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Study of short-term reversals in stocks of the S&P100 stock market index

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ABSTRACT:
Short-term reversals in stock prices, which are price reversals following large price moves in the positive or negative direction, have been studied for several decades, with much of the existing literature finding that price reversals tend to occur following large price movements in stocks. Recent research has increasingly focused on shorter time intervals, and this study examines short-term reversals using daily data for stocks listed in the S&P100 index. The aim of the study is to investigate whether short-term stock price reversals persist during the COVID-19 crisis and the post-COVID period, during a time of rapid changes in market behavior, fintech development, increased retail investor participation, and the emergence of meme stocks.

The analysis uses daily market data from 2018 to 2025 and applies event study methodology to evaluate return behavior following large daily price movements. Return reversals are examined using both raw returns and abnormal returns across multiple threshold levels. In addition to two and eight percent thresholds that are tested in previous studies, the levels of six and four present thresholds are added to this study to allow an assessment of whether reversal effects are present even after more moderate price changes than have been tested previously tested.

The results show statistically significant short-term reversals in raw returns following both large price increases and large price decreases for all threshold levels examined over the full sample period. In contrast, abnormal return results are less conclusive, with evidence of a delayed and relatively weak reversal following positive price shocks and continued momentum following negative shocks. Robustness analysis indicates that reversal effects are not consistent over time: years with high concentrations of large price movements display strong and significant reversals, while periods with fewer extreme events show weaker or insignificant effects and, in some cases, momentum behavior. The findings overall indicate that short-term reversals in daily market movements exist in recent years, but they vary in strength from one period to another.

KEYWORDS: shares, financial markets, efficiency, predictability, anomalies

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TIIVISTELMÄ:
Osakehintojen lyhyen aikavälin käänneilmiötä (short-term reversal) on tutkittu useita vuosikymmeniä. Suuremassa osassa aikaisempaa tutkimuskirjallisuutta vahvistetaan, että osakehinnoilla on taipumus suunnan kääntymiselle suurten hintaliiketapahtumien jälkeen. Viimeaikainen tutkimus on keskittynyt yhä lyhyempien aikavälien tarkasteluun. Tässä tutkielmassa selvitetään lyhyen aikavälin käänneilmiötä käyttämällä S&P100-indeksiin listattujen osakkeiden päivätason dataa. Tutkielman tavoitteena on selvittää, onko osakehintojen lyhyen aikavälin käänneilmiötä nähty edelleen COVID-19-kriisin ja sen jälkeisten vuosien ajan. Tässä ajassa on ollut markkinaheilahtelua, finanssiteknologian (fintech) nopeaa kehitystä, vahvaa kasvua yksityissijoittajien osallistumisessa osakemarkkinoihin sekä meemiosakkeiden esiintymistä.

Tutkielman analyysissa käytetään päivittäistä markkinadataa vuosilta 2018–2025, ja sovelletaan tapahtumatutkimusmenetelmää markkinakäyttäytymisen arvioimiseksi suurten päivittäisten hintamuutosten jälkeen. Osakehintojen liikkeitä tarkastellaan sekä raakatuottojen että ylituottojen avulla useilla eri kynnystasoilla. Aiemmissa tutkimuksissa testattujen kymmenen ja kahdeksan prosentin kynnysarvojen lisäksi tässä tutkielmassa sovelletaan myös kuuden ja neljän prosentin tasoja. Nämä matalammat tasot mahdollistavat arvioimaan, esiintyykö lyhyen aikavälin kääntéitä myös matalampien hintamuutosten jälkeen verrattuna aiempiin tutkimuksiin.

Tutkielman tulokset näyttävät tilastollisesti merkitsevä lyhyen aikavälin käänneilmiötä raakatuotoissa sekä suurten hinnannousujen että hinnanlaskujen jälkeen kaikille testatuille kynnystasoille koko tutkimusajanjaksolle. Vastaavasti ylituottoja koskevat tulokset ovat vähemmän yksiselitteisiä. Positiivisten hintashokkien jälkeen on todettu viivästynyttä ja suhteellisen heikkoa käänneilmiötä, kun taas negatiivisten shokkien jälkeen esiintyy jatkuvaa momentum-ilmiötä. Robustiustarkastelu osoittaa, ettei käänneilmiö ole lyhyemmillä yhden vuoden ajanjaksoilla yhdenmukaista. Niinä vuosina, kun esiintyy suuria hintaliikkeitä tiheämmin, käänneilmiö on vahvempi ja tilastollisesti merkitsevä. Vastaavasti vuosina, milloin on vähemmän ääritapahtumia, vaikutukset ovat lievempiä ja ilman tilastollista merkitystä. Joinakin vuosina huomataan jopa momentum-käyttäytymistä. Kaiken kaikkiaan havainnot osoittavat, että viime vuosina päivittäisissä markkinaliikkeissä esiintyy lyhyen aikavälin käänneilmiötä, mutta sen voimakkuus vaihtelee vuodesta toiseen.

AVAINSANAT: osakkeet, rahoitusmarkkinat, tehokkuus, ennustettavuus, anomaliat

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Abbreviations

AI	–	Artificial Intelligence
AMEX	–	American Stock Exchange
AR	–	Abnormal Return
BMI	–	Broad Market Index
CAPM	–	Capital Asset Pricing Model
CAR	–	Cumulative Abnormal Return
CRSP	–	Center for Research in Security Prices
DJIA	–	Dow Jones Industrial Average
ER	–	Expected Return
EMH	–	Efficient Market Hypothesis
FinTech	–	Financial Technology
NYSE	–	New York Stock Exchange
NASDAQ	–	National Association of Securities Dealers Automated Quotations
OEX	–	S&P 100 Index (CBOE ticker symbol)
PFOF	–	Payment for Order Flow
RR	–	Raw Return
S&P100	–	Standard & Poor’s 100 Stock Index
S&P500	–	Standard & Poor’s 500 Stock Index
VIX	–	CBOE Volatility Index

1 Introduction

Predictability of the stock market has fascinated researchers and investors alike for centuries, as to find a method or algorithm that can produce abnormal returns above the market average for an informed investor. The ideology of finding a method that is tested to provide for increased abnormal returns with relatively low risk would allow for an investor to remove their own subjective biases, feelings and premonitions, and allow for the application of an algorithm to provide for consistently higher than market returns over a prolonged period. A theory of predictability of stock price behavior after large stock price movements that has been studied heavily over the years is the reversal effect in stocks.

This study is focused on the short-term reversal effect, which in an anomaly that has been the focus of study for over 40 years, in which there is a tendency for stocks with high (low) return in a previous period to underperform (overperform) in the following period. Studies of the phenomenon typically indicate its occurrence is mainly due to investor overreaction, but also influenced by liquidity issues, institutional behavior, trading frictions and transaction costs. (Zaremba et al., 2019)

Return reversals have been studied at various intervals to include both longer-term, such as multiple months to several years, and shorter-term time periods, such as one or multiple successive days after the initial price movement. The focus of this study will be on short-term reversals of one to five days. Other durations will also be visited in the theoretical review. Event study methodology will be deployed to evaluate stock price performance following abnormal events during the time window under evaluation.

1.1 Background and motivation

In the mid-1900’s the study of market theory experienced a breakthrough method in defining how to calculate expected returns for stocks with the publication of the capital asset pricing model (CAPM) devised by William Sharpe in 1964. The method was novel in its field to attribute a single market factor to calculate expected returns, which is still used in finance today. For many years, the CAPM was the only popular method with only one market factor. With the introduction of Fama and French's three-factor model in 1993, the concept of additional explanatory factors to pricing behavior gained popularity by adding the dimensions of firm size and factor of value-versus-growth. (Stambaugh & Yuan, 2017) The CAPM is still used for evaluating portfolio performance decades after its inauguration. With the introduction of the CAPM, once a common method for evaluating an asset expected value over time became available, it became a fascinating study to try to understand which other factors contribute to providing exceptional returns above that which is offered by the overall market. (Fama & French, 2004)

The concept of short-term reversal in stocks has been studied by many over the years. A few of the top early studies concluded that market reversals have appeared in shorter and longer durations in many different markets throughout most of the past century. Additional studies have shown that depending on the market and time-period, there may not be any significance in the results, indicating everything happens by chance or driven by other factors, or some find that the same strategy does not provide for abnormal returns at all.

We understand that we live in a society that is growing in capability and dependence on artificial intelligence (AI) and increasing capability to process high frequency data. From this we can derive several possible theories, to include, that has the market efficiency has improved to more quickly process and price in new information to the market (Chopra et al., 2024), or is now making for larger overreactions in the market as more participants are using the same tools in attempt to make the same types of trades simultaneously, creating for higher levels of overreaction or herding behavior. (Klein, 2022)

Media endorsements of individual stocks are also known to contribute to mispricing in equities. Known phenomena of the past have been linked to publications in the New York Times about pharmaceutical advancements that have been published months earlier, but the news coverage incites investment behavior that is not related to any release of new information (Huberman & Regev, 2001), which has advanced to, for example, television show buy or sell recommendations made on a popular investment show host that is driving investor behavior (Engelberg et al., 2012). Moving forward, as technology advances, it becomes possible to interpret signals from high frequency data. Analysis of market behavior has been studied using high frequency social media data, showing that certain key words used in social media content can be leveraged as information to which trades can add be used for creating a profitable trading strategy (Sun et al., 2016). As technology advances, there are increasingly more signals, using increasingly massive amounts of information, that can be incorporated investor behavior which may constitute to changes in how the market behaves, to include with reversal behavior in stocks.

My motivation for this study is to review the literature that is currently available and test the market from the COVID and post-COVID time-periods we have recently experienced for short-term reversals, to see if the results are similar or different from past study results, as the world of finance and participation in the stock market has dramatically changed in the past decade with globalization, digitalization and streamlining of financial services to include buying and selling of stocks.

1.2 Previous main studies

In 1985, De Bondt and Thaler published their research findings on over 50 years of monthly market returns data for the New York Stock Exchange (NYSE), between January 1926 and December 1982. The main findings of the study indicate that the 35 worst performing stocks of the index over a 36-month period experienced a reversal in the following 36-month period that provided an average of 19.6% above the market average. Contrarily, the 35 best performing stocks of the same three-year period reversed to lag the market average returns by 5.0% in their following three-year period. The reversal in the stocks was consistent with their hypothesis that there is an overreaction by the market in the extreme mover stocks in the opposite direction afterwards. The behavior was concluded to validate the study hypothesis that markets tend to overreact to information. A surprise in the results indicated that most of the difference occurred in the second and third year of the three-year portfolio holding period. Additionally, most of the excess returns were realized in the months of January, indicating a seasonal effect. (De Bondt & Thaler, 1985)

In 1993, Jegadeesh and Titman published findings that are countering the results of De Bondt & Thaler (1985). The study examined NYSE and AMEX stocks between 1965 and 1989 and modeled a strategy where the portfolio formation period to define the extreme stocks was set using between 1 to 4 quarters, which are typical earnings cycles, and used a strategy of building portfolios of stocks for each of ten deciles in terms of percentage of stock price change during the evaluated portfolio formation period. At the end of the portfolio formation period, there is a one-week lag, before formation of the holding portfolios, which are held for a period of 1, 2, 3, or 4 quarters. The top and bottom decile portfolios were then evaluated for the total of 16 separate possible scenarios of duration of the portfolio formation period and holding period. The study finds the stocks having performed well (poorly) in the past, generate significant positive (negative) returns over both 3- and 12-month holding periods. (Jegadeesh & Titman, 1993)

In a study by Eugene Fama and Kenneth French (1996), they explore market pricing anomalies through the lens of multiple factors. They concluded that the CAPM cannot explain pricing anomalies and tested how well the Fama and French three factor model is able to explain pricing behavior in stocks. For anomalies such as long-term return reversal that is documented by DeBondt & Thaler (1985) as well as industry specific effects on price can be mostly explained using the three-factor model. At this point, Fama and French acknowledged an 'important hole' in their work, in terms of a variable that is related to relative distress, which was left for future study with a declaration that this issue is still far from being closed. It is however clearly found that the risk-return relationship of the three-factor model cannot explain the continuation of short-term returns that were documented by Jegadeesh & Titman (1993). (Fama & French, 1996)

In a 2012 study by Stefan Nagel, the reversal strategy has been applied to daily stock prices to evaluate if a reversal in price exists in daily stock data. It was concluded that the CBOE S&P500 implied volatility index (VIX) is highly predictive of the level of returns that can be obtained from a short-term reversal strategy. The strategy used by Nagel is unique in selection of stocks to be included in the study to buy (sell) the stocks that performed the worst (best) during the past five trading days to form a no-cost portfolio strategy and finds that the three-month moving average of daily returns from the reversal strategy is highly correlated with the VIX index. The study included stocks that trade in the NYSE, AMEX and Nasdaq stock exchanges in sample period from January 1998 to December 2010. Daily returns during periods of crisis such as Long-Term Capital Management crisis in 1998 and Nasdaq decline in 2000-2001, the daily reversal returns were about 1%, and during the financial crisis in 2007-2008, returns even higher. During the more stable period of growth before the 2007 crisis, the daily three-month average return had tapered down to about 0,2%. The strategy was able to provide positive returns throughout the complete sample period. (Nagel, 2012)

In 2013, Da, Liu and Schaumburg studied short-term reversals to find that a strategy of selling (buying) the top (bottom) performing decile of stocks can provide abnormal returns while investigating a sample of about 2350 stocks listed in the Center for Research in Securities Prices (CRSP) database, covering about 75% of the U.S. stock universe in terms of market capitalization between 1982 and 2009. The selected sample of stocks had the requirement to have analyst coverage, so this made the tendency for the stocks in the study to have higher than average market capitalization. In the model used in their study, they measure the residual returns of stocks in the previous month and sort into deciles by residual returns. They find that the strategy of buying losers and selling winners can create positive raw returns of 0.67% per month during the examined period. The study further focused on identifying the reasons for the existence of the short-term reversal effect and found that the results can be further enhanced by sorting stocks by industry and making decile rankings based on the stock placement in the industry ranking. This strategy was the benchmark for the study, and it generated a return of 1,57% per month with a highly significant t-value for the period that was evaluated. (Da et al., 2013)

The study of reversals is not limited to any one specific time interval in data, as the phenomenon has been evident in daily data as well as longer term, such as weekly, monthly and quarterly as well. The premise to the predictability of reversals is that a large movement in a stock is generally an overreaction by the market causing for a retraction following large movements, whereas the absence of a reversal would be an indication of continued momentum, or underreaction by the market, which results in a movement of the stock price in the same direction as the initial large movement after an event.

