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US Tech ETF Momentum Strategies

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By

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Abstract

Momentum strategies sustained on buying past winners and selling past losers undermined the paradigm of the financial markets, grounded on the Efficient Market Hypothesis, due to being possible to uncover profitable trading patterns by solely analysing past stock behaviour. Afterward, behavioural finance emerged, relying on cognitive bias and investor irrationality to interpret momentum.

This paper tests the implementation of momentum strategies using sectorial ETFs, particularly US technological ETFs. ETFs are financial instruments that track indexes and compose a basket of diversified securities. Consequently, 20 technological ETFs traded daily from 2010-2019 (10 years) were selected and implemented a total of 36 momentum strategies with rising formation periods.

The WML portfolios delivered returns non-significant from zero throughout all timeframes. Notably, the returns of the winners and losers' portfolios unveiled similar positive results. These results are justified by the exceptional performance of the technological indexes, driven by overconfident agents and government politics to stimulate technological innovation. Hence, ETF lower exposure to idiosyncratic risk assembled with favourable market conditions resulted in losers portfolios with positive returns. Lastly, the differential between the ETFs price and the NAV are structurally corrected by AP´s, making it more complex for ETFs prices to drift away from the NAV, undermining the conditions to surface momentum.

Keywords: Exchange-Traded Fund (ETF), Momentum, Behavioural Finance, Risk, Technological Sector

Resumo

Momentum Trading suportado na compra de *winners* e na venda de *losers*, comprometeu o paradigma dos mercados financeiros alicerçado na Teoria dos Mercados Eficientes, devido a ser viável encontrar padrões lucrativos de *trading* pela análise do comportamento passado de ações. Posteriormente, emergiram as Finanças Comportamentais, apoiadas em enviesamentos cognitivos e na racionalidade limitada dos agentes de mercado para interpretar *momentum*.

Este estudo testa a implementação de estratégias de *momentum* utilizando *ETFs* sectoriais, particularmente *ETFs* tecnológicos dos Estados Unidos da América. *ETFs* são instrumentos financeiros que replicam a performance de índices e são compostos por um conjunto diversificado de ações. Consequentemente, foram selecionados 20 *ETFs* tecnológicos negociados diariamente entre 2010-2019 (10 anos) e concretizados um total de 36 estratégias de *momentum* com períodos de formação crescentes.

O portfolio *WML* conferiu retornos não significativos ao longo de todos os prazos. Em particular, os retornos dos portfolios *winners* e *losers* revelaram resultados positivos. Estes resultados são justificados pela performance exceptional dos índices tecnológicos, suportados pela excessiva confiança dos investidores neste setor e em políticas estatais que promovem a inovação. Adicionalmente, a menor exposição dos *ETFs* ao risco idiossincrático reunido com as condições favoráveis de mercado proporcionou os retornos positivos dos *losers* portfolios. Por último, o diferencial entre o preço dos *ETFs* e o *NAV* são estruturalmente corrigidos pelos *AP´s*, tornando mais complexo que os preços dos *ETFs* se afastem do *NAV*, não criando condições favoráveis para emergir *momentum.*

Palavras-Chave: *Exchange-Traded Fund (ETF)*, *Momentum*, Finanças Comportamentais, Risco, Setor Tecnológico

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1. Introduction

1.1 General Framework

The finance paradigm has considerably progressed since economists developed and performed valuation metrics to pursue the abstract concept of *fundamental value* and its possible discrepancies from stock price to obtain some upside. At this time, Wall Street was popular, mysterious, and exclusive to some wealthy investors and exceptional individuals that traded in that "dome". The progression of technology introduced the concepts of decentralized finance (cryptocurrencies) and automated & high-frequency trading. These developments disrupted the contemporaneous model, consequences are abundant, and its aftermath remains undisclosed.

The pursuit of trading strategies that convey superior returns to investors has been a constant endeavour amongst academics and investors, nevertheless for entirely different reasons. While academics are searching for the true nature of financial markets, investors are trying to achieve abnormal returns and profits. Surged a stock price abnormality found by Jegadeesh & Titman (1993) called momentum, which conceptually is defined as the continuation or persistence of a stock price trend, whether positive or negative, considering their past performance. These results implied severe theoretical obstacles to the contemporaneous financial markets paradigm supported by the Efficient Market Hypothesis.

This theory reflects that markets are efficient due to "prices fully reflecting all available information" (Fama, 1970). The most significant ramification of the Efficient Market Hypothesis is that investors should engage in passive portfolio management. Hence, it does not make sense to buy and sell securities frequently, incurring in high transaction costs and diminishing net returns. Additionally, the momentum predictability pattern violated the essential pillars of the EMH, the weak form efficient market perspective, due to being possible to achieve abnormal returns solely considering past stock behaviour.

Fama (1998) classified this anomaly as an "open puzzle", giving rise to behavioural explanations to interpret momentum profits. The behaviourist approach to these obstacles lies in recognising human limitation (Shiller, 2003), bounded rationality (Ritter, 2003), and cognitive biases that undermine the feasibility of agents in the market having full computing capability and optimal decision-making.

Recent empirical investigations regarding the manifestation of cross-sectional price momentum proved controversial. While studies supported the persistence of momentum (Geczy & Samonov, 2015) and several branches emerged, as style momentum (Barberis & Shleifer, 2003), time-series momentum (Moskowitz et al., 2012), and factor momentum (Gupta & Kelly, 2019). Other analyses sustained that the anomaly has considerably decreased (Bhattacharya et al., 2017).

This work analyses the profitability of momentum applying Exchange-Traded Funds. ETFs trade as common stocks, and a share is a claim on a trust that holds a specified pool of diversified assets (Gastineau, 2002). This instrument functions similarly to passively managed index mutual funds, as they are composed of a portfolio that contains financial instruments (e.g., stocks, bonds) that track a particular index. ETFs were introduced in the US market in January 1993, with the SPDR, who tracked the S&P 500. It currently remains the largest ETF traded in the market, with over 325 million USD in assets under management in 2020[1]. The ETFs market has been in constant and steady growth over the past 20 years. However, the variation of global assets managed in ETFs has significantly augmented recently, over 30% in 2019, to 6.194 billion USD, and almost 25% in

[1] Source: statista.com

2020 to 7.736 billion USD[2]. US Technological ETFs are mainly composed of NASDAQ-100 firms. In the US markets, tech ETFs have almost 170 billion USD in assets under management[3].

These numbers support the notion that the ETFs market is booming, vibrant, and attractive for investors due to superior liquidity, lack of short sales constraints, and a decisive diversification aspect that provides benefits to reduce idiosyncratic risk. Hence, it is crucial to investigate and extend the empirical evidence regarding momentum to a modern financial instrument to examine its profitability.

1.2 Research Gap

Momentum strategies were implemented for most financial instruments, such as mutual and index funds (Grinblatt et al., 1995; O'Neal, 2000), bonds (Jostova et al., 2013), currencies (Menkhoff et al., 2012) and more recently ETFs (Li et al., 2019; Tse, 2015).

Considering the features and architecture of ETFs, this instrument might be beneficial to explore sectorial momentum as analysed by Moskowitz & Grinblatt (1999). These authors argue that industry momentum encompasses most of the price momentum effect reported in the literature. Nonetheless, Grundy & Martin (2001) have an opposing view and found that industry momentum on its own does not explain stock momentum profitability. Lee & Swaminathan (2000) complied and asserted that industry momentum only describes 20% of abnormal returns provided by standard momentum.

Consequently, a gap and dispute in the literature rely on the lack of inter-sectorial and industry analysis to effectively discriminate the source of abnormal profits. Therefore, it is essential to analyse if particular industries or sectors bear

[2] Source: statista.com
[3] Source: etf.com

the profitability of the market momentum anomaly and if it is feasible to consider ETFs to implement sectorial momentum strategies due to their unique attributes and traits.

1.3 Research Question

The research question that this work intends to answer is: Do strategies of buying winners and selling losers (momentum) generate significant abnormal returns in the US ETFs Technology indexes?".

The studies developed in the literature that encompass momentum trading strategies with ETFs are scarce. The results are diverse, due to the implementation of different approaches and methodologies to the concept of momentum.

Therefore, it is fundamental to perform a sectorial analysis within the ETFs market that analyses the cross-sectional price momentum profitability unveiled and developed by Jegadeesh & Titman (1993). The selection of the technological sector to conduct this analysis is not casual. It relies on the importance that enterprises in this sector have in our society. Additionally, technological firms are highly dependent on intangible assets whose valuation is unclear. Hence, individuals might develop behavioural biases towards the firms in this sector, influencing ETFs prices to drift from their underlying net asset value (NAV), consequently driving momentum profits.

In sum, it is determinant to assess if momentum trading strategies using technological ETFs can provide upside to individual investors and fund managers.

1.4 Originality

The distinguishable traits in this work rely on two main branches, first aims at providing empirical work with a contemporary and extended timeframe. Thus, it will be analysed evidence between 2010-2019, excluding the bear markets of 2007-2009.

Secondly, to the best of our knowledge, no academic studies focused entirely on the profitability of momentum strategies within a specific ETF sector and considered unique industry motives to its presence. However, it is essential to assert that some studies focus on the reunion between momentum profitability and the ETFs market as a whole (De Jong & Rhee, 2008; Li et al., 2019; Yu & Webb, 2020). In clear contrast to the approach conveyed by this work, intending to provide discriminative evidence of momentum profitability within an ETFs sector, specifically the technological sector.

1.5 Contributions to Knowledge

The main contribution of this work to academic knowledge is to extend the empirical evidence of momentum profitability regarding a specific investment vehicle, namely Exchange-Traded-Funds. Hence, ETFs specific characteristics and operational structure contributes with supplementary theoretical evidence of cross-sectional momentum. The focus on the technology sector provides new empirical evidence considering the contemporary timeframes analysed and delivers specific industry motives to the potential manifestation of the anomaly.

Concerning stakeholders, this work contributes with additional investor insight about the implementation of trading strategies within the tech sector and considers the employment of ETF to execute them. ETF providers may also draw valuable conclusions about the effectiveness of these funds.

In addition, this study might become helpful to regulatory institutions, specifically the SEC (Security Exchanges Commissions), due to being implemented in the US market. Consequently, the SEC might take valuable insights that provide equilibrium to financial markets, regardless of mentioning the nefarious effects that deregulatory financial policies caused in the worldwide economy.

1.6 Layout of the Following Chapters

This work will be structured and conducted in the following manner; Chapter 2 will consist of a literary review that extends and deepens the concepts briefly presented above to develop the hypotheses. Chapter 3 will present all the data and methodology to test the hypothesis and achieve the results conveyed in Chapter 4.

Finally, Chapter 5 will discuss this work's primary results and contributions and regard this study's main limitations.

2. Literature Review

2.1 Main Concept

Momentum characterizes return predictability based on past returns. Hence, it entails selecting securities with positive (negative) market trends and buying (selling) them. A distinction between momentum and trending is essential; while momentum is positive feedback (DeLong et al., 1990) across securities, trending is a statistical regularity (time-series event).

Momentum regards cross-sectional patterns. Levy (1967) first developed the notion of "strength" strategies by buying stocks that overperformed in the past 27 weeks and holding these stocks for another 26 weeks[4], achieving abnormal returns. This author argued that securities co-movement drives dependencies in successive price changes.

Nonetheless, Jegadeesh & Titman (1993) furthered this hypothesis and documented reliable momentum profits in the medium-term horizon. They argue that by comparing and segregating securities with positive returns to those underperforming, it can be exceeded the profitability of buy-and-hold strategies by buying winners and selling losers. This approach identifies and selects stocks, forming zero-cost portfolios dependent on the relative performance of the top and bottom securities. This "strength" strategy entails the comparison of stock returns. Therefore implicates a cross-sectional analysis that might depend on the cross-serial correlation of returns (lead-lag relations among stocks), suggesting that this anomaly isolates idiosyncratic factors while ranking stocks and forming portfolios (Grundy & Martin, 2001). This approach is consistent with much of the literature that attributes momentum profits to firm-specific events. Consequently, agents either underreact or overreact to idiosyncratic news.

[4] The author omitted tests for statistical significance

Several branches from cross-sectional momentum emerged in the literature, such as factor momentum (Ehsani & Linnainmaa, 2019), relying on buying the top-performing factors and selling the bottom-ones. Also, industry momentum (Moskowitz & Grinblatt, 1999) and EPS momentum (Chordia & Shivakumar, 2006) gained track in the literature, both derived from the same notion, the persistence of a stock price trend dependent on, respectively, industry returns or earnings-per-share past events.

Moskowitz et al. (2012) developed a conceptually divergent approach to the widely investigated cross-sectional momentum. These authors documented a "time-series" or "trend momentum" effect and showed that buying and selling securities based on their absolute past performance achieved abnormal returns. The distinction between these two frameworks is simple, while time-series momentum selects securities based on their absolute past performance compared to a fixed benchmark, cross-sectional momentum ranks and select securities relying on their relative performance to form the best/worst portfolios.

The development of this new concept proved controversial due to studies finding that time-series momentum (TS) provided superior returns than the cross-section (CS) approach, implying that the stock selection rule on the time-series approach is advantageous (Asness et al., 2013). TS momentum superior performance is a consequence of the stock selection process being more in tune with market conditions. Hence, in bull (bear) markets, the weights of the portfolio tilt to winner (loser) stocks, increasing returns (Cooper et al., 2004; Goyal & Jegadeesh, 2018). Additionally, the TS approach entails variable diversification and portfolio size, given that the long and short positions are dynamic. Conversely, in the CS technique, securities are ranked, and portfolio size formation is rigid. Hence, long and short positions are equal, producing a problem if markets are firmly up (down) biased. Nonetheless, the CS profitability is less contingent on market states.

This work analyses CS momentum because it provides a solid technique to rank, select and form portfolios instead of relying on arbitrary benchmarks to select the winners and losers' portfolios. Another argument favouring CS momentum is that the results are less dependent on market continuation (transitions) to achieve abnormal returns. Additionally, the extensive theoretical and empirical work confirms the reliability of cross-sectional momentum in distinct frameworks.

Finally, considering the inherent structure of the financial instrument applied to perform the momentum analysis (ETFs), it is essential to discriminate the winner and loser funds adequately, and cross-sectional momentum provides the most practical framework.

2.2 Main Theories

The economic community supported the Efficient Market Hypothesis premises based on the random-walk theory and risk-based pricing models for several decades. Nonetheless, several unexplained pricing anomalies from the informationally efficient theory surfaced, like calendar anomalies, the size effect, and momentum. The development of behavioural finance relying on cognitive biases and prospect theory conveyed alternative explanations to some of these market abnormalities.

