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Μεταπτυχιακή Διπλωματική Εργασία

COMPARISON OF MOMENTUM STRATEGIES

του

ΚΟΥΣΟΥΛΗ ΚΥΡΙΑΚΟΥ
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ΕΠΙΒΛΕΠΩΝ ΚΑΘΗΓΗΤΗΣ: Μ. ΑΝΘΡΩΠΕΛΟΣ
ΕΞΕΤΑΣΤΙΚΗ ΕΠΙΤΡΟΠΗ: Ν. ΚΟΥΡΟΓΕΝΗΣ
Π. ΑΣΗΜΑΚΟΠΟΥΛΟΣ

(Αθήνα, Σεπτέμβριος 2024)

DEDICATIONS

This thesis is dedicated to my family.

To my parents, Nikolaos and Athina, whose unconditional love, unwavering support, and sacrifices have been the foundation of my success. Your belief in me has always been my guiding light. To my siblings, Stefanos and Klio, for their constant encouragement and for always being there to share in my joys and challenges. To my friends, whose support and camaraderie have made this journey not only possible but also enjoyable. To my tutors whose guidance was necessary for this thesis to be completed.

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Abstract:
This Master's thesis aims to offer a thorough comparison of various momentum strategies employed in financial markets. Momentum strategies have garnered considerable attention in both academic literature and practical investment due to their potential for generating excess returns. This research intends to explore and assess the performance of different momentum strategies across a range of asset classes and time periods.

Keywords: Financial markets, Greece, Momentum Strategy, Investment decisions

Περίληψη:
Αυτή η διπλωματική εργασία στοχεύει να παρέχει μια ολοκληρωμένη σύγκριση των διαφόρων στρατηγικών ορμής που χρησιμοποιούνται στις χρηματοπιστωτικές αγορές. Οι στρατηγικές ορμής έχουν κερδίσει σημαντική προσοχή τόσο στην ακαδημαϊκή βιβλιογραφία όσο και στις πρακτικές επενδυτικές εφαρμογές λόγω της δυνατότητάς τους να δημιουργούν υπερβολικές αποδόσεις. Αυτή η έρευνα επιδιώκει να διερευνήσει και να αξιολογήσει την απόδοση διαφορετικών στρατηγικών ορμής σε διάφορες κατηγορίες περιουσιακών στοιχείων και περιόδους.

Λέξεις-κλειδιά: Χρηματοπιστωτικές αγορές, Ελλάδα, Στρατηγική ορμής, Επενδυτικές αποφάσεις

Table of Contents

List of Figures

List of Tables

1. Introduction

This thesis compares the Jegadeesh and Titman (1993) momentum strategy with adaptations utilized by other scholars. For literature purposes, we include idiosyncratic alpha, along with moving average, relative strength, and a combination of relative strength and moving average momentum indicators. The price momentum anomaly has been well-discussed in the context of stock market anomalies, suggesting that buying winners and selling losers can be profitable. However, these momentum strategies are volatile and carry significant market crash risks. A comparative investigation will be useful in determining whether these adaptations can provide risk-adjusted returns.

1.1 Background

An increasing body of literature exists on stock market anomalies in discovering and providing to investors with superior returns. The unusual behavior, against the theories of asset-pricing, of the assets are the stock market anomalies and are responsible for profit opportunities based on market inefficiency (Schwert, 2003). Examples of these anomalies are the week anomaly, the outperformance both for small-cap and low-book value stocks, and the January effect (Cooper et al., 2006; Dicle et al., 2014; Hou et al., 2020). When an anomaly in the market is exploited, it tends to vanish or reverse (Black, 1993; Schwert, 2003; McLean & Pontiff, 2016). The present study aims to research the momentum anomaly in the market. Momentum ano

Moreover, the robust evidence of an anomaly, in empirical literature, does not always lead to gains in expected returns (Roll, 1994). The challenges associated with practical applications underscore the effectiveness of capital markets, aligning with Fama's (1970) Efficient Market Hypothesis. However, the price momentum has remained over time. Buying the previous winners and selling the previous losers is the price momentum anomaly and can provide return gains to the investor. Momentum's supporting evidence is widespread and extensive: According to Jegadeesh and Titman (1993) past winners and losses tend to have higher or lower future returns respectively. Momentum presents a challenge to the Capital Asset Pricing Model (CAPM) as an explanatory factor (Sharpe, 1964; Lintner, 1965; Mossin, 1966), and on three and five-factor models of Fama and French, (1994, 1996).

Rouwenhorst (1998, 1999) demonstrates that momentum strategies generate abnormal returns in both developed and emerging international equity markets. Moskowitz and Grinblatt (1999) find evidence of momentum within industry portfolios. Asness et al. (1997) and Chan et al. (2000) identify momentum in country equity indices, whereas Okunev and White (2003) and Menkhoff et al. (2012) observe momentum in currency markets. Erb and Harvey (2006) affirm the presence of momentum in commodity futures. Asness et al. (2013) not only support these findings but also reveal a common factor structure underlying momentum returns across different asset classes. Chui et al. (2010) report persistent momentum globally, except in Asia, attributing cross-country differences in libertarianism as a possible explanation. Docherty and Hurst (2018) show that momentum is stronger in countries with a short-term focus. Griffin et al. (2003) argue that macroeconomic risk factors do not solely drive momentum returns, while Fama and French (2012) highlight the dominance of local momentum factors over global ones in influencing the valuation of size-momentum portfolios across various regions. This anomaly continues to generate debate among scholars.

1.2 Problem Discussion

Momentum is often used because of the abnormal returns that provides, while its gains are an anomaly that has not disappeared among discovery (Hou et al., 2020). The imperfections that exist in momentum strategies are often debated in the literature. According to Asness et al. (2014), momentum returns derived from the stock of small-cap have disappeared because of the trading cost's introduction. Moreover, profound evidence of momentum established in regions such as Europe and North America, while contrasting results have been found for Japan and Asia (Chui et al., 2000; Hameed & Kusnadi, 2002; Fama & French 2012). Additionally, the momentum is not a guarantee for a positive return strategy.

Additionally, crash risk is one of momentum's strategy most significant issues. Crask risk is the potential of a sudden and extended negative returns period. The downside potential of momentum strategies, which can wipe out past returns in a short period was highlighted both in Daniel and Moskowitz (2016) and Barrosso and Santa Clara (2015) literature. This occurs during market panic and high uncertainty periods. The reasoning behind those crushes is often denoted by the dynamic exposure, to systematic risk, of momentum strategies, at the same time behavioral models tend to be a possible explanation. The result is potential drawdowns of the returns and is the reason behind critics of momentum strategies, for this reason, literature searches optimizations of the original momentum strategy.

These optimizations of momentum strategies tend to try to minimize downside risks while reducing the exposure to the market. Idiosyncratic momentum introduced by Blitz et al. (2011, 2020) is an adaption of the original price momentum, that constructs buy winners and sell losers portfolio. This strategy is based on the Fama and French three-factor model's residuals. Moreover, the alpha momentum strategy was introduced by Huhn and Scholz (2018) and is similar to the idiosyncratic momentum approach. Both approaches show lower levels of drawdowns and volatility without sacrificing profits. It is demonstrated by many scholars that volatility is forecastable, thus severe drawdowns can be avoided and returns can be maximized.

A comprehensive overview comparison of the classic price momentum strategies of Jegadeesh and Titman (1993), the adaptions are lacking in literature according to our knowledge. Those adoptions are compared with classic momentum strategy and not against each other, which can investigate the possible return and volatility differences. We aim to apply and compare different momentum strategies in Greece's stock market from August 2nd, 2019, to June 9th, 2023.

1.3 Research purpose

This thesis aims to compare the classic price momentum strategy introduced by Jegadeesh and `Titman (1993) with idiosyncratic, alpha, relative strength, moving average, and a combination of both relative strength and moving average. The idiosyncratic momentum strategy has been introduced by Blitz et al. (2011, 2020), the alpha momentum strategy by Huhn and Scholz (2018), and while relative strength index introduced by Welles (1978). The strategies will evaluate different performance measures such as weekly stock returns, maximum drawdowns, crash risk, and volatility. These measures of performance will be constructed for the Greek stock market from 2019 to 2023. The contribution of the present research is three-fold. First, will we provide evidence of momentum anomaly in Greek stock returns. Second, original results for the potential existence of the momentum during 2019-2023, in the Greek stock market will be presented. Third, this study explores the performances and the unprecedented insights of various momentum strategies, assessing the best performed momentum strategy.

2. Literature Review

This section will describe the academic background, the findings, and the theories of momentum strategies topic, establishing the base of our research approach, and fulfilling the purpose of the study. Firstly, we will explain the subject of behavioral finance establishing and explaining the Efficient Market Hypothesis theory that appears to be seriously challenged by momentum anomaly. Second a detailed analysis of the momentum potential explanations and risks will be discussed. The final step involves outlining the adaptation of the original momentum strategy for future comparison purposes.

2.1 Behavioral Finance

Traditional finance hypothesizes the assumption of rational acting of individuals and the exhibit of efficiency in financial markets (De Bondt et al., 2010). An alternative viewpoint contends that abnormal returns do not arise from the conventional finance perspective of settling for additional risk. Rather, they are thought to exhale from the predictable and systematic irrational conduct of investors (Antonacci, 2014). Behavioral finance provides empirical evidence that challenges the assumption of human rationality in financial decision-making, while highlighting that people are not necessarily rational, affirming finance as a social science (De Bondt et al., 2010).

Behavioral finance research has empirically illustrated the impact of psychological factors on financial markets, simplifying the reasons and mechanisms behind market inefficiencies (Sewell, 2010). According to Tversky in 1995, individuals are vulnerable to judgemental biases. Therefore, behavioral finance supports argue that investors demonstrate irrational behavior, leading to inefficiencies in the market, driving asset prices to not fully reflect all the available information (Shiller, 2003).

Tversky (1995) compared the traditional economic rationality model with empirical findings from psychology. The rational expectations assumption suggests that individuals make logical, unbiased, and accurate predictions by utilizing all available information (Kahneman & Tversky, 1974). However, Tversky (1995) notes that people's decision-making often deviates from this traditional concept of rationality in finance. Cognitive biases significantly impact decisions, and expectations tend to exhibit predictable biases (De Bondt et al., 2010).

According to Kahneman and Tversky (1974), the underlying causes of such biases are largely explained by three primary heuristics (i.e., anchoring, representativeness, and availability). Heuristics are mental shortcuts employed to reduce the judgmental burden of decision-making. Overconfidence in personal judgments and decisions influenced by the framing of a problem exemplifies anchoring. Representativeness occurs when intuitive reasoning is distorted by mental shortcuts (De Bondt & Thaler, 1989). Additionally, availability bias happens when recent and vivid information disproportionately impacts current decision-making (Kahneman & Tversky, 1974).

Behavioral finance challenges the common assumption of risk aversion found in most financial models. It highlights that investors are often loss-averse, tending to seek risk when faced with losses and being reluctant to sell stocks that have decreased in value. Conversely, when stock prices rise, risk aversion prevails, leading investors to sell appreciating stocks prematurely to secure profits (Tversky, 1995). This phenomenon, known as the disposition effect, significantly impacts the momentum of asset prices, a topic that will be further explored in the momentum section.

While alternative mathematical logic for empirical observation is effective, modern finance necessitates rational solutions to normative issues. This method is viewed as a suitable foundation for understanding real behavior (De Bondt et al., 2010).

The field of behavioral finance began to attract attention in the 1990s, challenging the foundational rationality of the Efficient Market Hypothesis (EMH).

2.2 Efficient Market Hypothesis

Fama (1970) posits the Efficient Market Hypothesis (EMH), which states that investors cannot consistently outperform the market because any anomalies are swiftly eliminated through arbitrage. In an efficient market, asset prices fully reflect all available information. Fama contended that with rational and well-informed investors, all relevant information would be consistently incorporated into asset prices, making the current market price the best estimate for any given asset at any time. However, this hypothesis rests on several assumptions: (i) the absence of trading costs; (ii) equal access to information for all market participants; (iii) rational investor behavior; and (iv) the correction of price deviations by rational investors exploiting arbitrage opportunities when irrational behavior occurs.

Fama (1970), evident that these assumptions and conditions do not represent the markets. However, he argues that these conditions and assumptions are not necessary but sufficient, and thus there are no concerns. Moreover, he provides the three forms of EMH: (i) Weak Form Efficiency is characterized by an information set limited to historical prices. Analyzing these historical prices technically does not enable the prediction of future prices. Because of this, relying entirely on historical prices for long-term investment strategies does not yield excess returns; (ii) In the context of Semi-strong Form Efficiency, excess returns cannot be systematically achieved over time through technical or fundamental analysis using publicly available information. This includes information such as stock splits or annual earnings announcements. Therefore, employing public information alone cannot lead to outperforming the market; (iii) the Strong Form Efficiency posits that market prices incorporate all available and pertinent market information. Even insider information is ineffective in generating returns that surpass the market.

