UNIVERSIDADE CATÓLICA PORTUGUESA

# Price Momentum Profitability in the US Tech Stock Market

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March 2019

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Final Assignment presented to
Universidade Católica Portuguesa
for the obtainment of the master's degree in Finance

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March 2019

# Abstract

Trading momentum has been a highlighted theme during the last decades due to conflicting points of view within the academia and investment community. Despite the recurring studies regarding momentum, there are still no consensus about the significance of momentum returns neither about the causes behind it. In addition, the investor's community embraced the momentum effect which results in the creation of successive funds and Exchange-Traded-Funds (ETF) that follows momentum trading strategies. The aim of this paper is to observe the momentum effect in the United States Technological equity markets. This study looks at the 200 biggest tech firms in the United States, in the time-frame from 2008 to 2018, and finds empirical evidence of positive and significant momentum returns. Reasons for the observation of momentum returns might be explained by behavioural theories which theorize the effect of psychological biases in the investment decisions. The implication for this study aims to clarify the state of momentum trading strategies nowadays with tight focus on the tech industry.

**Keywords**: Price Momentum, Trading Momentum, Behavioral Finance, Herding, High-Tech United States

# Resumo

O *momentum trading* tem sido um tema em destaque nas últimas décadas devido a pontos de vista conflitantes dentro da comunidade académica e de investimentos. Apesar dos vários estudos acerca do tema, continua sem existir consenso em relação ao significado dos retornos do *momentum* e às causas por detrás desta anomalia. Adicionalmente, a comunidade de investidores adotou o *momentum effect,* o que se traduziu na criação de fundos e *Exchange-Traded-Funds* (*ETF)* que seguem as estratégias de *momentum trading*. O objetivo deste artigo é observar o *momentum* nos mercados de capitais no sector tecnológico dos Estados Unidos. Este estudo analisa as 200 maiores empresas de tecnologia nos Estados Unidos, entre 2008 e 2018, e encontra evidências empíricas de retornos positivos e estatisticamente significativos do *momentum*. As razões para a observação dos retornos de *momentum* podem ser explicadas por teorias comportamentais que teorizam o efeito de enviesamentos psicológicos nas decisões de investimento. A implicação para este estudo visa esclarecer a rentabilidade das estratégias de *momentum trading,* atualmente, com foco particular na indústria de tecnologia.

**Palavras Chave**: *Price Momentum, Trading Momentum*, Finanças Comportamentais, *Herding*, Tecnologia Estados Unidos da América

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# Chapter 1

# 1. Introduction

## 1.1 General Framework

*The momentum effect* is an asset price movement phenomenon. More specifically, it represents a price drift not backed up by fundamental changes, creating a gap between price and intrinsic value (Chordia & Shivakumar, 2002; Chui & Wei, 2003; Hanauer, 2014; Jegadeesh & Titman, 2011).

This singularity of asset pricing dynamics originated momentum short-term trading techniques, which can be recapitulated as "buying winners and selling losers"; traders take advantage of volatility and herding behavior in the markets by being the first opening and closing positions.

The most basic and popular form of momentum is applied in the context of stocks. It may be considered *a cross-sectional momentum* (Jagadeesh & Titman, 2002), meaning stocks are ranked from best to worst, as opposed to a *time-series momentum* (Moskowitz, 2012), which focuses on following market trends.

Momentum, also known as *relative strength,* has given origin to *price momentum*, *industry momentum* and *earnings momentum,* all of which have similarities in terms of process, which may be overviewed in a couple of steps: anchoring and conservativism, which are associated with novelties. Along with the slow diffusion of information, this creates an underreaction. In addition, the disposition effect creates a selling pressure on the stocks. Following this, with time, the catch-up process begins, and the mass of investors acknowledges the value of a particular stock. Ultimately, an overreaction occurs, beginning with the herding effect, a behavioral instinct that increases with newly arrived investors. Furthermore, there is an enhanced expectation of future prospects of the stock based on projecting past trends into the future, a concept widely known as *representativeness*.

In 1993 Jegadeesh and Titman published what would become the first study documenting momentum effect anomalies. In this work *momentum* was defined as: when a stock has had its best or worst performance in the past 3-12 months, this will continue into the next 3-12 month period. Since its discovery, the momentum effect has become a popular and debatable topic. The controversy arose from the fact that momentum is an undeniable flaw for the Efficient Market Hypothesis (EMH), since the (Jegadeesh & Titman, 1993) paper suggested that it may be impossible to use past information to predict future performance.

Furthermore, it is still unclear what is driving the momentum movement. There is an ongoing debate between explanatory risk theories, behaviorally based theories and a mix of both. There are a wide range of possibilities of factors to explain momentum, with no definitive answer.

Finally, the momentum effect has a unique characteristic that makes it a paradigmatic subject in the academic field of finance: even after its discovery, momentum has still been observed in the data. Even the crowding effect and capacity constraints do not seem to fully affect momentum returns (Noel et al. , 2014). Unlike other anomalies that have been observed over recent years, momentum has not faded away and in fact, remains relevant between investor’s community nowadays. In addition, momentum has had notorious growth as a subject of study and as an investment philosophy ever since its discovery in the '90s by Jegadeesh and Titman. By way of illustration, the search term ‘’Price Momentum'' appears in 857,000 results in Google Scholar. On Wall Street, momentum has gained numerous supporters; there are 39 ETF's (Exchange Traded Funds) in the US, with a total of $15B under management.

The focus of this study is the cross-sectional price momentum in the United States High Technological Sector. Studying this sector is of extreme relevance due to its meaningful impact on the U.S. economy, the characteristically high volatility and the fact that this sector presented a speculative bubble and the subsequent crash in 2001.

The relevance of technology increases over time; innovation and agility are rapidly becoming essential to competition not only at a corporate level but also in the global ecosystem. Technological development influences supply, and, the demand is also larger and more sophisticated. This results in faster approval of novelties, with new products reaching 50 million users faster than ever, and featuring more complexities powered by, for instance, Artificial Intelligence (AI) and the Internet of Things (IoT).

What differentiates the technological sector from others is that technology possesses a disruptive force and thus represents a great evolutionary trigger (Carpenter, 2002; Deng et al., 2016). Particularly, technology has impacted the financial industry by catalyzing the creation of new tools and investment vehicles such as ETF's (Exchange Traded Funds) or algorithms for High-Frequency Trading (Galariotis, 2006; Deng et al., 2016; Shynkevich, 2012).

The United States' tech market showed a historically and outstanding growth. The biggest 4 tech companies represent a total of $3256,52 billion in market capitalization, and the average compounded growth rate in recent years is 15%. Remarkably, Facebook grew by 48%, Amazon grew by 25% and Apple Inc. grew by 17%. In the last 10 years, venture capital has achieved 4,380 deals in the U.S., which represents the primary source of funds for young companies. Silicon Valley absorbs the majority of the deals, 30% of the total, followed by the NY Metropolitan Area with 12%, and New England with 11%.

In the U.S., the top ten startups represent a total of $278,3 Billion, with Uber, Airbnb, SpaceX, Stripe, and Lyft being the most valued. Startups are high growth firms, with the previously mentioned top ten startups growing in valuation between 47,13% and 80,21% in the last five years—remarkable for young firms. In many cases, firms have had to go public in order to obtain more financing. The IPO activity has been growing in the U.S., especially in the tech sector. From 2014-2017, the IPO activity regarding tech firms has grown stably by 3%.

Regarding economic impact, high-tech industries must be considered to be a cornerstone of the United States' economy, with a total output of $1.6 trillion in 2017, which represents 9.2% of the U.S. economy and 31% of the worldwide high-tech total. Although the number of IPOs has been stable, the proceeds from these IPOs have been growing by 10%. This suggests that the entry valuation of the firms has been increasingly evolving. Outstandingly, in 2012 in the U.S., $20 Billion were raised by IPOs—an all-time record.

When it comes to market trends, the Digital Transformation will grow 18% annually between 2014 and 2025. This means that industries are reaching digital business maturity at a faster pace than ever. Logically, industry automation is also growing, with real economies becoming more autonomous due to technologies such as the Internet of Things and Cloud Computing. IT automated services revenues will grow 33% by 2026, and non-automated IT services will rise 4%. Spending on IT services will reach a total of $311,6 Billion by 2020, up from $275,2 Billion in 2014.

Additionally, new technologies have developed. One worth mentioning is public computing services, which is growing and is expected to achieve spending of $278,3 Billion by 2021, impressive growth for an industry that only represented $58,6 Billion in 2009. However, the private sector was not the only one investing in High-Tech development. The United States has an impressive investment in research and development, 3% of the GDP being spent on R&D, which represents approximately $581,7 billion. The major investments are made in software, tech consulting services, and telecom services.

Considering job creation, the technological firms assume a crucial role in the U.S. employing a total of 11,5 million people, 194,000 of which during the last year. In relative measures, the U.S. tech sector represents approximately 10% of the total active U.S. population. The salaries denote how competitive the industry is, with the average yearly wage in the high-tech industry in the United States at $112,890, double the overall average U.S. wage.