2.2.1 Random-Walk Theory

A clear definition of how the stock market behaves and interprets information has been the target of several perspectives and theories throughout the years. Bachelier (1900) proposed the following axiom: "L´ ésperance mathematique du spéculateur est nul" (p. 34), meaning that the mathematical expectation of the speculator to have abnormal returns is null. This postulation influenced the development of the Random Walk Theory. His work has three levels of complexity; the first level conceives securities prices as an unbiased price estimator. The second level, the most known “random walk” hypothesis, is defined by past prices not influencing the behaviour of future prices. The third and last level asserts that the distribution of prices follows a Gaussian random value. The culmination of Bachelier's work asserts that successive price changes are independent, identically distributed random variables and assumes that the behaviour of stock prices is not predictable by past changes no more than a series of random variables.

This view has two propositions: (1) successive price changes are independent, and (2) prices must follow a distribution function. The independence assumption is explained in a simple form: if new information independently reaches the market throughout time, then price changes will also be independent. From a statistical point of view, it is critical to evaluate if successive price changes are independent or not. However, small dependences may not be relevant for market makers because trading costs might take any profits away resulting from these deviations.

The distribution function of successive price changes is essential because it allows investors to assess their risk exposure. Suppose the distribution of price follows a gaussian or normal distribution. In that case, the investor knows that the probability of occurring abnormal values is low, and most price volatility will fit in a range of previously acceptable values. Kendall & Hill (1953) and Osborne (1959) also supported the Random Walk view, although with different approaches.

2.2.2 Efficient Market Hypothesis

Fama (1970) provided a breakthrough definition of how financial markets behave. It asserted that a market in which “prices fully reflect all available information” is efficient, thus the Efficient Market Hypothesis Theorem. This author relied on two models to support his theory. The "fair game" model, dependent on the risk-return binomial; hence, achieving higher returns entails incurring higher risks, and the random-walk theory, which postulates that price changes are independent. Fama categorized markets in three different forms, contingent on the information set, Φ, presented below.

The literature highly debates this theory, and several studies presented evidence of financial market inefficiency (e.g., momentum, reversals, calendar anomalies). Grossman & Stiglitz (1980) argue that information cost undermines the possibility of an informationally efficient theory. In comparison, Malkiel (2003) attributes these anomalies to pure chance.

Market efficiency tests rely on pricing models (i.e., CAPM) to capture investors' assessment of new information, price adjustments, and security expected returns. The joint-hypothesis problem emerges if the pricing model delivers abnormal returns, then practitioners are not sure if the model is misspecified or financial markets are inefficient. Hence, abnormal returns may be due to an inefficient market, the pricing model being misspecified, or both. For this reason, the EMH is not an empirically refutable hypothesis.

2.2.2.1 Weak-Form

Fama (1970) defines markets in weak form efficient if the information set, Φ, contains all historical information (e.g., prices, returns, volume of trading).

According to the random-walk theory, price changes are independent. Hence, if current securities prices include all historical information, market agents cannot develop trading strategies based on past information to create profitable predictability patterns. Since there is no correlation between successive price changes, this form contradicts investors implementing technical/chart analysis to achieve superior returns.

In sum, the weak-form denies that agents in the market can earn excess returns from the market line and argues that stock price behaviour is random. Thus, the forecasting of future stock returns dependent on past returns is infeasible.

2.2.2.2 Semi-Strong Form

The semi-strong form of the Efficient Market Hypothesis examines the immediacy and effectiveness of price adjustments to selected and predetermined occasions. Therefore, the information set, Φ, is extended to regard all publicly available information in the markets.

This form argues that market agents cannot achieve superior returns from analysing public information. If public information is available to all rational market agents, then an information release would immediately reflect in the securities price. Hence, securities prices adjust immediately to relevant public information by moving the price to a new equilibrium, reflecting changes in supply and demand.

Event studies assess stock price responses and adjustments to predetermined corporate announcements (e.g., dividends, annual reports, mergers). The financial operations examined seem to reflect a general prediction; prices take at least a day to adjust to new information fully. Hence, a substantial dispersion of returns related to excess volatility near event announcements prevents reaching market equilibrium instantaneously.

2.2.2.3 Strong-Form

The strong-form version of the Efficient Market Hypothesis, commonly recognized as private information tests, are drastic and most likely unattainable. It states that stock prices reflect all information relevant to the firm, including information available only to company insiders. Hence, the information set, Φ, is broadened to include both public and private information. Accordingly, no individual with access to monopolistic information achieves excessive returns (Finnerty, 1976).

The main objection to the strong-form interpretation is the concept of insider trading. Insider trading contradicts this form of market efficiency because investors with private information not reflected in current stock prices might have superior returns. Lorie & Niederhoffer (1968) and Jaffe (1974) confirmed this premise and concluded that insiders with private information might act on it and achieve abnormal returns.

2.2.2.4 Conclusions

Conventional finance theory relies on pillars that explain most decision-making processes in financial markets and corporate finance. It depends on the CAPM (Black, 1972; Lintner, 1965; Sharpe, 1964), an asset pricing model; Portfolio Theory (Markowitz, 1952), which introduced the concept of portfolio diversification; Expected Utility Theory (Neuman-Morgenstern, 1944), that modelled decision making; and the Efficient Market Hypothesis (Fama, 1970).

The market efficiency theorem as an empirical postulation has a decisive role in finance. Nonetheless, the most critical inference of the EMH is the impossibility of developing any trading systems that outperform an excess risk-adjusted average returns. However, deviations from this condition have been plentiful in the literature, such as the weekend effect (Smirlock & Starks, 1986), turn-of-the-month and turn-of-the-year effect (Agrawal & Tandon, 1994), the January effect (Keims, 1983), and momentum (Jegadeesh & Titman, 1993).

In addition to these empirical deviations, several distinguished investors such as Warren Buffet, George Soros, and Benjamin Graham consistently beat the market with two-digit return rates throughout years and some even decades. The most prominent example is Warren Buffet, with an excess rate of return of over 30% for longer than ten years.

One of the most important ramifications of the EMH is that investors should rely on passive portfolio management, and the continuous trade of securities in the market would not entail superior returns. Conversely, it would diminish net returns induced by high transaction costs. Thus, the development of these active trading strategies directly contradicts the EMH.

By examining this and other discrepancies from the conventional finance paradigms, the concept of Behavioural Finance emerged, relying on a set of foundations that will be discussed below. However, most of these postulations originate from the backbone of economic theories, the whole rationality premise that lacks validity. Curiously, J.M. Keynes in 1930 asserted the following about this issue: “Markets can stay irrational longer than you can stay solvent”.

2.2.3 Behavioural Finance

The inception of behavioural finance began in the 1980s by the controversy around some extraordinary volatility in the stock market that was not explained by the efficient market theorem and standard risk-based models. This deviation had a crucial corollary to the behaviour of financial markets, implying that changes in stock prices occur for no fundamental reason but rather for exogenous factors. After observing this issue, the concept of behavioural finance emerged, relying on more pragmatic premises, anchored in psychological aspects that attempt to explain stock price behaviour. Economic theories depend on an abstract concept coined the *homo economicus*; this figure evokes a set of premises that may not be entirely reliable due to asserting that individuals have perfect rationality, perfect self-interest, and perfect information. This framework allows them to fully comprehend, analyse and compute all alternatives to achieve a fully optimized decision. Weber (1922) theorizes about the impossibility of economic agents being absolutely rational. Simon (1972) takes it a step further and asserts that an agent's rationality is bounded; however, agents do not intend to maximize utility; they seek satisfaction. Thus, maximization is not feasible because agents do not have all the information and computing capabilities to assess all possibilities and outcomes; thus, they cannot be fully rational.

The behaviourist and psychological proposition to these shortcomings assert that individuals' beliefs and expectations are not constant and cognitive biases are an essential aspect that can undermine optimal decision making, distorting financial markets' "efficient" behaviour.

Behavioural finance tries to explain these deviations by taking the more challenging path of modelling bounded rationality, inconsistent beliefs, and preferences. It relies on Prospect Theory instead of Expected Utility Theory and on a set of heuristics that are the bedrock to describe behavioural theories associated with momentum. Several EMH anomalies are explained by a behaviourist and psychological concept to financial markets, such as herding (Lakonishok et al., 1991; Hirshleifer and Teoh, 2003), cascades (Bikhchandani et al., 1992), and momentum (Jegadeesh & Titman, 1993).

A frequent critic raised by economists on the behavioural finance approach is that the psychological path towards resolving market abnormalities is limited because the range of behavioural patterns that surpass the rationality assumptions is endless and empirical testing is ambiguous.

2.2.3.1 Prospect Theory Vs. Expected Utility Theory

Neuman-Morgenstern (1944) developed an influential theory in economics, the Expected Utility Theory (EUT), to model decision-making.

EUT predicts a dominant preference between alternatives; this theory suggests that choices under risk and uncertainty are consistent throughout time, established by linear probability weighting. EUT establishes a decision-making chain that leads to a stable preference choice. This approach was prevalent for several years until the rise of Prospect Theory (PT), anchored on decision biases.

PT argues that individuals simplify subjects to reduce cognitive efforts, influencing how individuals acquire, process, and evaluate information (Hogarth, 1987), consequently distorting optimal decision making.

The path of both theories is substantially distinct when it concerns the linearity of decision weights, while EUT examines the value of choice by contrasting the probability occurrence of each possibility linearly; PT argues against this proposition due to individuals perverting preferences and decisions weights. Let us take an example between two different options: (1) the ability to have a 1% probability of winning 100€ and (2) the ability to win 1€ with a 99% chance. The decision seems obvious. A utility maximiser individual would pick option (1) because it gives the ability to win 1€ and the second option only gives the ability to win 0.99€. Hence the first alternative would be chosen.

On the contrary, PT asserts that the probability decision between the odds presented earlier is not linear. As a result, individuals consider high probability events as certainties. Hence, the second example would be an inevitability. In addition, events with a low probability of occurrence are treated as more likely to happen. Thus, the first example would have a higher fabricated probability to the individual.

Regarding decisions formed relative to a fixed reference, EUT advocates that decisions are made concerning a change in the outcome of a particular event and not if that event will lead to a gain or loss. The choice should demonstrate the risk aversion corollary, consequently, an individual would choose a "preference for a certain alternative over a riskier alternative of equal value" (Sebora & Cornwall, 1995). In opposition, Prospect Theory suggests that choices are made considering the gain or loss that the outcome of those preferences generates to the individual current wealth. Consequently, in PT, the risk function is S-shaped, representing that individuals are risk-averse in circumstances that involve significant gains and risk-seeking in situations that implicate large losses (Tversky & Kahneman, 1979).

Subsequently, are presented the primary cognitive bias that subverts beliefs and preferences, as defined by Bayesian decision theory, and the maximization of expected utility.

2.2.3.2 Cognitive Bias

The human being has limited cognitive abilities and several time constraints when facing a problem. Several psychologists consider that judgment and cognitive biases deviate the assessment of alternatives and the decision-making process. Limited attention, memory, and processing skills undermine agents' complete rationality assumption. The results are physiological (e.g., heart rate accelerates, pupils dilate) and cognitive, such as: heuristics; overconfidence; cognitive dissonance; conservatism and representativeness; and the disposition effect. These biases subvert optimal investment decision-making.

Heuristics	• Reduced mental processes, conscious or unconscious that do not account for all the information and disregards part of the knowledge to make quicker decisions.
Overconfidence	• Individuals consider themselves superior (smarter, better) then they actually are, overestimating the precision of their estimates.
Cognitive Dissonance	• Performing actions contrary to own beliefs leading to mental discomfort and stress.
Conservatism/ Representativeness	• Cautious in the incorporation of new evidence, overweighting base rates, allocating too much value to past experiences and belief (conservatism). • Inputting too much value on recent experiences, leading to the underweighting of base rates (representativeness).
Disposition Effect	• Hesitation to sell securities that have decreased in value and greater tendency to short assets that have realized gains.

Figure 1 - Cognitive Bias Definitions

Evidence of poor decision-making is extensive in the literature, such as excessive trading (Odean, 1998) and under-diversification of portfolios (Ritter, 2003). Heuristics is a fundamental concept because it allows reducing the complexity of decision-making. Nonetheless often leads investors to make biased decisions. They are framed in the broader scope of the Two Systems theory by Kahneman (2011). This author suggests that the decision process entails two different structures. System 1 works automatically with little mental effort and without an impression of voluntary control (heuristics). System 2 relies on the subject dedicating their complete concentration skills and attention to more complex activities.

Some factors derive from heuristics, such as the conservative effect, leading investors to under-react to informational events (e.g., earnings announcements, dividends) and anchoring to the *status quo*. In opposition, the representativeness bias drives investors to detect random stock patterns and believing that current positive stock behaviour represents a future upward trend.

Several other concepts are important to underline, such as overconfidence. It arises when one investor believes too strongly in their abilities to assess stock future price behaviour. Hence, overconfident agents excessively trade, overreact to private signals and underreact to private information. Market behaviour from overconfident investors disrupts financial equilibrium, creating a significant gap between price and fundamental value. Cognitive dissonance is a crucial concept because investors cannot accept bad outcomes and take corrective decisions. Hence, agents face conflicting beliefs when market behaviour does not correspond to their past investment decisions.

In sum, investors' decision-making is not entirely rational as predicted by the seminal economic theories. Hence, cognitive bias associated with complex decisions and uncertain environments undermine optimal investor decision-making.

2.3 Momentum

The exploration of predictable patterns in the stock market to achieve excess returns has been extensive. Three major trading strategies emerged in the literature: short-term contrarian strategies, medium-term continuation, and long-term reversals.

Jegadeesh (1990) and Lehmann (1990) demonstrated that variation in equity returns until one month is predictable. Hence, a reversal strategy that buys (sells) the underperforming (overperforming) securities based on their prior-month returns and holds them for another month achieves 2% profits. Behavioural explanations argue that investors' overreaction to information, fads, or cognitive errors explain short-term reversal profits (Subrahmanyam, 2005). The rational approach argues in favour of price pressures caused by supply and demand shocks.

Jegadeesh & Titman (1993) built portfolios based on past cumulative stock returns over 3 to 12 preceding months, ranking them according to their performance. They found that strategies buying past winners and selling past losers showed significant abnormal returns in most timeframes. The strategy outcome of the (J=6; K=6) zero-cost portfolio provided 12,0% excess returns per year. To rationalize these results JT, argues that momentum is caused by underreaction to firm-specific factors in the short-term and reported that between 2 to 5 years after portfolio formation, these results tended to mean-revert, which they justify to the overreaction of long-term firm-specific prospects. Hence, agents slowly adapt their preferences to new market information, gradually incorporating their expectations to stock prices.