EMH theory has received plenty of criticism relying on market history and irrational price movement times. Malkiel (2003), using the 1987 crash and the 1999 Dot-com bubble as examples of mispricing and irrational exuberance of assets points out that the random walk theory proposes that investors cannot consistently capitalize on mispriced stocks due to the generally random nature of price movements. Apart from that, Grossman and Stiglitz (1980) note that for professionals' goals achieved for excess returns, there's the need of existence for inefficient markets, providing incentives for information discovery that does not reflect the current asset prices. The debate referring to favor and against the EMH has a large number of practitioners driving to producing new investment strategies that can take advantage of inefficient markets and discover market anomalies (Hou et al., 2020). Nevertheless, statistical significance tests have proven that many of the referring anomalies are not significant, while those that exhibit statistical significance weaken or disappear after the publishing of the research (Black, 1993; Schwert, 2003; McLean & Pontiff, 2016). The momentum effect will be discussed below and is one of the anomalies that remains pervasive and persists in financial literature.

2.3 Random walk theory

According to, Malkiel (1973) the random walk theory proposes that investors cannot consistently capitalize on mispriced stocks due to the generally random nature of price movements. These movements are driven by unforeseen events, thus supporting the EMH. He states, that according to the random walk theory, stocks exhibit a Brownian movement, following an unpredictable and random path. As a result, methods for calculating future stock prices are considered ineffective in the long run, and past movements or trends cannot reliably predict future ones. Moreover, he suggests that attempting to outperform the market without accepting additional risk is impossible. Despite this, critics argue that stocks do maintain price trends, such as momentum, in the long term (Shiller, 2003).

The random walk theory does not suggest that prices are inherently irrational; instead, prices can be logically set by investors. The theory proposes that changes in prices are unpredictable due to the inability to foresee news events. For this reason, the reactions of both rational and irrational investors contribute to a random path of price movements.

2.4 Inefficiency of markets

Market inefficiency arises when a market fails to fully combine all available information into asset pricing. This means that market prices may not accurately reflect all the available information (Stout, 2002). Empirical observations have identified various inefficiencies stemming from market asymmetries (Shiller, 2003). Such as behavior finance explained above and:

2.4.1 The cost of information

Grossman and Stiglitz (1980) investigate the concept of efficient markets, asserting that while the EMH is true, indicating that information is costly, competitive markets can break down. This perspective posits that prices indeed reflect all available information. The argument against perfect reflection arises from the high cost of information, essentially, if prices fully incorporate all the available information, those who invested capital to acquire such information would receive no reward for their efforts, eliminating the motivation to seek new information and create a situation where prices no longer accurately reflect the available information (Grossman & Stiglitz, 1980).

Grossman and Stiglitz's (1980) model suggests that the pursuit of new information is profitable, as informed investors can exploit arbitrage opportunities, correcting the mispricing of securities and restoring market equilibrium. Despite the evident cost of information, with providers like Bloomberg charging substantial fees for access, the paradox lies in the fact that the more investors seek information due to market inefficiencies the more efficient markets become. This movement toward efficiency reduces the discovery of arbitrage opportunities, leading to a perception among investors that seeking information is no longer worthwhile due to declining marginal opportunities, and therefore, investors may cease seeking information, contributing to a less efficient market. In summary, the cost of information plays a pivotal role in explaining market inefficiencies (Grossman & Stiglitz, 1980).

2.4.2 Anomalies of the Market

Several market anomalies challenge the Efficient Market Hypothesis (EMH), as identified by academics and market participants. These anomalies refer to recurring patterns that result in abnormal returns, contradicting both the semi-strong and weak forms of EMH (Latif et al., 2011). Abnormal returns can emerge from the synthesis of all available public information, with price momentum observed through historical price analysis, which can then predict future prices (Jegadeesh & Titman, 1993). Key market anomalies include:

(i) The January Effect: This phenomenon occurs when stock market returns are higher in January compared to other months, often attributed to "tax-selling." Investors sell underperforming stocks at year-end to offset their capital gains tax, making these stocks attractive in January (Thaler, 1987).

(ii) The Reversal Effect: Due to market overreactions and underreactions, stocks ranked over a three to five-year horizon experience a reversal, where past winners become losers and past losers become winners. Mean reversion is also evident in the short term, typically one month or less. For mean reversion to occur, some evidence of momentum must be present (De Bondt & Thaler, 1989; Antonacci, 2014).

(iii) The Size Effect: Companies with smaller market capitalizations tend to outperform larger firms because smaller firms have greater potential and ability to grow rapidly compared to large, mature firms (Banz, 1981).

(iv) The Value Effect: Firms with a high earnings-to-price ratio tend to demonstrate higher returns than those with a low earnings-to-price ratio. A similar trend is observed with firms that have a higher book-to-market ratio (Brooks & Anderson, 2006).

Further investigation into these anomalies can unveil opportunities ripe for exploitation. One prominent market anomaly, recognized for its robustness and enduring nature and the focal point of this research thesis, is momentum.

2.5 Momentum

The EMH relies on the assumption that all information is available to all investors, and their actions reflect this information in asset prices, implying swift adjustments of prices to new information, and eliminating the possibility of any investor gaining a subsequent advantage, as all market participants receive the same information simultaneously (Boyle, 2020). Consequently, outperforming the market in an efficient market is considered unrealistic without assuming additional risk beyond the market average. Moreover, the competitive dynamics among market participants are expected to move asset prices toward equilibrium (Clarke et al., 2001). However, the momentum effect suggests a challenge to weak-form efficiency, as it relies on historical prices to identify price momentum, which is then used to predict future prices (Jegadeesh & Titman, 1993).

Momentum was first identified by Cowles and Jones in 1937, who manually analyzed NYSE stocks from 1920 to 1935. They discovered that stocks performing above the median in one year tended to continue outperforming the median in the following year. While their research laid the groundwork for the concept of momentum, substantial further investigation into this phenomenon did not occur until the 1990s.

In 1993, Jegadeesh and Titman conducted a pioneering study on momentum investing, showing that selecting stocks based on their past 3 to 12-month returns and holding them for a similar period could yield excess returns. Their approach was inspired by De Bondt and Thaler's earlier research (1985, 1987), which proposed that investing in stocks that had underperformed over the past 3 to 5 years could also generate excess returns if held for the same duration. This concept is grounded in the overreaction hypothesis, which posits that market prices can deviate from their intrinsic values due to market overreactions to unexpected events. According to this hypothesis, such deviations are often followed by corrections, creating opportunities for excess returns. Jegadeesh and Titman (1993) argued against this overreaction explanation results. The behavioral explanation has been criticized by Chan (1988), Zarowin (1990), and Ball & Kothari (1989), who explain the contrarian investment strategy by other factors, some of them are the firm size and the systematic risk. In addition, Fama and French (1996) evidence no significant outperformance utilizing their three-factor model, and their research during 1996 and 2016, utilizing their model, was unable to explain Jegadeesh and Titman’s 1993 momentum effects. Since then, financial momentum has evolved into a prevalent market phenomenon and has been recognized as one of the most durable and persistent effects in finance (Antonacci, 2016).

An expanding body of research has shown that stock returns can be predicted using a range of firm-specific variables (Jegadeesh & Titman, 2011). Evidence suggests that U.S. stocks that have performed well over a 3 to 12-month period are likely to continue doing well in the subsequent 3 to 12 months, whereas stocks with poor performance tend to lag further behind (Jegadeesh & Titman, 1993).

Researchers have replicated these findings across different markets in over 40 countries, spanning various periods and testing conditions, with the majority finding the presence of momentum and yielding similar results. Strong support for the investigation of the momentum strategy in financial literature, similar to Jegadeesh & Titman (1993) has been made by scholars such as Fana and French (1996), Grundy & Martin (2001), and Jegadeesh and Titman (2001), for the United States listed stocks. Nonetheless, evidence of the momentum effect has been found in the international markets (Rouwenhorst, 1998; Griffin et al. 2003; Chui, Titman & Wei, 2010; Fama and French, 2012; Asness et al., 2013) Twelve European countries had been investigated by Rouwenhorst (1998), who found a 1% per month outperform of the past winners to past losers. Excess returns using momentum in different countries and assets (i.e., governmental, and corporate bonds) found by Asness et al., (2013). Studies that support the momentum in currencies have been published by Okunev & White (2003) and Moskowitz, Ooi & Pedersen (2012), momentum on commodities has been studied by Gorton, Hayashi & Rouwenhorst (2013), and Erb and Harvey (2006), industries momentum has investigated by Moskowitz and Grinblatt (1999). Carhart (1997) investigated momentum in mutual funds and Bhojraj & Swaminathan (2006) and Chan, Hameed & Tong (2000) investigated the momentum on country indexes.

Instead of these findings, Chui et al. (2000, 2010) and Fama and French (2012) discovered extreme momentum returns in Europe, Pacific Asia, and North America, but they could not find evidence of momentum profits in Japan. Hameed and Kusnadi (2002) could not find the effects of momentum in six different Asian countries' stock markets, while they concluded that the contributing factors of momentum profits are not presented in those markets like other markets such as the United States. From this another interesting debate in momentum literature occurred, that tries to explain the reason behind momentum strategies abnormal returns.

Additionally, extensive momentum studies examining both long (short) term returns reveal moneymaking strategies, leading to the shared conclusion the that stock prices tend to overreact to information (Jegadeesh & Titman, 2011). The momentum strategies have demonstrated profitability in most major global markets, although exceptions exist. Moreover, momentum is not confined to stock markets but extends across a diverse range of asset classes and industries (Moskowitz & Grinblatt, 1999). Notably, the momentum effect exhibits a pattern of seasonality, particularly in January, with negative and positive returns effect yielding in all other months, representing an inverse pattern compared to the traditional January effect (Jegadeesh & Titman, 2011). Tracking the Jegadeesh and Titman (1993) findings, many researchers propose many explanations about the profitability that occurs from momentum strategies with a focus on behavioral explanations.

2.5.1 Explanations of Momentum

Over the past few decades, there has been significant growth in the literature on the momentum effect, providing evidence that its existence. Nevertheless, the underlying driver of the effect of momentum remains undetermined, and no consent has been reached among scholars and market partitioners. This has given rise to two divergent arguments: one from the standpoint of conventional finance and the other from the perspective of behavioral finance.

The conventional finance contends that the Efficient Markets Hypothesis lasts, with the investors acting rationally. The supporters of rationality focus on how rational investors respond to unpredictable market changes, potentially leading to anomalies of momentum (Scowcroft & Sefton, 2005). In contrast, behavioral finance proposes that investors do not always behave rationally, and influenced by psychological biases and heuristics when processing new market information.

According to Chan, Jegadeesh, and Lakonishok (1996), investors' momentum profits are explained by their underreaction to fresh firm-specific information. Similarly presents of behavioral model explanations have been presented by Barberis et al. (1998), Hong, Lim, and Stein (2000), and Hong and Stein (1999) where they use as a possible explanation for the delayed overreaction of investors to information, which putting pressure to the stock prices and causing deviation from their long-term values. The behavior model foretells a future reversion of the effect, a turn back to the fundamental values of the stock prices. Jagadeesh and Titman (1993,2001) and Moskowitz et al. (2012) present evidence that the profitability of momentum portfolios turns negative after 13-60 months. Moreover, profitability driven by middle-term perspectives for the past seven to twelve months instead of past performance has been found by Novy and Marx's (2012) research.

2.5.2 Behavioural Explanations

Empirically observed momentum profits suggest a challenge for risk-based models, motivating researchers to turn to behavioral models for explanations. According to Jegadeesh & Titman (2011), many of these models indicate that the effect of momentum arises from the autocorrelation that exists in atomical stock returns, a notion consistent with available evidence. However, they state that the opinions among researchers regarding whether this autocorrelation is a result of delayed overreaction or underreaction.

When abnormal returns result from a delayed overreaction, a subsequent reversal is expected, leading to negative returns following the initial momentum gains during the holding period. Contrariwise, if autocorrelation is due to underreaction, normal returns would be anticipated in the period after the abnormal returns observed during the holding period (Jegadeesh & Titman, 2011). Behavioral finance provides the most comprehensive explanation for the momentum effect. Kahneman and Tversky (1974) identify three key heuristics in the economics of behavior, that influence the investor’s decision-making ability: (i) availability; (ii) anchoring and adjustment; (iii) representativeness. The availability heuristic leads investors to overemphasize vivid and recent information, causing market overreactions. Anchoring and adjustment can lead to underreactions, as investors base their judgments on historical data and resist altering their views, resulting in slower market responses (Kahneman & Tversky, 1974). The slow incorporation of new information due to anchoring can cause price momentum as investors gradually adjust their expectations. Price momentum can also be attributed to investor underreaction due to their limited capacity to process and interpret information effectively (Barberis et al., 1998). Alternatively, the effect of momentum may arise from overreaction driven by high investor confidence and an appreciation of their abilities and the information available to them (De Bondt et al., 2010). This confidence can be further reinforced by confirmation bias, especially following positive market outcomes (Kahneman & Tversky, 1974).