1.3 Purpose of study

The aim of this study is to investigate if short-term reversals have been present in the recent history of the S&P100 index listed stocks. This index has not specifically been visited in studies completed and has its own characteristics that make it intriguing for further study. The index is comprised of large capitalization, liquid stocks which ease possible concerns of liquidity and small market size that might be too heavily influencing the results for this type of study. Additionally, there will be multiple threshold levels evaluated to provide for a more comprehensive view of reversals with variations in the degree of severity of the initial price movement in a stock that has not been implemented in literature to this scale before.

The purpose of this study is to test if short-term reversals are present in the COVID and post-COVID markets and evaluate how the phenomenon has developed over the same period, where the market dynamics have changed significantly. As noted by Aldasoro et al. (2025), in the current market environment, information is shared and processed faster and at higher volume than before, and there is more automation used in making trading decisions, which allows for increased trading frequency. Artificial intelligence (AI) technologies have emerged with increasing ability to process information, aid in risk management, and even enhance customer service within the financial sector. With AI, there come also challenges, as the models used lose clarity which rely heavily on the availability of data. (Aldasoro et al., 2025)

Further changes in the market are related to the dramatic increase of retail investors during the studied period. During the COVID-19 pandemic, “meme stocks” emerged where a large number of retail investors engaged in coordinated buying of specific stocks, such as GameStop, Bed Bath & Beyond, and AMC over a short period of time. The impact of the sudden generated demand for these stocks was that prices surged to unexpectedly very high levels, based on any valuation method. Some of the companies, such as AMC and Gamestop, realized the situation and used this sudden hype in stock price to raise a large amount of capital, which in turn improved permanently and improved their financial positions. The emergence of a surge of “meme stocks” was a dramatic shift in shareholder base away from traditional institutional ownership to individual investors. (Aggarwal et al., 2023)

1.4 Intended contribution

With the growth of automated technology and artificial intelligence, at the same time as more investment decisions are made by individual participants in the stock market, it has become a pivotal time to evaluate what effect the new market environment is having on reversal behavior. It can be theorized that reversals may be muted with AI driven algorithms and rapid automated transactions that would add efficiency to the market. AI may have limitations that are not yet understood, due to the ‘black box’ type functionality of AI processing. Alternatively, the introduction of larger number of individual decision makers to the market that have the combined strength to, at least for short periods of time, overcome standard valuation-based methods, and may itself create for more radical movements in stock prices, which may have increased the overreaction of the market to have an amplifying effect on reversal behavior of stocks during this period.

The intended contribution from this study aims to assess if short-term reversals exist in the COVID and post-COVID stock market, and if the phenomenon has weakened or strengthened during the examined period in the S&P100 index stocks. During these years, there have been many advances in technology which have been adopted to a changing market environment to include FinTech, AI and other factors such markets being influenced by posting on social media platforms such as Reddit and Twitter (X). Furthermore, the scope is expanded beyond what has been typically studied in literature to examine not only large positive and negative daily moves in a stock price of 8 to 10 percent in daily trading, but to also examine what effect there is on reversal with also lower thresholds of 4 and 6 percent. The addition of lower thresholds to the study is expected to provide insight into if the short-term reversal theory is expandable to lower thresholds, which would provide for significantly more events to be evaluated from any studied period.

1.5 Limitations and assumptions

The limitations faced during this study are to be able to account for additions and subtractions to and from the S&P100 index during the study window and finding a single data source for all 100 stocks. Furthermore, stocks that are dropped from the index are removed from being included in the statistics for any threshold levels exceeded, starting five days prior to delisting date as the model is requiring the price movement information to be available for five days after the event.

2 Theoretical Background

It has long been theorized that financial markets are efficient, and prices reflect all available information. The work of Eugene Fama (1970) in modelling efficient market hypothesis has been a cornerstone of theory on which security prices behavior has been evaluated afterwards. Prior to this work, theories projected security prices as being random walk, which is implying that historical prices of stocks do not contain any information to predict the future price, as the price is fully reflecting all information. In the random walk model, it was assumed also that the changes in price are also normally distributed. (Fama, 1970)

2.1 Efficient market hypothesis

Efficient market hypothesis (EMH) by Fama (1970) opened the concept that information is efficiently priced into the market and level of risk and market return are the factors which expected returns can be calculated. The forms of efficiency fall into three hierarchical categories. The first and most simple form is weak-form efficiency, which is an assumption that past trading information is priced into the historical prices of a stock and that there is no value that can be gained from the information. Any new information is quickly priced in and thus there are no serial correlations that can be derived to produce an edge over the market. Consequently, this equates to a market which would not allow an investor to earn abnormal returns using technical analysis. Second, semi-strong form efficiency is an expansion to include all information made publicly available. This type of information includes earnings announcements and stock splits for example. The assumption with semi-strong form is that prices adjust to this new information immediately. The third form of efficiency in the model is strong-form efficiency, which in addition, evaluates private information. The assumption in this form is that all available information, including any information that is privately held, is always priced into a security. Strong-form market is considered the benchmark against which deviation from market efficiency can be judged. Although there were a few deviations to strong-form efficiency identified, such as monopolistic access of information of unexecuted limit orders to specialists on the major security exchanges and corporate insiders having access to internal firm specific information, it was found that overall, the market was efficient and contradictory evidence was sparse. (Fama, 1970)

Supporting evidence for efficient markets can be found in Fama, Fisher, Jensen, and Roll (1969) study, *Adjustment of Stock Prices to New Information*. The study evaluates how stock prices adjust to stock splits using an early form of event study methodology. The study uses monthly data to evaluate efficiency and find that there is an increase in the price of the shares of a stock prior to its announcement of a split. The stock split was seen as an indication to the market that dividends will substantially increase after the split. It was concluded that as soon as the split announcement was made, the average abnormal returns leveled off in the following months as the market had efficiently priced in the expected increase of dividend to the stock price. (Fama, et al., 1969)

Several decades after the Fama (1970) publication, other exceptions were pointed out by the Malkiel (2003) study. Although Malkiel states that the market is remarkably efficient in its utilization of information, there are exceptions where pricing mistakes are made. The definition of efficient market for this study was that an efficient market does not allow investors to earn above-average returns without accepting above-average risks. One noted exception, the ‘internet bubble’ of the late 1990s, shows how irrationality can affect the market. Irrationality can create valuations that are not realistic by any calculation methods, as was seen with the valuation of Palm Pilot, during the height of the internet boom. After a spinoff move, initially only 5% of Palm Pilot shares were sold to the public, while the remaining 95% was held by 3Com. Based on the value of Palm Pilot shares held by 3Com during the peak valuation period, the value exceeded the market capitalization of 3Com in entirety, which is implying the value of all business excluding their stake in Palm Pilot is negative. The irrationality, however, did not provide any arbitrage opportunities for anyone, even though the prices did eventually adjust to levels that can be considered likely reasonable values. Furthermore, the study discusses momentum and reversals in stocks have been known to occur. It was an accepted notion that in the short run, when stocks are measured in days or weeks, some positive serial correlation was understood to exist. Return reversals, or negative correlation with past returns, appeared over longer holding periods. Serial correlations in the positive or negative direction would imply that some form of inefficiency is present in the market. In conclusion, pricing irregularities and even predictable patterns in stock returns can appear and persist for a short time. (Malkiel, 2003)

This study of short-term reversals evaluates if exceptions to efficient market theory can be found in the period 2018 to 2025 in the stocks of the S&P100 index. Positive findings of short-term reversals would be an indication of inconsistency in the weak-form efficient market theory as historical prices would give an indication of the future direction of the price of stock.

2.2 Main theory

The phenomenon of short-term return reversals, which is the focus of this study, presents an exception to the efficient market hypothesis and has been studied extensively in the past several decades. There are varying conclusions made in the study outcomes which we will examine more closely in this section. The basic premise of the theory is that stocks are monitored for a set timeframe after which there is a long position taken in the worst performing stocks and short position in the best performing stocks for a profitable trading strategy. Over the past decades of studying the short-term reversal effect, the consensus has been stated that the phenomenon exists but is very difficult to profit from due to the costs associated with implementing the strategy being equal or greater than the returns produced by the trading activities. (De Groot, 2012) Naturally, as this consensus has been made, there have been many studies made to counter this result. More recent studies have shown that profiting from stock reversals is possible and enhanced by refining the strategy from a simple reversal strategy by integrating other factors to enhance the results.

Theory suggests that “large price moves in stocks contain some element of overreaction to unobserved stimuli.” (Kudryavtsev, 2018). This theory is backed up by many studies such as De Bondt & Thaler (1985), Jegadeesh & Titman (1993), Daniel et. Al (1998), and Hong & Stein (1999). Bremer & Sweeney (1991) bring forth contradictory evidence to popular asset pricing models due to the reversal effect that he observed on the stock price in the following days after a daily fall of 10% or more. He observed that daily stock returns after such an extreme event are, on average, much larger than would be expected. Furthermore, the recovery period for that stock after such a shock event is much longer than would be expected in an efficient market that is able to price quickly and in full any new relevant information. After a fall of 10% in stock price, the calculated daily stock returns on average of 1.773% on the first day following the event, and 2.215% cumulative rise by the second day for the stock. (Bremer & Sweeney, 1991)

De Groot et al. (2012) has opted for wider definitions in scope to include thousands of stocks, including the Citigroup US Broad Market Index (BMI) containing 1500 of the largest US stocks and the Citigroup European Broad Market Index with 1000 of the region’s largest stocks. In the study, two decades of data between 1990 and 2009 were evaluated. Reversal strategy profitability was partially attributed to higher bid-ask spreads in favor of the technical traders implementing a reversal strategy, as the strategy, by design, buys (sells) stocks for which market supply (demand) is larger than the demand (supply). The study findings indicate that reversal strategies generate 30 to 50 basis points per week net profits, and that the largest net reversal profits were from large cap stocks, especially during the decade of 2000-2009, during periods where market liquidity increased dramatically. (De Groot et al., 2012)

In the Da et al. (2013) study, which evaluated a 27-year sample period between 1982 and 2009, the study concluded that short-term reversal is “pervasive and much greater than previously documented.” The study explored if the type of shock is making a difference in the level of reversal to follow it. By testing whether the shock was related to information about the company fundamentals or related to other types of information, he found that would result in a differing reversal behavior. The results suggested that firm-specific information tends to cause a price overreaction. There is strong evidence to support the theory that reversals of recent losers are driven by liquidity shocks, and reversals of recent winners are driven by investor sentiment. The reversal strategy deployed in the study produced a positive three-factor alpha of 1.34% per month. The result was enhanced fourfold over a standard reversal strategy by utilizing the method which included large stocks with analyst coverage. (Da et al., 2013)

It was contemplated in the Han & Liu (2024) study, timing for buying and holding stocks is difficult due to the unpredictability of return reversals. The study investigates the most volatile time periods of the first decade in 2000, specifically during the financial crisis period in 2008 and 2009. The study finds that in down-trending markets, the market usually experiences a reversal after severe declines, however the challenge for investors is finding optimal timing in entering and exiting positions, which is difficult to predict. Using data from US indexes S&P500, DJIA, Russell 2000, as well as comparatively CSI 300 in China, the findings showed that the optimal buy/sell point in a reversal strategy is a function of the stock return, volatility and the intensity of the reversal. In a volatile market, investors should buy and hold stock as early as possible when volatility and intensity of return reversal increase, following a large downturn. (Han & Liu, 2024)

The evidence of overreaction in the market due to new information becoming available is understood to be the driver for reversal behavior of stocks. Enhancing the return magnitude there have been many factors evaluated for their individual contribution. For this study, we are interested in testing new data on how this phenomenon has evolved in recent years.