Long-term reversals, documented by DeBondt & Thaler (1985), investigates the relationship between individual securities returns over a wider timespan and found statistically significant 3-year mean-reversion returns in NYSE stocks. Hence, past losers beat past winners over a 3-to-5-year period. Following these results, a contrarian strategy that invests in under-priced stocks and sells over-priced stocks provides superior returns. These authors suggested that agents overreact to positive (adverse) new events pushing the stock well above (below) their fundamental value; this is consonant with the representativeness heuristics (Tversky & Kahneman, 1974). A few remarks should be made. Primarily, most of the portfolio's annual returns occurred in January. These results relate to a widely investigated seasonal anomaly in the literature, arguing increased stock prices in January. Secondly, the winner portfolios are composed of underperforming asymmetric stocks throughout the years. Lastly, Fama & French (1996) 3- Factor model accounted for the long-term reversal excess returns.

In short, within a month and between three to five-year stocks show a reversal pattern, such is justified by investors overreacting to idiosyncratic events. In the intermediate horizon is prevalent momentum and is justified by underreaction to firm-specific news. This framework contradicts the EMH even in its weak-form due to market agents being able to exploit profitable trading strategies solely relying on the behaviour of past stock prices.

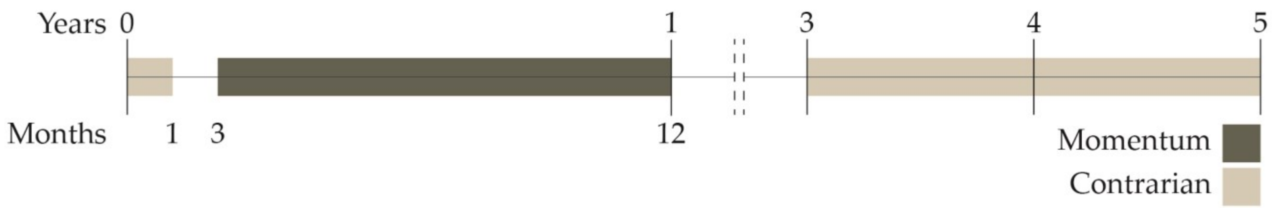

Figure 2 - Momentum Vs. Contrarian Strategies Time Line

Lee & Swaminathan (2000) argue the co-existence of these phenomenon's, asserting that stocks move through two alternates states in their life cycle, desirable (high volume winner) and undesirable (low volume loser). These authors assert that trading volume forecasts the persistence of momentum. Hence, high (low) volume winners (losers) develop faster momentum reversals.

Jegadeesh & Titman (2001) complied with this view by supporting that momentum returns reverse in the long run. Conversely, George & Hwang (2007, 2004) argued that intermediate-momentum might not be followed by long-term reversals and attributed momentum to anchoring bias and long-term reversals to capital gain lock-in theory. Conrad & Yavuz (2017) complied by providing evidence that individual stocks that contribute to momentum profitability do not experience long-term reversals. Additionally, they asserted that sorting stocks on size and B/M helps distinguish between winner and loser momentum stocks.

Momentum trading strategies are the premier market anomaly. The following two chapter focuses on the two most regarded explanations to momentum profitability in the literature, risk-based and behavioural explanations. The risk-based framework relies on the notion of market efficiency and the presence of excess returns being a fair compensation for the risk incurred (CAPM, FF-3 Factor model). Behavioural theorems rely upon agent irrationality and cognitive biases causing price drifts.

2.3.1 Momentum and Risk

Asset-pricing theory governs the description and quantification of security returns, namely the CAPM[5] and the Fama French Factorial Model[6]. CAPM relies on Beta, which assesses changes in securities in relation to the market portfolio, providing a benchmark for systematic risk. After the discovery of the size (Banz, 1981) and value effect (Rosenberg et al., 1985), Fama & French (1993) extended the CAPM framework to a multifactor concept. The efficient market theory

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[5] CAPM (one-factor model) is one of the most adopted and thought models due to its straightforward interpretation. Thus, it asserts that by diversifying a portfolio, the firm-specific risk is diminished, and equilibrium prices are dependent on the market securities line provided by Beta. This framework did not encompass several anomalies, namely the size effect, B/M effect, and the E/P effect.

[6] Fama & French (1993) provided a three-factor model that captured most of these deviations. Hence the model uses firm-specific characteristics proxying for systematic risk factors that add to the market index model (CAPM). The model is simply interpreted, in excess of the risk-free rate, expected returns are described by the difference between the return of a portfolio of small stocks and large stocks (SMB) and the difference between the return of a portfolio of high B/M stocks and low B/M stocks (HML).

acknowledges that profits should only be related to systematic risks because unsystematic risks can be diversified. Fama & French (1996) and Jegadeesh & Titman (2001) asserted that the CAPM and the FF-3 Factor model does not capture price momentum positive and significant monthly alphas.

Jegadeesh & Titman (1993) examined momentum excess returns by decomposing them into three components: two sources of systematic risk and one related to unsystematic risks. Their results showed that the extreme portfolios betas are superior to the average sample. Additionally, past winners' betas are inferior to past losers, implying that the loser portfolios' stocks are riskier than winners. The second term related to the serial covariance of factor portfolio returns also failed to explain the strategy profitability. Lastly, the positive serial covariance of the market model residuals for individual stocks suggests that securities underreact to idiosyncratic information, favouring behavioural explanations.

Conrad & Kaul (1998) decomposed momentum returns following the work of Lehmann (1990) and Lo & MacKinlay (1990). Consequently, momentum profits could be attributable to two different sources, time-series predictability and cross-sectional dispersion in returns. These authors imputed momentum profitability to cross-sectional dispersion in mean returns of individual securities. This suggests that higher (lower) returns of past winners (losers) result from their higher (lower) unconditional expected returns rather than from underreaction to idiosyncratic news. Consequently, the cross-sectional difference in expected returns is determined by the inherent risk of the firms.

Conversely, Jegadeesh & Titman (2002) disagreed with these results, arguing that reversals in the post-holding period reject this claim. Additionally, they asserted that Conrad & Kaul (1998) ignore the impact of the error term in their estimates. Hence, their results are subject to sample bias.

Grundy & Martin (2001) argued that sorting stocks to form portfolios considering their past returns generated significant time-varying exposure to systematic factors. If the market declined significantly in the formation period, then high-beta (low-beta) stocks would sharply depreciate (appreciate). Hence, following bear markets, winner (loser) portfolios are loaded in low-beta (high beta), undermining momentum profitability. Consequently, factor models ignore the dynamic change in factor exposure of a momentum strategy. These authors argued that adjusting the momentum portfolio by dynamically hedging market and size risk magnified momentum profits and decreased variability of returns, potentially providing a better trading strategy. Nonetheless, in their empirical tests was used ex-post factor betas and Daniel & Moskowitz (2016) argued that if these authors used ex-ante betas this approach would not generate these results.

Another approach arguing that momentum premium is a compensation for risk was developed by Johnson (2002). This author related expected returns as a function of firm growth rates. Consequently, a positive (negative) firm event provides information to investors that the long-term expected return prospects have improved (deteriorated). The positive relation between past returns and expected future returns, driven by firm performance, induces momentum.

Daniel & Titman (1999) showed that high B/M firms with a significant weight in intangible assets produce superior momentum profits. They argue that investors overreact to news related to intangible assets due to their complex recognition and valuation. Sagi & Seasholes (2007) related momentum with growth options. These authors implemented a firm-specific factor, specifically B/M, to proxy for growth options. They argue that firms with superior past performance have better future growth options and superior future expected returns. Hence, firms with higher B/M (growth options) have higher momentum profits than firms without lower B/M (without growth options).

Chordia & Shivakumar (2002) found that momentum returns were explained by macroeconomic variables associated with business cycles, and momentum profitability is only positive during expansionary periods. Kim et al. (2014) incorporated a flexible econometric model to combine cross-sectional and time-series approaches. Their main results support the notion that momentum profits are time-varying, and their risk varies across business cycles. Thus, winner stocks are riskier in expansions, while loser stocks are riskier in recessions. Consistently, Daniel & Moskowitz (2016) revealed that momentum undergoes short periods of extreme bad performance following bear markets, leading to severe crashes[7]. Usually, these periods are associated with the economy recovering from recessions; hence volatility is unusually high. Corroborating these findings, Barroso & Santa-Clara (2015) showed that the distribution of momentum strategies entailed negative skewness and kurtosis, which implicates investors being highly exposed to risk.

In sum, several risk-based models argue that the momentum premium is compensation for additional risks. Hence, several authors argue that the momentum profitability emerges from the excess risk of winners versus the losers (Berk et al., 1999; Conrad & Kaul, 1998; Sagi & Seasholes, 2007). Nonetheless, these approaches are unable to encompass momentum risk premia entirely and justify long-term reversals.

2.3.2 Momentum and Behaviourism

The lack of empirical validity on risk measures to explain momentum profitability led to the development of behavioural theories. These models argue that stock price drifts from fundamental values resulting from investor misreaction to firm-specific events driven by cognitive biases. The most notable behavioural models to interpret momentum are Barberis et al. (1998), Daniel et

[7] In 2009, a momentum strategy in US markets would entail a negative 70.00% return in just three months.

al. (1998), and Hong & Stein (1999); nonetheless, several others emerged in the literature.

The BSV model asserts that individuals do not form decisions based on the random walk assumption, and they extrapolate stock patterns from random sequences. These authors performed an analysis encompassed by the one asset, one investor approach and examined how investors react to earnings announcements. They argue that individuals differ between two states; in the first state, earnings are mean reverting; in the second state, earnings experience continuous growth. Hence, in the first state, agents underweight new information that reaches the market (conservatism), and prices adjust slowly to a news event, leading to underreaction. In the second state, investors wrongly regard a set of positive earnings announcements and extrapolate that these results will persist (representative heuristics). Hence investors' expectations of future earnings will be upward biased, driven by overreaction. The reunion between the conservative effect and the representative heuristics will lead to short-term momentum and long-term reversals.

DHS presents a model that builds on two psychological concepts, overconfidence and biased self-attribution. These authors' primary purpose is to question if prices overreact to private information and underreact to public information in an individual base methodology. Their findings established that an overconfident agent overweighs private information, inducing the stock price to overreact. Naturally, when subsequent public information reaches the market, they develop a self-attribution bias. Hence, if information confirms the private information signal, momentum materializes. Nonetheless, if information contradicts the private signal, the stock price will be reverted to its fundamentals. The DHS model asserts that investors' continued overreaction causes momentum, followed by a slow correction.

The previous studies focused on the psychological biases that surface on individual investors in the presence of market events. Hong & Stein (1999) take a different approach and rely on the interaction between agents in the market, namely, news-watchers and momentum traders. News-watchers are active in the market and emphasize their decisions on fundamentals to buy or sell a security, creating short-term underreaction due to their delayed market reaction. Momentum traders try to profit from this underreaction provoked by news-watchers. Their decision-making process is simpler and quicker, analysing recent stock price behaviour and not relying on fundamentals. This process generates long-term overreaction. Complementary to the gradual diffusion of information approach, Hong et al. (2000) reported that momentum profitability is more robust in stocks with low analyst coverage.

The DHS model states that momentum is stronger when market trends persist, while HS predicts that momentum should be higher in bull trends (UP markets) than in bear trends (DOWN markets). Cooper et al. (2004) deepen the subject of the effect of market transitions and their relation to momentum profits by arguing that momentum profits prevail in periods that follow bull markets (UP trends) but not in bear markets (DOWN trends). These authors associated high market performance conditional on overreaction to information. Hence, when overreaction reaches his peak, steadily transitions, and reduces momentum profits (reversals).

Conversely, Asem & Tian (2010) showed that the momentum effect is more robust when following a UP trend. Additionally, they document abnormal momentum returns in DOWN (UP) trends when the market continues its downward (upward) trajectory and significant losses when transitioning to bull (bear) trends. These findings are also consistent with the DHS approach and contradict the HS model.

This large-scale approach is undoubtedly contingent on individual responses. Li et al. (2008) studied the asymmetric reactions to firm-specific information, showing that winners are more sensitive to news than losers, while losers are more sensitive to distant news. Consistently, BenMabrouk & Souayeh (2020) argued that winners and losers show asymmetric reactions to good and bad news. Winners are more sensitive to good news, while losers are more sensitive to bad news. Antoniou et al. (2013) argued that agents react accurately to news that confirms their convictions. However, respond adversely to news contrary to their beliefs; this framework is consistent with the cognitive dissonance effect. Hence, when investors face contrary signals, their constructed beliefs endure mental distress, causing underreaction and, consequently, momentum.

Grinblatt & Moskowitz (2004) suggested that momentum profits are more robust when returns accumulate gradually than when they exhibit irregular behaviour. Complementary with this vision, Da et al. (2014) employed the "frog-in-the-pan[8]" approach, where reduced investor attention takes a decisive element. Hence, the aspect of limited attention (Hou et al., 2009) framed in an environment where investors are overwhelmed by information induces underreaction because information arrives in smaller amounts and is not processed and acted on conveniently.

Grinblatt & Han (2005) rely on the disposition effect to explain underreaction and consequently momentum. Thus hesitation from investors to sell losers' stocks and enthusiasm to short winners causes the price to underreact to fundamental news about losers' stocks. Another approach explained short-term momentum and long-term reversals based on a single-bias, overconfidence (Luo et al., 2018). The general authorial framework is feasible; some agents become informed before others. Additionally, they branch overconfidence into two

[8] The frog-in-the-pan serves as a metaphor, where the frog will jump out of a pan containing boiling water since high temperature will motivate an immediate reaction. However, if the water in the pan is slowly raised, the frog will underreact and perish.

forms: overestimating self-information (originates reversals) and underestimating third party's information (originates momentum). Thus, momentum surfaces when overconfident investors are convinced that other agents have not received market information, which causes them to underreact to the signal.

In sum, there are several explanations in the literature for momentum; some argue that momentum is generated by overreaction (DHS), while others assert that momentum is provoked by underreaction (BSV and HS). However, theoretical and empirical investigations are still unable to acknowledge the true drivers of momentum. Hence, the development of alternative explanations to momentum is unlimited, and without researchers' efforts to test for mutual exclusivity amongst these different alternatives, conclusions might never emerge.

2.3.3 Empirical Evidence

The momentum concept was examined and investigated in several other timeframes (Grundy & Martin, 2001; Hwang & Rubesam, 2015; Jegadeesh & Titman, 2011), countries (Chui et al., 2010; Rouwenhorst, 1998), sectors (Moskowitz & Grinblatt, 1999; Nijman et al., 2004) and asset classes (Asness et al., 2013; Jostova et al., 2013; Menkhoff et al., 2012). To examine the extension and reliability of these results, it will follow a comprehensive analysis of these empirical endeavours and their importance to financial markets.

2.3.3.1 Significant Momentum

The seminal authors Jegadeesh & Titman (1993) developed momentum strategies from 1965-1989 in the US. They found evidence that selecting stocks based on their 12-months previous returns and holding them for another three months produced 1.49% monthly profits (t-statistics of 4.28), considering a one-week lag and monthly rebalances. Additionally, the most consistent results disregarding the holding period were developed with portfolios that ranked stocks considering the 6-month prior returns. Consequently, these portfolios generated persistent 1% monthly returns. JT argued in favour of underreaction to firm-specific information to explain momentum profitability.