Finally, the representativeness heuristic, a cognitive shortcut, involves investors evaluating the probability of an event based on its similarity to a general mental model (De Bondt et al., 2010; De Bondt & Thaler, 1985). This bias, which can be inherently flawed, may lead to poor decision-making and cause prices to deviate from their fundamental values in market (Kahneman & Tversky, 1974). Additionally, the disposition effect provides a more nuanced explanation for underreactions. This effect occurs when investors delay selling stocks that are declining in value, hoping for a rebound, while they quickly sell stocks that are rising to lock in gains (Grinblatt & Han, 2002). This behavior can be linked to mental accounting, where investors tend to find unrealized losses less troubling than realized losses (Antonacci, 2014). A realized loss implies a stock sold at a negative profit, making it a realized financial setback, unlike an unrealized loss, where the stock has not been sold and the loss remains theoretical.

The disposition effect is consistent with Tversky's (1995) findings, which reveal that investors often exhibit a loss aversion, displaying risk-seeking behavior when facing potential losses but avoiding risk when anticipating gains (Tversky, 1995). Additionally, underreactions to new information are linked to a conservative bias, which contributes to profits from momentum Barberis et al., 1998). De Long et al. (1990) establish the delayed concept of overreaction, showing that investment strategies that involve buying (selling) stocks with past gains (losses) can cause market prices to stray from their fundamental values. This concept is supported by later models that observe both long (medium)-term price reversion (Hong & Stein, 1999). However, market overreactions are often driven by biases such as the representativeness bias, the confirmation bias, and the herding effect (De Bondt & Forbes, 1999). More specifically, the herding effect occurs when investors mimic the actions of others, assuming that these individuals have conducted thorough analysis (Spyrou, 2013). On the other hand, confirmation bias leads investors to focus more on information that supports their preexisting beliefs and opinions (Cipriano & Gruca, 2014).

Behavioral finance explains the effect of momentum as stemming from an initial market underreaction caused by anchoring, conservatism bias, slow information spread, and loss aversion. Over time, this is followed by a catch-up phase that leads to an overreaction, driven by factors such as herding, confirmation bias, representativeness bias and overconfidence, which further amplify the momentum.

The momentum anomaly has become a focal point of extensive research, with scholars exploring behavioral explanations for this phenomenon, making momentum an intriguing area for future research. The lack of a broad consensus on the driving force behind momentum underscores the complexity of this phenomenon. Behavioral finance convincingly links the momentum effect to cognitive biases and irrational behavior, this contrasts with traditional finance, which assumes rational behavior in market participants.

2.5.3 Industry Momentum

According to, Moskowitz and Grinblatt (1999) found that momentum in industry plays a significant role in influencing individual stock momentum. The profitability of strategies based on individual stock momentum appears to be heavily driven by industry momentum (Scowcroft & Sefton, 2005). According to their research, nearly all of the 12-month profits from individual stock momentum could be attributed to industry momentum strategies. These strategies often lacked diversification, as winners and losers were typically from the same industry. However, industry momentum strategies were found to be more profitable and practical compared to individual stock momentum strategies. Industry momentum remained strong and effective, particularly among the most liquid and largest stocks, consistently capturing momentum in stocks across various time horizons, unlike the reverse situation. Additionally, Moskowitz and Grinblatt suggested that a substantial portion of the 12-month returns from individual stock momentum might be linked to tax-loss selling at year-end. This implies that industry momentum could be key to understanding anomalies related to return persistence. Scowcroft and Sefton (2005) concluded that return momentum does not result from variations in industry exposure to systematic risk or from differences in cross-sectional mean returns within industries.

2.5.4 Risk

A risk-based explanation for momentum strategies' abnormal returns has been derived due to the compensation, under rationality for risk. There exist two basic explanations for the risk-based models (i.e., the prospects of the riskier growth and the beta risk compensation). A correlation between past and current returns has been found by Johnson (2002), while firms experience high return periods is a signal for the investors that the prospects of long-term growth will be improved, increasing the expected returns and the momentum. Time-varying risk factor model, that drives momentum proposed by Zhang (2004), expects firms of strong past performance to experience bigger beta risk, compensating the investors with growth to the expected returns in the future (Grundy & Martin, 2001; Chordia & Shivakumar, 2002; Ahn, Conrad & Dittmar, 2003; Ruenzi & Weigert, 2018).

According to Scowcroft & Sefton (2005), the EMH contends that all investors act rationally, attributing profits of momentum to compensation for assuming additional risks. However, traditional linear rational pricing models, including the three-factor risk model of Fama and French (1970) and the Capital Asset Pricing Model (CAPM), fall short of explaining the momentum effect. Moreover, they stated that in a large-cap context, industry momentum emerges as the primary driver of price return momentum, while in a small-cap context, individual stock momentum takes on a more prominent role (Scowcroft & Sefton, 2005). Despite extensive efforts to incorporate various risk factors into the analysis of the momentum effect, researchers have faced limited success.

2.5.5 Other Explanations

Trading costs play a crucial role in creating market inefficiencies and contribute to anomalies like momentum. While much of the research on momentum strategies has been conducted without accounting for realistic transaction costs, implementing such strategies often incurs substantial trading expenses (Li et al., 2009). However, momentum strategies frequently target small stocks with relatively low prices and trading volumes, further amplifying transaction costs. Moreover, trading with momentum involves frequent buying (selling) of winning (losing) stocks (Antonacci, 2014). Li et al. (2009) note that high-frequency trading, coupled with lower trading volumes and wider bid-ask spreads, leads to a significant increased of liquidity risk. This results in substantial transaction costs, with average round-trip costs reaching up to 3.77% for the winning stocks and about 6.71% for losing stocks. Losers incur higher costs due to their smaller market capitalization, lower trading volumes, and lower prices compared to winners.

Li et al. (2009) highlight that average round-trip quoted spreads demonstrate a notable asymmetry in trading costs, with losers experiencing a spread of 3.76% compared to 2.21% for winners. This disparity indicates that selling losing stocks is a major factor driving up the trading costs associated with momentum strategies. The trading volume and the size of stocks play a significant role, with transaction costs being notably higher for small-cap losers compared to winners. Besides trading costs taxes and, brokerage fees further reduce the likelihood of momentum strategies. Research by Carhart (1997) and Clare et al. (2010) reveals that transaction costs severely impact the profitability of these strategies, making them difficult to implement effectively. They observed that strategies focusing on the top 10% of better-performing momentum stocks faced issues with large spreads, low liquidity, and frequent trading, which significantly increased transaction costs. In contrast, strategies with lower trading frequencies, such as monthly rebalancing or those using larger, more liquid indexes with smaller spreads, yielded superior returns by optimizing the cost structure. For instance, strategies that selected the top 10%, 20%, and 50% of winners (losers) and aimed to minimize transaction costs achieved net average returns of 18.24%, 15.84%, and 12.49%, respectively (Li et al., 2009). Antonacci (2014) further demonstrated that adopting a low-cost approach, such as low-frequency trading in large, liquid indexes with narrow spreads, can significantly improve returns.

2.5.6 Momentum Investing problems

Momentum investing, like many other investment strategies, is not without its challenges. Like most investment approaches, momentum investing has its shortcomings. The primary issues associated with momentum investing are quoted beneath:

2.5.6.1 Momentum Strategy Crashes

Instead of the support that the price of the momentum strategy provides significant returns there exist many critiques. The major point of this criticism metion to as “momentum crashes”, states that momentum strategy can be characterized by abrupt and persistent negative returns. These happen mainly during market panic and periods characterized by high volatility. According to Daniel and Moskowitz's (2016) study of the momentum of United States equities during 1927-2013, the loser portfolio returns faced a 232% increase in 1932 July and August, while only a 32% gain was observed in the winner’s portfolio. Moreover, during the time of the Global Financial Crisis and especially during the year 2009 from March to May, 8% merely returns observed for the past winners, while the losers gain 163% returns. The relative drawdowns that can be observed in momentum strategies for turbulent periods have been discussed in the literature by many scholars (Grundy & Martin, 2001; Gutierrez & Hameed, 2004; Daniel, Jagannathan & Kim, 2012; Barroso & Santa-Clara, 2015).

A common reason behind the momentum strategy crashes is factors such as exposure to systematic risk (Grundy &Martin, 2001; Daniel & Moskowitz, 2016; Blitz et al., 2020). The nature of the strategy, selling (buying) past losers (winners), and exposure of the momentum portfolio to decreased (increased) to low (high) beta stocks in bear (bull) markets. Because of this, during trend reversals of the market, substantial vulnerability Is created to negative returns for the portfolios following momentum. The time-varying systematic risk exposure at first was suggested by Kothari and Shanken (1992) and verified, as an explanation for crashes of momentum by Grundy and Martin (2001) and Daniel and Moskowitz (2016). The relatively strong performance characterized by the loser portfolio occurs in periods of market rebounds, because of crases, and the winner's portfolio's poor performance is emphasized by Daniel and Moskowitz (2016).

For managing the risk that carries a momentum strategy has been proposed plenty of different hedging strategies. According to Grundy and Martin (2001) for someone to reduce volatility without affecting the average returns should aid in dynamic hedging the strategy and size factors. These improved performance findings have been criticized by Daniel and Moscowitz (2016) for the reason that results were based on the use of forward-looking betas hedging factor exposures. This is a bias problem for the estimated returns, while also making the strategy inexecutable. Also has been demonstrated by the authors the similarity of hedging strategies using ex-ante betas do not lead to the improvement of the performance.

However, according to Barroso and Santa-Clara (2015), Daniel and Moscowitz (2016), and Moreira and Muir (2017) the risk of the momentum strategy can highly be predicted and managed accordingly. Moreira and Muir (2017) create a volatility-adjust momentum portfolio applying the inverse of the realized variance during the last month so it can scale the monthly returns, which leads to increased performance. A realized volatility, of the previous 6 months, the momentum portfolio was scaled by Barroso and Santa-Clara (2015) which targets the constant volatility level over time. Their results are consistent with Moreira and Muir's (2017) findings, indicating a substantial increase in the Sharpe Ratio while the momentum risk was reduced to a maximum of -96.69 to -45.20 percent. Different subsamples were utilized by the authors to robust these findings.

However, with the improved performance of Barroso and Santa-Clara's (2015) constant volatility approach, Daniel and Moscowitz (2016) create a momentum strategy that outperforms the previous model and can be characterized as dynamic. This model can be characterized as a constant volatility model extension and forecasts both the returns and volatility of a portfolio utilizing dynamic weights. This dynamic approach exploits the momentum premium predictability instead of just reducing the model's volatility. The bibliography has suggested various of ways to risk-adjust the volatile nature of price moment strategies.

2.5.6.2 Scalability

Momentum is characterized by high turnover, incurring potential expenses for funds that actively trade relevant stocks, and may drive to suboptimal efficiency of tax (Antonacci, 2014). The associated cost, when frequent selling and buying of shares, can accrue significantly over a year. Due to the volatility of momentum stocks, they display wide bid-ask spreads, contributing to increased trading costs and potentially less momentum returns, particularly considering the strategy's high turnover nature (Clare, et al., 2010). Trading costs can vary significantly based on factors such as trading volume, frequency, spreads, and whether the strategy involves independent stocks or indexes.

The strategy proves more profitable when the investor is perceptive and maintains a concentrated portfolio of momentum stocks, that are top performing (Antonacci, 2014). Additionally, holding a larger and less selective portfolio is likely to result decrease in returns. The holding period also plays a crucial role in influencing momentum returns, with longer periods before rebalancing leading to a greater decrease in returns (Jegadeesh & Titman, 1993). A momentum investor, seeking optimal returns, should pursue a concentrated and focused portfolio, engaging in continuous rebalancing, preferably through monthly rebalancing, but no less than quarterly period rebalancing. Additionally, another challenge related to ascendance is the concentration of all momentum investors on the same top-performing stocks, which arises when substantial amounts of capital flow into and out of the same selected stocks each month as investors seek to enter and exit their positions (Antonacci, 2014). Ultimately, the profitability of momentum investing could decrease as large amounts of capital flow in and out of a limited number of high-performing stocks.

2.5.6.3 Duration and Market Timing

Momentum is generally observed as an intermediate-term trend, typically using a look-back period of 3 to 12 months (Jegadeesh & Titman, 2011). The effect of momentum is especially strong within a 6 to 12-month timeframe (Antonacci, 2014). Studies indicate that stocks tend to revert to the mean over longer periods, such as 3 to 5 years, and also in very short-term intervals of 1 month or less (De Bondt & Thaler, 1989). Shorter look-back periods often lead to increased fluctuations (Antonacci, 2014). Therefore, extending the look-back period to just under 12 months can help minimize fluctuations and reduce trading costs. However, the main challenge with momentum investing is its transient nature, as the effect is most significant over a 3 to 12-month period, requiring frequent portfolio rebalancing and making long-term holding impractical. Furthermore, Antonacci (2014) pointed out that momentum strategies can face difficulties during periods of high market volatility. This is because such strategies often overweight cyclical stocks, which are more negatively impacted during market corrections, particularly in the latter stages of a market rally.

2.5.7 Momentum Strategy Adaptions

Exposure to systematic risk, for the momentum strategy, is reduced according to the literature through various ways. Alpha momentum and idiosyncratic momentum are two of the strategies for reducing the risk. It is also considered in the bibliography the absolute and the relative momentum and the combined momentum strategy of both (i.e., Dual momentum).

