries. First, both studies investigated whether high or low ST value affects stocks next month returns. They did so by constructing univariate portfolios. In U.S. stocks the average return for equally weighted portfolio were -1.28% and for value weighted portfolio -0.6%. In the other hand, across 49 countries for equally weighted portfolios average return were -0.34%. Interestingly, if the period is extended for 3, 6 or 12 months the significant silence effect cannot be detected. For the value-weighted portfolios no salience-anomaly can be found. According to Cosemans & Frehen (2021) the return difference between high and low ST portfolios cannot be explained by the common risk factors. In addition, both studies find that ST effect appear mostly on micro-cap and small-cap firms with greater limits of arbitrage. Noteworthy, equal weighted portfolio for microcaps returns average -0.63% in global markets which is almost a double of the comparable values for the sample of all firms. (Cakici & Zaremba, 2022)

Cosemans & Frehen (2021) proceeds to investigate bivariate portfolios to find out if salience effect is widespread or concentrated in stocks with extreme characteristics. Test results show that salience effect remain remarkable after accounting for each of the characteristics. For equally weighted portfolio the average return spread between the high- and low ST deciles ranges from -0.48% to 1.22%. Moreover, five-factor alphas on the high-low ST portfolio are 60bps (equally weighted) and 30 bps (value-weighted) per month. And on annual basis this corresponds to alphas of 7.2% and 3.6%. These results suggest that salience effect is widespread among the stocks. Furthermore, they find evidence among salience and investor sentiment. During high-sentiment equally weighted portfolios return equals -1.41% and low-sentiment -0.88%, difference of 53 bps is significant at 5% level. However, value weighted portfolios spread widens by 72 bps.

According to Cakici & Zaremba (2022) salience effect is more pronounced among emerging markets but there are some interesting exceptions. In France, China and South Korea the effect is powerful, whereas in some countries like Chile and Peru it does not appear even in the microcap segment. Interestingly, the UK displays highly significant positive returns. This can be explained by the structure the UK is driven by the smallest firms in the segment. Unlike the other G7 countries (Canada, France, Germany, Italy, Japan, the UK, and the US) UK is the only one where the positive returns occur. In addition, the authors states that the results of salience effect seen among microcap cannot be recorded on the medium cap or large cap firms, and this is why the authors call the firm size as the Achilles' heel of salience phenomenon.

Cosemans & Frehen (2021) measured ST effect alternatively. Usually, ST effect is measured of stock's daily close-to-close returns, but now they measured it of stock's open-to-open returns. They find that return spread between high- and low ST deciles drops by 50% from 90 bps to 47 bps per month, which is significant at the 1% level. Furthermore, they compare the predictive ability of ST measures calculated using daily returns over the past month, quarter or year to differentiate salience effect from reversal. Results show that return and alpha spreads decrease between high- and low ST deciles when ST is calculated over long period. Fama-MacBeth results show that the predictive power of ST measures weakens when more distant returns are used. This is explained by investors cognitive limitations, which may affect the DMs to focus on the most recent returns. As well investors tend to less stress distant returns, because they think that those are less representative of future earnings. In addition, Cosemans & Frehen (2021) states that in the first stage of decision-making visibility is that what stock attract investors' attention and then are included in their consideration set. In the second stage salience influences the selection process by highlighting specific returns. This highly aligns with the study by Barber & Odean (2008).

Cakici & Zaremba (2022) takes a closer look at the US tests. They find that the abnormal returns vanish over time. Further they excluded the daily return reversal by dropping the last day of the estimation period. After eliminating the last day, the average return of equal weighted portfolio declines from -1.25% to -0.85%. The results for value weighted portfolio are more stunning mean return changing from -0.45% to -0.13%. Cakici & Zaremba (2022) also find that the average market returns on the equal weighted (value weighted) salience strategy in a broad global sample equaled -1.51% (-0.98%) during volatile markets and -0.50% (-0.09%) during stable market. They also measured the impact of past market returns i.e. bull market and bear market. After a bear market global salience strategy equal -1.59 (-1.19%). Conversely, after a bull market returns equal -0.40 (0.15%). Returns are visibly smaller after a bull market.