This industry keeps growing in size. Throughout last year, 34,000 new tech establishments were created, with the U.S. total reaching 503,000. This growth is also reflected in the capital markets. In the last twelve months, IPO's were done with a total value of $6,500 million U.S. dollars.

The chosen object of study comprises the 200 most prominent tech firms in the U.S., using market capitalization as a proxy for size. Tech's stock market presents a high potential for momentum observation given its specificities. To begin with, technology is an evolutionary trigger, hence it is often mispriced in the early stages of the development of certain technologies. Secondly, this market relies heavily on an intangible asset which has low salvage value and does not always result in the predicted benefits for the firm. Finally, start-up firms have limited access to debt markets which makes these firms heavily dependable of IPO's to obtain capital. Consequently, firms need higher valuations to receive more capital which may result in conflicts of interests.

## 1.2 Research Gap

Recent studies provided valuable insights about market dynamics, but it is evident that the full spectrum of information about momentum has not yet been uncovered. The primary missing information is related to the profitability of momentum. Its absence is due to the fact that studies focus on momentum as a market dynamic, which can be upwards or downwards, and not as a trading strategy applied in the market. In real circumstances, investors face other costs such as commissions, fees, and taxes, which may affect the final profitability of the trading operations (Demirer et al., 2015; Jegadeesh & Titman, 2011).

In addition, past studies on price-momentum focused primarily on the market as a whole; it is, therefore, unclear if sectors present similar degrees of momentum or if some sectors are more propitious to momentum than others.

There is also a paucity of consensual empirical evidence to explain momentum. Many theories exist, namely, risk and behavioral models. Many scholars have suggested that the origin of momentum is a combination of risk and behavioral factors; however, they do not clarify the magnitude of each factor. The academic community is far from unanimity as to the origin of momentum, and eagerly awaits a unifying and accurate explanation (Chan & Docherty, 2016; Demirer et al., 2015).

Moreover, the market timing is still vague; it is widely known that it is almost impossible to time the market and it is equally hard to define what moved the market cycle in a given situation. In the field of price momentum, the relationships between momentum and contrarian cycles are still undetermined at some degree.

Finally, there are yet some uncertainties around the long-term observation of momentum and its relation to the efficient market hypothesis. It is uncertain if the market will become more efficient as it matures or if momentum strategies will maintain their profitability as more traders and investors enter the market (Shynkevich, 2012).

## 1.3 Research Question

The primary goal of this work is to answer the following question: Are momentum trading strategies profitable whenever applied to the 200 biggest U.S. high-tech firms?

This question is relevant given the outlook of the industry today. Investment and stock management processes are changing, primarily due to the growing percentage of Automated Trading Systems and the High-Frequency Trading (Shefrin & Statman, 2000; Shynkevich, 2012). The appearance of automated trading and stock selection has transformed the industry, and consequently many argue that market efficiency is enhanced as more decision-making processes are performed by AI and algorithms. In addition, because high-tech is the primary economic driver in the U.S. and has had phenomenal growth in recent years, it is important to understand investors' perceptions and behaviors regarding these firms.

## 1.4 Originality

The approach to this topic is original in its chosen sample and emphasis on a specific sector. In the past, some studies have focused on the tech market, but with the goal of conducting an event study of the 2001 crash, without the focus on momentum. This study is also unique in that, to the best of my knowledge, there is no scientific study of tech stock momentum during 2008-2018. However, there are recent studies that addressed the momentum problematic in 2016 and 2015 (Geczy, 2015; Geczy & Samonov, 2016). Unlike these studies, which focus on the entire U.S. market, this work is focused specifically on the U.S. tech-sector, providing valuable insights into the sector dynamics that may not be seen when the market is studied as an entire group of stocks.

In past studies, tech-sector stocks appear grouped with other firms from the same exchange where they are listed, revealing limited information about the momentum phenomena within the tech sector (Jegadeesh & Titman, 1993; Conrad & Kaul, 1998). In this study, the U.S. tech sector is considered independently for a specific duration of time.

## 1.5 Contributions to academic knowledge

This study contributes to the academic knowledge of price momentum in the field of finance, introducing new empirical evidence comprising new data. This study contributes with new information about momentum trading strategies. It will be useful for individual investors and fund managers interested in applying momentum trading strategies in the U.S. tech market. It also contributes to the understanding of momentum dynamics for managers of high-tech companies, who will benefit from awareness of short-term fluctuations of price due to external factors.

Additionally, this study unveils information that might be useful for market regulators like SEC (Security Exchange Commission) in the sense that from a regulatory standing point it is important to understand if there are distortions in relation to EMH and to what degree can happen a gap between price and intrinsic value.

## 1.6 The layout of the following chapters

After this introductory Chapter, the work is organised as follows. Chapter 2 offers a review of the existing literature regarding the main theories considered in this study. It will also review empirical evidence of momentum phenomena in different contexts such as countries and sectors.

In Chapter 3, the employed methodology of this study is discussed, more specifically, how the portfolios were built and how the impact of the strategy is measured.

In Chapter 4, the relevant data and results are presented and discussed.

Lastly, Chapter 5 finalises this work with the primary conclusions derived from the results of this study, and what they imply for the current understanding of momentum. In this chapter, suggestions for future studies are also discussed.

# Chapter 2

# 2. Literature review

## 2.1 Concepts

*Momentum* is a comprehensive concept with definitions across several scientific fields. Even within finance, momentum is defined differently by different academics. Since the pioneer study of Jegadeesh & Titman, in 1993, different theories and concepts have emerged, and different types of momentum have been identified, including industry and earnings momentum.

In terms of the stock market, *momentum* refers to the continuation of good and bad performances of stock that have had historical good and bad performances, respectively (Jegadeesh & Titman, 1993). *Earnings momentum* occurs when corporate earnings per share (EPS) growth is accelerating or decelerating from the previous period, and, in contrast to that predicted by EMH and other conventional models, the price reaction is disproportionate to the real change in value. For example, a firm whose earnings exceeded the analyst consensus for earnings, and the price has been adjusted to this new information, but it keeps drifting higher—inconsistent with EMH. Earnings momentum can be defined as the continuation of the positive or negative trend when a specific firm beats the earnings expectations or not, respectively (Chordia & Shivakumar, 2002). When these anomalies are observed, there are several implications for the conventional models and the efficient market hypothesis.

Market momentum is an overall market sentiment indicator that can support the pressure to buy and sell, whether compliant or not with market trends (Neal, 2009). The industry momentum effect is the general continuation of a stock price movement upwards or downwards within the same industry, even when no fundamental change in value justifies the change in price (Hong & Stein, 1997).

Price momentum has been comprehensively studied, and these studies have consequently resulted in numerous definitions and perspectives. Price momentum may be defined as the continuation of a stock's price movement when that stock has had its best or the worst performance in the past three to twelve months—this movement will continue into the next three to twelve month periods (Jegadeesh & Titman, 1993, 2011; Taffler, 1999).

Alternatively, (Daniel, 1998) described momentum as a positive short-term autocorrelation of stock returns for individual stock and the market as a whole. Momentum can also be explained as the observation of price drifts, long-term reversals, and cross-sectional forecasting power for scaled-up price ratios (Barberis, 2003). Price trends are not continuous, and one of the findings of the Barberis study was that momentum tends to reverse in the long term for several reasons, both technical and fundamental. Generally speaking, momentum shows that there is an asymmetry between new information that enters the market and the corresponding shift in prices (Chan, 2016; Fama & French, 1996; Galariotis, 2010). Even assuming a semi-strong-form of EMH, where all the publicly available information is incorporated rapidly, it is noticeable that the trends of momentum and contrarian cycles are inconsistent with this hypothesis (Antoniou et al., 2006; Jegadeesh & Titman, 2011).

This work leans towards the behavioral explanation presented in (Barberis, 1993) which models' momentum as an initial underreaction in the relation of new information that is later overcompensated by the massive pool of investors within the market.

This study focuses solely on price momentum and its profitability. This focus was determined due to the easily accessible information; the increasing popularity of momentum within the investment community, resulting in several new related products and investment strategies; and the abundance of empirical evidence confirming the profitability of price momentum in the past that might suggest a need for an update of the Efficient Market Hypothesis.

## 2.2 Main Theories

Since the EMH (Efficient Market Hypothesis) was first developed, the majority of the academic community of finance has accepted it as a cornerstone of conventional financial theories. Later, when anomalies began to be identified, a great debate arose between those that believe in market efficiency and those that do not. Momentum and other anomalies play an essential role in this field because they demonstrate serious discrepancies in the EMH.

### 2.2.1 Efficient Market Hypothesis

The efficient market hypothesis (EMH) was first documented in the 1970s by Eugene F. Fama, as presented in his article "Efficient Capital Markets: A Review of Theory and Empirical Work." It changed academic views about the markets and has since served as a foundation for the major conventional theories of finance. This study revealed the EMH and presented to the world for the first time the concept of the efficient market where stock prices "fully reflect" all public and private information (Malkiel & Fama, 1970).