2.5.7.1 Idiosyncratic (residual) momentum

The idiosyncratic momentum strategy was proposed by Blitz et al. (2011) to overcome the crash risk of the price momentum strategy. This strategy uses the Fama-French tree-factor model and is based on the idiosyncratic returns of the stocks. While the traditional price momentum strategy displays exposure to time-varying factors of the Fama-French three-factor model, the idiosyncratic momentum approach reduces stock return volatility, making this approach less prone to those factors. This strategy is almost neutral to market movements and delivers positive returns in economic growth and recession periods. Moreover, according to Jagadeesh and Titman (1993) excess returns of price momentum can be explained by the concertation of capital in stocks of small-cap, this is not a case for the idiosyncratic momentum because the strategy maintains neutrality concerning Fama-French size factors.

To form the idiosyncratic momentum strategy the methodology of Jegadeesh and Titman (1993) must be followed forming the idiosyncratic returns instead of the past return total. To construct this strategy, Blitz et al., (2011, 2020) follow several stages. First, they follow Jegadeesh and Titman's (1993) methodology for the available stocks and a period over 36 months. The definition of idiosyncratic momentum can be characterized as the sum of the idiosyncratic returns, for the last 12 months, the same time the previous month is skipped for short-term reversals, a stock anomaly that describes the stocks that strongly performed over the past months in the next month and vice-versa (Lehman, 1990; Jagadeesh, 1990). The recent month that is skipped results in the ignorance of the delayed reaction effect for the momentum strategy. Second, they formed an equal-weight portfolio excluding micro-caps, the stocks with low market capitalization. Lastly, they form the portfolio following the Jagadeesh and Titman (1993) winners minus losers traditional price momentum.

Blitz et al. (2011, 2020) findings show similar returns for an idiosyncratic momentum portfolio as price momentum, but with half return volatility, the result of this is a higher Sharpe ratio, which is a measure of risk-adjusted portfolio returns. Idiosyncratic momentum shows profits both on bear and bull markets, against the behavioral explanation of momentum anomaly. Additionally, they found that a lower beta exposure is presented in the idiosyncratic momentum, indicating less sensitivity, of this approach, to the price movements of the market.

The results of this research go against the momentum profits risk-based explanation that suggests greater excess returns for greater beta risk.

The literature has documented the superiority of idiosyncratic momentum against to original price momentum. Idiosyncratic momentum in Japan and China was found to be a profitable strategy according to Chang et al. (2018) and Lin (2019) respectively. Hanauer and Windmuller (2019) evidence the outperformance of normal and volatility-adjusted price momentum strategies by Idiosyncratic momentum. In addition, Zaremba et al. (2018), found outperformance and higher Sharpe ratios of standard momentum by idiosyncratic momentum for international equities.

2.5.7.2 Alpha momentum

Another strategy that leverages stock-specific return characteristics is the alpha momentum strategy. Blitz et al. (2011, 2020) focus on idiosyncratic returns rather than factor returns in their momentum strategy. In contrast, Huhn and Scholz (2018) use alpha (α_i), derived from the estimated regression of the Fama-French three-factor model. Unlike earlier studies that rely on stock-specific returns, Huhn and Scholz estimate alpha based on daily stock returns exclusively during the formation period. This approach aims to provide a more precise estimate by increasing the number of observations, thus minimizing the impact of potential differences in stock exposure to factors before and after the study period. Consequently, their methodology does not require a 36-month history of stock returns. Their approach aligns with Jegadeesh and Titman (1993) in terms of momentum strategy but differs in its use of historical alpha values.

The comparison of Huhn and Scholz's (2018) alpha momentum strategy with the price momentum yields higher returns on the United States stock market, while there is no clear evidence for either strategy's dominance in Europe. Additionally, alpha momentum strategy profits, for Europe and the U.S. are less volatile. Country and industry indices, according to the research of Zaremba et al. (2019) support the alpha momentum strategy. Conversely, Huhn and Scholz (2018), used for the alpha's estimation monthly returns instead of daily. At the same time, they discuss that their approach has better results in microstructural large sample datasets providing different timing sessions in the worldwide context and efficiency. Many settings robust the alpha momentum such as different wight techniques, covering the estimated alphas of other models such as capital asset pricing model and trading costs.

2.5.7.3 *Benchmark Performance*

Momentum is a powerful and widely applicable investment strategy. Antonacci (2016) demonstrated that momentum strategies are more effective with indices compared to individual stocks, showing that stock index momentum strategies tend to outperform those based on individual stocks. As a result, the dual momentum strategy addresses many of the problems associated with other approaches.

2.5.7.3.1 Dual Momentum

Momentum describes the observed strain of asset prices to persist in their direction, resulting in autocorrelation on the positive side (Jegadeesh & Titman, 2011). Typically, declining asset prices continue to decrease, while rising asset prices tend to rise further. This financial anomaly is not fully explained by traditional theory, which suggests that a price increase should not necessarily lead to further gains. One explanation for momentum profits is a delayed response to new information (Lewellen, 2000). Momentum profits can arise from slow adjustments to firm-specific news (Jegadeesh & Titman, 2011). Dual Momentum strategies are based on combining Relative Momentum with Absolute Momentum.

2.5.7.3.2 Cross-sectional or relative momentum

Jagadeesh and Titman (1993) employed a technique known as cross-sectional momentum, which Antonacci (2016) refers to as relative momentum. Furthermore, cross-sectional momentum involves assessing the relative strength of stocks or asset classes to identify past winners (losers), by comparing price trends across different securities or markets (Shell, 2021). This approach evaluates the relative performance of various stocks or markets and ranks them to determine where gains or losses have occurred.

2.5.7.3.3 Time-series or Absolute Momentum

Time-series momentum also called absolute momentum, involves analyzing the percentence of change in stock or market prices over time (Shell, 2021). This approach uses historical return trends to forecast future performance, suggesting that absolute momentum is as universally applicable and robust as well as relative momentum (Antonacci, 2016).

2.5.7.3.4 Dual Momentum as a Strategy

Researchers focusing on relative momentum typically employ both long and short positions across different market segments, as long positions can hedge against short positions and vice versa. However, Antonacci (2016) argues that when implementing dual momentum, it is preferable to maintain long positions exclusively over the long term. Antonacci introduced the concept of dual momentum to describe a strategy that integrates both absolute and relative momentum. This approach involves first selecting assets based on relative momentum, meaning the asset that has appreciated more compared to others is chosen. Then, the selected asset is evaluated for positive absolute momentum, which involves assessing its performance over a specified period to identify excess returns. Absolute momentum can also be measured by removing the risk-free rate; if the asset still shows excess returns, it is considered to have positive absolute momentum. Importantly, absolute momentum is evaluated independently of the asset's relative performance, meaning an asset can have positive relative momentum while exhibiting negative absolute momentum. In essence, dual momentum combines the principles of relative strength price momentum with trend-following absolute momentum (Antonacci, 2016).

Antonacci (2016) illustrates the dual momentum strategy, which highlights the challenges of international diversification in a globalized economy. Despite the global presence of large corporations, international diversification at the company level may offer limited benefits. Antonacci (2016) observed that a strong U.S. dollar often leads to underperformance of U.S. stocks relative to non-U.S. stocks. Despite this, many global investors maintain a portfolio of both U.S. and non-U.S. stocks, a practice known as vertical diversification (Antonacci, 2014). For example, a portfolio consisting of 60% S&P 500 Index and 40% MSCI ACWI ex U.S. may suffer if either component underperforms.

Antonacci (2014) argues that applying relative momentum to the S&P 500 and MSCI ACWI ex U.S. can offer horizontal diversification, which is dynamic over time. This strategy allows investors to shift their investments towards the strongest-performing asset, thereby achieving diversification across different periods. However, this approach can be vulnerable during bear markets, where investors often reduce equity risk by investing in treasury bonds. While bonds provide lower returns compared to equities, Antonacci (2016) employs absolute momentum to address this issue. This strategy enables investors to invest in equities when they are performing well or switch to bonds when they outperform.

The absolute momentum model involves monthly rebalancing between the S&P 500 Index and the Barclays US Aggregate Bond Index based on a 12-month look-back period. Similar to relative momentum, absolute momentum follows trends and avoids entering or exiting trades at market peaks, responding in a manner akin to moving averages but with enhanced results (Antonacci, 2014).

Dual momentum integrates both relative and absolute momentum strategies. Relative momentum evaluates performance relative to other assets, while absolute momentum assesses performance based on past returns over the previous 12 months. Antonacci's (2016) dual momentum strategy uses absolute momentum to decide between investing in stocks or bonds. If stocks are preferred, relative momentum is then used to determine whether to invest in U.S. stocks or non-U.S. stocks. For example, if the S&P 500 shows positive absolute momentum, indicating strong performance over the past 12 months, the strategy assesses its relative momentum compared to non-U.S. stocks. Investment is made in whichever asset shows positive relative momentum. Conversely, if the S&P 500 exhibits negative absolute momentum, the strategy shifts investments to the Barclays U.S. Aggregate Bond Index. This evaluation and rebalancing process is conducted monthly. Antonacci (2014) observed that this approach yields specific results based on these criteria.

2.5.7.3.5 Empirical Findings Overview

The dual momentum strategy demonstrated notable performance improvements using 38 years of historical data, without relying on smart betas, risk parity, or overly complex models (Antonacci, 2016). These enhancements were observed across all four areas investigated by Antonacci (2016): equities, real estate, credit risk, and economic stress. The key findings from Antonacci’s (2016) research are as follows:

First, dual momentum proves most effective on the long side of the market, as both relative and absolute momentum influence expected returns. Absolute momentum’s trend-following capabilities can substantially reduce downside risk while capitalizing on upward trends. Additionally, dual momentum portfolios benefit from low correlations among assets, making multi-asset portfolios appealing to investors.

Second, while avoiding high volatility, investors still achieve desirable returns. Portfolio managers prioritize minimizing downside variability over total volatility. Consequently, absolute momentum is particularly valuable for mitigating potential drawdowns associated with high downside volatility, while leveraging upward volatility to generate returns.

Third, the dual momentum strategy allows for targeting and isolating specific risk factors, enhancing diversification and flexibility within momentum portfolios. This implements dual momentum both straightforward and effective.

In summary, absolute momentum serves as an effective asset filtering mechanism that significantly mitigates losses and reduces the strategy's left tail risk. It acts as a protective measure, allowing market exposure only when it is advantageous (i.e., when absolute momentum is positive). By combining relative and absolute momentum, the strategy capitalizes on upward volatility to generate abnormal returns, making it proficient at capturing risk premia from volatile assets. Additionally, dual momentum enhances diversification and flexibility by selecting assets only when both relative and absolute momentum signals are positive, targeting those with a higher likelihood of sustained appreciation.

3. Methodology

The main objective of the present study is to investigate and compare portfolios of different momentum strategies. First, the data sources and types utilized for this thesis will be elaborated, followed by the chosen market and period of the study. Second, the performance metrics of the momentum portfolios will be presented. Third, the momentum strategy portfolio construction and indicators will be manifest. Finally, the results of the final sample will be discussed.

3.1 Data

The data this MSc thesis utilizes for the research are the weekly prices of stocks listed on the Financial Times Stock Exchange / Athens Stock Exchange (FTSE / ATHEX 20) from August 2^{nd}, 2019, to June 9^{th}, 2023, retrieved from the DataStream database. DataStream provides reliability on the data usage as it has been utilized by several momentum strategies scholars (Chan et al., 2000; Asness et al., 2013; Huhn & Scholz, 2018; Barroso & Santa-Clara, 2015; Zaremba et al., 2018, 2019). FTSE / ATHEX 20 contains the twenty-five largest companies listed on the Athens Stock Exchange. Furthermore, the FTSE/ATHEC Large Cap (ATF) index is utilized as a benchmark and a proxy of the Greek market the data of the index are retrieved from investing.com. In addition, as a proxy for the risk-free ratio (rf) the German 10-year bond yield is considered, and those data are retrieved from Federal Reserve Economic Data (FRED).

3.2 Performance metrics

In this subsection, the performance measures that this thesis utilizes to compare the discussed models will be presented.

3.2.1 Returns and Jensen's alpha

As long as we have a low number of returns from 12 to 52, we can use the arithmetic mean to calculate the average returns of the portfolio. An alternative way for the average return calculation is the geometric mean that considers the compound effect that occurred in a time series. Geometric mean provides accurate estimations for momentum strategies returns. We will consider the arithmetic mean instead to calculate the average returns:

$$\mu_p = \frac{1}{n}\sum_{n=1}^{m} r_n^{(p)}$$

Where μ_p is the calculated average monthly return; $r_n^{(p)}$the return of the periods of the portfolio during the n period; m the number of them considered periods. The average excess return of the period (μ_p^e) for the portfolio compared to the associated risk-free rate can be defined as:

$$\alpha = r^{(p)} - (rf + \beta(r_b - rf))$$

where α is Jensen's alpha; rf the risk-free rate; β the beta of the portfolio; $r^{(p)}$ and r_b the portfolio returns and benchmark respectively. Positive Jensen's alpha indicates overcompensation of the risk taken and vice-versa.