2.3 Large movements in stocks

The study of reversals in stocks is mainly in agreement that stock returns exhibit reversals within short horizons (Jegadeesh et al., 2025), even though anomalies have been found that present evidence of momentum in certain subsets of data. Jiang & Zhu (2017) conclude that large jumps in a stock's price that are infrequent in nature are typically triggered by the arrival of unexpected information. The definition of what is considered a large movement in the daily price of a stock varies between studies. The definition of what is triggering an event to be included in a reversal dataset is an important factor in the outcome and differences in methodology are important variables in explaining the differences in results between studies.

For methodologies that are constructing a portfolio of stocks, to be bought and sold daily, typically, the daily most winning and losing stocks are sorted by daily percentage increase or decrease and placed into smaller subsets such as deciles or quintiles (De Groot et al., 2012; Kang et al., 2025), or top and bottom performing set number of stocks (Atkins & Dyl, 1990), that are then used to implement the strategy, such as creating a no-cost portfolio to follow set holding time rules.

In reversal studies, which are constructed as event studies, such as this study, the threshold level is often set at 10% daily price movement (Bremer & Sweeney, 1991; Cox & Peterson, 1994; Kudryavtsev, 2018). The 8% threshold level was used by Kudryavtsev (2018) also. Other defined trigger methods that are used are focused on elements that their study is intended on proving, such as price movement or volatility triggers based on an estimation window from prior to the event (Kudryavtsev, 2018; Ma et al., 2023).

There is consistency in the studies that they are all having threshold methods that show indication of a large abnormal event, after which the price behavior is intended to be investigated in detail. Studies, such as Kudryavtsev (2018), compare different methodologies of defining the trigger for an event and find that although there are differences in results, the results still confirm a common indication of the existence of the reversals in the dataset.

2.4 Reversal vs. Momentum

As defined in the introduction, when the price of a stock changes direction after a large spike or drop, it is called a reversal. When the price of the stock continues in the same direction as the large movement, this is called momentum. Where reversals are a signal of investor overreaction, the momentum is due to investor underreaction. As per the Jagadeesh (2025) study, it is expected that a reversal appears during a short lag period from the time of initial spike or drop in a stock's price, but in an intermediate period is no longer predictable, and in longer term reverts to the stocks' own momentum trajectory.

A model of stock price behavior of overreaction (underreaction) when investors are overconfident (underconfident) was introduced by Daniel et al. (1998) that explains how the price of a stock changes over time and level of confidence within the investors that are engaged.

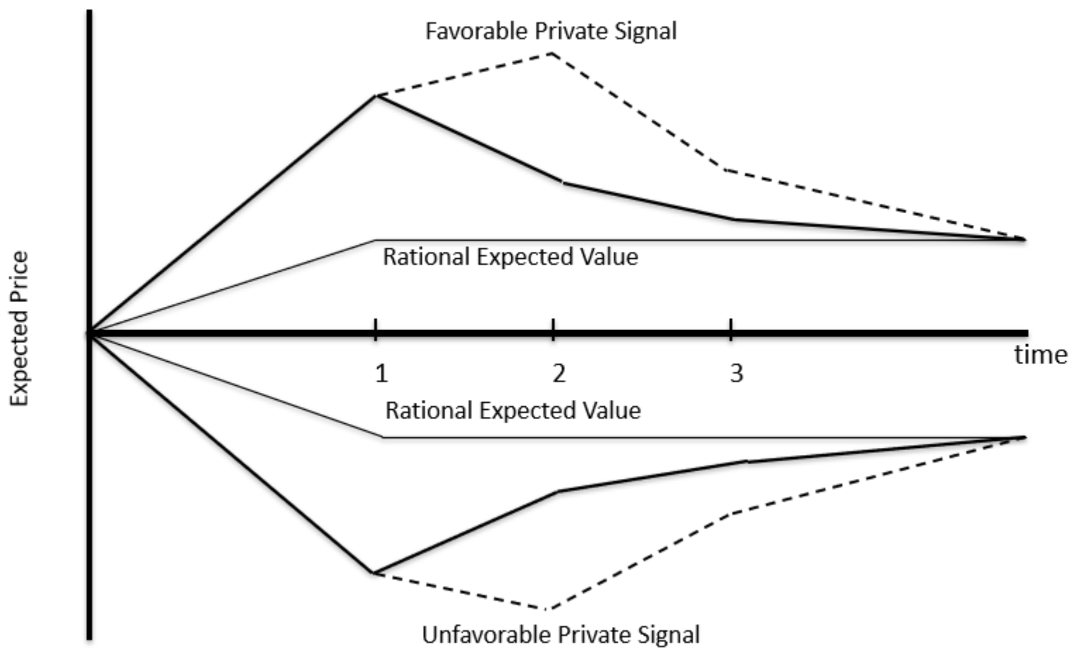

Figure 1. *Expected price movement after initial event (Daniel et al., 1998)*

With the initial release of public information on day 1, if investors are over-confident (under-confident), it creates a spike (drop) in price to exceed the rational expected value effect of the information that is received. The size of the spike (drop) on day 1, beyond the rational expected value is dependent on the level of overconfidence (under-confidence) that the investors have based on the public information received. The valuation of this public signal is displayed in the dark line. Private information is information or understanding that is not available to all market participants, which develops after public information is received and processed. If there is overconfidence in the private signal, the second day valuation may still rise further, even though the price related to the public signal is reverting towards the rational expected value. As shown, based on the level of overconfidence in public or private information, it may take more than one day for the reversal effect to be seen in stock price. (Daniel et al., 1998)

In a model created by Hong & Stein (1999) to explain under and overreaction, they define the market being comprised of two groups of rational agents each with own limitations. The "news-watchers" observes some part of private information but is unable to extract information from other news-watchers' information. Furthermore, the news-watchers make their own forecasts based on signals they privately observe related to future fundamentals. They are limited in that they do not consider current or past prices in their decisions. The other group of participants are the momentum traders, who condition their decisions on past price changes, but their limitation lies with the simplicity of their model for making decisions. Private information is slow to spread within the news-watchers, which creates underreaction in the price of the stock. Momentum traders receive the signal from past price changes initiated by the news-watchers and try to exploit the underreaction, and by doing so, they create an excessive momentum to eliminate the underreaction and eventually cause an overreaction. (Hong & Stein, 1999)

As theorized by Hong & Stein (1999) the overreaction is not created by the news-watchers, and thus, the information itself is not causing any overreaction in a stock, but rather the overreaction is created when momentum traders are following suit and causing for an overreaction. In time, the market prices in the new information, but a large overreaction, such as creating a meaningful spike (drop) in the prices of a stock that would also result in a reversal, would require a sufficient overreaction to be created by the momentum traders following any specific event.

3 Literature review and hypothesis

The literature review is comprised of theoretical views of the finding of short-term reversals in daily data and further evaluation of some of the factors are found to influence reversals in stocks.

3.1 Daily return reversals

The study of return reversals in daily market data gained the spotlight in the early 1990's. One of the first studies to declare reversal behavior in daily data was the Marc Bremer and Richard Sweeney (1991) study, where they found that after a 10% drop in the daily stock price, the following day return is 1,773% above its average return from the entire sample period, and 2.215% above average two days following the event. The data tested was from the period 1962 to 1986 for Fortune 500 stocks in the US. The average event was a -13% drop, which exhibited a slow decline in the 20 days prior to the event, and after the event a bounce back towards the long-term average price. (Bremer & Sweeney, 1991)

In the Cox & Peterson (1994) study of short-term reversals after one-day declines, he evaluated the daily returns following a 10% drop in price of NYSE and AMEX listed stocks between 1963 and 1991. The reversal effect was evaluated for six different subperiods, where findings indicated that although in the first period, between 1963 and 1967, they showed a strong reversal returns of 1,73% average abnormal returns in NYSE listed stocks and 1.15% for AMEX listed stocks on the first day following the event. Over time, the reversal effect was diluted and -0,16% for NYSE and -0,14% for AMEX in the final period of 1987 to 1991. The returns in NYSE and AMEX turned positive, to momentum, however, in the final period, on the second day, following the initial drop event, with returns of 0,08% and 0,90% respectively. Cox & Peterson (1994) concluded that following October 1987, there is on average no reversal in the NYSE and for AMEX no significant average reversal exists. The absence of reversal in the most recent years in the study may be an indication of "overall greater general level of liquidity in the securities market" and the results are consistent with the hypothesis that increased market liquidity over time may reduce the degree of reversals. (Cox & Peterson, 1994)

3.2 Reversal factors

In the literature review, several factors were notably repeated in the articles, indicating that there has been a lot of historical interest in how these factors are related to reversal behavior.

3.2.1 Transaction costs

Early studies have disregarded profiting from a reversal strategy due to the trading costs associated with the implementation of studied schemes. Short-term reversal strategies are generally dismissed in literature due to their high turnover which creates a concern of non-viability after accounting for transaction costs. (Blitz et al., 2023) When bid-ask spreads are considered, traders could not profit from the reversals that were observed by Atkins & Dyl (1990), however, it is concluded also that the market is efficient when all transactions costs are considered.

Trading costs were analyzed based on day of week by Foster & Viswanathan (1990) to find that trading costs and the variation in price changes are the highest on Mondays, and that the effects are even more pronounced for companies with better public reporting in place. The volumes of Monday are lower than other days of the week, with higher bid-ask spreads. Prices become less sensitive to changes later in the week, as more information is released through trading activity early in the week. (Foster & Viswanathan, 1990)

In the De Groot, et al. (2012) study, the analysis results reveal that optimization of the strategy to minimize trading costs can make a reversal strategy profitable overall. Higher trading costs are often associated with low liquidity stocks which tend to be in smaller capitalization stocks. To overcome this hurdle, the strategy evaluated high liquidity stocks that have lower trading costs in the period 1990-2009. Additionally, the strategy is further optimized to reduce the number of buy and sell transactions. Profitability was found to be possible by focusing on the largest US stocks, with significant reversal profits of 30 basis points per week. De Groot et al. (2012) found that net reversal profits to be large and positive in the first decade of the 21st century, during which market liquidity had dramatically increased already from the prior decades. In parallel, the study finds that reversal profits are smaller from European stocks due to lower liquidity which coincides with higher transaction costs. (De Groot et al., 2012)

The idea of short selling is common within a reversal strategy to implement a no cost portfolio. Engelberg et al. (2012) determine that there is a potential limiter to profitability for selling stock that are not already in ownership, as when the trader is having the belief that a stock is overpriced, there may be a high cost to the strategy of shorting at a time where there is a lot of demand for the borrowing of the same shares. (Engelberg et al., 2012)

The issue of trading costs has been minimized for many US stocks with the discontinuation of commissions by major online brokerages in 2019, which has reduced entry and exit costs for retail investors. The zero-commission trading is based on a payment for order flow (PFOF) system. First emerging with Robinhood's trading platform in the mid-2010's, individual investors were able to access the markets without commissions to the retail investor, as the income stream has traditionally been paid by two different channels, commissions from the individual investor as well as payment from the market maker. The model used originally by Robinhood is dependent on volume being high enough in commission-free trading to offset the revenues that would come from the collection of commissions from the retail traders. The Robinhood trading platform which was adopted in large by young investors as the app of choice successfully brought in large trading volumes. In 2019, large brokerages Charles Schwab and TD Ameritrade followed suit to eliminate commissions for their customers as well. (Aggarwal et al., 2023)

It is argued by Blitz, et al. (2023), that short-term signals “should not be discarded too easily for a number of reasons”. Standard methodology has disproportionally given high weight to small-cap stocks which are only about 10% of stock market capitalization. As trading costs are much higher for small-cap stocks due to their lower liquidity, a focus on high liquidity stocks (typically higher capitalization) could be applied to create a short-term strategy where the expected gains would be greater than the expected costs of execution of the strategy. Additional performance improvements can be made by using a combination of short-term signals, rather than only one. The application of multiple signals with low correlations can be used to optimize diversification, which results in higher gross returns and lower volatility. (Blitz, et al., 2023)

In recent years, the prevalence of FinTech companies has grown in quantity and range of services offered. Ullah et al. (2025) studied that in the Chinese stock market, that firms operating in areas where there is higher FinTech development have higher stock price liquidity. Furthermore, the relationship between FinTech and liquidity is more pronounced when in presence of higher media coverage. The report concludes that the development of FinTech promotes financial transparency, which promotes information efficiency, which results in increased stock liquidity. (Ullah et al., 2025)

The concern that trading costs may erode potential profitability from reversal trading is valid for many existing markets still today. The implementation of a trading strategy to include low liquidity stocks and stocks in indexes that are not available through commission-free would result with higher likelihood that any potential trading profits from the strategy would be consumed by commissions. In this study, to minimize the potential negative effects of trading costs, the stocks to be analyzed are from the S&P100 that includes only large capitalization, high liquidity stocks, which ensures minimal costs for the implementation of the strategy.