The cornerstone of the EMH is the fact that a stock's prices reflect all available information, including new information that is instantaneously incorporated, originating new prices. Based on this theory, an efficient market should not represent an arbitrage opportunity, and the price is equivalent to the intrinsic value of the stock (Fama & French, 1996; Malkiel & Fama, 1970). This hypothesis represents a significant advancement for the academic community, making it easier to model asset price dynamics. Additionally, EMH represented a drawback for Wall Street due to its implication that it is a hopeless task to maintain active portfolio management with the objective of outperforming the market.

The EMH makes assumptions about the market, in which it is possible to reflect all available information in the asset prices. EMH is conceivable in an efficient market without transaction costs, and in which all information is accessible to everyone in the same way without associated costs (Malkiel & Fama, 1970). However, this is where the first flaw in EMH was indicated: equal information distribution between different investors is not likely to be present in capital markets, and this absence is a potential source of market inefficiency (Jensen, 1978).

Most of the empirical studies on market efficiency were founded on the rationale of beating market performance in order to demonstrate inefficiency. These studies have the benefit of focusing on real trading and investment strategies conducted by real market participants (Moskowitz et al., 2014; Korajczyk & Sadka, 2004). For illustration, one study considered mutual fund managers and respective performances. If the realized returns are superior when benchmarked with the market, even after risk-adjustment, the market can be considered inefficient due to the information possessed by the outperformer (Jensen, 1978).

The definition of market efficiency is too general to be meticulously tested. Therefore, the authors of the EMH created three different definitions of efficiency based on the degree of information available. These are weak, semi-strong, and strong form efficiency.

#### 2.2.1.1 Weak-Form Efficiency

The weak-form alternative of EMH states that stock prices reflect only historical information (Malkiel & Fama, 1970), meaning that studying the past performance of stocks would not support consistent market outperformance

(Fama & French, 1996). The fact that historical prices are already incorporated in the assets' prices indicates that neither technical analysis nor fundamental analysis should deliver superior returns, consistently over time. Several studies aimed to test this form of EMH in order to identify some predictability or patterns in daily prices (Fama & French, 2008).

Kendall and Hill (1953) analyzed the price movements of commodities and stocks by looking at daily data; however, no pattern emerged. These results were later confirmed when tests revealed a scarcity of patterns in daily price movements, suggesting that prices have a random distribution and are therefore completely unpredictable (Godfrey et at. , 1964).

Moreover, in a competitive market, the stock price must follow a random walk. If the stock prices are predictable, then investors have access to arbitrage opportunities; in competitive markets, however, the easy profit is ephemeral (Brealey et al., 2011). For example, if market participants know the future price of a certain stock, they will buy it. This buying pressure drives price upwards until there is no more profit to be made. The new stock price has already incorporated the positive information and has become again unpredictable—random behavior until new information enters the market (Godfrey et al., 1964; Malkiel & Fama, 1970).

#### 2.2.1.2 Semi-Strong Efficiency

The intermediate form of the efficient market postulates that prices reflect past information and all publicly available information (Malkiel & Fama, 1970). This means that prices remain stable and will adjust immediately when new information is turned public, such as earnings reports, mergers, acquisitions, buybacks and dividends (Keown & Pinkerton, 1981; Malkiel & Fama, 1970). This implies that information such as company reports, state of the economy, or any other publicly available information relevant to stock value is available for investors. Additionally, every investor is assumed to be rational and able to determine the factors which affect stock prices.

This makes it impossible for the investor to attain abnormal returns using any form of analysis, technical or fundamental, based on publicly available information. When new information is available to investors, the stock prices are immediately adjusted to reflect the new information. The investor will interpret the new information and how it will affect the stock price. In this situation, the investor would not be able to profit consistently from these events, given the instantaneous incorporation of information (Malkiel & Fama, 1970). Naturally, there would be no time to react between the release of a given announcement and the subsequent price adjustment (Jensen, 1978; Markowitz, 1991).

A method to test this form of efficiency is to perform an "event study'' and observe how the market adjusts stock prices after new information is made available. If the price adjustment is not immediate, the conditions will not be met for semi-strong efficiency.

#### 2.2.1.3 Strong-Form Efficiency

The market is robustly efficient when the information reflected in the stock price is all publicly available and private information held by market partakers (Fama & French, 1996). In the strong-form of the hypothesis, it is assumed that all information is available to everybody. The data includes both public and private information. Public information is press releases, news, past information, and other widely known facts (Lesmond, 2004; Malkiel & Fama, 1970). On the other hand, private information is the CEO's strategy in the firm, M&A plans, and even unpublished firm reports—for example, unpublished company reports or future acquisition and growth strategies, information usually only possessed by high-level executives. This said, in strong-form market efficiency, it is possible to observe investors incurring profits and losses, but it would be impossible to witness a consistent market outperformance (Alexander & Dimitriu, 2004). This view is advantageous in the sense that it is an absolute model of a stock's prices, but in this kind of model, it would be impossible to consistently outperform the market (Fama & French, 1996; Markowitz, 1991).

Some event studies have reported that the market reacts before earnings announcements are made public and it is believed that this is caused by inside trading. Inside trading is successful exploitation of superior information in order to gain superior returns—contradictory to this form of the EMH (Keown & Pinkerton, 1981). Consistent insider trading results in a market outperformance by 5% over an 8-month span according to (Egerton, 1973). This empirical evidence in which access to private information is exploited in order to obtain superior returns is a counter-argument to the strong-form efficient hypothesis, as it is possible to conclude that not all private and public information is reflected in the stock prices.

#### 2.2.1.4 Market Efficiency Nowadays

Evidence and belief in the EMH has created new trends in the financial industry. It convinced some to peg their returns to the market through the use of financial products such as mutual funds and, more recently, ETF—products that offer a low-cost solution for diversification and a low effort investment solution (Shynkevich, 2012). Choosing passive investment demonstrates that investors had given up on exploiting information to achieve outstanding performance. This is not a significant trend in financial markets; in a hypothetical scenario where all information gathering and analysis stopped, market prices could not react to the new information (Grossman & Stiglitz, 1980). A market where prices do not react to new information is uncompetitive, a failure of a necessary condition of market efficiency. Conclusively, an efficient market requires that some market participants try to benefit from collecting and studying information (Grossman & Stiglitz, 1980; Malkiel & Fama, 1970).

Another assumption that must be analysed is the significant cost of information—it is not widely available to the mass of market participants. This said, stock prices are not capable of reflecting all existing information because there would be no incentive to conduct harmful research without compensation (Grossman & Stiglitz, 1980; Jensen, 1978). There is a direct inverse relationship between market efficiency and motivation to search for new information (Grossman & Stiglitz, 1980).

Wall Street is an industry fertile for success, some more long-lasting than others. However, it is undeniable that some great investors have a long track record of outperformance. For example, Warren Buffet has outperformed the market for the last 50 years, and George Soros has had an excess return of 21% annually for 31 years. These statistics confirm that it is possible to consistently beat the market, and there are implications regarding market efficiency (Alexander & Dimitriu, 2004). These claims can be interpreted through portfolio theory, which states that in not feasible the construction of portfolios with positive alphas and that the market's portfolio is the best option available (Markowitz, 1991).

Some studies have identified a new source of inefficiency due to behavioural factors. If the market intervenient builds portfolios with unreasonable expectations and misinterpreted information, basing their decisions on aspects other than a reward-to-volatility ratio, then these newly created portfolios will be inefficient (Ritter, 2003). Dechow and Sloan (1997) claimed that the market portfolio can be inefficient if a large percentage of investors do not have rational expectations and misinterpret information due to, for example, the belief that they are beating the market when they are not, or, taking into account other factors besides reward-to-risk-ratio in their investment decisions.

Since all trades are made by two counterparties, it is evident that for every good decision, there is a bad decision on the other side. For each outperformance, there is a consequent underperformance (Fama & French, 2008; Geczy et al., 2014). The consistent success of some investors is due to the predictability of the behavior of individual investors who commit errors that are being continuously exploited.

In practical terms, there are frictions within investing that limit market efficiency. From an academic point of view, which is not necessarily representative of reality, investors act independently, with the option of going long or short with residual transaction friction. This is not applicable in the real world. There are many more investors going long compared to those going short. This conceptual problem demonstrates the limits of EMH.

At the same time, there are also transaction costs and informational availability issues. Regarding large-cap equities, the information is highly disseminated, and transaction costs are low. Nevertheless, for less liquid markets, there are much higher transaction costs and the information is not so widely available.

From a market structure perspective, markets with less efficiency (Mid-Low Cap) are more fertile to active asset management. Clearly, active portfolio managers do a better job in the small/mid cap (SMC) relative to large cap equities. SMC has fewer investors active, less analyst coverage, and likely have higher borrowing costs for shorting than large cap; hence they are less efficient.

The U.S. equity market is one of the most efficient in the world given the number of investors, its liquidity, and diversification. The average performance of active fund managers has trailed the S&P 500 by over 1% annualized for the past three- and five-year periods. In Canada, for example, with fewer investors and a market that is less diversified, active funds have tended to add value during this period, based on the 2015 year-end SPIVA report.

The degree of market efficiency clearly has a relationship with the market structure. Markets with fewer participants, higher transaction costs, and less ease of information gathering tend to be less efficient markets, which gives active management an edge in less efficient markets and passive investing an edge in more efficient markets (Menkhoff et al., 2006).