4.2 Social media

Sprenger et al. (2014) study investigates how different type of information affect stock prices. The authors collect data for six-months of S&P 500 firms. First findings are about the impact of news spikes compared to earnings announcement inside 5 days surrounding the event. They find that market reaction is the strongest on the event day itself (Average Abnormal return, "AAR" =0.01215, $p<0.01$). Positive returns occur 2 to 3 days in a row before the news release. Following negative returns on all days after the event day. Trading volume spikes day before the actual event. Explained either because the expectation of new information or insider information. However, results with earning announcements are slightly different. Unlike news spike, there is observed to be positive returns after earnings announcement, (for instance, days after the event date ACAR=0.2733, $p<10\%$). Trading volume is higher on event day and on the following days. According to Sprenger et al. (2014) investors share more bullish than bearish messages in online forums. In addition, cumulative returns around the events shows clear overreaction, which then diminish in the following few days. On top, splitting events into bullish and bearish events according to "surprise" variable. After a bullish announcement they find a significant positive market reaction by the cumulative returns (ACAR=0.3800, $p<0.1$). Conversely, after a bearish event they do not find any significant reaction.

Study by Ajjoub et al. (2021) find many similar results as the previous study. Ajjoub et al. (2021) investigates the effect of Donald Trump's Tweets on stock prices of media firms and non-media firms. The authors find that positive tweets cause average abnormal return ("AAR") to be positive on that day when the tweet is published for both media and non-media firms. Conversely, negative tweets do not cause any significant movements in both cases. This could be because investors have become numb on Trump's criticism. For non-media firms, negative tweets tend to lead to significant negative abnormal returns. This effect diminishes when the tweet reiterates already known information. The study also finds that positive media tweets became more impactful after the 2016 election, reflecting a shift in market perception of Trump's influence once he assumed office. Matching research have been done by Kim et al. (2021). Kim et al. (2021) states that there is a correlation between the number of tweets and sentiment of the tweets and the price of Tesla's stock. In addition, they note that the correlation becomes more apparent in the long run.

Another social media platform "Reddit" influenced stock markets on significant volume. Even though it has not been widely considered as a platform that could influence the stock markets. A study by Long et al. (2023) investigates the role of reddit, particularly the role of discussion on the r/WallStreetBets subreddit on the price dynamics of GameStop (GME). They collected 10.8 million comments from the r/WallStreetBets subreddit for the first two calendar months of 2021. From its beginning the case was widely discussed in public platforms such as newspapers and tv-news. The sentiments and words used in Reddit differs substantially from Twitter, due to Reddit's chaotic character. The mostly used words were ranked on a scale from +4 to -4. To be extremely positive (+4), neutral (0) or extremely negative (-4). For example, "to the moon" received a rank (+3.5) and "diamond hand" (+2,4). The negative such as "loss" received rank (-2.5) and "wrong" (-1.8). The relationship between the NET sentiment and opening and closing GME prices were much stronger during the up-market days. Discussion forums influence was high pre bull market and during bull market. When GME stock turned bearish the forum was not able to prevent this downturn. To conclude, Reddit's power of transmitting positive sentiments during bull market is strong. But this sentiment and salient information is not strong enough to stop a downfall of the GME stock.

4.3 Cryptocurrencies

Cai & Zhao (2024) examines whether the salience effect occurs in cross-sectional crypto returns. They use data from over 4000 cryptocurrencies valued over one million USD. They develop a salience measure ST, capturing the disparity between salience-weighted and equal-weighted return. This salient-based asset-pricing model predicts that cryptos with positive ST have lower future returns and vice versa. To start with the results, above-mentioned assumption is correct. Besides, the magnitude of salience effect in cryptos is significantly higher than in equities. For example, average return for the long-short strategy which buys high and sells low ST cryptos generates -25.9% (t-value = -8.7) monthly for the EW portfolio and -32.4% (t-value -2.3) for the VW portfolio. These numbers are 20 times the numbers seen in equity markets (See Table 3). By investigating the ST effects relationship for known risk factors the authors find that portfolio generates 3.2% alpha weekly and 24.6% monthly. In terms of risk factors, the weekly results indicates that portfolio is mostly positively influenced by smaller-sized assets and negatively by past performance. So, this suggest that salience effect is unique and cannot be explained by common risk factors.

The study by Chen et al. (2022) is like the previous one. Their study finds similar results, that cryptos with higher ST values earn lower returns in future and vice versa. Chen et al. (2022) furthers the investigation by performing a bivariate dependent-sort portfolio analysis. This suggest that ST effect may be stronger among small cryptocurrencies. Where Cai & Zhao (2024) find that ST effect among cryptos are 20 times the number witnessed in equity market, conversely Chen et al. (2022) find the same multiplier to be 13 times. Furthermore, according to Chen et al. (2022) there is negative relationship between ST value and future earnings among micro-cap cryptocurrencies. Conversely, among large-cap cryptocurrencies the relationship is positive. In turn, Cai & Zhao (2024) stress the size-factor, and note that bigger cryptocurrencies attract more institutional investors. Those are more regulated and integrated to mainstream finance, hence the ST effect is not so noticeable among large cap cryptos.