Grundy & Martin (2001) performed an extended empirical analysis between 1926-1995 in the US, providing discriminative momentum evidence between this timeframe. These authors considered the (J=6; K=1) strategy with a skipping period of one month and equally weighted portfolios. They found that momentum strategies were profitable in the United States on the overall sample (1926-1995), earning an average monthly return of 0.44% (t-statistic of 1.83).

From 1926 to 1945 momentum profitability was negative (WML = -0.91% with a t-statistic of -1.36). This timespan entailed several turbulent circumstances (The Great Depression (1929-1933) and the Second World War (1939-1945)), suggesting that momentum is highly dependent on market states. The most significant results were documented between 1945-1962, providing an average monthly profit of 1.15% (t-statistic of 5.08). From 1962-1995 momentum strategies provided significant 0.86% monthly returns. This period overlaps with JT timeframe investigation, providing coincidental positive momentum profits. Grundy & Martin (2001) argue that momentum strategies take advantage of market dynamics, buying (selling) positive beta stocks and selling (buying) negative beta stocks, in bull (bear) markets.

Geczy & Samonov (2015) developed the most extensive momentum investigation with a time span of 215-years (1800-2014). These authors documented that cross-sectional price momentum in the US achieved 0.51% (t-stat of 6.0) excess returns per month, showing significant momentum effects in all asset classes, except in commodities. They found that momentum betas experience substantial variability driven by market states, consistent with Grundy & Martin (2001).

The previous research is restricted to US markets. Hence, Rouwenhorst (1998) investigated the momentum effect in 12 European countries[9] from 1978-1995. Conceptually this author applied the same methods of JT seminal work, considering equal-weight portfolios that are not rebalanced monthly and have a one-month lag. The author developed two analyses, an integrated investigation with the country data combined and country discriminated evidence.

The integrated analysis provided consistent results with the United States. Hence, reliable and significant momentum profits were found in all strategies. The most profitable momentum strategy produced a monthly return of 1.45% (t-statistics of 4.5) and implied a (J=9; K=3) strategy. They showed that the average losers' stocks are substantially smaller than the average winner's stocks. Additionally, average returns are negatively related to size; thus, SMB factor cannot explain the momentum effect, implying that positions must be held in illiquid small stocks, which can be challenging. Additionally, the Winner and Loser portfolios have almost double the standard deviation from the sample average portfolios, suggesting higher exposures to volatility and risk (Daniel & Moskowitz, 2016). These results are correlated to JT evidence in the United States and suggest a common component driving the profitability of these strategies.

Regarding individual country momentum, the author unveiled statistically significant momentum profits in each country except Sweden. Additionally, the highest momentum profits were obtained in Spain (1.32% per month; t-statistics of 2.28). More importantly, these authors disregarded the view that momentum was related to country-specific market performance. Hence, after controlling for geographical composition of momentum portfolios, average excess returns only

[9] The countries analysed were: Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom.

marginally decreased. Such suggests that country momentum is inconsequential to justify stock momentum profitability.

Galariotis (2010) found statistically significant momentum profits in the Australian Stock Market from 2000 to 2007. The most successful strategy was the (J=9; K=6) with 2.7% (t-statistics of 3.62) returns per month. Evidence also showed that the winners' portfolios generated the majority of momentum profits. This evidence contrasts with Hong et al. (2000) and Lesmond et al. (2004) asymmetric return composition, arguing that losers' portfolios drive momentum profitability. Galariotis results align with most of the momentum literature in the Australian Stock Market (Demir et al. 2004, Hurn & Pavlov 2003).

Griffin et al. (2003) investigated the momentum anomaly in a sample of 40 countries, using the (J=6; K=6) trading strategy. They found significant momentum profits in Europe, America (except the US), and Africa, while Asia (except Japan) was non-significant. These authors also analysed emerging country momentum, reporting that developed countries earn higher momentum profits than emerging countries. Rouwenhorst (1999) showed that 6 out of 20 emerging markets exhibited significant momentum profits. The distinct economic and market conditions between developed and emerging countries could provide additional insight into the momentum anomaly. Hence, if return factors in emerging and developed countries are identical, the momentum anomaly could be attributable to how investors set prices in financial markets.

Regarding industry momentum strategies, Moskowitz & Grinblatt (1999) examined the United States and found significant returns by going long in good performing industries and short in weak performing ones. This industry strategy is still profitable after controlling for book-to-market, size, and cross-sectional dispersion in mean returns. Most importantly, they argue that industry momentum encompasses most of the momentum effect reported in the literature. Unlike stock momentum, industry momentum is stronger at the one-month horizon, when usually it should dominate reversals. These authors asserted that, unlike individual stock momentum, the winner portfolios drove industry momentum profitability. Nijman et al. (2004) tested the same premise in Europe. Hence, they examined if industry momentum was the source of stock momentum in Europe. Nonetheless, between 1990-2000 these authors found that countries or industries cannot explain positive momentum profitability. Additionally, they found that momentum is more significant in small growth stocks.

Menkhoff et al. (2012) lengthened the profitability of momentum strategies to foreign exchange markets. In a sample of 48 countries from 1976-2010, they found significant momentum profits of 10%/year and attributed these results to investor misreaction. A meaningful conclusion was that portfolios were skewed to smaller currencies with high transaction costs, consonant with the stock momentum evidence. Jostova et al. (2013) documented significant momentum profitability in the corporate bond segment, discriminating between IG/NIG[10] bonds. Bond momentum profits came primarily from high credit risk winners' portfolios and NIG bonds. Additionally, these authors supported that idiosyncratic information in NIG firms disseminates more gradually and is harder to interpret, driving momentum profitability (Hong & Stein, 1999).

In sum, the manifestation of momentum strategies in extended timeframes, most continents, and several financial instruments (e.g., stocks, bonds, currencies), gathered with the lack of common risk factors to justify it, supports the behavioural explanations to momentum profitability. In addition, empirical evidence shows agglutinant aspects: loser portfolios comprising small illiquid stocks and extreme portfolios showing unusual standard deviation associated with significant risk and volatility.

[10] IG: Investment Grade; NIG: Non-Investment Grade

2.3.3.2 Non-Significant Momentum

Jegadeesh & Titman (2011) showed that momentum profits have decreased over the century and displayed increasing fluctuations. In 2009, the last year of study, momentum profits provided a negative annual raw return of -36.50%. The market decline associated with the 2008/2009 financial crisis induced winners to gravitate to low beta stocks and losers to high beta stocks. Hence, sharp market transitions resulted in significant losses (Asem & Tian, 2010).

Bhattacharya et al. (2017) examinates momentum strategies in the US and found that from 1999 to 2012, the WML portfolios did not provide significant abnormal returns[11]. These authors tried to associate the decline in momentum abnormal returns with increased market volatility following the dot-com bubble crash. However, a comparative analysis between timeframes did not render the expected results. Hence, it was not the unprecedented market volatility that erased momentum profitability. Hwang & Rubesam (2015) empirical investigation also provided that from 2000-2010 momentum strategies did not produce significantly positive results and justified it with the dot-com bubble. They asserted that momentum profitability endured after uncovering the anomaly (Jegadeesh & Titman, 1993) due to the extremely high performance of the high-tech and telecom sectors. Therefore, these two sectors accounted for almost half of the momentum profits documented from 1994 to 2000. Consequently, average momentum returns were 2.25% a month, while 1.15% came from high-tech and telecom stocks.

Interestingly, these authors argue that different sectors in different timeframes drive momentum profitability. Accordingly, from 1976-1982 the energy sector is paramount to momentum profits. In the 1980s, the financial sector contributed to the winners' portfolios' excessive returns. This view is consonant with industry

[11] Adopted the selection and ranking approach of Jegadeesh & Titman (1993) – Top/Bottom Decile Portfolios -, and George & Hwang (2004) – 52 Week high - both did not deliever momentum profitability.

momentum (Moskowitz & Grinblatt, 1999), encompassing most individual stock momentum returns.

In the literature, some approaches justified the decrease in momentum profitability. Primarily, the result of intensified arbitrage activities induced by decimalization[12]. Hence, competition between arbitrageurs to buy the winner stocks and short the losers cause increased investors' reaction to price changes. Chordia et al. (2014) supported this view by asserting that the decrease in bid-ask spreads (tick size) reduces transaction costs, intensifying arbitrage activities. Additionally, markets may have become more efficient due to information getting integrated into prices more rapidly. Griffin et al. (2010) confirmed that stock price responses experienced a significant reduction in delay.

Regarding country momentum, and considering the framework devised in the previous sub-section, it is essential to underline that empirical inquiries showed that Asian countries momentum profitability provides non-significant profitability (Hameed & Kusnadi, 2002).

Chui et al. (2003) analysis in Asian markets[13] followed the JT methodological approach (J=6; K=6) from 1976-2007. These authors found that the momentum effect is not statistically significant in Asian markets. Nonetheless, when the authors excluded Japan from the aggregate sample, momentum became profitable. These results provided an extensive discussion of the idiosyncratic factors that determined Japan's lack of profitability. The same authors developed the most compelling approach by studying the dichotomy between individualism and collectivism in Western and Eastern cultures (Chui et al., 2010). Western cultures tend to be overconfident in their skills, while Eastern cultures behave as a collective relying on peer consensus—this psychological discrimination associates with the DHS framework. Hence, individuals in

[12] In the turn of the century was introducted quoting stocks in decimals (decimalization) instead of fractions of 1/8 and 1/16.
[13] The countries were: Hong Kong, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan and Thailand.

Eastern countries (collectivists) are less overconfident in their trading abilities, having fewer biased decisions that generate momentum profits.

An important component to assess the significance of momentum profitability is transaction costs. Momentum strategies rely on intensive trading and demand holding positions for extended periods (up to 1 year) to achieve profitability. Several trading cost components are examined in the literature: commissions, bid-ask spreads, immediacy costs, short sales costs, and taxes.

Lesmond et al. (2004) argue that momentum profits are not sustained after accounting for transaction costs. They asserted that agents would be buying at the ask price and selling at the bid price after including transaction costs. At this point, the price impact (i.e., the stock price behaviour) can erase all profits. Thus, they argue that momentum profits are an illusion.

They also found that momentum strategies with higher returns are correlated with larger trading costs stocks, and most profits are associated with short positions in losers' stocks than long positions in winner stocks (Grinblatt & Moskowitz, 2004). This relates to the asymmetry of trading costs between long and short positions introduced by Korajczyk & Sadka (2004). Generally, shorting the loser's portfolio entails trading stocks that have underperformed in the short run. Thus, these stocks lean to small firms, which requires a more significant effort to trade them and involves higher transaction costs due to their small market value, low price, and low liquidity.

Li et al. (2010) focused on how different holding periods can alter the annual profitability of momentum strategies due to transaction costs. The (J=6; K=6) strategy entails twice the transaction costs of a (J=6; K=12) strategy. Hence, the holding period choice can seriously undermine its annual profitability. Consistent with this framework, these authors concluded that strategies with a 6-month holding period yield insignificant profitability. Conversely, strategies with a 12-month holding period provide significant profitability of 5%. Agyei-

Ampomah (2007) framework supported the view that momentum only occurs for the 12-month holding period strategies and does not persist when holding periods are inferior to 12-months, such as 3-month and 6-month holding periods.

Altogether, there is compelling evidence that momentum significance has been steadily decreasing for the last two decades. This can be justified with increased market efficiency and more precise stock price responses to market events. Another concept that undermines the profitability of momentum is transaction costs because momentum requires intensive trading (Lesmond et al., 2004).

2.3.3.3 ETFs

ETFs allow individual investors to employ cross-sectional momentum strategies without buying (selling) a massive number of securities. Hence, Andreu et al. (2013) researched if ETFs could be employed to capture country (Bhojraj & Swaminathan, 2006) and industry (Moskowitz & Grinblatt, 1999) momentum[14]. They found profits superior to 5%/ year in country and industry portfolios. However, the short sampling period and reduced amount of ETFs analysed undermined the significance of the results, which were not statistically different from zero. Tse (2015) increased the sampling period from 1990 to 2014 and examined 25 momentum strategies, implementing them to take advantage of industry and country momentum. They achieved statistically robust and opposite results than Andreu et al. (2013). Hence, the author established that momentum strategies in country and sector ETFs are not profitable.

Yu & Webb (2020) lengthened their analysis and employed four different momentum ranking methodologies (52-week high (low) momentum[15]; Past 12 and 6-month return) to construct their portfolios. Their analysis conveyed an

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[14] Industry Momentum was investigated from 1998-2009 and country Momentum was assessed from 1996-2009. For both samples was implemented a (J=6; K=6) strategy following the JT approach.

[15] Price at month *t* relative to the highest (lowest) price in the prior 52 weeks

extensive ETF sample due to their reduced data requirements (two full years of trading). Additionally, they developed an analysis assessing if future portfolio performance is affected by price-based or total returns ETF[16]. They found that portfolio performance is very similar in both cases and differences were marginal. The results delivered profitability in momentum strategies between 2007-2018 (not considering the financial crisis period of 2008-2009) for one of four momentum strategies, the 52-week high variable. Hence, relying on the proximity of the ETF price to its maximum value (52-week high) produces superior results than past performance and market signals (J-months past performance).

Li et al. (2019) contributed with an extensive framework to analyse momentum ETFs and provided interesting empirical results. They found that momentum profits are significant when ETFs are ranked based on the 24 to 48-month past returns. The strategy based on a 36-month formation period and a one-month holding period deliver 1.15%/month abnormal returns (t-statistic of 2.13). It is determinant to clarify that these results were achieved utilizing value-weighted portfolios instead of equal weighted.

The post-holding results are intriguing because after 78-months of portfolio formation, momentum profits are erased, which has several implications on commonly discussed behavioural sources of momentum in the literature. The post-formation period results are inconsistent with the BSV and HS framework because they rely on agents' underreaction and consequent incomplete reversal. Thus, momentum profits should not disappear. Conversely, these results are coherent with the DHS theoretical framework of delayed overreaction and complete momentum profits reversals.

Empirical evidence regarding ETFs momentum strategies is scarce. It unveils contradictory results depending on methodological issues and cyclical

[16] Total return ETF includes the price behaviour plus dividend yield.

performance, suggesting that this trading strategy is sensitive to selecting and ranking procedures. The empirical investigation of Li et al. (2019) extended the formation periods to 24-48 months providing significant momentum profits. This result grants additional discussion and analysis to assess in this work.

2.4 Research Context

2.4.1 Macroeconomic Framework

The empirical analysis conveyed in this work encompasses the 2010-2019 period. Hence, it is particularly relevant to analyse global economic conditions and the US macroeconomic framework to assess market and economic conditions.