Investor behavior is another limitation of the EMH. Investors don't act independently and often behave as a herd. All investors experience cognitive biases in some way (Menkhoff et al., 2006). For professionals in investment management, it is important to check and audit their own processes in order to identify these biases. It is also prudent to understand which markets present more efficiency and how external factors affect them.

### 2.2.2 Risk-based models for price movements

The EMH assumes that stock prices are unpredictable, following a random walk. Many classical models were developed to describe price movements, most of them based on the relationship between risk and reward. One of the most frequently used asset pricing models in the academic community is the Capital Asset Pricing Model (CAPM) (Merton, 2010). This popular model was developed in the 1960s, and its main advantages are the security application and its natural results due to the relationship between expected return and risk (Markowitz, 1991; Merton, 2010).

As every model CAPM works with certain assumptions that are categorized by some as unrealistic. The models assume that all investors share the same risk-aversion profile, hence their decisions are based solely on the reward to risk relationship. It is assumed that every asset and transaction can be infinitely divisible, and that short-selling is possible and unlimited for every asset. There are no transactions nor tax costs and the capital borrowing and lending rate for every amount is the risk-free rate.

Empirical studies performed in recent years demonstrated that the CAPM performs poorly in terms of accuracy (Fama & French, 2008). Portfolios with high betas return much higher than predicted, and portfolios with low betas return lower (Fama & French, 2004). As these empirical results suggest imprecision of the CAPM, the search continued for financial models to systematically explain asset's returns, and in 1993, Fama and French created the Three-Factor-Model (FF3F). They claimed that the anomalies identified in the CAPM were captured and explained by the FF3F, which said that realized gains above the risk-free rate are manifestations of three possible factors (Fama & French, 1996, 2004): the excess gain made by the market portfolio; the SMB (small minus big) factor, which is the difference between the return of a portfolio with small stocks and one with big stocks; and lastly, HML (high minus low) factors, the difference in the returns between a portfolio of high book-to-market stocks and one of low book-to-market stocks (Fama & French, 2004).

FF3F explained most of the cross-sectional variations in stock returns (Fama & French, 1996), and identified that portfolios are formed based primarily on three criteria: cash flow/price, earnings/price, and sales growth. Additionally, the observed long-term reversals found by DeBondt & Thaler (1985) were also explained by the model (Fama & French, 2008). Nevertheless, FF3F was not able to explain the momentum phenomenon identified by Jegadeesh & Titman (1993), whose statement ''Momentum is the prime anomaly'' has kept up an ongoing debate (Fama & French, 2008; Jegadeesh & Titman, 1993, 2011).

### 2.2.3 Behavioral Financial Models

If the market complies with the efficient market hypothesis, then is it assumed that all stocks are priced accordingly to their fundamental value, making any outperformance virtually impossible in the market (Fama & French, 1996, 2004). However, when empirical tests identified flaws in the conventional models, some scholars began to research alternatives that would explain price movements. These theories emerged from a new scope of market dynamics: behavioral. A behavioral perspective analyses the market and its dynamics based on its participants. Proponents of behavioral models argued that the gap between prices and fundamental value of assets exists because of the subjective psychological decisions of investors (Barberis, 1997). Following several psychological studies where possible sources of inefficiency were identified, financiers began to develop financial models based on a psychological foundation.

### 2.2.4 Heuristics

Heuristics are simplifications of the assessment of probability, making people's decision-making processes faster and more comfortable (Cialdini & Goldstein, 2004). Heuristics are behaviors with a subjective psychological foundation, however, they are not always irrational since in some circumstances the marginal benefit from a decision without heuristics is not enough to compensate the assessment time of the full decision. In the financial markets, decision-making based on heuristics means that decisions are not made based solely on information, which contradicts assumptions of the EMH.

Heuristics is useful for solving daily and inconsequential problems, however, oversimplification is not effective in every situation, and may cause systematic errors (Cialdini & Goldstein, 2004; Cialdini et al., 1999; Kubilay & Bayrakdaroglu, 2016). Heuristics are mental shortcuts used to help in the decision-making process, and they have been identified not only in simple general decisions but also in more complex processes, such as investing (Cialdini & Goldstein, 2004). This study covers four key heuristics: conservatism, representativeness, overconfidence, and herding.

#### 2.2.4.1 Conservatism

Conservatism may be translated as aversion to change and loss. In this case, the impact of specific evidence is underestimated in favor of this aversion. This may encourage an investor to overestimate potential short-term losses and underestimate long-term returns and diversification profits. In practice, investors pay more attention to short-term volatility in their investments (Lam et al., 2010). Although it is not unusual for an average share to fluctuate a few percentage points over a brief period of time, a short-term investor may not react favorably to adverse changes. The same phenomenon can happen in the opposite direction when investors cannot correctly measure the long-term value of firms, which will retard the market reaction and it will take longer for the price to reflect the value of the asset (Daniel et al., 1998; Kahneman & Tversky, 1979; Lam et al., 2010). For instance, a firm's announcement of a strong earnings report will not be fully priced in the stock if the majority of investors make conservative decisions (Barberis et al., 1997). Although it is probable that the price will slowly converge towards its fair value, conservatism causes a differential between fair value and price. This behavior is the cornerstone of many models, and it is seen as a potential explanation for momentum (Daniel et al., 1998).

#### 2.2.4.2 Representativeness

Representativeness is the process by which people characterize general populations based on a small sample. (Barberis, 2003) claimed that people frequently make judgements on particular events based on stereotypes. Additionally, is indicated that the process is not exclusively unconscious and that some people choose to rely on representativeness to make decisions. While conservatism causes people to underemphasize the sample evidence, in contrast, representativeness causes people to overemphasise sample evidence (Daniel et al., 1998; Kahneman & Tversky, 1979; Lam et al., 2010). Representativeness does not cause problems by itself, and it can even be a good solution for trivial issues. Yet, it is important to note that frequent reliance on this principle can trigger a bias in which a large group of decision makers draws hasty conclusions by analysing a data sample that does not adequately represent the facts. In the literature, this is referred to as sample size neglect (Barberis, 2003).

An example of representativeness and sample size neglect in capital markets: investors that value stocks because of their excellent performance in previous months, assuming that the trend will continue, although analysis of a more significant period of historical data demonstrates that it is not a sound investment (Daniel et al., 1998).

#### 2.2.4.3 Overconfidence

Overconfidence is a psychological bias in which people overestimate their accuracy or the probability that a specific outcome will occur (Campbell, 2004; Lam et al., 2010; Shiller, 1999). Empirical evidence has indicated that decision makers tend to be overconfident about their judgments. This bias inflates self-esteem about skills and ability to successfully carry out a particular task. In some cases, a person's subjective belief in their judgment is higher than the scientific accuracy of those judgments (Barberis, 2003; Daniel et al., 1998; Kahneman & Tversky, 1979).

Several studies have indicated that events categorised by people as *certain*, actually only occur 80% of the time, while events categorised as *impossible* occur 20% of the time (Daniel et al., 1998).

This increased confidence, paired with self-attribution, can cause imperfections in the decision-making process. Self-attribution is a cognitive process that results in tendential attribution of successes to their own abilities and justification of their failures to external factors (Hong & Stein, 1997). These investors are also overoptimistic about their own abilities, which results in excessive trading above reasonable diversification standards (Parasuraman, 2003).

#### 2.2.4.4 Herding Effect

The herding effect has a significant impact on the decision-making process (Barberis, 2003; Hong et al., 2005; Schmeling, 2009; Shiller, 1999). Unlike the other heuristics referred earlier, herding results from one's relationship with surrounding factors and not from internal biases. Herding derives from the social proof principle which states that people tend to behave like their peers in order to reflect correctness (Cialdini & Goldstein, 2004; Cialdini et al., 1999). This kind of social influence can be observed in large groups that follow one another's decisions, right or wrong. In capital markets, an example of herd behavior is when no one wants to miss the opportunity of buying the next big thing (Cialdini & Goldstein, 2004; Cialdini et al., 1999). Similar to other heuristics, herding is not bad behavior on its own, but it can lead to erratic price estimations and speculative bubbles (Shiller, 2006).

It is believed that the repetition of crashes and crises in the financial market are due to ''crowd'' behavior that induces individuals to imitate the actions of larger groups, even when these actions are wrong or irrational. This bias has several causes (Schmeling, 2009; Shiller, 1999). First, there is social pressure for conformity combined with a desire to be accepted by a group, rather than being an outsider. Second, there is the collective reasoning that encourages investors to join the crowd with the belief that the crowd is right. The market reflects the interdependency of its participants and the market; each action affects market developments and vice-versa. There is a feedback relationship between the market and its participants (Barberis, 2003; Hong & Stein, 2005). The herd effect may become serious in times of crisis and high volatility.

### 2.2.5 Conclusions

Investor sentiment and psychology affect their decision-making processes, known as psychological biases (Cialdini & Goldstein, 2004; Cialdini et al., 1999). Because investors may make decisions not based solely on information, this is an inconsistency with the EMH.