3.2.2 Trading volume

Trading volume, or the frequency at which a specific stock exchanges ownership, has been studied as one variable that may contain information related to the future price of a stock. In the Conrad et al. (1994) study, it was found that market adjusted reversal returns are stronger for stocks that show the largest increases in volume when using weekly data from NASDAQ listed stocks between 1983 and 1990. High transaction stocks exhibit a reversal effect, with negative covariance. Furthermore, the returns of low volume stocks are positively co-varying, indicating that the tendency for low volume stocks to have continued momentum of a stock price in the same direction as is the original movement in the stock. (Conrad et al., 1994) In a similar study, Michael Cooper (1999) looked at NYSE and AMEX securities weekly return behavior, and evaluated the effect of weekly volume on the lagged return of stocks to find that increasing volume stocks experience greater reversals, whereas stocks that are decreasing in volume tend to have weaker reversals and positive autocorrelation. The data used in this study was from 1962 to 1993. (Cooper, 1999)

The Pritamani & Singal (2001) study further evaluated the effect of volume with the idea that volume increases occur due to actions of informed traders, liquidity traders, or both simultaneously. For example, portfolio rebalancing after large price moves could result in price reversals. For strategic traders, they tend to move more slowly, which often leads to continuation of price momentum, as new information is slowly incorporated over time. To define a substantial movement in volume, they use the average volume from the previous 60-day period and compare it to the volume of the large price movement event. The top quintile jumps in volume are evaluated separately to find that those stocks with the highest increases in volume are positively correlated. 75% of events related to public announcements have volume increases, and when there is a volume increase along with public announcements, positive events are followed by statistically significant 1.98% positive abnormal returns and negative events with significant -1.68% abnormal returns. (Pritamani & Singal, 2001)

The Avramov et al. (2006) study further evaluates the relationship between the type of trader, volume and serial correlation to conclude that informed trading does not cause price reversals, and it is accompanied by low trading volume. Short-run reversals are a product of non-informed trading which is accompanied by high trading volume. A price shock is caused by either public information or exogenous selling pressure by non-informed traders. As a result, price changes that are accompanied by high (low) trading volume should (should not) revert. (Avramov et al., 2006)

In the Zhou (2010) study of the Chinese stock market, it is found that reversal behavior is found in Chinese investor behavior that cannot be explained by portfolio construction, market risk or firm size. The study used event study methodology to evaluate the effect of volume shocks on short-run price of Chinese stocks. By constructing portfolios of stocks based on a 29-day average volume, the daily volume that belongs to the top decile in volume as measured in percentage over the mean volume, were placed into one portfolio, where the bottom decile in volume was placed in a second portfolio. It was found that in this market, high-volume and small-sized stocks are preferred, and following a volume shock, a portfolio built of the highest volume stock would provide a net -1.65% average cumulative return reversal in the following thirty days. (Zhou, 2010)

3.2.3 Liquidity

Liquidity is a measure of how easily a non-cash asset such as stock is convertible into cash. The ease at which an investor can make changes in their investment holdings is understood to have value and an additional premium is required by the investor if they are willing to take the risk at a time when there is a sudden change in liquidity in the negative direction, or a liquidity shock. In a study of liquidity shocks in stocks, Acharya & Pedersen (2005) find that positive shocks in liquidity are associated with low immediate returns and high predicted future returns. Illiquid stocks have high liquidity risks in times of down markets with “flight to liquidity” behavior by investors. Investors are willing to pay a premium for stocks that are liquid, when the market return is low. The premium required by the investor to hold an illiquid stock becomes small, when the market as a whole is illiquid. The study compares results using the CAPM market model versus a model of CAPM that adjusts for liquidity to find that expected liquidity (3.5%) and liquidity risk (1.1%) explain about 4.6% of the cross-sectional returns annually. The evidence shows that liquidity risk is a factor above liquidity level and market risk. Small stocks are illiquid in comparison to large stocks, which makes them contain high liquidity risk. An investor's underreaction to liquidity shocks would provide a brief period of positive returns, but a drift to negative returns appears in time. (Acharya & Pedersen, 2005)

Jennifer Huang and Jiang Wang (2009) examined the effect of liquidity on market crashes and find that when there is a shortage of liquidity, the price always decreases and tends to drop significantly in a way that resembles a crash, when there is a sudden surge in the need for liquidity. When assessing the mechanism at the trader level, each participant brings with them only a partial supply or demand for the assets. There is a mismatch in timing, where different size orders which are not synchronized and therefore cause for a mismatch, and thus the temporary order imbalances which have a need for liquidity. This mismatch causes the asset price to deviate from its fundamentals. When the liquidity crashes, the stock price also crashes but recovers eventually. (Huang & Wang, 2009)

De Groot et al. (2012) notes that evidence for short-term stock reversals is seen when the market lacks sufficient liquidity to offset price effects that are caused by unexpected buying and selling pressure. The balancing is done by market makers which set prices at which they are willing to sell at times of high demand. The reversals are induced by inventory imbalances for which profits are made by bearing the risk of illiquidity. The explanation further projects that reversals should become smaller over time as market liquidity is dramatically increased. The model theory predicts that reversals are stronger for small cap stocks which typically have lower turnover. Under the liquidity hypothesis, reversals may not even exist in large cap stocks. The notion was dismissed however, as a large and positive reversal returns were evident in the largest 500 and 100 US stocks between 1995 and 2009. (De Groot et al., 2012)

The liquidity of stocks has been studied to have a positive correlation with reversal returns. Hameed and Mian (2015) show that return reversals are resulting from order imbalances and non-informational price shocks. The reversals are indicative of compensation to those that are supplying liquidity at a time where liquidity is low. The reversal effect is found to be stronger during market declines and times of high volatility. Profitability of the reversal strategies appears to be correlated with periods of liquidity crisis. The highest reversal returns, using a 12-month average return come at times of market crises such as stock market crash of October 1987, terrorist attacks of September 11, 2001, and Euro crisis of 2010. (Hameed & Mian, 2015)

A study by Li et al. (2024) finds that creating portfolios of extreme decile stocks in terms of abnormal trading volume provides for positive (negative) returns in the short (long) run. The findings in the study indicate that although a spike in trading volume may create abnormal positive returns in the short run, the stocks will gradually revert to their long-term means. The positive returns initially gained in the initial phase following the spikes in trading volume are in time consumed and the stocks' returns turn negative as mispricing is corrected in the market. (Li et al., 2024)

3.2.4 Other factors

There are still other factors that have been evaluated over the years of studying reversals in stocks, as the CAPM and Fama and French market models do not very well explain the behavior in stocks following extreme movements.

In the Hameed & Mian (2015) study into industry effect onto reversal returns using monthly data from between 1968 and 2010, the pair find that that although reversals exist in stocks , depending on the industry category, the results differ. The methodology used to measure reversal strength was in creating a no-cost portfolio with buy and hold strategy, with skipping of one day past end of month, over a one-month holding period after the event. There was a total of 17 industry categories evaluated and noted that the intra-industry returns in the Chemicals industry showed reversal returns of 1,42%, whereas the smallest intra-industry 0,71% occurred in Consumer Durables. The overall industry portfolio evaluated generated a return of 1.14% per month and risk-adjusted return of 0,97% monthly. (Hameed & Mian, 2015)

Several studies have been published on what effect company size has on return reversals. DeBondt (1987) expresses in his results that the removal of small firms from his results did not make any significant changes to the study results. Furthermore, Cox & Peterson (1994) when correcting for bid-ask spread in prices, there was no size effect in his study results. Zhou (2010) however finds that smaller stocks exhibit a quicker reversal.

In the Li et al. (2024) study, it is concluded that investor sentiment may have an impact on reversal strength. The data used in the study spanned from 1970 to 2020. The study investigated extreme investor sentiment of either persistently high, or persistently low values can give information about future reversal strength based on the amount of time that the extreme sentiment has been in place. There is a tendency for stocks with short history of extreme investor sentiment to continue with price momentum, whereas stocks with a prolonged history of extreme sentiment to be more likely to experience return reversals. The longer the duration of extreme sentiment has been in place, the less likely it is to persist further. The erosion of extreme sentiment is likely to result in reversals in price. (Li et al., 2024)

3.3 Contradicting study results

In the study by Pritamani and Singal (2001), the results were somewhat mixed. They examined the behavior of all stocks listed in the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) between 1990 and 1992. To define the threshold value for a large change, they calculated individually for each stock three standard deviations away from the mean based on previous 250-day time window prior to the event. The reasoning for using standard deviations was to include for each stock the level that would be equally large in terms of its individual volatility. They were especially interested in what effect large price changes have accompanied by an increase in volume, and whether there was a specific public announcement on the same day or not. The study concluded that if there is a large price event along with a public announcement, the price continues with momentum in the 20-day period. The momentum was even more pronounced if there was increased volume on the same day. Conversely, large price movements without accompanying public announcements or volume increase had a tendency for reversal. (Pritamani & Singal, 2001)

In their 2018 paper, which was revised in 2022, Medhat and Schmeling study the effect of turnover of a stock in comparison to its reversal returns. The monthly market data used in the study was from the period of July 1963 to December 2018, for all stocks from three major US indexes of NYSE, AMEX, and NASDAQ. The results showed that there is a significant short-term reversal among low turnover stocks based on the previous month's returns, but conversely, the high turnover stocks show short-term momentum, which is a continuation effect on returns from the previous month. Enhancement to the monthly strategy can be made by skipping the last few days of the formation month to avoid end-of-month liquidity trading, which implies some element of short-term momentum is present. (Medhat & Schmeling, 2022)

In a study by Zaremba et al. (2019), using monthly data to evaluate the short-term reversal effect, spanning across not only equity indexes but also other assets of government bonds, treasury bills, commodities, and currencies, the findings indicate that although there is a weak but significant correlation between different asset classes, there is no evidence of short-term reversal effect with equity indexes. The data included stock market index returns representing total returns on 45 different equity markets, to include developed, emerging, and frontier countries. On the contrary, the equity indices produced substantial profits when using a momentum strategy instead. The momentum strategy payoff is greatest during times of "high idiosyncratic volatility" and "excessive return dispersion." (Zaremba et al., 2019)

Although many scholarly articles confirm the existence of short-term reversals in stocks, there is also evidence, especially from more recent studies, that elements of momentum are seen in the market in conditions where the reversal theory would expect the opposite results. With the appearance of conflicting results, this study plays a pivotal role in helping to understand which the expected behavior moving forward is.

3.4 Recent developments

In the Chen et al. (2025) study on maximizing short-term reversals, behavioral aspects of market participants were evaluated, found that there is a new channel of retail investors which prefer lottery like payoffs, which has an amplifying effect on market overreactions, which has an increasing effect on the profitability of short-term reversal strategies. The mechanism evolves over a short period of time where risk-averse market makers create increase in volatility due to uninformed liquidity trades, which leads to a reduction in price efficiency in the US stock market. (Chen et al., 2025) Although this study was focused on reversals within weekly returns, the noted behavior may have an impact on daily reversals, if this phenomenon is prolonging the time for a reversal to appear.

3.5 Hypothesis

Studies have incorporated different factors into helping explain the reversal effect of stocks. The selection of S&P100 for this study is intended to minimize the effect of external variables that may create unwanted bias into the results as it is comprised of mainly high liquidity and large capitalization shock, which have higher trading volume, higher stock prices, and lower transaction costs as compared to other indices.

This study will use event study methodology to investigate the behavior of stock prices during and after large positive or negative changes in daily stock prices. Statistical testing of significance will be applied to the post event window of a large movement in a stock price following the event for a period of one to five days to test for evidence of short-term reversal in the post-COVID stock market. It will be tested if the raw returns (R) and abnormal returns (AR) of a stock revert after a large daily price movement event during the period 2019 to 2025 in the S&P100 for the threshold levels of ±4%, ±6%, ±8%, and ±10%.

> H_0 = There is no significant short-term reversal effect in raw returns of the S&P100 during 2019 to 2025.
>
> H_1 = There is a significant short-term reversal effect in raw returns of the S&P100 during 2019 to 2025.
>
> H_3 = There is no significant short-term reversal effect to cumulative abnormal returns the S&P100 during 2019 to 2025.
>
> H_4 = There is a significant short-term reversal effect to cumulative abnormal returns the S&P100 during 2019 to 2025.

Although prior research identifies several different variables that can help predict the degree of reversal or momentum following large price movements, finding evidence of a reversal effect during the 2019 to 2025 period would suggest that the underlying elements that are driving this market behavior are still in effect in the data driven market of today. Furthermore, the study results may unveil new information, which may also bring new insight and possible suggestions for further study.