3.2.2 Sharpe Ratio

An assessment portfolio performance commonly used in the literature metric is called the Sharpe Ratio, a relatively simple measure of performance that considers both risk and returns introduced by Sharpe (1966) and calculated by:

$$SR=\frac{\mu_p^e}{\sigma_p}$$

where μ_p^e refers to the average portfolio excess returns of the period and $\sigma_p$to the portfolio's standard deviation. The higher the Sharpe Ratio the greater the risk-adjusted return of a portfolio is, measuring for different portfolios.

3.2.3 Maximum Drawdown

Another measure of the downside risk of a momentum portfolio is the Maximum drawdown (MDD) used by Blitz et al. (2011). This measure is the comparison of the cumulative returns now to the all-time high till that time.

$$D_{(v)} = \left[\max_{n\in(0,v)} r^{(p)}(n) - r^{(p)}(v)\right]$$

$$MDD\ (N) = \max_{v\in(0,N)} D(v)$$

where $r^{(p)}(\nu)$ and $\max_{n\in(0,\nu)} r^{(p)}(n)$ are the cumulative returns at ν time and the peak of cumulative returns during the n period respectively. The MDD can be only 0 or negative because it measures the greater cumulative loss for a momentum portfolio.

3.2.4 Skewness & Kurtosis

Skewness and Kurtosis are both used, commonly as performance measures that can provide the analysis with further insights referring to the distribution of the results. The data's asymmetry of the distribution is described as skewness. Negative skewness refers to the left tail being longer than the right tail, while the mean is presented on the peaks left side and vice-versa. Kurtosis refers to the thickness of the tails describing when the distribution is fat, or light tailed. Higher kurtosis indicates a fat-tail distribution with extreme outliers and vice versa. The combination of high kurtosis with negative skewness, for a portfolio, indicates severe risk for the investor because a left fat-tail implies important portfolio crash risk which swiftly erases periods of positive returns.

3.2.5 Traynor's Ratio

The Treynor Ratio (TR) is a metric for assessing the return on an investment relative to its systematic risk, measuring the amount of return earned per unit of risk. Also known as the reward-to-volatility ratio, it quantifies the excess return generated by a portfolio above the return expected given its risk, where risk is represented by the portfolio's beta—a measure of systematic risk. Developed by American economist Jack Treynor in the 1960s, who also created the Capital Asset Pricing Model (CAPM), the Treynor Ratio evaluates how well a portfolio compensates investors for taking on risk. The CAPM, which Treynor also developed, provides a theoretical framework for estimating the minimum acceptable return on an asset, aiding investors in deciding whether to include an asset in a diversified portfolio.

$$TR = \frac{portofolio\ return - risk\ free\ rate}{portofolio\ beta}$$

3.3 Momentum Strategy Construction

In this master's thesis, except the traditional price momentum of Jagadeesh and Titman (1993), we utilize three momentum indicators (i.e., Relative Strength Index (RSI), Moving Average (MA), and both indicators) to calculate the momentum portfolios. Furthermore, for literature reasons, we will describe the Idiosyncratic momentum and the alpha momentum strategy construction, but we will not include them in our research as long as the sample of momentum portfolio returns are relatively low.

Momentum portfolios methodology was first considered by Jagadeesh and Titman (1993) and later utilized by several scholars among them Blitz et al. (2011, 2020), Huhn & Scholz (2018), and Daniel & Moskowitz (2016).

First, the weekly returns (r) of the studied market assets (t), where n is the number of the weeks and r_{n-1} considered the closing price of the asset, are constructed,

$$r_{t,n} = \frac{r_{t,n-1} - r_{t,n}}{r_{t,n-1}} * 100$$

Following the individual stock returns calculation, we rank all stocks based on their performance in the last *J* period. The literature has found that the most implemented and rewarding period is the last 12 months, this period will also be considered in our research as 52 weeks as long as we use weekly data and a year has 52 trading weeks. According to Novy-Marx (2012), intermediacies past performance horizon drives the momentum. Following this statement, we will include in ranking just the stocks that have available returns in the last *n-13* to *n* period. The present month, n-1, will not be considered because we want to consider the short-term reversals (Lehman, 1990; Jegadeesh, 1990). Hence, the back looking period will start from n-13 to n-2 as we can see in Figure 1.

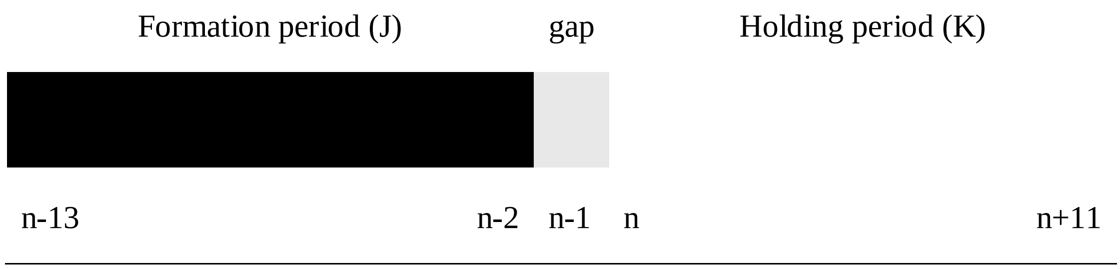

Figure 1. Momentum portfolio construction for the K holding period and J formation period, include a one-week gap period so the short-term reversals are considered.

The ranking of the available stocks by their performance during J period will be followed by forming 10 equal-weight portfolios with the most profitable stocks and 10 with the worst performance stocks. The type of momentum strategy utilized affects the performance of portfolio measures. This process is repeated every month for the selected period. Then the strategy is to long the winner's portfolio and short the loser's portfolio. While the middle portfolios will be ignored. The result is a portfolio of zero cost, which equals the value amount of assets sold and bought. Winner minus loser portfolio returns is calculated by the following equation:

$$r_{por,n} = r_n^{(w)} - r_n^{(l)}$$

Where $r_{por,n}$ is the winner minus loser portfolio returns while *w* and *l* represent winners and losers respectively. The holding of the portfolio (K) will be rebalanced after the final month.

This part will be repeated for the available weekly-rolling window, resulting in a time-series containing portfolio returns.[1]

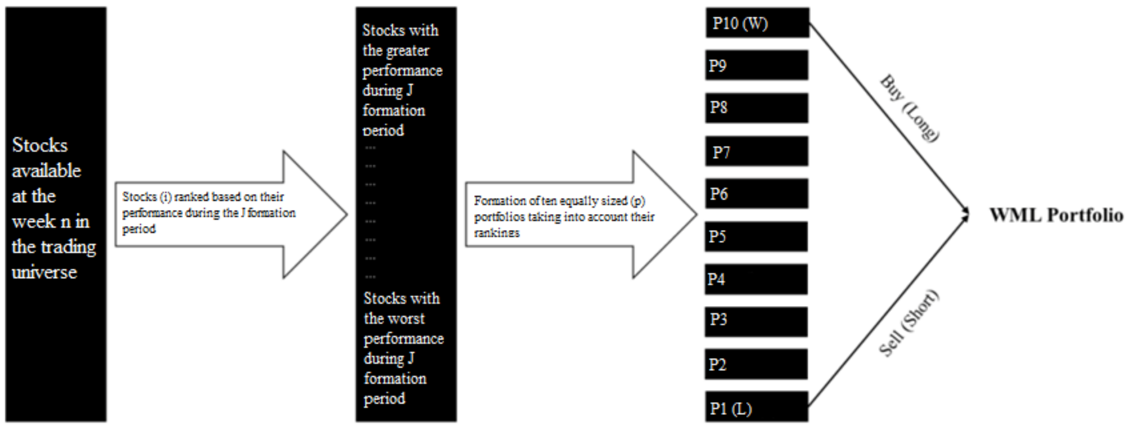

Figure 2. Momentum portfolios (p) construction for tth month accordant to the performance of each stock for J period formation. The process, presented in this figure is repeated through K weeks for the sample period. As a result, is the returns of the WNL portfolio.

Momentum strategies that maintain for holding periods over one week, K>1 the weekly returns calculated utilizing the approach of the overlapping portfolio. This happens to obtain a greater number of observations leading to the robustness of the results of the returns, and the avoidance of effects such as seasonality. For each *n* week, the overlapping sub-portfolios held equally the *K* holding period. The first sub-portfolio is constructed at *n-K+1* week. According to the equal weight approach, the sub-portfolios are given weights *1/K*, so they provide respective weekly returns. Total weekly returns are then calculated by a summary of the sub-portfolio returns weighted.

$$r_n^{(por)} = \frac{1}{K}\sum_{o=1}^{K} r_{o,n}^{(sp)}$$

where $r_{o,n}^{(sp)}$ are the sub-portfolios o, at week n.

Sub-portfolio 1	formation period (J)		Gap	n-2	n-1	n	
sub portfolio 2		formation period (J)		Gap	n-1	n	n+1

[1] Trading expenses (i.e., borrowing interest and transaction costs) are not included in the portfolio returns. This is because the aim of the present thesis is the comparison of momentum strategies with similar structure costs and therefore the trading expenses is outside of the scope of the present research, but trading costs should notice that when momentum strategies are compared with benchmark or different holding period.

sub portfolio 3	formation period (J)	Gap	n	n+1	n+2

Figure 3. Overlapping portfolio construction for momentum strategies indicators. This illustration shows a three-week holding period (i.e., K=3). To calculate the portfolio momentum $r_n^{(por)}$ the sub-portfolio's returns $r_{o,n}^{(sp)}$ are summed at time n and multiplied by 1/K

3.3.1 Momentum indicators

In this sub-section, we will consider momentum indicators utilized for our research (i.e., price momentum, moving average, relative strength index, and moving average and relative strength index combination) and for literature reasons (i.e., idiosyncratic momentum, alpha momentum).

3.3.1.1 Price Momentum

For the price momentum, the methodology of Jegadeesh and Titman (1993) will be followed. The decile portfolios, for the *n* week, are based on cumulative returns in the available stock's cumulative returns during the studied period, leading the stock ranking to a descending order based on their cumulative returns.

$$cr_{t,n} = \prod_{r=n-13}^{n-2}(1 + r_{t,n})$$

where the stock cumulative returns t is represented by $cr_{t,n}$, for the formation period of n-13 till n-2. Then we buy the winner's portfolio and sell the loser's portfolio, resulting in the winners minus the loser's portfolio. The weights of both losers and winners are considered equal, resulting in a weighted portfolio with zero cost.

3.3.1.2 Idiosyncratic momentum

The portfolios formed for idiosyncratic momentum are based on idiosyncratic returns. By starting the n week, we estimate a regression for the n-36 to n model, utilizing the Fama-French three-factor model (Gutiereze & Prinsky, 2007; Blitz et al., 2011; Chang et al., 2018; Blitz et al., 2020). The Fama-French three-factor model is quoted below.

$$r_{t,n} = a_t + \beta_{t,M} R_n^e + \beta_{t,SMB} SMB_n + \beta_{t,HML} HML_n + \varepsilon_{t,n}$$

where the excess market returns are represented by R_n^e, the size factors are represented by SMB and HML; a_t and $\varepsilon_{t,n}$ denotes to alpha and the idiosyncratic returns respectively. Thus, we can divide the stock returns to a_t and $\varepsilon_{t,n}$ denoting to stock-specific excess returns and $\beta_{t,M} R_n^e + \beta_{t,SMB} SMB_n + \beta_{t,HML} HML_n$ which denotes to factor-related returns. A must for a stock to be included in the regression is the 36-month past period history. The $\varepsilon_{t,n}$, idiosyncratic returns can be calculated as:

$$\varepsilon_{t,n} = r_{t,n} - a_t - \beta_{t,M} R_n^e - \beta_{t,SMB} SMB_n - \beta_{t,HML} HML_n$$

Finally, the volatility is adjusted according to the mean of the specific idiosyncratic returns of all stocks from n-13 to n-2, to form the idiosyncratic momentum score (IMS_t), which will be utilized for ranking the stocks.

$$IMS_{t,n} = \frac{\sum_{n-13}^{n-2} \varepsilon_{t,n}}{\sqrt{\sum_{n-13}^{n-2}(\varepsilon_{t,n} - \bar{\varepsilon}_t)^2}}$$

where $\varepsilon_{t,n}$ denotes the idiosyncratic return of stock t at time n; $\bar{\varepsilon}_t$ $refe$rs to the idiosyncratic return of stock t during the back looking period J. We rank the stocks based on $IMS_{t,}$ score and divide into deciles, so we can form the n-time portfolio. For top and bottom deciles an equal-weight portfolio will be created to result in a WML portfolio.

3.3.1.3 Alpha Momentum

To form the alpha momentum strategy, we will construct the portfolios according to price momentum. The difference between those strategies is that it does not rely on commutive returns for n period but in a regression of alpha values for every stock during the back-looking period. Thus, the alphas will be obtained by estimating a regression for n time utilizing the Fama-French three-factor model (Huhn & Scholz, 2018; Zaremba et al., 2019).

$$a_t = r_{t,n} - a_t - \beta_{t,M} R_n^e - \beta_{t,SMB} SMB_n - \beta_{t,HML} HML_n - \varepsilon_{t,n}$$

where a_t denotes stock-specific alpha. Note monthly stock returns will be utilized in the regression due to structural differences and issues (Zaremba et al., 2019). The stocks then will be ranked based on the values of alphas that the regression has estimated. Moreover, the portfolios of WML will be formed for period n.