Theories were developed in Finance based on investor behavior. Heuristics is an approach using small mental probabilities and fast, efficient rules in order to reduce mental effort during the decision-making process. While it can lead to correct decisions, it can also lead to wrong ones due to errors in judgment or psychological deviations (Barberis, 2003; Hong et al., 2005; Schmeling, 2009; Shiller, 1999). The heuristics most included in economic theories are Representativeness, Conservatism, Herding, Availability, Anchoring, Gambler's Fallacy, and Overconfidence.

In the markets, it is possible to observe the collective independent decisions of millions of investors. When these decisions are extreme or the trends are long-lasting, these heuristic behaviours can result in a financial crisis.

### 2.2.6 Theory of Overaction and Underreaction

It is noticeble that, of all the identified anomalies, momentum and reversals were by far the most challenging refutation of the EMH (Fama & French, 2008). This is due not only to the empirical evidence of superior returns without extra risks, but also because of the development of models that explained these returns through behavioural arguments.

After the discovery of momentum, a model was introduced to explain the discrepancies between price and fundamental value based on overreaction and underreaction (Barberis, 2003; Barberis et al., 1997; Breuer & Salzmann, 2014; Daniel et al., 1998). This particular model makes the following assumptions:

1. There are only one asset and one investor
2. The investor reflects the market forecast's consensus
3. The asset's earnings follow a random walk unpredictable to the investor
4. The assets earning has two possible stages: trending or mean reverting

In this model, if there is intercalation of negative news with positive news, then the consensual forecast for the market is the mean reversion. If there is a succession of good news, then the market consensus creates a trending state, increasing the amount invested in the asset, consequently creating momentum.

Alternatively, another model was developed to explain momentum phenomena through behavioural causes. Hong & Stein (1999) proposed a model that acknowledges that some investors are aware of momentum phenomena. The cornerstone of this model is the fact that the market contains two types of traders: news watchers that tend to underreact to new private information, and momentum traders that profit from the initial underreaction, causing the price movement to continue. The rationale of this theory is that private information is disseminated more slowly than in the competitive market, which complies with EMH. This theory was corroborated by empirical evidence that demonstrates an amplification of anomalies in firms with smaller media and analyst coverage (Daniel et al., 1998; Hong & Stein, 1997; Lam et al., 2010)

Although these two models work under different assumptions, their basic explanation of momentum is similar. Both assume an initial underreaction followed by correction and consequent overreaction (Barberis et al., 1997; Daniel et al., 1998; Hong & Stein, 1997). Not all behavioural models explain momentum in the same way. There is another model that divides investors into two groups: feedback traders and arbitrageurs. In practical terms, feedback traders buy assets that performed well during the previous 12 months, and the buying pressure increases the prices, creating a discrepancy between fundamental value and price (Barberis et al., 1997; Daniel et al., 1998; Hong & Stein, 1997). Arbitrageurs are aware of the trader's buying pressure and rather than creating selling pressure by short selling, they merely buy the asset and sell it at a higher price in the future (Barberis, 2003; Daniel et al., 1998; De Long, 1990; Neuzil et al., 2004). The combination of the actions of both groups is what drives momentum, according to the referred-to model.

Supplementary approaches were developed, one of them being a model that explains momentum through possession of private information. (Daniel et al., 1998) suggested that economic agents try to acquire private information about the future performance of firms, and due to overconfidence, those with private information overvalue it, increasing the disparity between fundamental value and price. This overreaction is corrected when public information is distributed to the masses, initiating mean-reversion in the long term. In the short-term, momentum is explained by investor’s biases, namely self-attribution and confirmation biases, which result in ignoring information that does not confirm their personal view. This retards the correction, meaning that the initial overconfidence is followed with further overconfidence in the short-term (Daniel et al., 2001; Daniel et al., 1998).

These models have in common their view that momentum is an anomaly that cannot be explained by additional risk. They offer behavioural explanations of momentum, only differing in the dynamics of the process. The models of Daniel et al. (1998) argue that the momentum effect is caused by overreaction followed by even more overreaction. Both Barberis et al. (1997) and Hong et al. (2005) argued that the momentum effect is caused by an initial under-reaction which is corrected later.

### 2.2.7 Prospect Theory

Another possible source of market inefficiency is the investor’s decision-making process. The EMH assumes it is a rational process, which has not been substantiated empirically (Barberis et al., 1997; Daniel et al., 1998; Hong & Stein, 1997). Conventional financial models assume that investors are rational and that their decisions are modelled on expected utility (EU). Subsequent studies have unveiled that the EU is not an accurate framework to describe investor preferences (Barberis, 2003). This said, one of the most realistic models outside of EU is prospect theory (Kahneman & Tversky, 1979). Prospect theory is an excellent fit because the theory was constructed based on empirical observations. Contrastingly, the EU was based on hypothetical rational behaviour.

Several differences can be found between EU and non-EU approaches. Prospect theory states that decision makers decide based on relative change and an EU framework states it is made based solely on final state wealth (Odean, 1998). In practice, investors are concerned with the difference between what they paid and the expected realised value.

Prospect theory assumes an S-shaped decision curve that is concave for gains and convex for losses (Kahneman & Tversky, 1979). Accordingly, this suggests risk aversion for gains and risk seeking for losses, prospect theory implies that massive losses affect the investors more than substantial gains. On the other side, the utility curve presented by the EU framework is smooth and concave, implying the same risk aversion for every interval (Kahneman & Tversky, 1979). The decision weight function is not linear in prospect theory. This implies that investors rely heavily on black swans[1] and disregard highly probable occurrences. Low probabilities are overstated while high probabilities are understated (Bogle, 2008; Godfrey et al., 1964).

[1] Black Swan: unpredictable or unforeseen event, typically one with extreme consequences.

### 2.2.8 January Seasonality

One of the observed patterns identified as evidence of momentum evidence is seasonality. Jegadeesh & Titman (1993) detected a seasonality effect in momentum returns. The Winner-minus-Losers (WML) portfolio had positive returns in all months except January, in fact, the WML portfolio delivered on average a negative 7% return in the first month of the year (Jegadeesh & Titman, 1993). Taxes may explain this effect. Investors tend to sell off their stock holdings with a negative performance over the last year in order to decrease tax expenses (Wachtel, 1942). Selling pressure drives the loser's prices even lower at the end of the tax year—a fact confirmed by high trading volume in December for shares that underperformed in the last 12 months. (Dyl, 1977) interpreted this as optimisation for tax purposes.

Since the mentioned sell-off is based on taxes rather than fundamentals, many investors are attracted by these dips in price that provide a lower cost-basis entry point. This stimulates a massive January buy-in, driving prices higher, resulting in a better relative performance of loser's prices. Lastly, given that the WML portfolio results in a long and short position of winners and losers, respectively, the sell-off in December and the sell-in in January grant a negative performance in January (Fama & French, 2008; Jegadeesh & Titman, 1993, 2011)

Similar to the other anomalies, the January effect has a greater manifestation in smaller firms since there is fewer media coverage and a smaller trade volume (Fama & French, 2008; Frazzini et al., 2014; Novy-Marx, 2016). Several studies have argued that market anomalies like weekend effect, holiday effect, and January effect have disappeared for large firms after the papers identifying the anomalies were published (Fama & French, 2008). However, it is not certain that the disappearance of anomalies is equally observed in large firms as it can to smaller ones (Marquering, 2006).

## 2.3 Empirical evidence

### 2.3.1 Behavioral Finance

Given the inconsistencies and anomalies in the financial markets that do not comply with the EMH, the academic community created behavioural models to explain the newly-observed dynamics of the capital markets (De Bondt et al.,2008). Further, (Kourtidis et al., 2011) argued that there it is necessary to understand the psychology of market participants in order to explain market abnormalities, such as asset price bubbles and crashes. This understanding will demonstrate, they argued, the efficiency of the financial markets.

These theories suggest that it is difficult to explain global financial markets without behavioural finance theory, and that the seemingly random transactions made by irrational market participants are explained by behavioural factors. These irrational market partakers can substantially impact price, especially if it happens for an extended period of time (Barberis, 2003). Behavioral finance focuses on psychological motivations of participants and takes into consideration the impact of inefficient market participants (Barberis, 2003). Traditional financial theories interpret participant choice as based on the goal of wealth maximization, however, behavioural finance focuses on actual behavior in financial markets (Kourtidis et al., 2011), including subjective psychological decisions. Behavioural finance is the study of the psychology of the market participants and their relationship with their financial environment (De Bondt et al., 2008; Shefrin & Statman, 2000; Statman & Anginer, 2008).

Several investing contradictions are not explained by modern portfolio theory which is premised upon rational and independent behavior. Modern portfolio theory, similar to CAPM and APT, assumes that investors are rational and independent, consequently, is rare to get abnormal returns in the market. The most important decision in modern financial theory is where investments will be allocated between the efficient market frontier and a risk-free interest rate. An assumption that participants make rational decisions implies that it is nearly impossible for anyone to consistently outperform the market in the long run; however, the investment community has a long history of investors who have outperformed the market consistently: Mr. Warren Buffett, Mr. Peter Lynch, Sir John Mark Templeton, Mr. Ginzo Korekawa, Mr. Andre Kostolany, Mr. Jim Slater, Mr. Jim Rogers, Mr. George Soros, Mr. Philip Fisher.