From 2007 to 2009, a financial crisis took over the global economy supported by Lehman´s Brothers' bankruptcy and the US subprime mortgage crisis. As a result, the United States entered into a tremendous recession (at its peak, the US GDP decreased 2.5% in 2009, and unemployment reached almost 10%[17]). After this global earthquake, economists forecasted prosperous following years; however, the euro-debt crisis undermined global economic conditions from 2012 to 2014. China's financial market instability from 2015 to 2016 further deteriorated global economic conditions. Lastly, since 2018 the global economy has been steadily declining, mainly pushed by the decrease in growth of Asian countries (lead by China) and the stagnant European economy.

In sum, global conditions in the last decade were affected by severe financial crises. Nonetheless, global GDP has been regularly positive and under 3% for most of the decade.

The United States, after the economic recessions of 2008-2009, sustained several financial and economic stimuli that the FED (e.g., holding interest rates

[17] Source. Bureau of Economic Analysis (www.bea.gov)

near zero) and the US government (e.g., subsidies, grants, tax exemptions) administered.

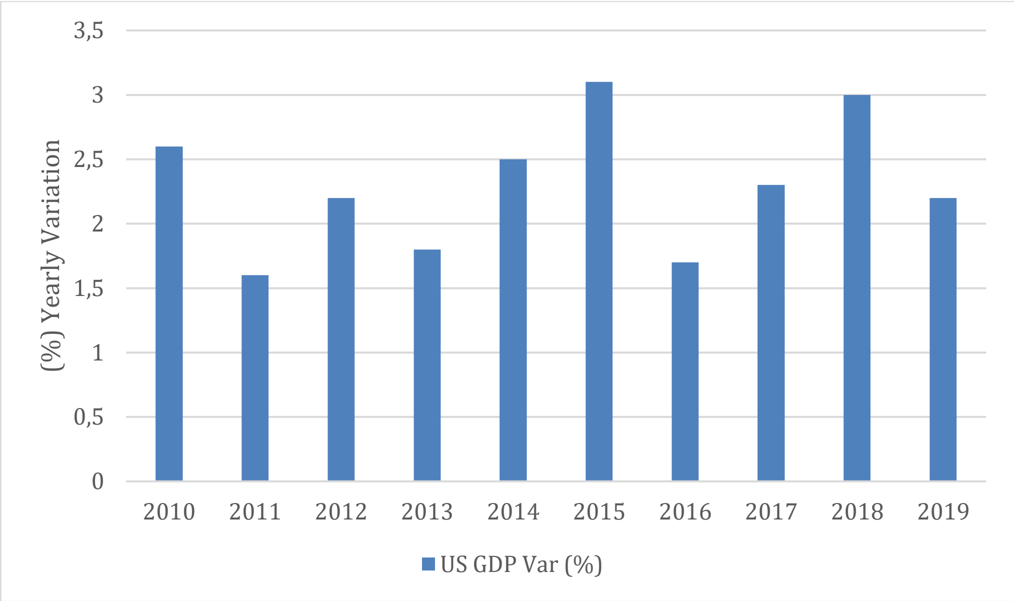

Figure 3 - US GDP Variation (Source: Statista)

The benefit from these policies led the US economy to positive, although anaemic growth between 2010-2019. Altogether, the unstable global framework and the modest US economy could guide us to believe that stock markets

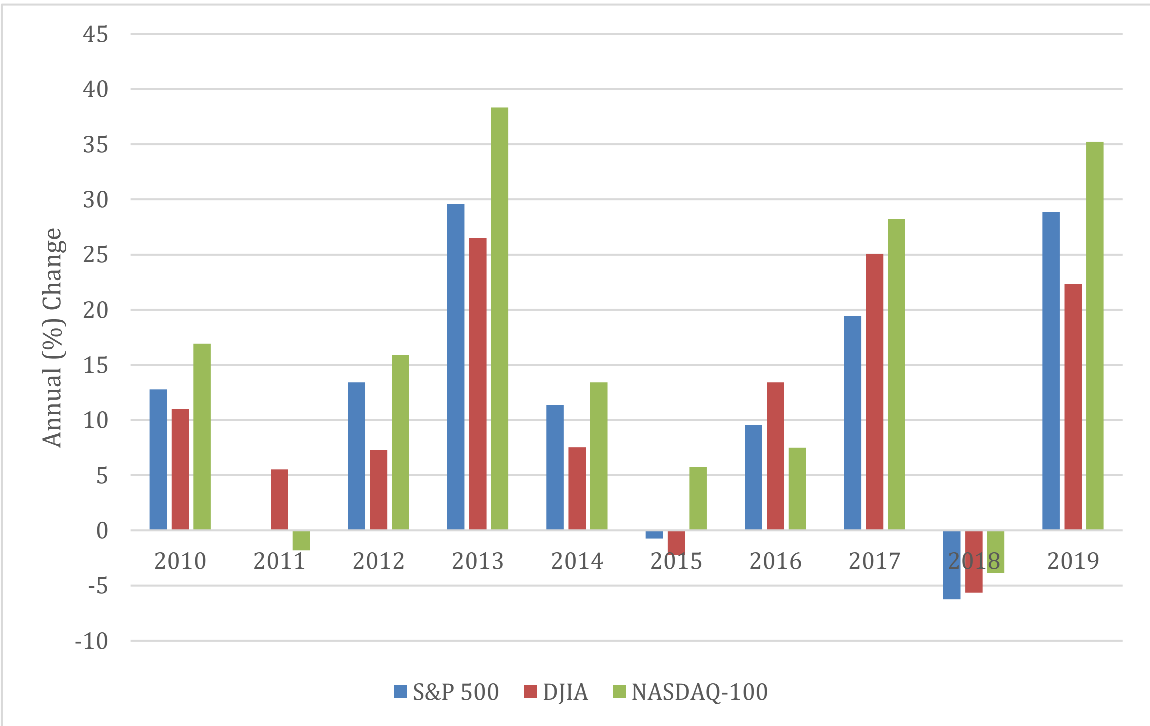

Figure 4 - Comparison between the three major US indexes (Source: Macrotrends)

experienced decaying results associated with economic uncertainty. Nonetheless, this is not verified.

In this timeframe, major US stock indexes (S&P 500, Dow Jones Industrial Average, and NASDAQ-100) realized consistent two-digit returns, starting one of the most extensive bull periods in history (Figure 4).

NASDAQ-100 Index performance is essential considering that the ETFs tech sector is analysed. Consequently, several technological ETFs track and are composed of firms listed in the NASDAQ-100. Hence, the regular two-digit annual variation throughout most of the 10-year analysis showed that this industry is essential to develop business communication and operations, optimized management, and made globalization possible. Even more important is the evidence showing that NASDAQ-100 provides better results than the S&P 500 and DJIA in bull markets (delivers higher growth) and in bear markets (conveys lower declines).

The technology sector has proved critical to economic development in this century. Firms in this industry make significant investments in R&D to have innovative products and services, achieving competitive advantages. Brown et al. (2017) reported that in the last 15 years, more than 80% of the total R&D expenses in the US come from technological firms. Hence, it is crucial to make a few remarks about this sector. Primarily, they rely on intensive R&D activities and have higher levels of intangible and unreported assets (e.g., patents, brands, talented human capital). Consequently, assets value is volatile, causing underlying firms to experience higher levels of risk, which can lead to under-investment because these firms find it more difficult to obtain external funding. Analysts also have a difficult task forecasting earnings due to the higher degree of uncertainty associated with intangible asset volatility.

The financial and legal contribution of the United States government in this sector is also substantial and aided the establishment of several technological firms. To this extent, consecutive US governments granted large-scale subsidies and tax breaks in R&D to finance new offices, jobs, and technological hubs across states. Let us illustrate; Apple earned almost 700M USD since 2009; Alphabet since 2000 received over 750M USD, and Facebook since 2010 harvested over 300M USD on subsidies and tax breaks[18]. Thus, the correct perception of the US government to wager on the technological sector paid off.

In sum, global economic conditions have been unstable; nonetheless, the US economy grew regularly. Most importantly, US major indexes have been consistently performing above average, notably the NASDAQ-100. Hence, the US technology sector continues to have a strong performance driven by continuous investment in R&D and innovation. Therefore, investors might have the opportunity to capitalize on the tech sector's forward momentum.

2.4.2 ETFs

Exchange-traded fund (ETF)[19] is a hybrid financial vehicle that tracks an index or a basket of securities. It offers investors a share in a pool of stocks, bonds, and other assets.

Passive investment strategies construct portfolios allocating a sizable amount to index funds, focusing on long-term strategies. These strategies replicate the performance of an index, minimizing the importance of fund managers' activities, consequently decreasing expenses. The rise of ETFs was driven by agents altering their investment criteria, favouring passive strategies at the expense of active ones (Figure 5).

[18] Source: https://www.goodjobsfirst.org/
[19] Detailed description of the structure and operative side of ETFs in the Appendix-A

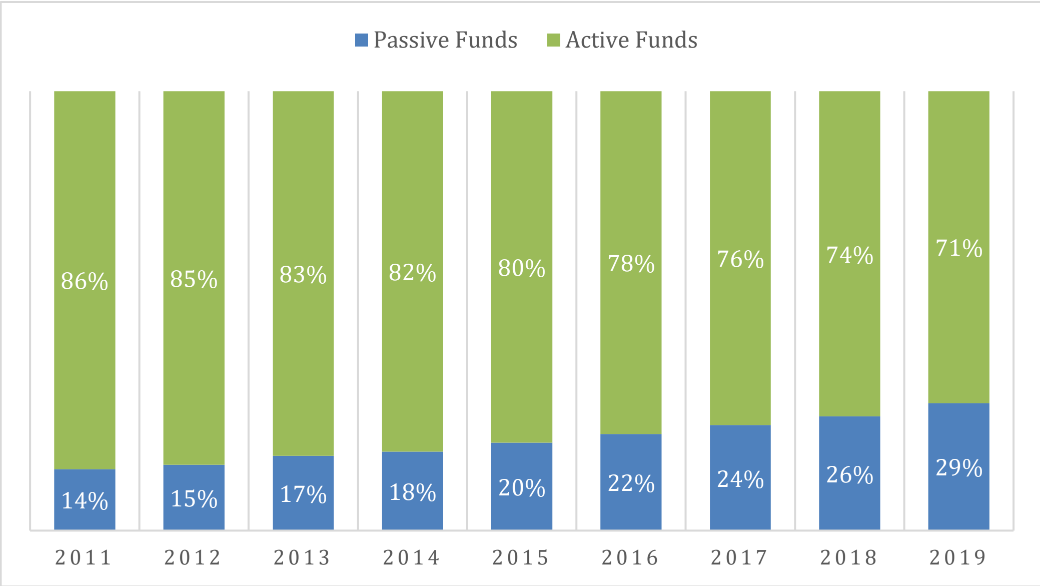

Figure 5 - Global Market Share of Total Assets (Source: EY)

ETFs carried out one of the most important innovations in financial markets and have grown in size, diversity, and market influence. In the United States, ETFs peaked in 2019 with 4.396 billion USD in assets under management (Figure 6), representing over 70% of the global ETF market.

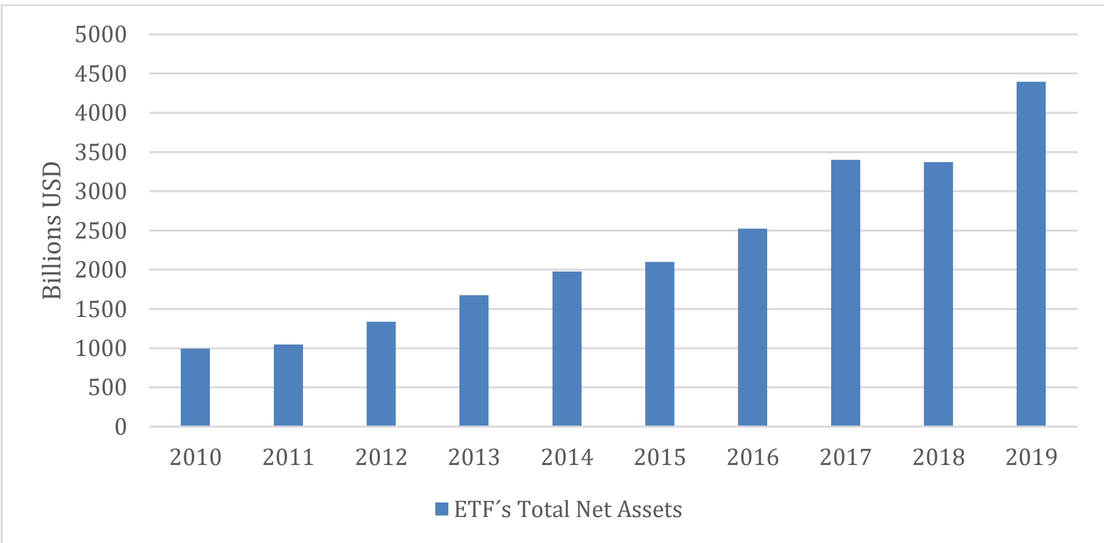

Figure 6 - Evolution of the Total Net Assets of US ETFs (Source: Statista)

Roll et al. (2014) conveyed a significant indicator of the steady increase of ETFs volume versus mutual funds. They found that SPDR trading volume increased 10.000%, while the underlying S&P 500 only increased by 100% between 1996 and 2009. BlackRock leads the ETF providers holding almost 37% of the market. Thus, this investment firm constructs more than one-third of all the ETFs traded in the market, following Vanguard (19.4%) and State Street (12.5%)[20].

Furthermore, market agents prevail using equity-based ETFs over fixed income and commodities (Figure 7).

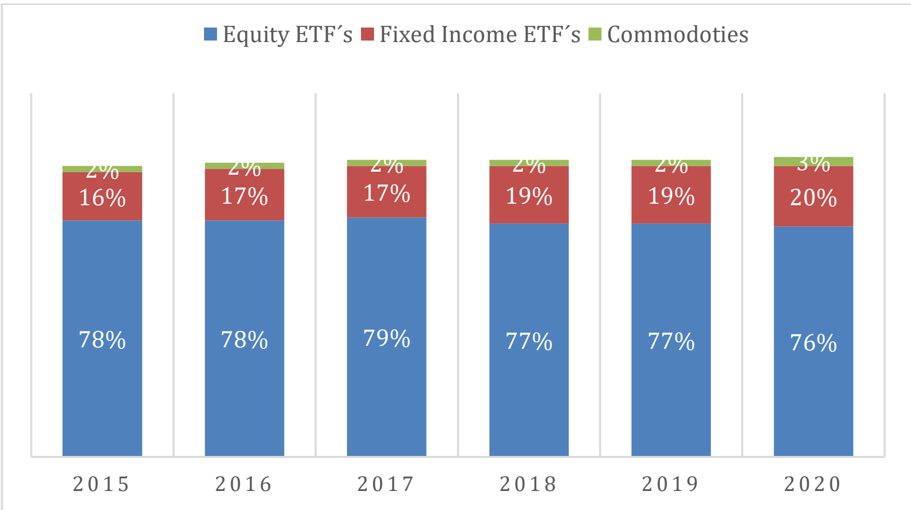

Figure 7 - Assets Under Management of US ETFs (Source: FactSet)

ETFs assemble beneficial characteristics to investors, such as intraday tradability (shares bought and sold at stock exchanges), price transparency (share traded approximately at the NAV), tax efficiency ("in-kind" redemptions), and lower transaction costs. Substantial development in the ETF domain creates smart beta or factor ETFs that cease to constitute passively managed products and establish an active investment. Consequently, instead of replicating an index, this new product focuses on replicating alternative indexes tilted towards certain factors (e.g., size, value, dividends, momentum), providing specific risk-return

[20] Source: Statista, referencing 2019

exposures. A more detailed explanation of all these features is provided in Appendix-A.