3.6 Structure of thesis

The structure of the remainder of this thesis includes a thorough review of the data an methodology used, empirical results from the application of the theory, and a conclusion with summarized learnings from this study.

4 Data and Methodology

This study uses data from stocks of all companies listed in the S&P100 stock index at the beginning of 2018. The data consists of daily market closing prices between 2018 – 2025, where data from the year 2018 is used as a referencing period, and the daily market changes are evaluated from the period January 2019 to December 2025. The time window spans several periods of higher volatility, including the COVID crisis as well as downturns in the economy due to geopolitical changes and conflicts. The S&P100 index was selected as the evaluated index due to its composition of mainly large cap stocks with high trading volume. Alternatives such as the DOW Jones Industrial Index, with only 30 stocks, comprised of dividend and lower volatility stocks with typically lower growth. The S&P500 index includes a high number of stocks, which would increase the complexity of the analysis, especially in having stocks with low share value, making smaller changes in stock prices constituting a higher value as a daily percentage change, which would likely skew results towards the performance of lower capitalization stocks if not adjusted for.

4.1 Interval selection

The theoretical portion of this thesis discusses various reversal strategies, of which there are many similarities found in different markets and equities tested. The reversal strategies, typically in earlier studies, were concentrated on assessing long-term reversals in which the portfolio formations were done every several years at longest intervals. The development over the years moved towards studies focused on monthly market data. In the more recent studies, the focus has included even shorter intervals, to include weekly data and daily data. Even shorter partial-day intervals such early in day trading or overnight trading have been studied to see if some advantage could be found to make the reversal strategies more profitable.

To study reversals that provide comparative results, it is needed to define the interval for which the large movement is measured as well as the possible retraction that is to follow it. It was concluded by De Bondt & Thaler (1987) paper that the summation of all effects is contributing to the equity price. There can be seasonal effects, short-term reversals and long-term reversals working independently of each other. Even though the economic significance of the long-term effects is substantial, each component can be evaluated as its own contribution. (De Bondt & Thaler, 1987).

The interval of daily reversals was selected for this study, as though it has been the subject of studies since the early 1990s, it has not been as large of a focus as have been monthly reversals. The daily frequency is manageable in data volume and can provide new information on how the phenomenon has developed in the most recent market data, during a period of large changes in technology and retail investor behavior. Over time, the tendency for reversal studies has been towards testing of increasingly shorter durations. As suggested in the Zaremba et al. (2019) study *Short-term momentum (almost) everywhere*, future study is especially relevant to be extended to high frequency data, such as daily data, when looking at reversal vs. momentum behavior in various asset classes to include equities among others.

4.2 Data and Descriptive Statistics

The data used for this study is daily market data from the S&P100 index for stocks that were listed in the index as of January 1, 2018. The daily stock price history and volume data is sourced from DataStream. Investing.com (2025) website was used as backup source to complete the dataset for two exceptions, where the stock symbol was not found in the DataStream database for the early in the period delisted stocks of DowDuPont (DWDP) and United Technologies Corporation (UTX) which ceased to trade on June 1, 2019, and April 2, 2020, respectively. As these stocks were delisted early in the studied period, any effect of the alternative data source on overall results is minimal.

The S&P100 has not been found to be individually assessed in other comparative studies and was selected for this study for several key reasons. The index is comprised of mainly large cap growth stocks with high liquidity and low transaction costs, which reduces the impact of any bias from microstructure effects such as large differences in bid-ask spreads and minimizes any offsets due to transaction costs bias. Furthermore, in previous studies using broader indexes, typically drop out stock based on low price to avoid higher levels of impact on the study, as a smaller nominal value change constitutes a larger percentage change in the daily value of the stock. Typically, low value of a stock is assessed if the daily close value is lower than 10 USD (Bremer & Sweeney, 1991; Pritamani & Singal, 2001) or 5 USD (Hameed & Mian, 2015; Zhu et al., 2021). For S&P100, during examined period of 2018 to 2025, none of the stocks start or end the period with share value below 10 USD. There are temporary brief periods, where two stocks closed at a price below the 5 USD daily value and five stocks in total close below the 10 USD value, mainly during the COVID-19 induced recession between March and May of 2020. For this study, the level of 5 USD is held, except for 10 events in total, where the stock price was temporarily below 5 USD, but still above 4 USD. Based on level of exposure, expected to have minimal effect on the overall results. The two stocks with exceptional events were Ford Motor (F) and Haliburton (HAL), with 8 and 2 events respectively, all during the year 2020.

Stocks that were delisted or removed due to mergers or other reasons were not replaced with the firms added to the index. The delisted firms remain in the dataset until the delisting date to avoid survivorship bias. (Butt et al., 2021) Additional concerns expressed in Shumway (2012) of delisting bias of stocks being delisted for negative reasons and being moved to OTC markets are not relevant for this stock dataset, as all delistings from the S&P100 in the period studied were due to either merger or acquisition related reasons. The total number of daily stock observations from the observation period was 175,999.

The daily closing values for the S&P100 index (OEX) for the time period between January 2019 and December 2025 are charted in Figure 2 along with the daily percentage change in index value to provide a visual indicator for volatility during this period.

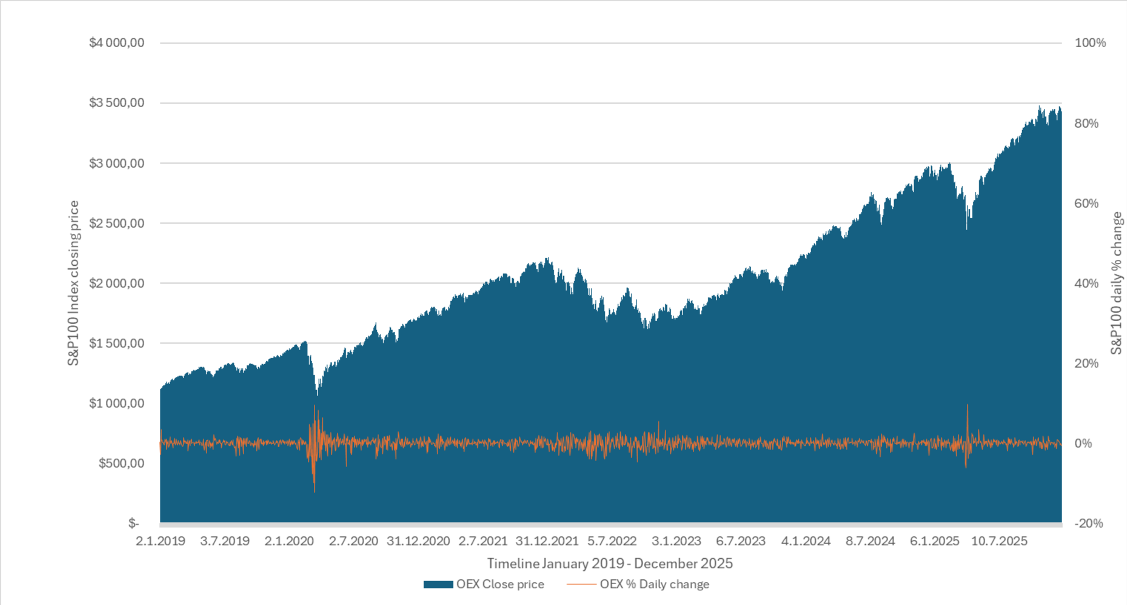

Figure 2. *S&P100 (OEX) daily change and cumulative performance between 2019 and 2025*

The S&P100 index at the beginning of the sample period in 2018 was comprised of 102 stocks. There was a total of 100 listed companies with two duplications as two companies also had listings for preferred shares. The duplicate listings were cleared by omitting the preferred shares from the calculations as in Jegadeesh et al. (2025).

Table 1. *Number of companies that are represented in the dataset at beginning of year.*

Number of companies included in data		
Year	Beginning of year	Count dropped during year
2018	100	2
2019	98	3
2020	95	3
2021	92	0
2022	92	0
2023	92	0
2024	92	0
2025	92	1

In the sample period of 2018 to 2025, a total of nine companies had delisted from the index for various reasons. The data set was cut off after the last trading day for each delisted stock, and no replacements were added to the scope to replace them.

4.3 The yearly S&P100 Index statistics

The index returns for S&P100 between the years 2018 and 2025 had the highest annual return of 26,88% in 2023 and the lowest return in 2022 with -25,00%. During the evaluated eight-year period, the market grew at an average annual rate of 13,31% with a daily average return of 0,053% per trading day.

Table 2. *Performance of S&P100 between 2018 and 2025*

S&P100 Index					
Year	Level on last trading day of previous year (close)	Level on last trading day of year (close)	Change during year (%)	Trading days in year	Average daliy change during the year (%)
2018	$1 183,15	$1 113,87	-6,03%	251	-0,02%
2019	$1 113,87	$1 442,17	25,83%	252	0,10%
2020	$1 442,17	$1 720,50	17,65%	253	0,07%
2021	$1 720,50	$2 194,58	24,34%	252	0,10%
2022	$2 194,58	$1 709,17	-25,00%	251	-0,10%
2023	$1 709,17	$2 236,19	26,88%	250	0,11%
2024	$2 236,19	$2 890,23	25,66%	252	0,10%
2025	$2 890,23	$3 432,34	17,19%	250	0,07%

4.4 Event study methodology

The main method for evaluating the data is event study methodology, which is modeled from the Craig MacKinlay (1997) publication, *Event Studies in Economics and Finance*, in the Journal of Economic Literature.

The first task for conducting an event study is to define the event and period for which stock prices will be examined. The period of interest for the study is at minimum, the day of the event, and the day following it. The event window is often expanded earlier than the event day, to provide insight into whether there has been any buildup in the stock prior to the event, with market anticipation to the direction of the event day movement, or if the movement appears to be effect of shock to the market, which is reversing the previous day’s trend. The day of the event is noted as Day 0. (MacKinlay, 1997)

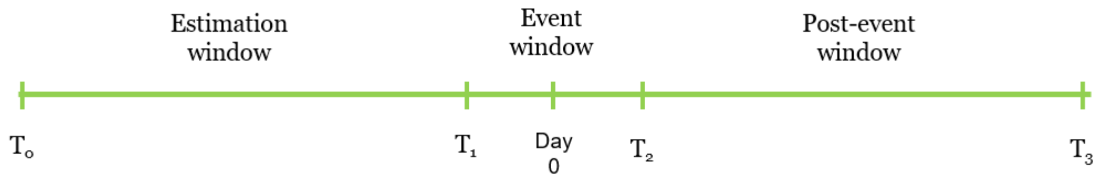

Figure 3. *Event study timeline (MacKinlay, 1997)*

Next, the estimation window needs to be defined. The estimation window is used to calculate normal or expected behavior for the stock and is most commonly, whenever feasible, to use the period just prior to the event window. The duration of the estimation window is defined based on what information is needed to be derived from it. As an example, 120 days could be used to estimate market model parameters prior to the event, meaning that the period between T_0 and T_1 is 120 days. The event window itself is not typically included in the estimation period to avoid influence of the event with the calculation normal performance of the stock. (MacKinlay, 1997)

For this study, the market model estimators are calculated from the time window T_0 and T_1 from 250 days to 30 days prior to the event day 0 to give about one year of data to calculate alpha and beta for the market model. The one-year estimation period was considered to be a requirement for good estimators also in research such as (Pritamani & Singal, 2001; Kudryavtsev, 2018). The post-event window can be used to measure the long-term effect of an event, which can include the normalization of the stock price towards a long-term mean, or evaluating longer term effects of the event on the stock price.

The pre-event and post-event time window varies from one study to another without any one defined duration. A 20-day pre-event between T_1 and Day 0 and post-event time window from T_2 and T_3 was used by Bremer & Sweeney (1991), whereas studies such as (Pritamani & Singal, 2001; Kudryavtsev, 2018) only evaluate the post-event time window, where the reversal becomes visible, for a period of 20 days. Atkins & Dyl (1990) evaluates daily reversals 10 days prior to the event and 30 days after the event. Cox & Peterson

(1994) follows only post-event period for three days individually and then combines the returns for the complete 4-to-20-day window in one calculation. Based on the observed variance in studies, and lack of consistency in one model, it is concluded that a time window of three days prior to event and five days post event is reasonable to view the possible reversal behavior using daily data, where reversal or momentum of the stock price is already defined in that time and can be used to answer to the thesis questions.