3.3.1.4 Relative Strength Index (RSI)

The Relative Strength Index (RSI) is another essential technical indicator that measures the speed and change of price movements. RSI values range from 0 to 100, with 70 and above typically considered overbought (indicating a potential price reversal to the downside), and 30 and below considered oversold (indicating a potential price reversal to the upside). To calculate the RSI for n weeks, we need to define the upward and downward indicators,

$$U_t = \begin{cases} 1, \ P_t > P_{t-1} \\ 0, \ P_t \leq P_{t-1} \end{cases}$$

and

$$D_t = \begin{cases} 0, \ P_t \geq P_{t-1} \\ 1, \ P_t < P_{t-1} \end{cases}$$

Then, the average numbers of upward (up) and downward (down) moves are calculated for the past n weeks.

$$up_{t,n} = \frac{U_t + U_{t-1} + \ldots + U_{t-n+1}}{n}$$

and

$$down_{t,n} = \frac{D_t + D_{t-1} + \ldots + D_{t-n+1}}{n}$$

Instead, we may use an exponential moving average. The upward and downward moves are calculated by Relative Strength (RS), during the last n week.

$$RS_{t,n} = \frac{up_{t,n}}{down_{t,n}}$$

The RSI index is given by,

$$RSI_{t,n} = 100\frac{RS_{t,n}}{1 + RS_{t,n}}$$

In this strategy, we set a threshold of 70 for the RSI. When a stock's RSI is above 70, it suggests that the stock is exhibiting strength in its recent price movements, indicating a bullish signal and a short position. Stocks with RSI above 30 are considered attractive for long positions, as they may have the momentum to continue rising. After forming the RSI index, we short the stocks according to their relative strength and then we form the winners minus losers' portfolios.

3.3.1.5 Moving Average (MA)

The Moving Average is a widely used indicator in technical analysis that smooths out price data to identify trends and filter out short-term fluctuations. In this strategy, we use a n-period MA, which calculates the average price of a stock over the past three periods. When the stock's current price is above this n-period MA, it indicates a bullish signal. This suggests that the stock's recent performance is strong, and its price has been consistently above the short-term average. As a result, we choose to "long" or buy stocks that meet this criterion.

Conversely, if a stock's price is below the n-week MA, it indicates a bearish signal. This suggests that the stock's recent performance has not been as strong, and its price has fallen below the short-term average. In this case, we choose to "short" or sell stocks that meet this criterion. Shorting stocks allows us to profit from expected price declines.

We calculate the SMA of each asset for an n-period according to the following equation:

$$SMA_{t,n} = \frac{P_t + \ldots + P_{t-n+1}}{n},$$

where P is the prices of t asset and n is the week. The same technique as the upfront strategies will be followed to construct the momentum portfolio. We calculate the momentum ranking of the stocks based on the comparison of the long-moving average to short short-moving average.

3.3.1.6 Moving Average and Relative Strength

The dual momentum we consider in the present study creates a matrix of nulls to track the position of the assets. Using the Moving Average (MA) and Relative Strength Index (RSI) momentum strategy, we choose long stocks whose price is above the n-week-long MA and whose RSI is above 70, while the stocks to be short need to have a price below the n-week long MA and RSI below 30. For long positions, we use 1, while for short positions we use -1 in the matrix, while the no position takes the no value zero.

By combining the n-week MA and the RSI, this strategy aims to capture stocks that are not only trading above their short-term average but are also displaying relative strength in their price trends. This dual approach seeks to improve the quality of investment decisions by identifying stocks that align with both indicators. It's important to note that the success of this strategy depends on the investor's ability to interpret and apply these technical indicators effectively, and it should be used in conjunction with other research and analysis methods for a comprehensive investment approach.

4. EMPIRICAL RESULTS

In the present section, the findings regarding the different momentum indicator strategies for the Greek stock market will be presented and discussed. First, an overview and analysis of the momentum strategies on the sample for the Greek stock market will be presented, with a discussion of subjects such as returns, volatility, and different factor exposures. Second, an depth examination of the chosen momentum strategies for different periods between the investigating years will be presented. Thirdly, the analysis of the selected momentum strategies for the Greek stock market will be presented in isolation to find differences and commonalities and to indicate the optimal momentum strategy model.

4.1 Momentum Strategies for Greece

The summary statistics of the considered stocks are preserved in Table 1. Results from the tested momentum strategies for Greece from 2 August 2019 to 9 of June 2023 is presented in Table 2, Table 3, Table 4, and Table 5 for different formation periods (J), 12 weeks, 24 weeks, 36 weeks, and 52 weeks respectively. It is observable that all the considered momentum strategies exist in the Greek stock markets. The returns that the momentum strategies demonstrate are statistically significant and different from zero.

4.1.1 Momentum Strategies for Greece J equals 12 weeks

More specifically from Table 1, we can see that for the formation period, J=12, and most of the strategies preserve positive returns greater than the benchmark of the period. The exceptions are for the price momentum and the holding period of 52 weeks, for the relative strength index momentum and 52 weeks, and for the combined relative strength index and moving average momentum strategy for the holding period of 36 weeks and 52 weeks. The results of the presence of abnormal returns are a robust contradiction of the presence of the EMH in the Greek stock markets. The greatest difference from the benchmark can be found in the moving average momentum and for the holding period of 24 weeks (10.37%). We can observe that all the considered momentum strategies have abnormal returns in the first two holding periods (i.e., 12, 24). The benchmark for every period tends to be different as we close the portfolios when the holding period ends. It is important to consider that the trading costs of momentum strategies are higher than the costs of the benchmarks. Hence, a smaller difference in returns would be implemented in practice. However, this thesis aims to compare the performance of different momentum strategies, assuming that they have a similar cost for their structure.

Previous findings suggest that momentum tends to deteriorate as the holding period length is increased (Moskowitz et al., 2012; Gutierrez & Prinsky, 2007; Griffin et al., 2003; Jegadeesh & Titman 2001,1993), which can also be observed in our findings. In the price momentum strategy, we can observe a decline in the returns from 2.42% to -0.65% which shows a reversal in the fundamental values of the stocks over time. Furthermore, Jensen's alpha implies an overcompensation of risk taken in comparison with the benchmark index and the rf.

The selected momentum strategies comparison for the same sample period for the look-back period (J) of 12 weeks is presented in Table 1. It is imperative to note that the sample stops on the end of the holding period making the sample unequal for comparison across different holding periods. Thus, we consider four different benchmark periods and we compared them with the four different holding periods of our sample. For K period of 12 weeks, the Relative strength index and moving average momentum strategy present a Sharpe ratio of 0.98 which is the highest between the studied strategies. Price momentum and Relative strength index momentum strategies preserve a 0.45 and a 0.35 Sharpe Ratio respectively, while the Moving average and the benchmark portfolios preserve a negative Sharpe ratio of -0.02 and -2.33 respectively. The highest Sharpe ratio of the Relative momentum Index and moving average is due to the greater returns than the other selected strategies (i.e., Price momentum, Moving average momentum and Relative Strength Index), while the standard deviation is greater than the moving average strategy (0.36) and the Relative strength strategy (0.39) and equal to Price momentum strategy (0.42), while the benchmark portfolio presents the lower standard deviation (0.01) but also negative returns. Nevertheless, both Jensen's alpha and Sharpe ratio are higher than the other strategies for the combination of the Relative Strength Index and Moving average momentum strategies for the holding period of 12 weeks.

For the holding period of 24 the moving average momentum strategy preserves the greatest returns (10.37), and the highest Sharpe ratio (0.84) among the investigating strategies, while also having the greatest Jensen's alpha (0.51). For the holding period of 36 weeks Moving Average momentum also preserves the greater results, with returns of 6.72% a greater Sharpe ratio of 0.29 a lower standard deviation of 0.6, a higher Jensen's alpha of 0.13, and a Traynor's ratio of -0.05. Similarly, for the holding period of 52 weeks Moving Average momentum also preserves the greater results, with returns of 4.89% a greater Sharpe ratio of 0.18 a lower standard deviation of 0.6, a higher Jensen's alpha of 0.2 and a Traynor's ratio of -0.02. This result indicates that the momentum strategy with the Moving Average indicator is the optimal between the 4 considered strategies with the greater returns and the lower risk for all the holding periods except for the holding period equal to 12 months where the combination of Relative Strength Index and Moving Average indicators seems to work better than the other strategies.

All three four considered momentum strategies seem to have statistically significant results different from zero except for price momentum and the Relative strength index and moving average for the holding period of 52, while the Relative strength index and moving average for the holding period of 36 weeks also preserves negative returns.

The considered four momentum strategies have differences not just in the returns and the volatility but they have different crash risks. The examination of Maximum Drawdown is an important measure in our study. The highest MDD for the 12-week holding period is achieved from Relative Strength and moving average momentum strategy. The Moving average momentum strategy has the highest MDD for the 24-week holding period while the benchmark portfolio for 36 and 52 preserves the highest MDD. Note that MDD is a negative number and a higher MDD for the studied strategy reveals a lower crash risk. The highest values of skewness and Kurtosis are preserved in the benchmark portfolio. The benchmark portfolio seems to be right-tailed with a fatter distribution indicating greater positive returns, which is not occurred by our strudy.

Table 1: Greek stock market performance measures for the discussed momentum strategies, referring to different (K) holding periods and a 12-weeks looking back period (J).

J=12 weeks	Price Momentum				Moving Average				Relative Strength Index				Relative Strength Index and Moving Average				Benchmark			
K (weeks)	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52
sum returns	2.42	6.18	0.74	-0.65	0.04	10.37	6.72	4.89	1.74	3.81	0.14	-2.84	5.09	6.85	-1.98	-6.49	-0.14	-0.28	-0.27	-0.23
average returns	0.20	0.26	0.02	-0.01	0.00	0.43	0.19	0.09	0.15	0.16	0.00	-0.05	0.42	0.29	-0.06	-0.12	-0.02	-0.01	-0.01	0.00
max	0.87	0.94	1.21	1.21	0.44	1.30	1.15	1.45	0.71	1.06	1.44	1.44	1.14	1.14	1.14	1.14	0.00	0.05	0.06	0.07
min	-0.49	-0.62	-1.86	-1.86	-0.66	-0.61	-1.32	-1.59	-0.55	-1.12	-1.55	-1.55	-0.39	-0.88	-2.26	-2.26	-0.04	-0.04	-0.05	-0.06
σ	0.42	0.46	0.70	0.71	0.36	0.50	0.60	0.60	0.39	0.57	0.70	0.67	0.42	0.48	0.81	0.88	0.01	0.02	0.02	0.03
Sharpe Ratio	0.45	0.54	0.01	0.00	-0.02	0.84	0.29	0.18	0.35	0.26	-0.01	-0.06	0.98	0.57	-0.09	-0.12	-2.33	-1.11	-0.92	0.35
Skewness	-0.09	-0.34	-0.78	-0.34	-0.60	-0.37	-0.83	-0.55	-0.41	-0.30	-0.24	-0.30	-0.22	-0.39	-0.95	-0.39	-0.09	1.43	1.10	0.81
Kurtosis	-0.90	-0.73	0.57	0.05	-0.60	-0.81	-0.03	0.63	-0.26	-0.21	-0.31	-0.15	0.10	0.18	0.45	0.10	-0.19	2.80	1.46	0.17
beta	6.92	9.06	-0.81	-4.34	6.87	8.50	-3.18	-6.12	2.13	9.10	-2.01	0.00	2.94	7.18	-4.02	-9.37	1.00	1.00	1.00	1.00
Jehnsens alpha	0.38	0.45	-0.01	0.05	0.06	0.51	0.13	0.20	0.16	0.24	-0.04	-0.04	0.44	0.35	-0.13	0.03	0.00	0.00	0.00	0.00
Maximum DrawDown	-1.56	-1.65	-2.53	-2.53	-2.49	-1.47	-2.15	-2.10	-1.79	-2.06	-2.08	-2.08	-1.34	-1.77	-2.99	-2.99	-9.46	-1.73	-1.87	-1.79
Traynors Ratio	0.03	0.03	-0.01	0.00	0.00	0.05	-0.05	-0.02	0.06	0.02	0.01	14.54	0.14	0.04	0.02	0.01	-0.03	-0.02	-0.02	0.01

4.1.2 Momentum Strategies for Greece J equals 24 weeks

From Table 2, we can observe the formation period, J equals to 24. Most strategies preserve positive returns greater than the benchmark of the period. The exceptions are for the price momentum and the holding period of 52 weeks, for the moving average the 36 and 52 holding period, for the relative strength index momentum the 36 and the 52 weeks, and for the combined relative strength index and moving average momentum strategy for the holding period of 36 weeks and 52 weeks. The results of the presence of abnormal returns are a robust contradiction of the presence of the EMH in the Greek stock markets. The greatest difference from the benchmark can be found in the Relative strength index combined with the moving average momentum strategy and for the holding period of 24 weeks (10.37%). We can observe that all the considered momentum strategies have abnormal returns in the first two holding periods (i.e., 12, 24). The benchmark for each period tends to vary as the portfolios are closed at the end of the holding period. It is important to note that the trading costs associated with momentum strategies are higher than those of the benchmarks. Therefore, in practice, a smaller difference in returns would be observed. However, this thesis aims to compare the performance of different momentum strategies, assuming that they incur similar costs for their structure.