Due to these notorious successes, the academic community began to question the presence of positive alphas in a world where the market is efficient. Consequently, different schools in Finance developed a theory known as Behavioral Finance. The leading scholars of this movement were Kahneman, Danien, and Amos Tversky, whose studies focused on decision-making under uncertainty (Tversky & Kahneman, 1974) and Prospect Theory (Kahneman & Tversky, 1979).

At a glance, behavioural finance exposes and accounts for the fact that investors are not always rational. Possible sub-theories and biases are currently being developed within behavioral finance to help explain investors' behavior: prospect theory, loss aversion, disappointment, status quo bias, gambler's fallacy, self-serving bias, money illusion, cognitive framing, mental accounting, anchoring, disposition effect, endowment effect, inequity aversion, reciprocity, intertemporal consumption, present-biased preferences, momentum investing, greed and fear, herd behavior, and sunk-cost fallacy.

According to (Kourtidis et al., 2011), numerous behavioural factors influence investors in the capital market. As stated in Subrahmanyam (2008), evidence suggested validity in the assumptions of behavioural models. Additionally, evidence indicated that non-risk-based factors have more influence on predicting the returns than risk-based factors. The evidence also indicated that institutional investors are capable of taking advantage of observed patterns within the market. These facts are corroborated by the evidence that shows that irrational agents not only influence the market in the short term but also in the long term (Subrahmanyam, 2008). However, the fact that these suggestions demonstrate market inefficiency and predictability of patterns does not guarantee large excess returns to individual participants.

According to behavioural finance, the main factors that affect the investment decisions of individuals are psychological biases (Breuer et al., 2014; Camerer, 1997; Kumar & Goyal, 2015). The outcome of decisions made due to psychological biases might be inefficient decisions or rational decisions not based on information, as the EMH predicted, but on intuition and feeling. The tenets of behavioural theory have implications for the conventional financial models, especially the EMH. In conventional models, it is assumed that information moves the markets and that decisions are made upon quantitative measures such as reward-to-risk ratios. Instead, in practical terms, decisions are often based on interpretation of information and the psychological heuristics referred to earlier (Cialdini & Goldstein, 2004; Daniel et al., 1998; De Bondt et al., 2008).

Very often, investors are not aware of their irrational behaviours. When investors are aware, they tend to make more conscious financial decisions. Hence, awareness of failures in perception increases the quality of decisions. Therefore, the maintenance of wealth is more likely to happen when an investor knows their own biases and tendencies (Kourtidis et al., 2011; Kubilay & Bayrakdaroglu, 2016; Parasuraman, 2003).

Scholars have researched the effect of behavioural biases, personality traits, personal control, and cultural factors on attitudes toward risk of individual investors (Daniel et al., 1998; Kourtidis et al., 2011; Kubilay & Bayrakdaroglu, 2016; Parasuraman, 2003). There is a strong relationship between personality characteristics and risk-taking, suggesting that prospect theory fails to estimate individual behaviours (Breuer et al., 2014; De Bondt et al., 2008; Shiller, 1999).

In sum, Behavioral Financial Theory is a response to the inability of conventional financial models to adequately describe market and individual behaviours. This theory acknowledges that decisions are not made equivalently in different individuals and it is not only information that controls the market. Behavioural finance theory also explains and describes what are considered to be anomalous events by traditional theories. This theory continues to be relevant not only because it explains how investors behave, but also because it offers new investment approaches.

### 2.3.2 Significant Price Momentum

Some existing literature and empirical evidence suggest the existence of the momentum effect in capital markets. In 1993, the pioneers of momentum studies, Jegadeesh and Titman, documented the momentum effect in the NYSE and AMEX between 1965 and 1989. Additionally, the authors provided a decomposition of momentum profits into its different sources and evaluated the relative importance of each source. The results demonstrated that profits are not due to the systematic risk of trading strategies. This evidence was supported in Conrad and Kaul (1998), which demonstrated that a broad range of trading strategies performed within the NYSE and AMEX stocks between 1926 and 1989 yielded statistically significant profits. They suggested that the source of this momentum effect was cross-sectional variations in expected returns rather than time-series dependence in returns. However, Jegadeesh and Titman (2002) claimed that Conrad and Kaul failed to account for sample biases in their tests. Furthermore, Jegadeesh and Titman (2002) provided unbiased empirical tests that indicated that cross-sectional differences in expected returns explain momentum profits only residually.

After these developments, several international studies were conducted and, in 2010, Emilios C. Galariotis investigated Australian momentum strategies and their performance stability during different time periods and market states. Galariotis' study applied his methodology to two independent samples, the first one based on the S&P/ ASX 200 constituents and the other on all equities in Australia. The main difference between the samples is that in the S&P/ASX 200 there are no liquidity issues while the market as a whole englobes many small and illiquid stocks (Galariotis, 2010). The results of this study confirmed momentum returns in the medium term in the Australian stock market, and that momentum performance was not related to sample biases. The results were in line with previous studies, with all 16 momentum strategies providing statistically significant returns ranging from 1,58% to 2,70% (Galariotis, 2010). The magnitude of the returns was higher when the strategy was applied to firms with higher market capitalisation, suggesting that the focus on the 200 biggest stocks should be optimal for momentum traders (Galariotis, 2010). Although returns remain positive in a crisis, they are significantly lower due to the negative performance of short positions on the loser.

More recently, Christopher C. Geczy published two separate studies that provided empirical evidence on price momentum for extended sample periods. In 2015, the author extended the price return momentum tests to the longest available histories of global financial asset returns, including country-specific sectors and stocks, fixed income, currencies, commodities, as well as U.S. stocks. He created a 215-year history of multi-asset momentum, thus confirming the significance of the momentum premium inside and across asset classes (Geczy, 2015). In 2016, the same author created a monthly dataset of U.S. security prices from 1801 and 1926. This data set made possible both in-sample and out-of-sample tests of momentum strategies, and the author demonstrated that price momentum has been significant since the beginning of the 19th century in the U.S. securities markets. The dataset includes 47 country indices, 48 currencies, 43 government bond indices, 76 commodities, 301 global sectors, and 34,795 U.S. stocks.

The results of the Geczy study suggested strong momentum returns across all the asset classes. Additionally, with the portfolios providing significant alphas, the returns were affected by changes in the different states of the market. Moreover, it was found that there are no reversals in the short-term and there are consistent long-term reversals for all asset classes. Finally, even with robust momentum related returns, it is essential to acknowledge the decade-long subperiod when the long-shorts momentum returns are negative (Geczy & Samonov, 2016).

### 2.3.3 Residual Price Momentum

Momentum has been demonstrated in several empirical tests. In the decades following the first scientific documentation of momentum, the existence of momentum strategies has shown consistent out-of-sample success when examined across geography, asset class, security type, and time. Nonetheless, there is one very remarkable exception. Several authors have documented that momentum does not present statistically significant positive returns in Japan.

One of the studies on the effectiveness of momentum strategies in the Japanese stock market explicitly was (Liu & Lee, 2001), which took into consideration the period of 1975 to 1997. The major conclusions of this research were: the momentum strategy portfolios that invest in past three-to-twelve-month winners and sell past three-to-twelve-month losers will go on to lose about 0.5% per month over the subsequent three to twelve months. This study demonstrates that the Japanese stock market has a different dynamic in the short and medium-term horizons, in that the prices are more likely to reverse than continuing the trend.

In 2001, a study was published which examines momentum profits in eight Asian markets with a focus on ownership structure, legal systems, and valuation uncertainty (Chui et al., 2001). The results revealed that momentum strategies, which buy past winners and sell past losers, are highly profitable when implemented in Asian stock markets outside Japan. It also documented that the momentum effect is stronger for independent firms than for group-affiliated firms. This study also presented weak evidence suggesting that foreign ownership can influence the momentum effect in Japanese firms (Chui et al., 2001). In Fama and French (2011), four regions (North America, Europe, Japan, and the Asian Pacific) were studied, and the results determined that Japan may be an exception to the momentum effect because, value premiums decrease with size, except for Japan and all the regions present positive momentum returns except Japan.

More recently, in (Moskowitz et al., 2013), evidence was provided on the use of value and momentum strategies globally, across asset classes. The focus of the study was the strong correlation between value and momentum strategies across diverse asset classes. The researchers compared this with current behavioural theories, and the results suggested that momentum premia is positive in every market, especially in Europe, but is statistically insignificant in Japan (Moskowitz et al., 2013).

### 2.3.4 Price Momentum with Positive Profitability

Price momentum is a well-studied effect in the capital markets. There is plenty of empirical evidence demonstrating its positive and significant profitability. Since the pioneer studies of Jegadeesh and Titman (1993), scholars have studied this phenomenon several times, for instance, Rouwenhorst (1998) found similar momentum profits in the European markets, and Moskowitz and Grinblatt (1999) found momentum profits across portfolios sorted by industry.