ETFs allow investors to take positions on entire asset classes, conferring them superior exposure to the systematic risk component than the idiosyncratic one. Barberis et al. (2005) found that securities included in indexes tend to comove with them. These authors argue that market frictions and investor sentiment in the incorporation of idiosyncratic news cause comovement[21]. According to Da & Shive (2018), ETFs increase the comovement in the returns of the stocks that compose the index. Hence when investors obtain ETF-associated information, they excessively trade the index, affecting the underlying securities through arbitrage, making them more susceptible to ETF-related news than firm-specific news. ETF structure might increase mispricing in the underlying security and procyclical trading patterns in the market, inducing momentum.

Bhattacharya & O'Hara (2018) also provided some interesting remarks about the relation between the ETFs and their underlying securities. They argued that ETFs increased investor capacity to reach illiquid markets and assets that previously were incapable of trading. Nonetheless, the market equilibrium might be seriously undermined by market agents being unable to assess if price changes are caused by fundamental factors associated with the asset or factors that are irrelevant to them. Hence, market instability is instigated when firm-specific news related to one asset influences another asset's price through the ETF price. They also showed that this unclear relation between assets and markets promotes the tendency for herding.

Petajisto (2017) argued that the potential difference between the ETF price and its NAV substantially varies over time and is more preponderant for illiquid assets. Additionally, Ben-david et al. (2017) theorize that ETFs present the most considerable price fluctuations from the NAV during periods of market stress.

[21] Common movement of individual stocks with national and international markets

The increased discrepancy between the ETF and the underlying securities might be associated with the AP´s and OLP´s[22] lacking incentives to create or redeem ETF shares to pursue arbitrage profits. Consequently, in financial stress periods, AP´s might face high arbitrage risks when buying (selling) ETFs and selling (buying) the underlying securities, making them unwilling to perform these activities. Additionally, imperfect arbitrage might increase ETF price fluctuations and intensify the effect of demand shocks. Hence, the arbitrage mechanism might induce excessive ETF price fluctuations.

Regarding tech ETFs, this sector conveys funds whose underlying securities are firms in the tech industry and track technological indexes. Hence momentum profitability is highly susceptible to this particular industry performance and determinants. As conveyed earlier, technological firms rely on intensive R&D investments and intangible assets. The complex recognition and valuation of intangible assets in these firms increase information asymmetry between managers and investors. Barron et al. (2002) complied with this view, asserting that increased R&D expenses increased risk and uncertainty, diminishing the degree of analyst consensus in technological stocks.

Most ETFs register under the Investment Company Act (ICA) as open-end management investment companies (85%). Consequently, they abide by strict limitations concerning the use of leverage, maintenance of accurate custody of their assets and are subject to regular reporting requirements and disclosure obligations. ETFs legislative framework supported in the ICA was updated, providing necessary modifications. These adjustments were motivated by ETFs holding different determinants to the classes of securities initially considered in the ICA. Mainly, the inclusion of illiquid assets (e.g., loans, credits) and controversial assets (e.g., cryptocurrencies) led the SEC to limit ETF creation and

[22] Official Liquidity Providers

registration. Consequently, there has been a history of "exemptive reliefs"[23] to register customized ETFs and a significant delay to create "customized baskets".

The rule 6c-11 ("ETFs rule") implemented on 23 December 2019 revised this framework, increasing ETF providers' autonomy. This new regulation can change the paradigm of investing and probably render mutual funds outdated, allowing the creation of customized baskets, inducing competition amongst providers, and opening the possibility for an expansion in actively managed ETFs.

2.5 Hypothesis Proposal

H1: The implementation of momentum trading strategies of buying winners and selling losers within the US ETFs technology sector is profitable.

This study tests the profitability of cross-sectional momentum strategies considering ETFs. Momentum is a primary anomaly to the Efficient Market Hypothesis, even in its weak form. Rational approaches supported on bearing additional risks revealed insufficient to explain momentum. Afterward, behavioural methods surfaced, asserting that no risk factors can entirely encompass momentum excess returns. Hence, several models dependent on investor irrationality and misreaction to informational events justified momentum profitability (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999).

Empirical evidence shows that momentum is prevalent amongst stocks (Jegadeesh & Titman, 1993), corporate bonds (Jostova et al., 2013), and foreign exchange markets (Menkhoff et al., 2012). Momentum profitability was uncovered in the US and extended to Europe (Rouwenhorst, 1998), Australia (Galariotis et al., 2007), Africa, emerging and developed countries (Griffin et al.,

[23] Approval from the legislator, in this case the SEC

2003). Altogether momentum strategies have profitable results worldwide, and in several time frames, the exception is Asia, particularly Japan. Arguments favouring collectivist cultures and less overconfident traders justify the lack of momentum profitability in some countries.

The implementation of ETFs momentum strategies aids investors, mainly individual investors, because cross-sectional stock momentum strategies entail trading a considerable number of securities to form portfolios, incurring in high transaction costs. Consequently, ETFs form baskets of diversified securities providing agents the ability to take exposures in entire industries. ETFs share several common aspects with stocks, such as intra-day liquidity, the possibility of short-selling, and buying on margin (Gastineau, 2008). Accordingly, ETFs are subject to investor market dynamics that induce deviating phenomenon's, such as underreaction, overreaction, and herding.

Another argument favouring ETF momentum profitability lies in the ETF´s share price divergence from its underlying NAV (Petajisto, 2017). Therefore, if AP´s do not arbitrage the difference between the fund share price and the value of its underlying securities (NAV), the discrepancy between them can diverge even further, driving momentum profits in ETF´s prices.

Empirical evidence regarding the profitability of momentum strategies in ETFs is scarce. Yu & Webb (2020) found profitable momentum strategies implementing the 52-week high variable to select funds. Interestingly, Li et al. (2019) showed momentum profitability in extended formation periods, from 24 to 48-months. This evidence suggests that ETF momentum demands extended formation periods to rank and construct portfolios instead of the common intermediate horizon (up to one year) implemented in most of the literature. Additionally, evidence regarding the profitability with the 52-week variable to select securities suggests that this asset class's momentum profitability is highly sensitive.

Favourable market and macroeconomic conditions are essential to momentum strategies' profitability (Cooper et al., 2004). Hence, despite the global economy growing at profoundly different paces, the United States, showed positive constant anaemic growth for the last ten years. Furthermore, the NASDAQ-100 index, representative of the tech industry, showed unprecedented growth in our timeframe. These results are partially driven by the US government granting subsidies and tax breaks to firms develop innovative products and services. Additionally, significant investment in R&D and intangible assets, whose value is complex to assess, creates substantial information asymmetry between agents and investors. Hence, government intervention assembled with uncertainty around tech firms′ asset intangibility creates a favourable environment to investors misinterpret and be excessively confident around firms in this industry, inducing momentum profitability.

In sum, it seems to be assembled all favourable conditions to implement momentum strategies in the financial markets, particularly utilizing ETFs.

3. Data and Methodology

3.1 Data

ETFs are issued on the primary market and traded by institutional and retail investors on the secondary market. Intrinsically, it was followed a quantitative approach based on secondary data provided by Thomson Reuters. Thomson Reuters is one of the three most prominent organizations, alongside Bloomberg and Dow Jones, to provide business news and financial information to market agents. Thomson Reuters offers a time series gathering service called DataStream. This platform features a vast financial database (over 65 years of data) and offers multiple analytical options[24].

The analysis conveys equity ETFs; consequently, bonds, commodities, mixed assets, or other ETFs are disregarded. In this way, we limit the analysis to ETFs that are most similar to individual stocks. Subsequently, the study focuses on capital gains or losses (price behaviour) and disregards the dividend yield portion.

In order to develop a more comprehensive timeframe analysis and avoid the financial crisis of 2007-2008, it was gathered daily stock prices from 01/01/2010 to 31/12/2019 (10 years) from two exchanges: NASDAQ-100 Stock Exchange Global Market and NYSE Arca.

Towards the objective of analysing the Exchange-Traded Funds' technological sector, it was selected from the Lipper Classification Scheme[25] the category: Equity Sector Information Tech (451020). The Equity Sector Information Tech segment includes IT Services; Software; Communications Equipment; Technology Hardware, Storage and Peripherals; Electronic Equipment,

[24] Source: https://www.refinitiv.com

[25] The LGC (Lipper Global Classification) gathers a consistent group of funds with comparable investment segments, such as: mutual funds, ETFs, hedge funds, amongst others.

Instruments, and Components; Semiconductors and Semiconductor Equipment. This segmentation provided a list of 134 ETFs issued on the primary market. From this series was removed 39 ETFs launched after 31/12/2019, or the assets were liquidated between our timeframe, which made the fund extinct. Hence, from the final list of ETFs in the Equity Sector Information Tech category, only 20 funds were traded daily for ten years and did not have missing observations.

In sum, the empirical analysis comprises a dataset of 20 ETFs from 01/01/2010 to 31/12/2019, culminating in 52.160 individual observations. This work assesses momentum strategies profitability, comparing these strategies with a benchmark: NASDAQ-100.

3.2 Variables

The raw ETFs prices were retrieved from the database and computed the daily returns of the sample. In order to compound the returns, there are two commonly used methods, discrete compounding and logarithmic compounding. The two methods can entail empirical differences, potentially causing biased results. Hence, utilizing the same compounding methods as in most momentum investigations allows to correctly and unbiasedly compare their conclusions. In cross-sectional momentum, most studies rely on logarithmic compounding (Chan et al., 2000; Chordia & Shivakumar, 2006).

Additionally, logarithmic compounding has theoretical and empirical benefits over discrete compounding, particularly considering multi-period returns (Husdon & Gregoriou, 2014). Compounded returns are time-additive; consequently, it is simpler to apply additive processes than multiplicative ones to determine time-series properties (Campbell et al., 1997). Roll (1983) and Dissanaike (1994) found that studies that use discrete returns to conclude on long-term returns can be biased. Hence, this work computes logarithmic returns in order to relate long-horizon returns sub-periods strongly:

$$r_{j,t} = \ln(P_{j,t} / P_{j,t-1})$$

Where:

- $r_{j,t}$: returns of security *j* at time t
- $P_{j,t}$: price of security *j* at time t
- $P_{j,t-1}$: price of security *j* at time t -1

Following the computation of the daily returns and to proceed with the ranking process that is adjacent to this strategy, it is necessary to compute the cumulative monthly returns of the ETFs, as such:

$$CR_{j,t}\ (M) = \sum_{t=1}^{m} r_{j,t}$$

After calculating the cumulative monthly returns, the ranking process begins by forming a Winner (W) and Loser (L) portfolio. The following formula equally weights the portfolio:

$$CR_{i,t}\ (M) = \frac{1}{N} \sum_{t=1}^{m} CR_{j,t}\ \ (M)$$

The profitability of the momentum strategy is computed by subtracting the Winner to the Loser portfolios in order to achieve the WML (Winner-minus-loser) returns:

$$CR_{WML,t}\ (M) = CR_{W,t}\ (M) - CR_{L,t}\ (M)$$

Finally, to compare the profitability between momentum strategies, it is necessary to compute the average monthly return considering the holding period (K) on the overall profitability:

$$M = \frac{1}{K} \sum_{t=1}^{T} CR_{WML,t} \ (M)$$

3.3 Methodology

The cross-sectional price momentum undertakes a simple characterization as drafted by Jegadeesh & Titman (1993, 2001) and sets its foundation on two concepts, the formation period (J) and holding period (K).

3.3.1 Formation Period

The objective of the formation period is to identify trends in stocks. A robust formation period is paramount to identify the information signals in the market thoroughly. A shorter formation period may induce investors to act on false signals. Hence, an optimal formation period is essential to determine and benefit from the security pricing cycle.

Jegadeesh & Titman (1993, 2001) formation period relied on ranking stocks considering their past J-months performance and distributing them into the winners and losers' portfolios. These authors relied on a relative measure to identify past performance:

$$r_{i,t} = \frac{P_{i,t}}{P_{i,t-1}}$$

Where:

- $P_{i,t}$: price of the security *i* at time t
- $P_{i,t-1}$: price of the security *i* at time t -1

George & Hwang (2004) proposed the 52-week high measure to analyse and rank past performance, characterized for:

$$r_{i,t} = \frac{P_{i,t-1}}{high_{i,t-1}}$$

Where:

- $P_{i,t-1}$: price of security i at the end of the month t - 1
- $high_{i,t-1}$: highest price of security i in the previous 12-months

This method compares the proximity of the current stock price with its 52-week highest price. It enhances momentum profits by favouring biases in traders' reaction to idiosyncratic news when the security is close to its highest level. This off-peak measure is beneficial to forecast future returns rather than focus on past stock behaviour.

Hence, the relative measure proposed by JT is constructed based on price changes and favours past information signals over a fixed past interval (e.g., three months). The 52-week high method provides a reference point to investors evaluate the impact of idiosyncratic news. This study favours the JT measure to acknowledge the full impact of price changes. Additionally, the idiosyncratic news influence on ETFs price might be compromised by the inherent structure of the product.

3.3.1.1 Portfolio Size and Weighting

Following the distribution of funds considering their past returns, it is essential to form a portfolio that contains the highest (lowest) return funds to buy (sell). Jegadeesh & Titman (1993), Rouwenhorst (1998), Chordia & Shivakumar (2002), amongst others, formed the zero-cost portfolio into deciles. Hence, they divided the sample into the 10% best (worst) performing stocks and assembled the P10 (P1) portfolio, purposely disregarding stocks in the middle range.

Griffin et al. (2003) differed on the approach to sort the securities in the portfolios, and instead of using deciles, they utilized the quintile sort (20%) for international equity markets, specifically in emerging and smaller sized developed markets; Asness et al. (2013) utilized a tercile sort to form portfolios. The portfolio size is not determinant, considering that the subject of study are funds that aggregate securities. Additionally, given the small sample of ETFs is essential to discriminate the overperforming and underperforming funds from the average sample. Hence, the JT approach will be implemented and formed the portfolios considering the top 10% best (worst) performers.