Previous findings suggest that momentum tends to deteriorate as the holding period length is increased (Moskowitz et al., 2012; Gutierrez & Prinsky, 2007; Griffin et al., 2003; Jegadeesh & Titman 2001,1993), which can also be observed in our findings. In the price momentum strategy, we can observe a decline in the returns from 2.63% to -0.65% which shows a reversal in the fundamental values of the stocks over time. Furthermore, Jensen's alpha implies an overcompensation of risk taken in comparison with the benchmark index and the rf.

The selected momentum strategies comparison for the same sample period for the look-back period (J) of 24 weeks is presented in Table 2. It is important to note that the sample concludes at the end of each holding period, resulting in unequal sample sizes for comparison across different holding periods. Therefore, we considered four different benchmark periods and compared them with the four different holding periods in our sample. For K period for 12 weeks, the Moving average momentum strategy and the Relative strength index and Moving average momentum strategy present a Sharpe ratio of 1.36 and 1.12 respectively which is the highest among the studied strategies. Price momentum and Relative strength index momentum strategies preserve a 0.6 and a 0.11 Sharpe Ratio respectively, while the benchmark portfolios preserve a negative Sharpe ratio of -1.4. The highest Sharpe ratio of the moving average is due to the greater returns than the other selected strategies (i.e., Price momentum, Relative Strength Index, Moving average momentum and Relative Strength Index), while the standard deviation of the compared models are greater than the moving average strategy (0.34), with a value of 0.35 for price momentum, a value of 0.41 for Relative strength index and lower for the Relative strength strategy (0.33), while the benchmark portfolio presents the lower standard deviation (0.02) but also negative returns. Nevertheless, both Jensen's alpha and Sharpe ratio are higher than the other strategies for the Moving average momentum strategy for the holding period of 12 weeks.

For the holding period of 24 the Relative Strength Index combined with moving average momentum strategy preserves the greatest returns (7.05), but not a higher Sharpe Ratio than the price momentum. The highest Sharpe ratio (0.59) among the investigating strategies is observed in price momentum strategy, while the most profitable strategy (Relative Strength Index and Moving average) preserves a Sharpe ratio of 0.52. The greatest Jensen's alpha (0.42) is for the most profitable strategy during this period (Relative Strength Index and Moving average). For the holding period of 36 weeks the price momentum strategy preserves the greater results, with returns of 2.79% a greater Sharpe ratio of 0.09 a lower standard deviation of 0.56, a higher Jensen's alpha of 0.1, and a Traynor's ratio of -0.03. Referring to Traynor's ratio the greatest value is presented on moving average strategy (0.09). Similarly, for the holding period of 52 weeks all the considered momentum strategies preserve negative returns lower than those of the benchmark portfolios. This result indicates that the momentum strategy with the Moving Average indicator is optimal among the 4 considered strategies with the greater returns and the lower risk for the holding period of 12 months, the Relative strength index and moving average strategy is the more profitable for the 24 months holding period and the price momentum is profits are greater than the other strategies for the 36 weeks holding period. For the 52 weeks, there is not a profitable strategy with the lower losses observed in the benchmark index. Overall, for the J period of 24 weeks, the most profitable strategy with the greatest returns among the different holding periods and among the different considered strategies is the Relative strength index and moving average for the 24-week holding period.

The four-momentum strategies considered differ not only in returns and volatility but also in crash risks. Examination of Maximum Drawdown is an important measure in our study. The highest MDD for the 12-week holding period is achieved from moving average momentum strategy (-1.08). The Relative Strength index strategy has the highest MDD for the 24-week holding period (-2.01), the price momentum has the highest MDD for 36 weeks (-3.24) and the Relative strength index for 52 weeks holding period (-3.77) while the benchmark portfolio for the highest losses indicating that a crash happens to the Greek stock market during the studied sample period. Note that MDD is a negative number and a higher MDD for the studied strategy reveals a lower crash risk. The highest values of skewness and Kurtosis are preserved in the price momentum portfolio for the holding period of 12 and 36 weeks and in the benchmark portfolio for the 24 and 52 holding weeks. The benchmark portfolio seems to be right-tailed with a fatter distribution indicating greater positive returns, which is not occurred by our study, the same is observed for the price momentum portfolio for 36 weeks, while the price momentum preserves a left skewness and a right kurtosis.

Table 2: Greek stock market performance measures for the discussed momentum strategies, referring to different (K) holding periods and a 24-weeks looking back period (J)

J=24 weeks	Price Momentum				Moving Average				Relative Strength Index				Relative Strength Index and Moving Average				Benchmark			
K (weeks)	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52
sum returns	2.63	5.84	2.79	-0.65	5.62	3.70	-1.66	-2.97	0.64	5.91	-0.32	-2.73	4.55	7.05	-2.51	-5.78	-0.16	-0.14	0.01	-0.01
average returns	0.22	0.24	0.08	-0.01	0.47	0.15	-0.05	-0.06	0.05	0.25	-0.01	-0.05	0.38	0.29	-0.07	-0.11	-0.01	-0.01	0.00	0.00
max	0.62	1.02	1.02	1.02	0.94	1.03	1.05	1.06	0.52	1.28	1.28	1.28	1.04	1.13	1.13	1.31	0.02	0.06	0.07	0.15
min	-0.59	-0.59	-1.39	-2.08	-0.05	-0.66	-1.68	-2.40	-0.63	-0.63	-1.72	-1.72	-0.11	-0.90	-1.91	-2.45	-0.03	-0.05	-0.05	-0.06
σ	0.35	0.39	0.56	0.64	0.34	0.47	0.80	0.75	0.41	0.53	0.75	0.74	0.33	0.54	0.84	0.90	0.02	0.03	0.03	0.04
Sharpe Ratio	0.60	0.59	0.09	0.15	1.36	0.30	-0.09	0.07	0.11	0.44	-0.05	0.08	1.12	0.52	-0.12	0.00	-1.40	-0.76	-0.96	3.02
Skewness	-1.19	-0.53	-1.04	-1.24	-0.33	0.10	-0.58	-1.08	-0.64	0.14	-0.41	-0.51	0.56	-0.57	-0.69	-0.88	0.58	0.92	0.60	1.48
Kurtosis	1.52	0.61	1.10	1.51	-1.42	-0.51	-0.78	1.06	-0.82	-0.46	-0.29	-0.18	0.06	0.14	-0.35	0.43	-0.98	1.11	-0.25	4.17
beta	6.04	6.69	1.64	2.81	2.18	9.01	-0.88	3.02	4.33	9.98	2.87	3.96	0.32	9.61	1.36	3.31	1.00	1.00	1.00	1.00
Jehnsens alpha	0.35	0.36	0.10	-0.21	0.48	0.27	-0.10	-0.28	0.09	0.37	0.05	-0.37	0.37	0.42	-0.06	-0.36	0.00	0.00	0.00	0.00
Maximum DrawDown	-1.95	-1.95	-3.24	-4.35	-1.08	-2.06	-3.70	-4.87	-2.01	-2.01	-3.77	-3.77	-1.17	-2.45	-4.07	-4.94	-10.49	-4.04	-3.78	-38.26
Traynors Ratio	0.03	0.03	0.03	0.03	0.21	0.02	0.09	0.02	0.01	0.02	-0.01	0.01	1.17	0.03	-0.07	0.00	-0.02	-0.02	-0.03	0.11

4.1.3 Momentum Strategies for Greece J equals 36 weeks

From Table 3, we can observe the formation period, J equals 36. The strategies that preserve positive returns for the holding period of 12 weeks are the price momentum, the moving average, and the Relative Strength Index combined with the Moving Average, for the 24 weeks all the considered strategies, and for the 36 and 52 weeks all the strategies have negative returns. The benchmark portfolio indicates positive returns for all studied holding periods. The results of the presence of abnormal returns are a robust contradiction of the presence of the EMH in the Greek stock markets for the positive return studied periods. The greatest difference from the benchmark can be found in the Moving Average strategy and for the holding period of 24 weeks (7.76%). We can observe that all the considered momentum strategies have abnormal returns in the first two holding periods (i.e., 12, 24) except for the 12-week holding period for the relative strength index strategy. The benchmark for each period tends to vary as the portfolios are closed at the end of the holding period. It is important to note that the trading costs associated with momentum strategies are higher than those of the benchmarks. Therefore, in practice, a smaller difference in returns would be observed. However, this thesis aims to compare the performance of different momentum strategies, assuming they incur similar costs for their structure.

Previous findings suggest that momentum tends to deteriorate as the holding period length is increased (Moskowitz et al., 2012; Gutierrez & Prinsky, 2007; Griffin et al., 2003; Jegadeesh & Titman 2001,1993), which can also be observed in our findings. In the price momentum strategy, we can observe a decline in the returns from 2.59% to -3.29% which shows a reversal in the fundamental values of the stocks over time. Furthermore, Jensen's alpha implies an overcompensation of risk taken in comparison with the benchmark index and the rf.

The selected momentum strategies comparison for the same sample period for the look-back period (J) of 36 weeks is presented in Table 3. It is important to note that the sample concludes at the end of each holding period, leading to unequal sample sizes when comparing different holding periods. Therefore, we considered four different benchmark periods and compared them with the four different holding periods in our sample. For K period for 12 the Moving average momentum strategy presents a Sharpe ratio of 0.78 which is the highest among the studied strategies. Price momentum, Relative strength index momentum and Relative strength index combined with moving average momentum strategies preserve a 0.49, -0.17, and 0.66 Sharpe Ratio respectively, while the benchmark portfolios preserve a negative Sharpe ratio of -0.4. The highest Sharpe ratio of the moving average is due to the greater returns than the other selected strategies (i.e., Price Momentum, Relative Strength Index, Moving average momentum and Relative Strength Index), while the standard deviation of the moving average (0.46) is greater than the price momentum (0.41), a value of 0.37 for Relative strength index and for the Relative strength strategy (0.42), while the benchmark portfolio presents the lower standard deviation (0.03). Nevertheless, we observe the highest Jensen's alpha (0.31) and the higher Sharpe ratio for the Moving average momentum strategy for the holding period of 12 weeks.

For the holding period of 24 weeks, the Moving Average momentum preserves the greatest returns (7.76), and a higher Sharpe Ratio (0.56) than the other studied strategies. The greatest Jensen's alpha (0.31) for the second most profitable strategy, with returns of 6.47, during this period (Relative Strength Index and Moving average). For the holding period of 36 weeks, the benchmark portfolio preserves the greater results, with returns of 2.51% a greater Sharpe ratio of 1.19 a lower standard deviation of 0.04, and a Traynor's ratio of -2.13%. Similarly, for the holding period of 52 weeks all the considered momentum strategies preserve negative returns lower than those of the benchmark portfolio. This result indicates that the momentum strategy with the Moving Average indicator is optimal among the 4 considered strategies with greater for the holding period of 12 and 24 months. For the 36 and 52 weeks, there is not a profitable strategy with profit observed only in the benchmark portfolio. Overall, for the J period of 36 weeks, the most profitable strategy with the greatest returns among the different holding periods and the different considered strategies is the moving average strategy for the 24-week holding period.

Examination of Maximum Drawdown, among the four considered strategies is an important measure in our study, due to its usage as a crash risk tool. The highest MDD for the 12-week holding period is achieved from the relative strength combined with the moving average momentum strategy (-1.42). The Moving average momentum strategy has the highest MDD for the 24-week holding period (-1.47), while the benchmark portfolio preserves the highest MDD for 36 and 52 weeks. Note that MDD is a negative number and a higher MDD for the studied strategy reveals a lower crash risk. The highest values of skewness and Kurtosis vary during different strategies, for the holding periods of 12 and 24 weeks giving us no clear evidence about the strategies' performance. For the 36 and 52 weeks the benchmark portfolio seems to be right-tailed with a fatter distribution indicating greater positive returns as it seems from the return results.