Momentum studies are relevant and attractive because of the consistent profitability of the strategy poses a challenge to the efficient market hypothesis. In fact, Jegadeesh and Titman (1993) found that the most profitable strategy is the 12 x 3 time-window: the stocks are selected based upon the performance of the last 12 months and are held for 3 months. The monthly return for the strategy is

1,31% without a time gap between stock selection and portfolio composition. The same strategy returns 1,49% when there is a lag between the selection and holding periods. The strategies recommending a 6-month selection period present a consistent return of about 1%, independent of the holding period. A 6X6 strategy was highly scrutinised by the authors, and provided a compounded return of 12,01% yearly (Jegadeesh & Titman, 1993). The returns were assessed to find possible sources, and the findings demonstrated robust seasonality in momentum returns, with winners outperforming losers in every month with the exception of January.

Additionally, Jegadeesh and Titman (1993) rejected the hypothesis that the return is justified by systematic risk. From the individual investor's standpoint, the risk-adjusted return with transaction taken in account is 9,29% on a yearly basis, which is statistically different from zero. This said, Jegadeesh and Titman concluded that the EMH could unequivocally be rejected in light of their findings.

An alternative study emerged in 1998 from Conrad and Kaul, and its results led to the conclusion that the momentum effect is in its majority, due to cross-sectional dispersion variation in mean returns. Consequently, the momentum effect can also be observed in a market that verifies the hypothesis of random walk (Conrad and Kaul, 1998). The periods of formation and holding comprised an interval of between 1 week and 36 months. Of a total of 36 strategies implemented, 21 presented statistically consistent positive returns, and 11 and 10 momentum and contrarian strategies respectively. Strategies that ranged from 3 to 12 months presented positive and significant returns, which is in line with the results obtained of Jegadeesh & Titman (1993). The most profitable strategy was demonstrated to be the 9x9 time-window from 1962 until 1989, with a 0,71% average return per month. A significance test for each period demonstrated the profitability of momentum-based strategies in the medium term (3-12 months) are profitable, excepting during the period from 1926 until

1947, in which contrarian strategies were successful. Finally, the study observed that contrarian profits were confined to the long-term (above 12 months) (Conrad & Kaul, 1998).

In 2011, Jegadeesh and Titman again studied the momentum phenomenon. This time, their goal was to work with liquid assets in the sample, which resulted in the exclusion of penny stocks and firms with low market capitalisation. From 1990 to 1998, the WML portfolio delivered 1,39% on a monthly basis. Their results revealed statistical significance at 1%. The study concluded that winners and losers' portfolios contributed similarly to momentum profits. Therefore, these results reinforce that early observations of the momentum effect were not a casual pattern in the data. They again reinforced the presence of inefficient behavior in the markets.

In 2008, the creators of EMH, Fama and French, acknowledged that there are patterns in stock returns that cannot be explained by CAPM. In the study, the regressions demonstrated that the size effect primarily has influence over microcaps. It was identified as an inverse relation between returns and asset growth (Fama & French, 2008).

### 2.3.5 Price Momentum with Null Profitability

In some cases in the markets, momentum presents statistically significant returns that are so limited that they are almost null. According to the empirical evidence, these limitations arose with the trading costs and the capacity constraints of momentum strategies. Lesmond et al. (2004) studied the profitability of relative strength or momentum trading strategies—buying past strong performers and selling past weak performers. The study suggested that standard relative strength strategies require frequent trading in disproportionately high-cost securities, such that trading costs prevent successful strategy execution. In the cross-section, it was found that stocks that generate large momentum returns are precisely those with high trading costs (Lesmond et al., 2004). The study concluded that the magnitude of the abnormal returns associated was diminished within markets where trading costs are very high. Alternatively, studies on the profitability of momentum strategies indicated that positive returns remain even after consideration of market friction. Intraday data measured proportional and non-proportional trading costs (Geczy et al., 2014).

Models that study the price impact of trading costs have suggested that abnormal returns decline with portfolio size; therefore, it is possible to calculate the break-even fund size that returns zero abnormal returns. The comparison between equal and value-weighted momentum strategies demonstrated that a portfolio that optimizes trading costs is a liquidity-weighted strategy. The results also showed that equal-weighted strategies had the best performance before trading costs and the worst after. The portfolios with the largest capacity for momentum strategies are liquidity-weighted and hybrid liquid/value-weighted portfolios, with a break-even of $5 billion. In other words, before the opportunity for momentum gain vanishes, it is possible to invest $5 billion (Geczy et al., 2014).

More recently, an article studied the after-trading-cost performance of anomalies and the impact of transaction cost mitigation. According to the data, the most efficient way to protect against trading costs is to introduce a buy/hold spread (Novy-Marx, 2016). Anomalies with a turnover lower than 50% per month generate significant net spreads when planned to mitigate transaction costs. It was also documented that the addition of new capital reduces strategy profitability with an inverse proportion to turnover. Moreover, strategies that were constructed based on size, value, and profitability have the largest capacity to receive new capital. Conclusively, transaction costs always reduce strategy profitability, increasing data-snooping concerns (Novy-Marx, 2016).

### 2.3.6 Price Momentum with Negative Profitability (Contrarian Profits)

The timing of trend reversals is still one of the most pressing unexplained characteristics of momentum strategies. In a trend reversal, a momentum inverts in the long term, and winners become losers and vice-versa. Consequently, the portfolio WML have a negative performance, generating profits for those on the other side. (Antoniou et al., 2006) documented the short-term contrarian profits and their sources within the London Stock Exchange. This study investigated the sources using the Fama and French (1996) three-factor model. Claiming that contrarian strategies for short-term horizons are profitable and more evident in the extreme capitalizations of the stock market. The profits prevailed even after accounting for market frictions, risk, and seasonality, and were documented for both equally and value-weighted portfolios. The authors proposed that the driving force of contrarian profits is the investor's overreaction to firm-specific information (Antoniou et al., 2006).

Additional international empirical evidence came from a study focused on the Athens Stock Exchange (ASE) (Galariotis & Spyrou, 2005). The results of this study concluded that the serial correlation is observed in equity returns, causing significant contrarian returns in the short term. Additionally, the contrarian profits are made larger through overreaction to the firm-specific factors than through underreaction to the common factors.

Dechow and Sloan (1997), examined the causes of the relationship between naïve investor expectations and positive returns of contrarian investment strategies. The authors found that stock prices appeared to reflect analysts' biased forecasts of future earnings growth naïvely. It was suggested that naïve belief in analysts' forecasts of future earnings growth could be responsible for more than 50% of high contrarian profits (Dechow & Sloan, 1997).

Jegadeesh (1993) examined the contribution of stock price overreaction and delayed reaction to the profitability of contrarian strategies. The evidence indicated that stock prices overreact to firm-specific information but react with a delay to common factors. Delayed reaction to common factors leads to a size-related lead-lag effect on stock returns. The article concluded that most contrarian profit is due to stock price overreaction and a small fraction can be attributed to the lead-lag effect (Jegadeesh & Titman, 1993).

A study from 2007 focused on the profitability of contrarian trading strategies within the Tokyo Stock Exchanges (TSE) with holding periods varying from 1 month to 3 years. Contrary to data found in the U.S and Europe markets, the Japanese Stock Market was found to deliver contrarian profits during all tested time periods. Conclusively, this study attributed contrarian profits to the lead-lag effect (Wei, 2007).

### 2.3.7 High-Tech Sector

Empirical evidence has demonstrated the dynamics of the high-tech sector and its consequential imperfections. Start-ups and high tech firms have limited access to debt as a financing source, so in these conditions, the most used and most essential funding source is new equity finance, which supports growth in high tech-firms (Carpenter & Petersen, 2002). There are three primary reasons for the financial imperfections in publicly traded tech companies. First, the high uncertainty of the financial outcome of R&D projects skews the returns and increases volatility. Second, there is a wide information gap between insiders and outsiders in high-tech firms. Even attempts at educating outsiders do not solve this asymmetry, due to insiders' limitation of information dissemination. High-tech firms prefer secrecy over patents to protect their business (Carpenter & Petersen, 2002). Third, high-tech firms depend heavily on intangible assets that offer limited collateral value. Commonly, research and development have a diminished salvage value in case of failure.

Conclusively, the Carpenter and Peterson study found that small and medium-sized high-tech firms make deficient use of debt as a financing source (2002). This has led high tech firms' dependence on new equity financing through an initial public offering (IPO). An IPO dramatically transforms firms, increasing their size (Carpenter & Petersen, 2002). High-tech firms, especially small ones, have financing constraints that are relaxed by raising capital on capital markets, which leads to a high volume of IPOs and the inability of outsiders to access the firm value—which leads to market imperfections. The tech industry tends to be fertile in misinterpretation and judgement based on intangible features. Therefore, the probability of momentum returns in this sector is higher than in sectors where firms are predominantly asset-in-place.

This study concluded that the momentum effect would appear more frequently in firms with high capitalisation (which are hence more liquid), within industries that individual investors find difficult to understand, that rely on intangible assets, in countries with volatile economies (Galariotis, 2010; Sagi & Seasholes, 2007). Additionally, there is no definitive theory to explain this phenomenon, but it is suggested that it is a combination of risk factors and behavioural factors. The data sufficiently demonstrates that momentum-based strategies provide positive returns across different countries, assets, and periods, defying the Efficient Market Hypothesis (Jegadeesh & Titman, 2011). Lastly, the momentum effect is an anomaly that has not disappeared since it was first observed. According to several studies, the main explanations for the effect is the high significant and arbitrage risk. The cost of arbitraging momentum is high.