Another essential aspect of portfolio formation is the weights that the securities will have on them. There are two common approaches in the literature, the equally-weighted portfolios and the value-weighted portfolios. The equally-weighted procedure builds a portfolio assigning the same weights to all securities. Instead, value-weighted portfolios are assembled by considering their past returns; consistently, securities proportion in the portfolios depends on their market-adjusted returns. An extensive literature concluded that equal-weighted portfolios have higher returns and volatilities than value-weighted portfolios with the same selected stocks (Breen et al., 1989; Canina et al., 1998; DeMiguel et al., 2009). The most significant advantage of implementing value-weighted portfolios is that illiquid securities that are more difficult to trade have a smaller weight in the portfolio. It is common to implement equal-weighted portfolios in the literature to analyse momentum (Grundy & Martin, 2001; Rouwenhorst, 1998, 1999; Yu & Webb, 2020). Nonetheless, several other essential studies utilize the value-weighted portfolio approach (Chan et al., 2000; Conrad & Kaul, 1998; W. Li et al., 2019; Moskowitz & Grinblatt, 1999).

This work will implement equal-weighted portfolios due to ETFs being highly liquid products traded between agents with ease; hence, there is no benefit in forming a value-weight portfolio. This approach aligns with Jegadeesh & Titman (1993) seminal study.

3.3.1.2 Skipping and Overlapping Periods

Afterward, the strategy may include a skipping period (e.g., one week, one month) to avoid short-term return reversals (Jegadeesh, 1990; Lehmann, 1990) generated by bid-ask spread pressures and lagged reaction effects. Blume and Stambaugh (1983) show that the profitability of momentum strategies could be undermined due to bid-ask bounce because the loser portfolio stocks are on average smaller than the stocks of the winner portfolio. The implemented strategy will not convey skipping periods.

Overlapping periods review the composition of the winner and loser portfolios periodically. Hence, a monthly review of the best and worst performing funds rebalances the portfolio acknowledging and updating the chosen ETFs with the best and worst performers. For instance, in a (J=3; K=3) strategy, a portfolio formed from January to March will be rebalanced considering the February to April price behaviour.

The materialization of overlapping periods is extensive in the literature and allows empowering the statistical tests. Non-overlapping periods fail to revise the portfolios traded. The advantage of this approach is lowering transaction costs. ETFs entail lower transaction costs, hence is implemented overlapping periods to empower the statistical significance.

3.3.2 Holding Period

The formation period selects securities and forms portfolios that overperformed or underperformed in the last J- months and buys (sells) them. Completed this step, the portfolios must be held by K-months exploiting upward or downward trends in stock prices.

The optimal holding period relies on the pricing cycle for the security and the formation period implemented. Taking into account that the strategy is prevalent in the medium-term, portfolios are held considering several quarterly period combinations. In total, Jegadeesh & Titman (1993) analysed 16 strategies for up to one year.

3.3.3 Statistical Significance

An essential component of every empirical analysis is the significance of the results due to measuring the coherence of the data considering a null hypothesis by the computation of a p-value (D.R. Cox, 1977). Hence, to test if the results are not due to chance, this study performs a two-sided t-test due to returns being able to acquire positive or negative values. The null hypothesis takes the value of zero. The t-obs is tested against three critical values: 10% (*), 5% (**), and 1% (***), given by the t-student distribution.

The following formula computes the t-obs:

$$t = \frac{r - \mu}{\frac{\sigma}{\sqrt{N}}}$$

Where:

- r: monthly average returns of the sample;
- μ: tested value against r;
- σ: standard deviation of the sample;
- N: size of the sample;

3.4 Software

Considering the massive amount of data retrieved, over 50 thousand observations, Excel was used to process the data. Microsoft developed Excel spreadsheet over 30 years ago. Excel is an essential tool to perform mathematical calculations because it provides data organization, graphing tools to analyse data, and a programming language application to build macros (McDonald, 2000).

4. Results and Discussion

4.1 Summary Statistics

As conveyed, from all the data retrieved, only 20 ETFs in the technological sector fulfilled the entire timespan to take part in the empirical testing. From the analysis of the average sample statistics compared to a benchmark (NASDAQ-100) in Table 1, and the individual ETFs statistics in Table 2, several notions consistent with ETF theory emerged. The average returns of the funds in the sample never surpassed the 1% monthly figure. Moreover, 85% of the average monthly return are uniformly around the same intervals. The two outliers are CHIC.P and CQQQ.P that displayed significantly lower monthly returns, respectively 0.39% and 0.59%, than their counterparts. Such is coherent with this investment vehicle being regarded as a passive instrument that tracks a benchmark. Consequently, the volatility in price behaviour is substantially lower than common stocks.

	ETFs sample	*NASDAQ-100*
Max (%)	14.55	12.26
Min (%)	-15.11	-9.33
Mean (%)	1.14	1.36
STD (%)	5.43	4.24
Variance (%)	0.30	0.18
Sharpe Ratio	0.16	0.24
Beta	1.08	-

Table 1 - Average Monthly Returns Statistics

A simple comparison with the monthly returns from the same timeframe to the NASDAQ-100 index produces a more peculiar result. The average monthly returns from all the funds in the timespan deliver 1.14% profits. In comparison, the NASDAQ-100 would provide a superior return of 1.36%. Consequently, investing in the NASDAQ-100 would produce superior profits than the ETF sample.

Regarding the risk analysis, both the variance and the standard deviation suggests valuable insights into the overall risk of the 10-year sample. Hence, both these indicators reveal general low-risk volatility in returns. Even more significant, the NASDAQ-100 delivers a lower risk-based framework than the overall sample. In sum, it is apparent that the NASDAQ-100 produces an overall better investment option than the ETFs sample, assembling higher monthly returns and a lower risk-based strategy, such is consonant with the risk-return portfolio analysis of Markowitz (1952). Coherently, the computation of the Sharpe ratio produces a return-to-volatility measure beneficial to assess investment performance. Hence a higher Sharpe ratio reflects a higher expected return premium per unit of risk. Ergo, the ETFs sample produces a Sharpe Ratio of 0.16, while the NASDAQ-100 achieves a superior ratio of 0.24.

Finally, the computation of beta measured the sample fluctuations concerning the NASDAQ-100. Hence the sample ETFs responsiveness to changes in the NASDAQ-100 produced a beta of 1.08. Consequently, the sample is highly correlated to the NASDAQ-100 index, producing 8% more volatility variation than the NASDAQ-100.

In sum, the summary statistics provide a coherent framework with the ETF financial structure. Hence, investors have a low-return, low-risk product that intrinsically aims at tracking a benchmark, not beating it.

Symbol	*FDN.P*	*QTEC.OQ*	*FXL.P*	*CHIC.P*	*CQQQ.P*	*PTF.OQ*	*PXQ.P*	*PSI.P*	*PSJ.P*	*PNQI.OQ*	*RYT.P*	*IGM.P*	*IGV.P*	*IXN.P*	*SOXX.OQ*	*IYW.P*	*XNTK.P*	*XSD.P*	*XLK.P*	*VGT.P*
Max (%)	13,65	14,79	14,54	20,88	18,20	14,89	18,31	18,77	13,39	15,55	14,31	12,13	14,02	11,17	13,90	11,55	13,36	15,04	10,67	11,92
Min (%)	-12,16	-13,60	-13,76	-20,50	-25,47	-15,19	-13,61	-18,78	-13,52	-14,60	-11,01	-10,73	-11,20	-10,10	-18,11	-10,06	-35,02	-16,25	-9,18	-9,30
Mean (%)	1,43	1,17	1,29	0,39	0,59	1,01	1,01	1,34	1,31	1,42	1,22	1,25	1,34	1,10	1,36	1,16	0,87	1,24	1,15	1,25
Std Dev (%)	5,05	5,21	5,19	6,91	7,47	5,54	5,76	6,70	4,65	5,40	4,87	4,58	4,76	4,50	6,07	4,66	5,90	6,45	4,27	4,59
Variance	0,25	0,27	0,27	0,47	0,55	0,30	0,33	0,45	0,21	0,29	0,24	0,21	0,22	0,20	0,37	0,21	0,34	0,41	0,18	0,21
Sharpe Ratio	0,218	0,161	0,186	0,009	0,036	0,123	0,119	0,151	0,211	0,202	0,184	0,201	0,213	0,173	0,170	0,180	0,092	0,143	0,194	0,201
Beta	1,03	1,08	1,11	1,07	1,25	1,10	1,10	1,23	0,92	1,08	1,05	1,03	0,98	1,01	1,17	1,04	1,23	1,19	0,95	1,03

Table 2 – Discriminate ETF Average Monthly Returns Statistics

4.2 Main Results

Momentum strategies were developed considering two different time windows. Primarily, momentum was framed up to one year (3, 6, 9, and 12 month formation periods), as established by the seminal authors Jegadeesh & Titman (1993) and several subsequent studies (Moskowitz & Grinblatt, 1999; Rouwenhorst, 1998).

Previous studies analysed the whole ETFs market and did not achieve profitable returns. Nonetheless, Li et al., (2019) extended the ETF portfolio formation periods from 24 to 48 months and attained significant returns. Hence, to provide a complete investigation, longer-term formation portfolios were analysed.

4.2.1 Medium-Term Strategies

The analysis develops 16 strategies dependent on four different timeframes: 3, 6, 9, and 12 months formation and holding periods. The results present the average monthly returns in three different tables: winners and losers portfolios; and WML (winner minus loser) returns. Each table will comprise a matrix of 16 strategies where the first horizontal row conveys the holding periods (K), and the first vertical columns express the formation periods (J).

Consequently, the WML portfolios reveal the momentum profitability of the different strategies implemented with ETFs. The t-statistics are presented in the table and calculated, implementing the Newey-West correction of standard errors for heteroskedasticity and autocorrelation (Newey & West, 1987). Although the momentum methodology does not require the development of regression procedures, it is consistent with the literature (Chan et al., 2000) to assess the reliability of standard errors in the sample. Hence, unlike the White-standard errors, the Newey-West standard errors (HAC) are calculated conditional on a choice of maximum lag, in this case, one month. Thereby, this approach provides robustness to arbitrary autocorrelation.

J \ *K*	**3**	**6**	**9**	**12**
3	0.37 %	0.19%	0.12%	0.09%
	(2.26)	(2.26)	(2.26)	(2.26)
6	0.42%	0.21%	0.14%	0.10%
	(2.47)	(2.47)	(2.47)	(2.47)
9	0.36%	0.18%	0.12%	0.09%
	(2.42)	(2.42)	(2.42)	(2.42)
12	0.39%	0.19%	0.13%	0.10%
	(2.30)	(2.30)	(2.30)	(2.30)

Table 3 - Returns of the Winner Portfolios Strategies (Medium-Term)

The analysis of Table 3 conveys several essential indicators. Primarily, it is apparent that the P10 (winners' portfolios) exhibit a uniform return pattern independent of the formation period. A significant result is a consistent decrease in returns considering an extended holding period. Additionally, although the percentage variation of returns dependent on the formation period is marginal between the strategies examined, the (J=6; K=3) strategy produces the highest annualized returns in the sample (5.16%).

Lastly, the test-statistics confirm that all the winners' portfolios achieve significant results at the 5% level, hence considering the sample, it is profitable to buy the winners' portfolios for all periods.

J \ K	3	6	9	12
3	0.29%	0.14%	0.10%	0.07%
	(1.69)	(1.69)	(1.69)	(1.69)
6	0.48%	0.24%	0.16%	0.12%
	(2.77)	(2.77)	(2.77)	(2.77)
9	0.39%	0.19%	0.13%	0.10%
	(2.41)	(2.41)	(2.41)	(2.41)
12	0.26%	0.13%	0.09%	0.07%
	(1.57)	(1.57)	(1.57)	(1.57)

Table 4 - Returns of the Loser Portfolios Strategies (Medium-Term)

The P1 (losers' portfolio) returns are conveyed above (table 4). Immediately from these results, is disclosed an apparent abnormality to the momentum theoretical and empirical framework. It was expected that the loser portfolio would produce negative monthly returns, which does not occur. Closer scrutiny reveals that the loser portfolio returns assemble positive figures throughout all the 16 strategies. Once more, the (J=6; K=3) strategy reveals the highest returns (5.91% annualized returns). Besides the portfolios formed by the lowest returns producing consistent positive returns, a more intriguing fact emerges. The loser portfolios (P1), constituted by six and nine-months formation periods, consistently achieve superior monthly returns than the winners' portfolios (P10) in the same timeframe.

Finally, regarding the statistical significance of the losers' portfolios returns, the results suggest that the portfolios comprised of six and nine-month formation periods (J) are statistically significant at the 5% and 2% levels. In comparison, the portfolios comprised of 3 months formation periods are significant at the 10% level. However, the portfolios constituted by the 12 months past returns do not achieve significance. Consequently, those results are not statistically different from zero.

J \ K	3	6	9	12
3	0.09%	0.04%	0.03%	0.02%
	(0.73)	(0.73)	(0.73)	(0.73)
6	-0.06%	-0.03%	-0.02%	-0.02%
	(-0.45)	(-0.45)	(-0.45)	(-0.45)
9	-0.02%	-0.01%	-0.01%	-0.01%
	(-0.16)	(-0.16)	(-0.16)	(-0.16)
12	0.12%	0.06%	0.04%	0.03%
	(0.88)	(0.88)	(0.88)	(0.88)

Table 5 - Returns of the WML Portfolios (Medium-Term)

Considering the empirical framework developed by the winners' and losers' portfolios, Table 5 presents the returns constructed from the Winner Minus Loser (WML) portfolio.

The overall results show that the implementation of momentum strategies utilizing ETFs produces marginal monthly positive or negative returns depending on the formation period. Consequently, for the 3 and 9-months formation periods, the strategy delivers a marginally profitable return for every holding period. Conversely, for the 6 and 9-month formation periods, the strategy delivers marginally negative returns. In every strategy, it is apparent the lack of significance. The WML provides positive or negative marginal returns that are not statistically significant from zero. By curiosity, the strategy that provided the highest annual return is the (J=12; K=3), delivering 1.45% annual return. This figure is inferior to a buy-and-hold strategy.

4.2.2 Long-Term Strategies

Considering the results provided by the medium-term framework and the lack of significant returns that emerged from the momentum strategies, an extended analysis consistent with Li et al. (2019) was developed. Consequently, these authors found profitable momentum strategies ranking ETF according to formation periods from 24 to 48 months. Hence, were developed 16 other strategies based on 18, 24, 30, and 36 formation periods, keeping the original 3, 6, 9, and 12-months holding periods.