4.5 Empirical Methods

The empirical study of short-term reversals is modeled as in Kudryavtsev (2018) by calculating both daily raw stock returns (R) and daily abnormal stock returns (AR) of stocks using the market model valuation methodology, following a large movement in stock price. Positive or negative daily stock price moves of 10%, 8%, 6% and 4% are used in the study as threshold levels which trigger an event to be included in the reversal analysis. Previous literature is using threshold levels of 10% is common (Bremer & Sweeney, 1991; Cox & Peterson, 1994; Kudryavtsev, 2018) and 8% has been also applied (Kudryavtsev 2018) The 6% and 4% threshold levels were added to this study to add another dimension by bringing in observations from times for lower volatility. Alternative methods, such as Atkins & Dyl (1990), uses a method taking the three greatest stock increase and decreases from each trading day to incorporate data more evenly through the evaluated period, but for this study it is reasonable to not mix methodologies, but instead, incorporate the lower volatility periods by testing at lower threshold levels for triggering the inclusion. The expansion into 6% and 4% thresholds has other benefits as well, such as in increasing the number of events occurring in the 100-stock index between 2019-2025, which is hoped to provide insight into how any possible reversal strength is affected by the amplitude of the stock price movement event. A third alternative used to capture lower amplitude events, which can be meaningful to lower volatility stocks, would be to consider a large price movement in a stock at three or four standard deviations. (Pritamani & Singal, 2001; Kudryavtsev, 2018) The method was dismissed for this study, as Kudryavtsev (2018) study showed that there was no meaningful difference in results between the percentage change and standard deviation inclusion methods.

Initially, the return results for all 100 stocks of the S&P100 are calculated for daily returns. If the daily increase or decrease in a stock price is exceeding the threshold evaluated, the event is included into the study for the given threshold level. The daily and cumulative returns are tested at durations between 1 and 5 trading days to evaluate reversal performance over a five-day window. The CAPM market model is used to calculate the abnormal return (AR) for each stock after the large price movement event. Changes to AR are calculated in the post event window to test the reversal theory. Statistical testing of significance with the one sample t-test will be applied to the post event window of 1, 2, 3, 4, and 5 days.

Daily individual stock returns are derived from these datasets using the following formula,

$$R_{it} = ln\,(\frac{P_{it}}{P_{it-1}}) \qquad (1)$$

where R_{it} is the daily return in stock price and P_{it} is the daily stock price. (Hull, 2026, p.345) The inclusion of the individual stock daily raw return (R_{it}) movement in the study as a large movement in stock price, the value of R_{it} exceeds the threshold levels of ±10% (Pritamani & Singal, 2001; Kudryavtsev, 2018), ±8% (Kudryavtsev, 2018), ±6%, and ±4% above in positive direction and below in negative direction,

$$|R_{it}| < 10\% \qquad (2)$$

$$|R_{it}| < 8\% \qquad (3)$$

where t_0 is defined as the event date. (Pritamani & Singal, 2001; Kudravstev, 2018)

In addition, for this study, the thresholds of ±6%, and ±4% are added, which is not occurring in previous literature, to expand on the scope and provide new insights to reversal behavior as the threshold level is decreased.

$$|R_{it}| < 6\% \qquad (4)$$

$$|R_{it}| < 4\% \qquad (5)$$

If the daily return of the stock exceeds the threshold, the event triggers inclusion into the reversal study and the returns for the following five days are recorded. As per MacKinlay (1997) event study methodology, events studies for securities are generally deployed daily closing prices. It is good to understand, as explained by Bremmer (1991), there is a level of bias that is left in this method, that cannot be removed, which is due to the bid-ask spread. If the last sale was a market order, likely the price would be available for anyone making the trade. If the last sale is at limit price of a specialist buying (selling) at the ask (bid) price, the price would be available for a would-be buyer, but if the last sale is a specialist buying (selling) at the bid (ask) price, the actual price for a would-be buyer would actually be higher (lower) than the closing price. (Bremmer, 1991) The level of bias is dependent on the bid-ask spread, which for the selected S&P100 is expected to be lower than many other indices, due to its high liquidity, which aims to minimize its effect in this study.

4.5.1 Raw returns

The reversal strength in raw returns ($RR_{i,t}$) is calculated for positive moving and negative moving stocks separately for each event in the five-day post-event period using the following formula,

$$RR_{i,t}(k) = \sum_{t=1}^{k} R_{i,t} \tag{6}$$

and for $\overline{RR}_{i,t}$ is the average raw reversal returns for stocks (i) for the day (t) after the event (k).

$$\overline{RR}_{i,t} = \frac{1}{N}\sum RR_{i,t}(k) \tag{7}$$

The average raw reversal returns ($\overline{RR}_{i,t}$) are calculated separately for large increases and large decreases. The following formula is used to calculate the statistical significance for day t after the event:

$$T = \frac{\hat{\mu} - \mu}{\hat{\sigma}_{\hat{\mu}}} \tag{8}$$

and

$$\hat{\sigma}_{\hat{\mu}} = \frac{\hat{\sigma}}{\sqrt{n}} \tag{9}$$

Where T is the t-statistic for the sample on day t after the event, $\hat{\mu}$ is the sample average for day t, μ is the hypothetical value, $\hat{\sigma}$ is the estimated sample standard deviation, and n is the number of individual triggered events. (Auer, 2022)

The data characteristics for reversal returns as shown below for both increases and decreases for the threshold levels of ±4%, ±6%, ±8%, and ±10%.

***Table 3**. Data characteristics of the event day (Day 0) raw returns for price increases and decreases.*

Characteristics of sample following price increase												
Increase	>4%			>6%			>8%			>10%		
Year	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median
2019	198	5,99%	4,96%	53	9,45%	8,12%	27	11,99%	10,27%	15	14,55%	12,61%
2020	1445	6,96%	5,93%	703	9,18%	8,03%	355	11,43%	10,34%	195	13,50%	12,61%
2021	332	5,53%	4,99%	78	7,99%	7,02%	23	10,98%	9,61%	8	14,84%	12,02%
2022	614	5,48%	4,86%	145	8,00%	7,19%	46	10,68%	9,59%	18	13,46%	12,13%
2023	273	5,57%	4,90%	76	7,80%	7,14%	25	9,91%	8,87%	5	14,84%	13,86%
2024	249	6,12%	5,11%	82	8,90%	7,56%	37	11,54%	10,83%	21	13,48%	12,31%
2025	360	6,54%	5,46%	153	9,03%	7,76%	71	11,52%	10,69%	44	13,07%	11,70%
2019-2025	3471	6,29%	5,32%	1290	8,87%	7,70%	584	11,33%	10,17%	306	13,54%	12,34%
Decrease	<-4%			<-6%			<-8%			<-10%		
Year	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median
2019	224	-6,09%	-4,81%	63	-9,77%	-7,78%	30	-13,07%	-9,85%	15	-17,30%	-13,70%
2020	1460	-7,18%	-5,71%	671	-9,97%	-8,41%	376	-12,36%	-10,57%	211	-15,04%	-13,55%
2021	315	-5,43%	-5,02%	73	-7,59%	-7,22%	17	-9,88%	-9,75%	6	-11,15%	-10,74%
2022	740	-5,68%	-4,96%	194	-8,31%	-7,22%	64	-11,43%	-9,18%	26	-15,41%	-13,22%
2023	258	-5,81%	-5,09%	78	-8,25%	-7,73%	34	-10,07%	-9,42%	13	-11,98%	-12,59%
2024	292	-6,20%	-5,20%	93	-9,32%	-7,65%	42	-12,34%	-9,91%	19	-16,25%	-13,43%
2025	523	-6,25%	-5,40%	200	-8,56%	-7,81%	90	-10,58%	-9,68%	37	-12,87%	-11,72%
2019-2025	3812	-6,39%	-5,27%	1372	-9,25%	-7,89%	653	-11,87%	-10,01%	327	-14,80%	-13,09%

4.5.2 Abnormal Returns

Abnormal returns, which are also known as market adjusted returns, are calculated for each threshold level separately for large price increases and large price decreases separately, as was for raw returns using the following methodology. The expected returns (ER_{it}) are also calculated for the reversal events using the CAPM market model formula below,

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t} \qquad (10)$$

where R_{it} is the return of stock *i* on day *t*. α is the intercept value and β is the slope value as calculated using ordinary least squares regression to estimate the parameters from data from the pre-event period of t-30 to t-250 of stock *i* on day *t*. R_{Mt} is the S&P100 daily return on day *t*. (Atkins & Dyl, 1990; Butt et al., 2021)

Abnormal returns ($AR_{i,t}$) for each stock event are calculated as below, (Atkins & Dyl, 1990)

$$AR_{i,t} = R_{i,t} - \alpha_i + \beta_i R_{M,t} \tag{11}$$

and cumulated over h days

$$CAR_{i,t}(1,h) = \sum_{h=1}^{t} AR_{i,t} \tag{12}$$

and average calculated

$$\overline{CAR}_{i,t} = \frac{1}{N}\sum_{h=1}^{k} CAR_{i,t} \tag{13}$$

where $\overline{CAR}_{i,t}$ is the average CARs for stocks (h) for the day (k) after the event. (Engelberg et al., 2012) The cumulative average reversal returns ($\overline{CAR}_{i,t}$) are calculated separately for large increases and large decreases.

The data characteristics for abnormal returns for the triggered stock on day 0 are shown below for both increases and decreases for the threshold levels of ±4%, ±6%, ±8%, and ±10%.

***Table 4**. Data characteristics of day 0 event day abnormal returns for price increases and decreases.*

Characteristics of sample following price increase												
Increase	>4%			>6%			>8%			>10%		
Year	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median
2019	198	5,07%	4,55%	53	9,15%	7,79%	27	11,84%	10,03%	15	14,67%	12,51%
2020	1445	3,98%	3,73%	703	5,23%	5,08%	355	6,62%	6,42%	195	8,38%	8,83%
2021	332	4,99%	4,63%	78	7,54%	6,72%	23	10,69%	9,63%	8	14,71%	12,24%
2022	614	3,62%	3,29%	145	5,75%	5,35%	46	8,02%	7,42%	18	10,99%	11,06%
2023	273	4,79%	4,34%	76	7,21%	6,91%	25	9,34%	8,60%	5	13,37%	13,82%
2024	249	5,60%	4,85%	82	8,23%	6,98%	37	10,70%	10,00%	21	12,72%	11,11%
2025	360	4,90%	4,57%	153	6,20%	6,25%	71	7,13%	7,01%	44	8,45%	8,57%
2019-2025	3471	4,35%	4,10%	1290	6,01%	5,98%	584	7,57%	7,71%	306	9,40%	9,83%

Characteristics of sample following price decrease												
Increase	>4%			>6%			>8%			>10%		
Year	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median
2019	224	-5,13%	-4,41%	63	-9,34%	-7,50%	30	-12,85%	-10,00%	15	-16,90%	-12,88%
2020	1460	-3,18%	-2,74%	671	-4,40%	-4,14%	376	-5,36%	-4,84%	211	-6,64%	-5,91%
2021	315	-4,66%	-4,35%	73	-7,22%	-6,74%	17	-9,53%	-10,08%	6	-10,90%	-10,31%
2022	740	-3,72%	-3,41%	194	-6,22%	-5,83%	64	-9,52%	-8,38%	26	-13,74%	-11,34%
2023	258	-5,28%	-4,85%	78	-7,81%	-7,49%	34	-9,68%	-9,19%	13	-11,47%	-11,74%
2024	292	-5,46%	-4,64%	93	-8,70%	-7,18%	42	-12,00%	-10,01%	19	-16,00%	-13,57%
2025	523	-4,85%	-4,58%	200	-6,62%	-6,44%	90	-8,05%	-7,88%	37	-10,92%	-10,40%
2019-2025	3812	-4,07%	-3,92%	1372	-5,84%	-5,84%	653	-7,24%	-7,11%	327	-8,97%	-8,62%

Similarly, the abnormal returns are tested for significance of reversal effect to abnormal returns as defined in equations 8 and 9.

5 Empirical results

5.1 Raw returns

In a review of raw returns from S&P100 stocks from the studied period of 2019 to 2025, we find that there is a statistically significant short-term reversal effect following both large increases and decreases in daily value, for all of the evaluated threshold levels of ±4%, ±6%, ±8%, and ±10% in the first day following the initial event.

Table 5. *Average daily change in stock price during event window for stocks with large increase.*

S&P100 large daily increases in stock price (2019 to 2025) Average daily increase/decrease (+/-)				
Days from event	>4% increase on day 0 (3471 events)	>6% increase on day 0 (1290 events)	>8% increase on day 0 (584 events)	>10% increase on day 0 (306 events)
-3	-0,59% ***	-0,99% ***	-0,86% ***	-0,80% **
-2	0,17% **	0,18%	-0,13%	-0,54% *
-1	-0,75% ***	-1,31% ***	-2,29% ***	-3,12% ***
0	6,29% ***	8,87% ***	11,33% ***	13,54% ***
1	-0,60% ***	-1,20% ***	-1,69% ***	-1,63% ***
2	0,21% ***	0,44% ***	1,05% ***	1,37% ***
3	-0,17% **	-0,49% ***	-1,25% ***	-1,76% ***
4	-0,26% ***	-0,50% ***	-0,18%	0,31%
5	0,05%	0,18%	-0,25%	-0,58% **

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

At the 10% level, which has been mainly used in previous literature (Pritamani & Singal, 2001; Kudryavtsev, 2018), there is an average -1,63% day 1 return following the initial event. Likewise, the method of 8% threshold (Kudryavtsev, 2018) also produced an average reversal return of -1,69% on day 1, which is a slightly larger post-event move at the 8% threshold on average, than was at the 10% threshold level. At a 6% threshold level, there is still -1,20% change in the average daily stock price following the event day. Even the 4% threshold that was tested shows that during the studied period, a reversal effect was producing on average a return of -0,60% at a 1% significance level.