Table 3: Greek stock market performance measures for the discussed momentum strategies, referring to different (K) holding periods and a 36-weeks looking back period (J)

J=36 weeks	Price Momentum				Moving Average				Relative Strength Index				Relative Strength Index and Moving Average				Benchmark			
K (weeks)	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52
sum returns	2.59	3.69	-0.14	-3.29	4.52	7.76	-1.40	-4.38	-0.59	2.59	-2.02	-4.35	3.53	6.47	-2.22	-3.43	0.01	0.15	0.21	0.13
average returns	0.22	0.15	0.00	-0.06	0.38	0.32	-0.04	-0.08	-0.05	0.11	-0.06	-0.08	0.29	0.27	-0.06	-0.07	0.00	0.01	0.01	0.00
max	1.03	1.03	1.03	1.03	0.91	1.39	1.03	1.55	0.39	1.02	1.02	1.02	0.91	1.19	1.19	1.33	0.06	0.07	0.15	0.15
min	-0.68	-0.94	-1.22	-1.55	-0.62	-0.66	-1.26	-2.40	-0.76	-0.76	-1.38	-1.55	-0.38	-0.87	-2.36	-2.36	-0.05	-0.05	-0.06	-0.06
σ	0.41	0.47	0.58	0.62	0.46	0.52	0.64	0.79	0.37	0.47	0.62	0.65	0.42	0.54	0.89	0.88	0.03	0.03	0.04	0.04
Sharpe Ratio	0.49	0.27	0.16	0.02	0.78	0.56	0.09	-0.01	-0.17	0.17	0.06	-0.01	0.66	0.45	0.04	0.01	-0.40	-0.68	2.51	2.21
Skewness	-0.18	-0.48	-0.44	-0.57	-0.80	0.02	-0.34	-0.78	-0.76	-0.05	-0.43	-0.56	-0.58	-0.64	-1.01	-0.95	0.46	0.26	1.19	1.38
Kurtosis	2.31	0.27	-0.79	-0.38	0.43	-0.19	-0.48	0.53	-0.24	-0.60	-0.32	-0.32	-0.71	-0.24	0.52	0.43	0.02	-0.80	2.78	3.55
beta	-2.57	0.61	-0.50	0.20	-3.98	-0.14	1.76	1.89	-1.69	1.05	1.75	1.89	-2.16	2.34	1.33	1.92	1.00	-2.57	0.61	-0.50
Jehnsens alpha	0.17	0.14	0.14	0.00	0.31	0.29	-0.11	-0.15	-0.09	0.11	-0.13	-0.15	0.25	0.31	-0.09	-0.14	0.00	0.17	0.14	0.14
Maximum DrawDown	-1.66	-1.91	-2.18	-2.50	-1.68	-1.47	-2.22	-2.55	-2.94	-1.75	-2.36	-2.53	-1.42	-1.73	-2.98	-2.77	-1.77	-1.66	-1.91	-2.18
Traynors Ratio	-0.08	0.21	-0.18	0.07	-0.09	-2.13	0.03	0.00	0.04	0.07	0.02	0.00	-0.13	0.10	0.03	0.01	-0.01	-0.08	0.21	-0.18

4.1.4 Momentum Strategies for Greece J equals 52 weeks

From Table 4, we can observe the formation period, J equals 52. The strategies that preserve positive returns for the holding period of 12 weeks for the price momentum, the moving average, and the Relative Strength Index combined with the Moving Average, for the 24 weeks all the considered strategies preserve positive returns, for the 36 weeks holding period we can observe positive returns for price momentum strategy and relative strength index combined with moving average strategy, and for 52 weeks all the strategies have negative returns except for and relative strength index combined with moving average strategy. The benchmark portfolio indicates negative returns for 12- and 36-weeks holding period while for 24 and 52 positive returns. The presence of abnormal returns is a robust contradiction of the presence of the EMH in the Greek stock markets for the positive return studied periods. The greatest difference from the benchmark can be found in the relative strength index combined with the moving average strategy and for the holding period of 24 weeks (7.32%). We can observe that all the considered momentum strategies have abnormal returns in the first two holding periods (i.e., 12, 24) except for the 12-week holding period for the relative strength index strategy. The benchmark for each period varies as the portfolios close at the end of the holding period. Since trading costs for momentum strategies are higher than those for benchmarks, the return differences in practice are smaller. However, this thesis compares the performance of different momentum strategies, assuming similar costs for their structure.

Previous findings suggest that momentum tends to deteriorate as the holding period length is increased (Moskowitz et al., 2012; Gutierrez & Prinsky, 2007; Griffin et al., 2003; Jegadeesh & Titman 2001,1993), which can also be observed in our findings. In the price momentum strategy, we can observe a decline in the returns from 3.1% to -3.89% which shows a reversal in the fundamental values of the stocks over time. Furthermore, Jensen's alpha implies an overcompensation of risk taken in comparison with the benchmark index and the rf.

The selected momentum strategies comparison for the same sample period for the look-back period (J) of 52 weeks is presented in Table 4. The sample concludes at the end of each holding period, resulting in unequal sample sizes for comparison. Thus, we considered four different benchmark periods and compared them with the four different holding periods in our sample.

For K period for 12 the price momentum strategy presents a Sharpe ratio of 0.79 which is the highest among the studied strategies. Moving average momentum, Relative strength index momentum and Relative strength index combined with moving average momentum strategies preserve a 0.67, 0.04, and 0.52 Sharpe Ratio respectively, while the benchmark portfolios preserve a Sharpe ratio of 0.71. The highest Sharpe ratio of the price momentum strategy is due to the greater returns (3.1%) than the others, except for the Moving average momentum strategy (3.66%) and the lower standard deviation selected strategies (i.e., Moving average momentum, Relative Strength Index, and Relative Strength Index combined with Moving average momentum), while the standard deviation of the price momentum (0.34) is lower than the moving average momentum (0.48), the value of 0.35 for Relative strength index and for the Relative strength strategy (0.5), while the benchmark portfolio presents the lower standard deviation (0.04). Nevertheless, we observe the highest Jensen's alpha (0.4) for the Moving average momentum strategy and the higher Sharpe ratio (0.79) for the price momentum strategy for the holding period of 12 weeks.

For the holding period of 24 weeks, the Moving Average momentum preserves the Relative strength index combined with the moving average momentum strategy (7.32), and a higher Sharpe Ratio (0.66) than the other studied strategies except for price momentum which preserves the highest Sharpe ratio during this period (0.79). The greatest Jensen's alpha (0.23) for the most profitable strategy is observed during this period (Relative Strength Index and Moving average). For the holding period of 36 weeks, the Relative Strength Index and Moving average strategy preserve the greater results, with returns of 4.15% a greater Sharpe ratio of 0.26 a low standard deviation of 0.75, and a Traynor's ratio of 1.55%. For the holding period of 52, we can observe positive returns just for the Relative Strength Index and Moving average strategy (0.58). This result indicates that the momentum strategy with price indicator is optimal among the 4 considered strategies for the holding period of 12 weeks. For the 24 and 36 weeks the Relative Strength Index and Moving average strategy. For 52 weeks the Relative Strength Index and Moving average strategy Overall, for the J period of 52 weeks, the most profitable strategy with the greatest returns among the different holding periods and the different considered strategies is the Relative Strength Index and Moving average strategy for the 24-week holding period.

A more comprehensive examination of Maximum Drawdown, among the four considered strategies is an important measure in our study, due to its usage as a crash risk tool. The highest MDD for the 12-week holding period is achieved from the price momentum strategy (-1.5), while the benchmark portfolio preserves the highest MDD of -1.38 for 24, 36 and 52 weeks. Note that MDD is a negative number and a higher MDD for the studied strategy reveals a lower crash risk. The highest values of skewness and Kurtosis vary during the 12 weeks holding period, while for the holding periods of 24, 36 and 52 weeks the benchmark portfolio seems to be right tailed with a fatter distribution indicating greater positive returns as it mostly seems from the return results.

Table 4: Greek stock market performance measures for the discussed momentum strategies, referring to different (K) holding periods and a 52-weeks looking back period (J)

J=52 weeks	Price Momentum				Moving Average				Relative Strength Index				Relative Strength Index and Moving Average				Benchmark			
K (weeks)	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52	12	24	36	52
sum returns	3.10	5.44	0.44	-3.89	3.66	5.16	-0.65	-3.63	-0.35	3.40	-1.69	-4.21	2.94	7.32	4.15	0.58	-0.08	0.00	-0.01	0.03
average returns	0.26	0.23	0.01	-0.07	0.30	0.22	-0.02	-0.07	-0.03	0.14	-0.05	-0.08	0.25	0.31	0.12	0.01	-0.01	0.00	0.00	0.00
max	0.90	0.97	0.97	0.97	0.83	1.09	1.09	1.03	0.39	1.03	1.03	1.03	0.88	1.72	1.72	1.72	0.07	0.15	0.15	0.15
min	-0.45	-0.75	-1.79	-2.12	-0.57	-0.90	-2.03	-1.55	-0.76	-0.76	-1.26	-1.55	-0.90	-0.90	-1.36	-2.16	-0.06	-0.06	-0.06	-0.06
σ	0.34	0.42	0.68	0.76	0.48	0.55	0.82	0.65	0.35	0.48	0.64	0.65	0.50	0.63	0.75	0.75	0.04	0.04	0.04	0.03
Sharpe Ratio	0.79	0.79	0.13	-0.02	0.67	0.59	0.07	-0.02	-0.04	0.52	0.05	-0.03	0.52	0.66	0.26	0.09	0.23	2.51	2.05	1.77
Skewness	-0.16	-0.29	-1.06	-1.08	-1.03	-0.43	-0.77	-0.51	-0.81	0.10	-0.31	-0.48	-0.90	-0.05	-0.14	-0.62	0.71	1.78	1.87	1.72
Kurtosis	1.20	0.10	1.01	0.62	-0.06	-0.58	-0.09	-0.37	0.17	-0.40	-0.49	-0.34	1.07	0.19	-0.44	0.56	0.20	4.80	5.52	5.80
beta	-2.36	1.61	1.73	0.79	-5.09	1.31	1.51	0.01	-2.45	2.01	1.08	-0.11	-2.68	1.70	0.78	-0.29	1.00	1.00	1.00	1.00
Jehnsens alpha	0.29	0.16	-0.04	-0.06	0.40	0.18	-0.06	-0.01	0.02	0.03	**-0.05**	**-0.02**	0.30	0.23	**0.13**	**0.09**	-0.01	**0.00**	**0.00**	**0.00**
Maximum DrawDown	-1.50	-1.77	-2.85	-3.19	-1.68	-1.83	-2.86	-2.50	-2.98	-1.74	-2.22	-2.50	-2.02	-1.53	-1.79	-2.26	-1.79	-1.38	-1.38	-1.38
Traynors Ratio	2.75	3.86	0.80	-0.15	2.33	2.88	0.44	-0.12	-0.14	2.56	0.29	-0.24	1.79	3.22	1.55	0.68	0.79	12.32	12.32	12.75

5. CONCLUSIONS

The findings from the analysis of momentum strategies in the Greek stock market reveal several key insights. All considered momentum strategies show statistically significant returns from August 2, 2019, to June 9, 2023, contradicting the Efficient Market Hypothesis (EMH). The analysis across different formation and holding periods (12, 24, 36, and 52 weeks) shows that momentum tends to deteriorate with increased holding periods, aligning with previous research. For a 12-week formation period, the moving average strategy with a 24-week holding period achieved the highest returns and Sharpe ratio, indicating optimal performance, while the combined Relative Strength Index (RSI) and moving average strategy showed superior results in terms of returns and risk-adjusted performance for various periods. For a 24-week formation period, the RSI combined with the moving average strategy yielded the highest returns for 24 weeks, though price momentum displayed the best Sharpe ratio. The moving average strategy outperformed others for holding periods of 12 and 24 weeks in a 36-week formation period, whereas all strategies showed negative returns for 36 and 52 weeks. The 52-week formation period highlighted the RSI combined with the moving average strategy as the most profitable, especially for the 24-week holding period, despite the negative performance in longer holding periods. Across all periods, the higher Jensen's alpha and Sharpe ratios for these strategies demonstrate their effectiveness in generating abnormal returns. Additionally, crash risk, measured by Maximum Drawdown (MDD), varied, with higher MDD values indicating lower crash risk, often favoring momentum strategies over benchmarks. Skewness and kurtosis analyses suggested that while the benchmark portfolios often showed right-tailed distributions with greater positive returns, this was not consistently reflected in momentum strategies.

The results of our study can be robust by the previous findings that suggest that momentum tends to deteriorate as the holding period length is increased (Moskowitz et al., 2012; Gutierrez & Prinsky, 2007; Griffin et al., 2003; Jegadeesh & Titman 2001,1993), which can also be observed in our findings.

Our research can benefit investors and traders in the Greek stock market by showing them which of the strategies can have potentially positive and highest gains while the volatility remains low. In our investigation, it is shown that investors seeking higher returns may prefer (J/K) 12/24 moving average strategy, while investors seeking lower volatility can invest in benchmark index. Moreover, this study supports the behavioral finance theory that market momentum can be exploited for profit, while it also highlights the importance of considering the crash risk in momentum strategy design.

The study is limited by the sample size and the specific period analyzed not capture the greater image of the strategies. Extending the sample period could reveal more comprehensive insights while it will allow us to study the returns and volatility of momentum strategies using the stochastic framework. Moreover, the assumption of similar trading costs across strategies is a simplification that might not hold in real-world scenarios. Varying costs could significantly affect the comparative performance. In addition, the study period included several significant market events, such as the COVID-19 pandemic and the Russo-Ukraine war, which may have disproportionately impacted certain strategies. While some of the findings are relevant to the U.S. stock market, their applicability to other markets or asset classes requires further investigation. In conclusion, this study provides valuable insights into the performance of different momentum strategies. Future research should aim to address the identified limitations by extending the sample size, incorporating more diverse data, and refining the methodological approach to trading costs.

Overall, the study underscores the superior performance of specific momentum strategies, particularly the moving average and combined RSI and moving average strategies, in generating higher returns and managing risk in the Greek stock market.

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9. APPENDIX