J \ K	**3**	**6**	**9**	**12**
18	0.31% (1.96)	0.15% (1.96)	0.10% (1.96)	0.08% (1.96)
24	0.48% (2.86)	0.24% (2.86)	0.16% (2.86)	0.12% (2.86)
30	0.47% (2.73)	0.24% (2.73)	0.16% (2.73)	0.12% (2.73)
36	0.49% (2.66)	0.25% (2.66)	0.16% (2.66)	0.12% (2.66)

Table 6 - Returns of the Winner Portfolios (Long-term)

Table 6 features the P10 (winners' portfolio) to the long-term strategies. In consonance with the medium-term strategies, monthly returns are positive in every timeframe and statistically significant at the 5% level.

Closer scrutiny of the P10 unveils a monthly exponential increase from the 18-month to the 24-month formation period. The increase in holding periods delivered more robust monthly returns inferring that the sort and ranking of funds are maximized at the 24-months formation. The (J=24; K=3) delivers the most profitable annualized returns (5.91%).

Hence, the portfolio returns are highly consistent with all the combination strategies for 24, 30, and 36-month formation and respective holding periods.

J \ *K*	***3***	***6***	***9***	***12***
18	0.39%	0.19%	0.13%	0.10%
	(2.23)	(2.23)	(2.23)	(2.23)
24	0.37%	0.18%	0.12%	0.09%
	(2.22)	(2.22)	(2.22)	(2.22)
30	0.37%	0.18%	0.12%	0.09%
	(2.38)	(2.38)	(2.38)	(2.38)
36	0.37%	0.19%	0.12%	0.09%
	(2.30)	(2.30)	(2.30)	(2.30)

Table 7 - Returns of the Loser Portfolios (Long-Term)

Despite the increase in formation periods, the loser portfolios (P1) returns expressed in Table 7 remain positive for all strategies, which is inconsistent with the literature (Chan et al., 2000; Tse, 2015).

The portfolios constructed with the new formation periods suggest that the monthly returns from all the strategies became uniform and mostly unchanged between them. Increasing the formation period to select the funds with the lowest returns delivered that the worst ETFs present a positive uniform return pattern. Indicating that there is no difference in the ETFs ranking process. Hence, the selection of funds between the different formation periods must have remained the same.

The t-statistics provide reliable evidence that the monthly returns of the P1 are statistically significant at the 5% level.

J \ K	3	6	9	12
18	-0.08%	-0.04%	-0.03%	-0.02%
	(-0.54)	(-0.54)	(-0.54)	(-0.54)
24	0.12%	0.06%	0.04%	0.03%
	(0.77)	(0.77)	(0.77)	(0.77)
30	0.11%	0.05%	0.04%	0.03%
	(0.66)	(0.66)	(0.66)	(0.66)
36	0.12%	0.06%	0.04%	0.03%
	(0.72)	(0.72)	(0.72)	(0.72)

Table 8 - Returns of the WML Portfolios (Long-Term)

The materialization of the WML portfolios suggests marginal positive returns, except for the portfolios formed considering 18-month formation periods. Hence, although some strategies provide marginal positive returns, it is not achieved statistical significance. Consequently, the results obtained are not statistically different from zero. Such is a natural consequence of the WML providing near-zero returns. Once again, the results are inferior to a buy-and-hold strategy.

In sum, the comparison between the WML portfolios of the medium-term and long-term strategies returns provides eminently similar results. In light of this outcome, the issue related to the absence of reliable negative returns in the P1 (losers´ portfolios) remains. Consequently, the losers´ portfolios do not provide negative returns to influence the profitability of the WML portfolio. The winners´ portfolio returns are in line with the literature, providing significant positive returns.

4.3 Hypothesis Validation

The results provided by the empirical analysis reject H1. Consequently, the implementation of momentum strategies utilizing US technological Exchange-Traded Funds delivered non-significant returns.

A closer look at the results conveys some critical remarks. As expected, the winner portfolios exhibited positive returns in the medium and long-term formation periods, which is consonant with the literature (Jegadeesh & Titman, 1993). However, the loser portfolios also presented positive returns in all timeframes, at times even superior returns than the winner portfolios. From the theoretical and empirical framework, it was expected that the loser portfolios conveyed negative returns. Consequently, the lack of profitability in momentum strategies is driven by the absence of negative returns in the loser portfolios. Additionally, winners and loser portfolios' returns with extended formation periods did not reveal significant differences. These results suggest that the selection of funds remained identical, independently of the extension of the formation period utilized, suggesting several justifications.

Primarily, the inherent condition of the ETFs architecture. The momentum anomaly is mainly associated with individual stocks forming portfolios considering their past returns. These stocks face extensive idiosyncratic risk and behavioural biases that induce momentum. Conversely, ETFs are composed of a basket of diversified assets and follow a predetermined index, entailing significantly lower idiosyncratic risk than individual stocks.

The macroeconomic analysis unveiled that the US GDP had anaemic positive growth for the last decade. Nonetheless, financial markets have been positively trending. These results seem to be supported by NASDAQ-100 performance and unprecedented growth, promoting the overall financial market's rise. Hence, firms in this sector show substantial capital expenditures in innovation and cutting-edge technology supported by government politics, excessive optimism of debt providers, and investor overconfidence.

The ETFs sample tracked technological indexes and is composed of firms in a sector with exceptional positive behaviour in the last decade, significantly influencing these results. This framework explains the lack of ETF downside returns in the technological sector. Discriminative analysis of the loser portfolios unveils complying results. Hence, on average, less than half of the losers' portfolios funds have monthly negative past returns.

Market dynamics seem to be creating similar conditions to the dot-com bubble in the late 1990s, indicating that some high-risk tech firms are being supported by speculative market conditions, government aids, and overconfident investors. This framework suggests future turbulence and market crashes.

Another important aspect is the role that AP´s and OLP´s have on the ETF structure. Consequently, most deviations between the ETF price and the NAV provide these market players arbitrage opportunities, that deliver profits. This ability makes ETFs more efficient and less exposed to market frictions, such as demand shocks, noise traders, and investor behavioural biases that stimulate the divergence between the ETF price and its underlying fundamentals. In this sense, ETFs provides lower prospects to be mispriced and drift from fundamental values. The development of this investment vehicle shows significant structural efficiency. Nonetheless, the relation between ETFs and the underlying securities price share is still opaque.

In sum, WML portfolios' non-significant profitability is the result of both portfolios providing positive results. Market determinants associated with a technological bull market resulted in tech firms and indexes performing above average, driven by overconfident investors and government aids. Additionally, the intrinsic ETFs architecture provides an efficient product that corrects some market deviating phenomena.

5. Conclusion

5.1 Main Results

This dissertation tested the profitability of momentum strategies with a commonly recognized passive financial vehicle (ETF), namely funds that constitute the technology sector. The empirical framework developed medium and long-term momentum strategies with a sample of 20 tech ETFs for a 10-year timespan (2010-2019). Results are homogeneous throughout all momentum strategies and unveiled non-significant profitability. Hence, the rejection of the hypothesis subject of study is indisputable. The inability to develop profitable ETF momentum strategies takes a few determinants.

Primarily the sectorial framework provided that the technological industry has been in an exponential upward trend. Hence, both firms and indexes positively influenced the performance of ETFs. Assembling these conditions with the intrinsic ETF structure provided loser portfolio with positive returns. Another argument concerns the ability of AP´s correct deviations from ETF price and its underlying NAV, undermining common price drifts away from fundamental value.

Regarding the contributions to Academia, the focus on the specific dynamics of an ETF sector and the assessment of an extended timeframe provides researchers' additional empirical data and analysis to evaluate the reliability of momentum strategies. This study provides evidence against momentum profitability focusing on the dynamic technology sector that entails unclear dynamics about assets' intangibility.

These results also imply a different perspective regarding the dichotomy between the behavioural and efficient approaches to financial markets. Considering that ETFs reduce idiosyncratic risk through a diversified portfolio, the fund will be more exposed to the systematic risk component than the firm-specific one. Hence, these results support the firm-specific news misreaction argument, that Jegadeesh & Titman (1993) provided to justify momentum profitability. Hence, if ETFs have reduced exposure to idiosyncratic risk, they are not subjected to behavioural and cognitive biases as individual stocks. Consequently, the development of ETFs in the market helps reducing deviating market phenomena, as investors misreaction and herding, promoting market efficiency.

5.2 Implications

The ramifications of this work are branched in two fields investors and regulatory institutions (SEC).

Concerning investors, whether individual or fund managers, this paper contributes with empirical evidence that implementing momentum strategies in the US tech ETF sector does not provide profitability. These results are motivated by winners and losers' portfolios, developing positive returns.

Considering these results, the regulatory institutions in the US (SEC) should stimulate the shift in investor preferences from active strategies to passive ones, supported by ETFs usage. The inherent ETF structure maintained by the dynamics between AP´s and OLP´s seem to provide a more efficient product that was not subject to momentum. This product might reduce market trends and decrease the influence of noise traders and speculators, promoting market efficiency. The adoption of extensive "exemptive reliefs" to create customized baskets provided the SEC capacity to limit the inclusion of asset classes that causes disrupt in the market (e.g., cryptocurrencies). However, the recent approval of the rule 6c-11 ("ETFs rule") seems counterintuitive in this framework, promoting additional deregulation and advantages to ETF sponsors to create customized baskets that undermine market efficiency.

5.3 Limitations

The empirical work was bounded by a specific sector in the Exchange-Traded Fund domain, specifically the equity-based technological indexes. Furthermore, it was considered cross-sectional price momentum and followed the Jegadeesh & Titman (1993) methodology. Hence, it would be compelling to test whether implementing different methodologies, such as the 52-week variable (Yu & Webb, 2020), value-weighted portfolios instead of the equal-weighted portfolios, would deliver significantly different results. The January effect (Jegadeesh & Titman, 1993) asserts that momentum reverses in January. The empirical testing did not consider this issue.

An essential condition in the methodology was the non-inclusion of a skipping period. The literature reports that this procedure avoids short-term return reversals generated by bid-ask spread pressures and price pressures (Blume & Stambaugh, 1983). Furthermore, due to the lack of profitability of momentum strategies, it was not pertinent to consider transaction costs (Korajczyk & Sadka, 2004).

Finally, a significant restriction concerns the lack of discriminatory evidence concerning the classes of ETFs utilized (e.g., leveraged ETFs, inverse ETFs, actively managed ETFs, synthetic ETFs). Hence the sample was assessed concerning the Lipper Classification Scheme but without knowing the ETF structure. It would be helpful to determine the structure of ETFs analysed.

5.4 Recommendations

ETFs rising importance and evolution is paramount. Hence, it is beneficial to extend this study, primarily to other sectors (e.g., industrials, energy, utilities, healthcare) and other classes of ETFs (e.g., fixed-income ETFs, commodities ETFs), to evaluate the prospect of momentum profitability. Additionally, assessing other momentum classes (e.g., time-series momentum, factor momentum) and assembling them with ETFs is essential to develop this subject.

Combining different ETFs (leveraged ETFs, inverse ETFs, synthetic ETFs) to construct the winner and the loser portfolios might deliver the momentum effect. Additionally, the rising use of active ETFs could mitigate the intrinsic limitations of traditional index funds and target specific investment criteria. Consequently, implementing momentum strategies utilizing active and smart betas ETFs could provide profitability. Another important aspect is the relation between the ETF price and the underlying securities behaviour. Hence, excessive demand for a particular fund might induce changes in stock price

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Appendix-A

Exchange-Traded Funds are investment vehicles that operate identically to mutual funds. It pools a set of securities in an aggregate form, providing investors a diversified portfolio that operates as traded securities (Gastineau, 2008). An index-based ETF replicates an index or invests in a representative sample of securities in the target index. More recently, the development of actively managed ETFs assembled a basket of securities to accomplish a particular investment objective. Both passive or active managed ETFs use several derivative instruments to meet their investment goals (e.g., futures, forwards, options, swaps).

The formation of an ETF encompasses a manager or sponsor that subscribes into legal contracts with Authorized Participants (AP´s). Sponsors create the ETF and establish the fund's investment objective, deciding whether it will be index-based or actively managed. AP´s are large financial institutions approved to trade directly with the ETF sponsor in the primary market.

ETFs capacitate investors to trade their shares continuously throughout the trading day, in opposition to mutual funds that only allow agents to buy and sell their positions at the end of the trading day at the Net Asset Value (NAV)[26]. ETF sponsors issue or redeems shares with AP´s in large segments, called creation units, in a direct transaction for a basket of securities and cash (creation/redemption system). By "creation," the ETFs' supply will grow, and "redemptions" encompasses a reduction in shares of the ETFs.

The comparison between mutual funds (open-end and closed-end) and ETFs is innate due to their common determinants. ETFs collect characteristics of open

[26] NAV is defined as the value of a fund´s assets subtracting its liabilities, according to the SEC, mutual funds and UIT´s (Unit Investment Trusts) are demanded to compute their NAV at least once every business day.

and closed-end funds. Thus, as open-end mutual funds, ETFs allow the issuance and redemption of shares within the fund, providing considerable liquidity to this instrument. Like closed-end funds, the ETF shares negotiate during the trading day in the secondary market at prices that can deviate from the NAV. The open-end property of this vehicle leads ETF share prices to often deviate from the NAV of the portfolio due to asynchronous trading between the ETF and the underlying asset. Imbalances in the supply and demand chain might also entail departures of ETFs share price compared to its underlying NAV implicating arbitrage opportunities in the market.

Nonetheless, the ETFs architecture and underlying structure promote corrections. Consequently, when the ETF price is lower than the NAV, the AP´s buy ETF shares and redeems them for the underlying securities. Conversely, when the ETF price is higher than the NAV, the AP´s buy the underlying securities and trade them for newly issued ETF shares (*arbitraging*).

ETFs present essential features that distinguish them from other investment products, such as (1) intra-day trading, including buying on margin and short-selling, (2) creation and redemption of fund shares "in-kind", and (3) tax efficiency. The intra-day trading property provides a form of liquidity that can be significant to some investors. Thus, in periods of market volatility, the ability to close a position throughout the day may be decisive to maintain profits.

The redemption "in-kind" feature is closely related to the tax-efficiency claims that this vehicle provides. First, redemption "in-kind" consists of investors redeeming ETF shares from the trusts and having the ability to obtain the underlying securities rather than redeeming in cash. This method provides a form of reducing capital gain realizations in comparison to traditional mutual funds. Consequently, when the ETF trustee distributes securities below market prices, it eliminates taxation of capital gains to ETF investors. The redemption "in-kind" feature contributes to solving the embedded capital gains[27] problem in the mutual fund industry (Poterba & Shoven, 2002).

A concern that arises from ETFs is that intraday trading might induce "overtrading". Barber & Odean (2000) established that individual investors who trade actively in the market obtain smaller gains than investors who trade less. Another problem comes from the absence of a classification program for ETFs that underlines standard guidelines for illiterate investors that emphasize the difference between several ETF products (e.g., levered, secured, synthetic, physical ETFs).

[27] Unrealized gains for which the fund investor is responsible. An unrealized gain is a potential profit that can only be obtained after the position is liquidated.