Similarly, for large decreases in S&P100 stock prices during 2019 to 2025, a price reversal effect is seen, that is slightly greater in amplitude at the higher threshold drops in price of 8%, and 10% than was seen in the reversal after positive increases in price. In Table 6, the daily returns are calculated for each negative threshold level drop in stock price on day 0.

***Table 6**. Average daily change in stock price during event window for stocks with large decrease.*

S&P100 large daily decreases in stock price (2019 to 2025) Average daily increase/decrease (+/-)				
Days from event	<-4% decrease on day 0 (3812 events)	<-6% decrease on day 0 (1372 events)	<-8% decrease on day 0 (653 events)	<-10% decrease on day 0 (327 events)
-3	-0,09%	-0,31% **	-0,80% ***	-1,65% ***
-2	-0,81% ***	-1,42% ***	-2,23% ***	-3,56% ***
-1	0,07%	0,03%	0,16%	0,53% **
0	-6,39% ***	-9,25% ***	-11,87% ***	-14,80% ***
1	0,23% ***	0,95% ***	1,80% ***	2,61% ***
2	-0,49% ***	-1,35% ***	-2,70% ***	-4,37% ***
3	0,03%	0,04%	-0,01%	-0,10%
4	0,32% ***	0,37% ***	0,40% **	0,33%
5	-0,37% ***	-0,78% ***	-1,35% ***	-1,59% ***

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

In total there were 327 individual stock events where the daily stock price declined by greater than 10%. For these events, the average return on day 1 following the event was a positive 2,61%, which is a strong indication of a stock price reversal. After a drop in price of greater than 8%, the stock price rebounded 1,80% on average on the following day during the studied period. For events at lower 6% threshold and 4% threshold drop in price, there was still a statistically significant reversal with an average positive move of 0,95% and 0,23% respectively, on the first trading day following the initial event at the 1% level. The results are also in line with (Atkins & Dyl, 1990; Zhu et al., 2021), which found that return reversals are stronger in large decline events than after large increases in stock prices.

Average cumulative raw returns, as was also visited in Kudryavtsev (2018), were evaluated for five days immediately following the initial event as shown in Table 7.

Table 7. *Average cumulative change in stock price during event window for stocks with large increase.*

S&P100 large daily increases in stock price (2019 to 2025) Cumulative average daily increase/decrease (+/-)				
from event	>4% increase on day 0 (3471 events)	>6% increase on day 0 (1290 events)	>8% increase on day 0 (584 events)	>10% increase on day 0 (306 events)
1	-0,60% ***	-1,20% ***	-1,69% ***	-1,63% ***
2	-0,38% ***	-0,76% ***	-0,64% **	-0,26%
3	-0,55% ***	-1,24% ***	-1,89% ***	-2,02% ***
4	-0,81% ***	-1,74% ***	-2,07% ***	-1,71% ***
5	-0,76% ***	-1,56% ***	-2,32% ***	-2,30% ***

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

On the day following a large increase in the value of a stock, there is statistically significant evidence of reversal in price at all thresholds. In the second day following the initial event, there appears a correction back towards momentum, but not to the magnitude of the first day reversal, which keeps the cumulative average negative on the second day post event. The third day following the initial event, on average, moves in as a reversal to the initial event on day 0 and increases the reversal effect. For threshold levels of 6%, 8% and 10%, the reversal strength on day three is slightly higher on average than it was on the first day following the event. Still after five days following a large increase in stock price for all threshold levels evaluated, there is still statistically significant reversal in with average returns following the large increases in stock price on day 0.

For large decreases in stock values, as seen in Table 8, there is similar evidence of a reversal in the average cumulative changes in stock price in all four threshold levels that were tested.

***Table 8**. Average cumulative change in stock price during event window for stocks with large decrease.*

S&P100 large daily decreases in stock price (2019 to 2025) Cumulative average daily increase/decrease (+/-)				
from event	<-4% decrease on day 0 (3812 events)	<-6% decrease on day 0 (1372 events)	<-8% decrease on day 0 (653 events)	<-10% decrease on day 0 (327 events)
1	0,23% ***	0,95% ***	1,80% ***	2,61% ***
2	-0,26% ***	-0,40% **	-0,89% ***	-1,75% ***
3	-0,23% **	-0,36%	-0,91% **	-1,85% ***
4	0,08%	0,02%	-0,50%	-1,52% **
5	-0,28% *	-0,76% **	-1,85% ***	-3,11% ***

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

The stock price on average, however, reverts to momentum after the second day. In the greater threshold levels of -8% and -10%, the reversal of cumulative raw returns is, on average, only seen for one day following the initial event, whereas the lower threshold levels of -4% and -6%, there is a low level of non-significant swing back to reversal, temporarily on the fourth day following the large price decrease event. The reversal in average stock price movements after negative events at all thresholds tested is significant at the 1% level, on the first day following the event but is short lived and, in most thresholds, turns and stays negative again in the following days.

5.2 Cumulative abnormal returns (CAR)

Daily abnormal returns (AR) are calculated for events for each threshold level studied for durations of one to five days as shown in Table 9.

Table 9. *Average change in daily abnormal returns (AR) during event window for stocks with large increase.*

S&P100 large daily increases in stock price (2019 to 2025) Average daily abnormal returns following event (+/-)				
Days from event	>4% increase on day 0 (3471 events)	>6% increase on day 0 (1290 events)	>8% increase on day 0 (584 events)	>10% increase on day 0 (306 events)
0	4,35% ***	6,01% ***	7,57% ***	9,40% ***
1	0,07%	0,01%	0,18%	0,53% **
2	-0,12% **	-0,19% **	-0,38% **	-0,51% **
3	-0,08%	-0,32% ***	-0,54% ***	-0,63% **
4	-0,01%	-0,09%	-0,18%	-0,05%
5	-0,05%	-0,06%	-0,08%	-0,07%

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

The average daily abnormal returns (AR) on event day 0 are lower than results from average raw returns on the day of event. At the 10% threshold level, the average abnormal returns show a momentum effect on day 1, with positive abnormal returns of 0,53% following an increase in stock price of 10% or more on the previous day. On the second day of trading following the initial event, the reversal appears with a negative average daily abnormal return of -0,51% with significance at the 5% level. The results for the other thresholds of 4%, 6% and 8% show similar direction also, but with smaller average percentage changes on the day. The results for day four and five show a weak negative trend, with no statistical significance.

For large drops in stock prices, the average abnormal returns show continued significant negative momentum for the first trading day and mostly insignificant move negative movement in the second trading day following the event, as shown in Table 10.

Table 10. *Average change in daily abnormal returns (AR) during event window for stocks with large decrease.*

S&P100 large daily decreases in stock price (2019 to 2025) Average daily abnormal returns following event (+/-)				
Days from event	<-4% decrease on day 0 (3812 events)	<-6% decrease on day 0 (1372 events)	<-8% decrease on day 0 (653 events)	<-10% decrease on day 0 (327 events)
0	-4,07% ***	-5,84% ***	-7,24% ***	-8,97% ***
1	-0,18% ***	-0,11%	-0,06%	-0,32%
2	-0,09%	-0,27% ***	-0,52% ***	-1,04% ***
3	0,07%	0,02%	-0,03%	0,02%
4	0,02%	-0,07%	-0,08%	0,09%
5	-0,03%	-0,07%	-0,12%	-0,06%

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

On the third and fourth days following the initial event, there are insignificant and mixed results with a tendency to break the losing streak temporarily at the 10%, 6% and 4% thresholds, but then an insignificant tendency to revert to a decline in price again on the fifth day following the event to follow the momentum of the original move in day 0.

When the daily average abnormal returns are cumulated over the holding period of one to five days following the initial event, in Table 11, there is a short reversal effect found in the average cumulative abnormal returns (CAR). The strongest reversal signal in abnormal returns is seen on the third day following the large price increase, with statistical significance only at the 6% and 8% thresholds at 1% and 5% respectively.

Table 11. *Average cumulative abnormal returns (CAR) during event window for stocks with large increase.*

S&P100 large daily increases in stock price (2019 to 2025) Average CAR following event (+/-)				
Days held from event	>4% increase on day 0 (3471 events)	>6% increase on day 0 (1290 events)	>8% increase on day 0 (584 events)	>10% increase on day 0 (306 events)
1	0,07%	0,01%	0,18%	0,53% **
2	-0,05%	-0,18%	-0,20%	0,02%
3	-0,13%	-0,49% ***	-0,74% **	-0,61%
4	-0,14%	-0,58% ***	-0,91% ***	-0,66%
5	-0,20% *	-0,65% ***	-0,99% ***	-0,73%

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

For these events triggered by positive moves in stocks, there is an insignificant momentum effect at all threshold levels, which fades out on the second day of trading for all but the 10% threshold level. The reversal in CAR for large increases in stocks is seen with a two-to-three-day lag.

For decreasing stocks, there is no reversal effect seen on average CAR after the initial event for any of the threshold levels tested, within the five-day post-event period evaluated as shown in Table 12.

Table 12. *Average cumulative abnormal returns (CAR) during event window for stocks with large decrease.*

S&P100 large daily decreases in stock price (2019 to 2025) Average CAR following event (+/-)				
Days held from event	<-4% decrease on day 0 (3812 events)	<-6% decrease on day 0 (1372 events)	<-8% decrease on day 0 (653 events)	<-10% decrease on day 0 (327 events)
1	-0,18% ***	-0,11%	-0,06%	-0,32% *
2	-0,26% ***	-0,38% ***	-0,58% ***	-1,36% ***
3	-0,19% **	-0,36% **	-0,61% ***	-1,34% ***
4	-0,17% *	-0,43% **	-0,69% ***	-1,25% ***
5	-0,20% *	-0,50% **	-0,82% ***	-1,31% ***

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

For negative events, there is a clear continuation of momentum for declining stocks for abnormal returns in S&P stocks in the period studied. Significance in results is found to be highest in days two to five in higher -8% and -10% threshold levels. For the 4% threshold level, the significance is greatest in the first two days post-event.

5.3 Robustness

The robustness of research of short-term reversals has been managed in different ways in past studies. Inherently, the objective is to change the parameters somewhat, to see if the results are still viable afterwards. The robustness check can be the elimination of top and bottom observations, such as has been done by removing the highest and lowest 5% of observed values. (Hameed & Mian, 2015) The use of multiple threshold levels has been used in several studies, such as Bremer & Sweeney (1991) with thresholds 7,5%, 10%, 15% and Kudryavtsev (2018) with thresholds of 8%, 10%. This study has also incorporated multiple threshold levels for also enhancing the robustness of the results.

Microstructure biases are often understood to enhance robustness to remove, e.g. the smallest capitalization stocks or lowest share price to eliminate possible bias. (Li et al., 2024) Also, separation by index (Jiang & Zhu, 2017) or industry (Hameed & Mian, 2015) have been done and results compared to complete dataset to increase the study robustness. For this study, we noted the exposure to small cap stocks is minimized by selection of the S&P100 index and splitting of index into smaller parts was not fitted into this study theory or model.

Additional robustness check for the studied period will model the breaking down of period evaluated into subperiods, such as was done by Hameed & Mian (2015). Hameed and Mian separated their data set into two parts which were two decades each, to observe what effect the period would have on his results. The period of 2018 to 2025 used in this study spans periods of growth and retraction of the market, with additional elements of advancement of technology and ease of market access. To evaluate the robustness of the study results, it is also tested how the short-term reversal effect appears in subperiods, for each year separately, between 2019 and 2025, for comparison. Table 13 shows how the Day 1 raw returns break down by year for large price increases for each threshold level evaluated.

Table 13. *Day 1 returns following large price increases by year.*

S&P100 large daily increases in stock price (2019 to 2025) Average daily raw returns on day 1 following event (+/-)				
Year	>4% increase on day 0 (3471 events)	>6% increase on day 0 (1290 events)	>8% increase on day 0 (584 events)	>10% increase on day 0 (306 events)
2019	0,32% **	0,57% *	0,71%	1,21%
2020	-1,28% ***	-1,80% ***	-2,01% ***	-1,64% ***
2021	0,07%	-0,27%	0,12%	-0,97%
2022	-0,10%	0,06%	-0,38%	-0,12%
2023	0,19%	-0,13%	-0,56%	0,05%
2024	-0,35% **	-0,87% **	-1,53% **	-1,55% **
2025	-0,57% ***	-1,42% ***	-2,92% ***	-3,52% ***

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

In breaking down the dataset into one-year increments, it becomes evident that the market is not behaving the same each calendar year. On average, a short-term reversal on the first day following event day 0 exists when evaluating raw returns for the complete period, which is in line with previous studies such as Bremer & Sweeney (1991), Kudryavtsev (1998), for which the used data is spanning even decades. When the data is segmented further into yearly increments, it is visible that there was no reversal in average raw returns during 2019 at any of the threshold levels. For the years 2021, 2022, and 2023, the results are mixed and without statistical significance between the different threshold levels. Only in the years 2020, 2024 and 2025 was there consistently a significant short-term reversal present in average raw returns after large increases of stock price on the first day following the initial event on all threshold levels evaluated.