Analysis shows that the reversal effect diminishes the significance of ST in regression models. The ST effect persist as an independent and economically meaningful predictor (Chen et al, 2022). Thus, underscoring that silence-driven biases cannot be entirely explained by mean-reverting behaviors like short-term reversal. Chen et al. (2022) find that ST effect has stronger impact on the pricing of cryptocurrencies with higher volatility, higher bid-ask spread and higher idiosyncratic volatility. The coefficients on the interaction terms *ST value times cryptocurrency's age* and *ST value times cryptocurrency's size* are positive, which indicates that arbitrage constraints and information costs are lower for large-cap and well-established cryptocurrencies.

Table 3. The salience effect measured on various assets

Authors, Year	Description	Time-period	Geo-graphic area(s)	Asset Class	Portfolio type	Salience effect (%)	T-value
Cai & Zhao, (2024)	Average monthly return for a strat-egy that buys high and sells low St value cryptos	2014-2021	Global	Crypto	Equal-Weighted	-25.9%	-8.7
Cai & Zhao, (2024)	Average monthly return for a strat-egy that buys high and sells low St value cryptos	2014-2021	Global	Crypto	Value-Weighted	-32.4%	-2.3
Cosemans & Frehen, (2021)	Average monthly return for a strat-egy that buys high and sells low St value U.S. eq-uity	1931-2015	U.S.	U.S. Equity Market	Equal-Weighted	-1.28%	-10.73
Cosemans & Frehen, (2021)	Average monthly return for a strat-egy that buys high and sells low St value U.S. eq-uity	1931-2015	U.S.	U.S. Equity Market	Value-Weighted	-0.60%	-4.08
Cakici & Za-remba, (2022)	Average monthly return for a strat-egy that buys high and sells low St value Micro-cap firms	1990-2020	Global	Global Micro-cap firms	Equal-Weighted	-0.63%	-8.27
Cakici & Za-remba, (2022)	Average monthly return for a strat-egy that buys high and sells low St value Micro-cap-firms	1990-2020	Global	Global Mirco-cap firms	Value-Weighted	-0.31%	-3.9

Table 3. presents the magnitude of salience effect on cryptocurrencies, U.S. equity market and micro firms. The magnitude is measured in percents, and t-value and it is measured to equally weighted portfolios and value weighted portfolios.

5 Conclusions

This thesis examines the effect of salience in the stock market. More specifically, how does salient information, such as extreme returns or news coverage, affect the investment decisions of investors in the asset markets. Different type of information affect peoples' mood differently. Also, salient information is pronounced more in specific circumstances than others. This thesis covers also a theory section explaining the related theories behind the research. Hypotheses were based on existing literature and relevant studies are used to answer them.

According to previous studies it can be said that investors' attention is attracted by different varieties of salient information. Previous research provides evidence that investors are more heavily affected by positive salient information. More specifically information that they expected or information that reinforce their own opinion. For instance, investors trading volume increases more when a stock price hits a 52-week high, than it declines when it hits 52-week low. Literature also suggest that investors react to positive information faster than to negative information. Thus, markets reactions are stronger for positive news during short period. Furthermore, investors are more likely to share bullish information rather than bearish. The same laws appear to be true also among cryptocurrencies. Hence, the literature confirms the first hypothesis to be true.

According, the second hypothesis show that salience is more frequently pronounced among riskier assets, such as micro-cap stocks and cryptocurrencies. According to the previous research individual investors are the ones that are mostly influenced by salient information, not the institutional ones. Also, stocks with less institutional investors are likely to be highly volatile. (i.e. salient information plays significantly bigger role among small companies). These findings support the second hypothesis.

After reading this thesis the reader should be aware of salience effect in a broader view. The reader can now recognise the circumstances where the salience effect affects the most. In addition, the reader can critically evaluate whether trading on fundamentals or emotional responses to salience. Consequently, the reader can make more rational and better investment decisions.

For future research, this thesis suggests that artificial intelligences' role as a salient information distributor should be researched. Also, the evolving market of cryptocurrencies should be studied more in future, because the regulation of those is likely to change heavily in the year 2025.

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