Large negative price changes are evaluated in Table 14 by year to support with stronger evidence for consistency short-term reversals in declining stocks for the first several years of the period studied, but still interestingly the results are changed during the second half of the period towards momentum in raw returns.

Table 14. *Day 1 returns following large price decreases by year.*

S&P100 large daily decreases in stock price (2019 to 2025) Average daily raw returns on day 1 following event (+/-)				
Days from event	<-4% decrease on day 0 (3812 events)	<-6% decrease on day 0 (1372 events)	<-8% decrease on day 0 (653 events)	<-10% decrease on day 0 (327 events)
2019	0,17%	0,38%	0,57%	0,90%
2020	0,83% ***	2,27% ***	3,59% ***	4,58% ***
2021	0,38% ***	0,05%	0,84% *	0,03%
2022	-0,37% ***	-0,18%	-0,27%	-0,40%
2023	0,02%	0,19%	0,40%	0,13%
2024	-0,36% **	-0,37%	-0,40%	-0,72%
2025	-0,23%	-0,96% ***	-2,05% ***	-2,76% ***

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

After large decreases in stock price, on average, reversals were present in all evaluated threshold levels for years 2019, 2020, 2021 and 2023 with year 2020 holding statistical significance at the 1% level. Statistical significance for the other years showing reversal after large declines was mainly absent, but interestingly, at the lowest threshold level of

4%, statistical significance at 1% was found in three years. The years of 2022, 2024 and 2025 show on average that price momentum occurs after a large change in stock price, rather than a reversal, with statistical significance mainly in year 2025, for all levels, besides the 4% lowest tier. The other years showing momentum in results were mainly statistically insignificant. As comparison, the year 2020 shows a strong reversal of 3,59% and 4,58% for the 8% and 10% thresholds respectively, but there is a show of strong momentum with -2,05% and -2,76% respectively in the year 2025.

Results from further evaluation of raw returns by year and by number of days after the initial event for positive moves in the stock price at the threshold level of 10% are shown in Table 15.

Table 15. *Average daily raw returns following large price increases by year.*

S&P100 large daily increases in stock price (2019 to 2025) Average daily raw returns for 10% increase following event (+/-)					
Days from event	Day1 (306 events)	Day 2 (306 events)	Day 3 (306 events)	Day 4 (306 events)	Day 5 (306 events)
2019	1,21%	0,86%	1,36% **	0,54%	-0,39%
2020	-1,64% ***	1,72% ***	-3,15% ***	0,39%	-0,59%
2021	-0,97%	2,43% *	-0,12%	0,28%	0,83%
2022	-0,12%	0,54%	-0,24%	0,92%	-0,80%
2023	0,05%	0,25%	0,34%	-0,57%	0,01%
2024	-1,55% **	0,13%	1,50% ***	-0,41%	-0,57%
2025	-3,52% ***	0,85% **	0,57% *	0,06%	-0,89% **

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

For the complete period between 2019 and 2025, at the 10% threshold level, the day 1 average raw return was -1,63% on the day following the initial event. The value is closely in line with the 2020 average raw return value of -1,64%, for which 195 of 306 (63,7%) of observations fall. The day 1 reversal was the greatest in year 2025 with -3,52% reversal on average for positive price change events triggered at the 10% level.

For declining stocks at the 10% threshold, the results vary widely from year to year also, as shown in Table 16.

***Table 16**. Average daily raw returns following large price decreases by year.*

S&P100 large daily decreases in stock price (2019 to 2025) Average daily raw returns for 10% decrease following event (+/-)					
Days from event	Day1 (327 events)	Day 2 (327 events)	Day 3 (327 events)	Day 4 (327 events)	Day 5 (327 events)
2019	0,90%	-0,20%	0,21%	-0,07%	0,35%
2020	4,58% ***	-6,49% ***	-0,27%	-0,08%	-2,21% ***
2021	0,03%	-0,06%	0,61%	-0,25%	0,28%
2022	-0,40%	-0,18%	-0,51%	0,64%	0,29%
2023	0,13%	-0,01%	0,58%	-0,60%	0,95%
2024	-0,72%	-0,55%	-0,19%	-0,11%	-0,04%
2025	-2,76% ***	-1,07% ***	0,75% **	3,25% ***	-2,16% ***

Asterisks denote 2-tailed p values *p<0,10 / **p<0,05 / ***p<0,01.

The strongest reversal in average raw returns was in year 2020, at -2.21% where 211 of 327 (64,5%) events fall into that year. A reversal in average raw returns was seen in the years 2019, 2020, 2021 and 2023 on the first day following the initial event. In the years 2024 and 2025, there was a strong momentum effect in returns with a continuation of -0,72% and -2,76% following the initial drop of over 10% on Day 0. In year 2025, there was a reversal after the third day of trading following the initial event, but in year 2024, insignificant negative trends in momentum in returns slowed down during the five-day post-event window, the cumulative average stayed below 0, indicating that during 2024, no reversal was present on in the average raw returns at all.

5.4 Interpretation of results

Reversals have been studied over a long period, with many studies agreeing that short-term reversals exist (Atkins & Dyl, 1990; Kudryavtsev, 2018; Jagadeesh, 2025). These studies have expanded to cover many different stock markets over many decades of data, most with similar findings. The study results for raw returns, as shown in Table 7 and Table 8 that include the complete dataset for the entire time period between 2019 and 2025 are in line with previous study findings, where a short-term reversal exists, also in the S&P100, in the seven-year period between 2019 and 2025.

This study also reviewed cumulative abnormal returns (CAR) of the stocks for both large increases and decrease events during the period for which results are found in Table 11 and Table 12. As a surprise, the result from abnormal returns is not in line with raw returns, as there was not a consistent reversal in abnormal returns of stocks on day 1 following the large change event. For large moves in the positive direction, the price correction was not seen on average until the second, and more strongly after the third trading day following the event. For negative large movers, there was no reversal at all on average for the five-day post-event window. Results from Kudryavtsev et al. (2018) shows similarly, that abnormal returns do not have significant reversals, but when the test was refined to isolate events occurring on days where the market direction matches the direction of the large price movement in the dataset and discarding events where the large price movement is in the opposite direction of the market. There generally was an insignificant tendency for momentum found for the events omitted. Although this study did not follow this method of isolating events based on market direction, similarities can be seen in results if the complete dataset had been used.

A possible explanation for this result comes from the way abnormal returns (AR) are calculated. Calculated abnormal returns rely on price volatility comparison between calculated beta of the stock as compared to the index average, from the evaluation window prior to the event, as is outlined in 4.4. It has been documented by Dubinsky et al. (2019) that the implied volatility of a stock is dramatically reduced after anticipated announcements. A sudden drop in price volatility in a stock would affect the abnormal returns directly, as abnormal returns are calculated using volatility expectations to calculate the expected return for the stock as in equations 10 and 11. A short run depression of volatility in price after a large price change would affect the abnormal returns as the stock's volatility is expected to follow the volatility of the market based on the average beta that was calculated from the estimation window. The expected returns would then be higher than actual, as expected volatility of the stock and actual volatility have formed a gap, making abnormal returns be calculated lower for the temporary time that volatility is suppressed after the large price movement event.

In evaluating raw returns from each calendar year separately in Table 13 and Table 14, it was evident that the reversal effect is not appearing equally throughout each year, but rather there are years where the effect is more pronounced, as well as years where the short-term reversal effect on average does not exist. Although on average throughout the period there was the existence of significant short-term reversals at all threshold levels, the results cannot be considered robust, the results are not consistent for the one-year intervals that were also tested separately.

To formulate a possible explanation, it is needed to review the data more closely. Most large positive and negative price change events occurred in 2020 in the year of the short COVID-19 led recession, as shown in Table 17.

***Table 17**. Percentage of total observations by year.*

	Percent of observations / total Large increases in stock price			
Year	>4%	>6%	>8%	>10%
2019	5,7%	4,1%	4,6%	4,9%
2020	41,6%	54,5%	60,8%	63,7%
2021	9,6%	6,0%	3,9%	2,6%
2022	17,7%	11,2%	7,9%	5,9%
2023	7,9%	5,9%	4,3%	1,6%
2024	7,2%	6,4%	6,3%	6,9%
2025	10,4%	11,9%	12,2%	14,4%
2019-2025	100,0%	100,0%	100,0%	100,0%

	Percent of observations / total Large decreases in stock price			
Year	<-4%	<-6%	<-8%	<-10%
2019	5,9%	4,6%	4,6%	4,6%
2020	38,3%	48,9%	57,6%	64,5%
2021	8,3%	5,3%	2,6%	1,8%
2022	19,4%	14,1%	9,8%	8,0%
2023	6,8%	5,7%	5,2%	4,0%
2024	7,7%	6,8%	6,4%	5,8%
2025	13,7%	14,6%	13,8%	11,3%
2019-2025	100,0%	100,0%	100,0%	100,0%

At the ±10% threshold, over two-thirds of the total observations were in the year 2020. The expansion of this study into lower threshold levels of ±4% and ±6%, along with the higher thresholds of ±8%, and ±10% already tested in other datasets by Kudryavtsev (2018) provides us with valuable insight that the short-term reversal effect, over a longer period of time, with less bias towards a specific time window where high volatility has been concentrated in the data.

6 Conclusion

This study evaluates short-term reversals from a period which has not yet found its way into studies as the data is new and the selected index S&P100 has not previously been individually assessed. Previous studies (Avramov et al., 2006; Kudryavtsev, 2018) typically have attempted to prove that reversals are universally applicable or find individual factors that can better explain reversal behavior. The aspect of evaluating shorter intervals such as one-year subperiods has not been found in prior studies, as also lower thresholds such as ±4% and ±6% changes in daily stock price to include into the study. The results are conclusive to previous results in that reversals exist on a longer timeline, such as the seven-year period in this study. Naturally, if the period is split into small enough subperiods, it can be expected to find more variance in the results. One year is, however, a long period of time, enough to include seasonal effects, such as January effect discussed by Hameed & Mian (2015), although Avramov et al. (2006) did tests to remove January observations during his robustness tests, and still his results were not much changed.

This study tests the null hypothesis for reversals in both raw returns as well as cumulative abnormal returns. The empirical results show statistically significant short-term reversals in raw returns following both large positive and large negative daily stock price movements. This reversal effect is most pronounced on the first trading day after the event, and it is observed consistently across all evaluated threshold levels (±4%, ±6%, ±8%, and ±10%) when analyzing the full sample period. Based on the results, we can reject the null hypothesis H_1 and accept the alternative hypothesis H_2 for short-term reversal effect in raw returns as these findings confirm the presence of statistically significant short-term reversals in S&P100 stocks at daily frequency in the period 2019 to 2025.

The analysis of cumulative abnormal returns (CAR), however, does not provide consistent evidence of a short-term reversal effect following large daily price movements. For large positive price increases, day 1 returns for 10% threshold shows a momentum effect at 5% significance, and other threshold levels indicate non-significant drifts in the same direction as the initial event. A delayed and weak reversal is observed around days two to three, but significance is limited to selected thresholds and short subperiods. For large negative price shocks, CAR results predominantly indicate momentum rather than reversal during the five-day post-event window. Overall, abnormal return measures do not confirm any short-term reversal effect in the S&P100 during the studied period. Therefore, as per the results, the null hypothesis H_3 is accepted, and alternative hypothesis H_4 is rejected for this thesis.

One factor that is affecting the overall results was in the methodology used, which was consistent also with previous studies also. The fact that the largest number of observations were concentrated into the year 2020, making it contribute heavily to the overall results. If the selected period would not include a downturned market, the results might be completely different, which is evidence to support contradicting study results that were discussed in section 3.3.

As noted by Kudryavtsev (2018), his inclination to include the lower threshold of 8% was to bring in substantially more observations into his study. Absolute thresholds levels mean that the sample used is biased towards highly volatile stocks (Kudryavtsev, 2018). What is also implied but not directly stated in his paper, is that this model is also biased towards periods of high volatility, such as was the year 2020.

This thesis opens a few questions that could be explored in future research. The study evaluated the lower threshold levels of ±4% and ±6% which also showed significant reversals occurred in raw returns. The lower thresholds have been dismissed by literature to this point, but might be considered to evaluate further, to test for optimal thresholds, instead of defining with an arbitrary number. Furthermore, it was noticed in the robustness tests that the short-term reversals are not occurring consistently over time and in some years revert to momentum after large increases in the prices of stocks. It has stayed outside of the scope of this study to evaluate for what the reasons for changes in yearly results have occurred during the first half of the 2020 decade.

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