Recent empirical evidence does not confirm the capacity constraints, stating that momentum strategies are more scalable than anticipated (Ratcliffe, 2016). The institutional investors who are more prominent money movers in the market are not fully able to engage in momentum trading, leaving the momentum strategies to the rest of the market. Also, the crowding effect has not been verified, because there are only a small number of funds applying factual momentum strategies (Noel et al., 2014).

## 2.4 Context of the Research

The era of 2001-2017 was remarkable due to the successive banking bailouts and the Keynesian Stimulus of government deficits, allied to the efforts of the Federal Reserve to maintain low-interest rates low, resulting in near-zero rates. These programs played a major role in economic recovery, helping households to pay down debts. This recovery resulted in real GDP level peaking by 2011, the household net worth reaching pre-crisis levels in 2012, and the unemployment rate recovering in September 2015. Public debt as a percentage of national debt rose in the 21st century, growing from 31% in 2000 to 52% in 2009. Public debt achieved the milestone of 77% of the GDP in 2017, and income inequality peaked in 2007, yet the U.S. still ranked 41st among 156 countries in 2017.

The outcome was that in 2017, the nominal GDP reached $19,5 trillion. The U.S. GDP comprises 70% personal consumption, 18% business investment, 17% government expenses, and a trading deficit of 3%. The growth of the U.S. GDP, according to the World Bank, was on average 1.7% from 2000 to the first half of 2014—50% lower than the period before. This slow growth can be attributed to ageing demographics, slower population growth, and growth in labour force, slower productivity growth, reduced corporate investment, greater income inequality reducing demand, lack of major innovations, and reduced labour power.

The object of this study is the tech sector in the United States; the sample is composed of 200 firms with the highest market capitalisation listed in the U.S. The firms were chosen according to their classification as Technology within the

Industry Classification Benchmark (ICB) system. Technological companies are a crucial part of the American markets, information confirmed by the fact that the five most prominent firms in the U.S. are technological firms. The five most significant players in the technology sector and respective market capitalisations are Apple with $926,9 billion, Amazon with $777,8 billion, Alphabet with $766,4 billion, Microsoft with 750,6 billion and Facebook with $541,5 billion.

Market performance, taking into account the index Nasdaq 100 as a proxy for the market, since its creation in 1988, the index returned 11,44% on an annual basis. The tech sector is known for its volatility and disruption in the real world by the incremental advances achieved by tech firms. As of the year 2018, the central firms with space for development are cloud computing, flexible consumption, machine learning and AI, DATA and cybersecurity. Given the highly competitive environment, the firms opt to develop business cooperation, M&A activities, and venture to invest.

Regulation is a practical matter in this sector. The model of ''self-regulation'' has failed to result in big scandals like recent privacy issue involving Facebook. The inability of policymakers to understand and access all the essential factors of the industry make regulations inadequate, and, the attempts in applying law combined with the lobbying power of big firms made regulation an issue. The complexity and systemic importance of technology, in fact, supports the need for a stricter approach to regulation. Ideally, the coordination of the administration with tech experts would create similar regulation across the U.S. regarding the most crucial issues. Further developments will determine if this is possible or not.

The trading rules applied in the sector are the same as those applied by the Security Exchange Commission (SEC) in other sectors. The government subsidises the high-tech sectors; these subsidies come in the form of tax-breaks attributed to job creation. In practice, when firms expand across the U.S., they are likely to receive tax breaks. For example, data centers for Apple, Amazon, Facebook, Google, and others have secured tax breaks.

Therefore, the United States and European economies have had very different developments in recent years. On the one hand, the American economy grew by between 0% and 5%, while Europe had a more modest growth between 0% and 2,5%. In the tech field, the U. S. leads the race, even with Europe trying to close the gap with Silicon Valley. In 2017, European venture capital firms completed a total of approximately $15 billion, and the amount invested by VC companies was $71,94 billion. 2017 was more productive in Europe than the U.S. in terms of IPOs, with 217 and 182 Initial Public Offers, respectively

An important case that should be discussed is the gap caused by the financial crisis during 2007 and 2008. American wealth declined by 20% during this crisis, and the S&P500 lost almost 45% of its value. The total equity was valued at $13 trillion in 2016 and dropped to $8.8 trillion in mid-2008. During this time, savings and investments lost $1,2 trillion and pension funds lost $1,3 trillion. The total losses across all assets reached $8,3 trillion (Roger, 2009). The 2007/2008 crisis represented a loss of $7.7 for the stock market across the world. The growth of the American GDP decreased from 2,9% to 2,2%. The main financial institutions began to lower rates of all kinds. For instance, the IMF forecasted growth was 1,9%, which decreased from 2,8%.

Moreover, the IMF estimated that, in 2009, American and European banks lost $1 trillion due to bad debts and toxic assets. These losses totaled $2,8 trillion during 2007 and 2010. During a market crash, the conditions that determine behavioural financial decisions change, and some phenomena are no longer available.

Tech stocks were the biggest winner in recent years, presenting gains in every year with the exception of 2008. The sector’s performance makes it very attractive for several types of investors, more so than more stable consumers’ stocks. A few large firms primarily trigger Tech's outperformance, notably, Apple, Microsoft, Alphabet, Amazon and Facebook delivered outstanding returns for their investors. The reason for this growth is the cash cow business models with a high conversion of revenue to cash, which is later used for dividends, share buybacks, and acquisitions. Interestingly, the largest firms by market cap have a larger weight within the sector-based indexes, meaning that the gains of the largest companies have a larger impact than those of the smallest.

According to modern portfolio theory, smaller stocks are expected to outperform larger stocks in the longer term, but this was not the case during the past 10 years. Specifically, in the tech industry, winners kept winning. For example, in 2018, shares of Apple, the largest company on American exchanges, is worth nearly two times what it was in May 2016.

## 2.5 Hypothesis

H1: It is profitable to execute momentum strategies, buying winners and selling losers, within the United States Tech Stocks.

This position is founded on the conclusions of the existing literature, including empirical evidence and context. First of all, is doubtful that conventional models can explain and capture behavioural biases and decisions (Kumar & Goyal, 2015). In addition, the momentum effect is an anomaly that has prevailed over time since its documentation and traditional models do not offer a reliable explanation of this phenomenon (Fama & French, 2008; Grossman & Stiglitz, 1980; Jegadeesh & Titman, 2011).

In response to a gap between theory and practice, academics have developed behavioural models that reflect and explain the possible causes of anomalous phenomena (Statman et al., 2008; Subrahmanyam, 2008). These models have demonstrated that certain anomalies appear in the market due to lack of efficiency in the markets. Included in these imperfections are: under and overreaction, conservatism, representativeness, and the herding effect, all of which demonstrate the weaknesses of the assumptions of the EMH (Cialdini & Goldstein, 2004). Moreover, the momentum effect is evidently active in the tech sector because anomalies are magnified when there is more likelihood for misinformation, over-enthusiasm, and misinterpretations that lead to disparity between real value and price. Given that the high-tech sector is susceptible to disruption, intangible assets, and over-enthusiasm, it these characteristics will result in a strong momentum effect (Carpenter & Petersen, 2002; Deng et al., 1999).

Empirical evidence has repeatedly demonstrated that momentum strategies that imply buying winners and selling losers deliver statistically significant positive returns. This evidence incorporates data from international markets such as the United States, Europe, Australia, and Japan (Antoniou et al., 2006; Geczy et al., 2014; Ritter, 2003). The primary exception is the Japanese stock market, which does not experience the momentum effect. However, given that the subject of this study is the United States Tech Sector, this exception does not represent an obstacle for this study. The robustness of momentum profits is not its only benefit; the data shows that momentum is also present in a time-series base and across different types of assets (Geczy, 2015; Geczy & Samonov, 2016; Jegadeesh & Titman, 2002). Several studies analyzed tech stocks in the past, so it is foreseeable that when studied on a standalone basis, the technological sector of the United States will also present the momentum effect.

Lastly, this study is well-timed given the social and economic conjecture of recent years. First of all, the sample period for this study begins in 2008, which is when tech stocks overcame the lack of trust caused by the Dotcom bubble. Moreover, 2008 marked the beginning of the bull market that extended until 2018, the longest in history. This growth was stimulated by globalization, the shift in demand for technological goods, and the Federal Reserve, given the quantitative easing performed in the same period. The general trends of the last decade are cloud computing, shared services platforms, social networks, and artificial intelligence. The fast-paced expansion of the technology sector with the constant creation of new technologies, allied with easy access to debt, created the conditions for misinterpretation and overenthusiasm around the tech stocks which is a powerful indicator that this sector is the perfect environment for observation of the momentum effect.

# Chapter 3

# 3. Data and Methodology

## 3.1 Data

The used data for this study is characterized as secondary data. This aspect of the study makes it easier to perform and execute assuming that 10 years of data were collected.

In order to determine if the momentum effect exists in the U.S. high-tech sector, observation must be conducted on stocks traded in the primary exchanges of the country, namely NYSE and NASDAQ. The information needed to calculate the stock returns is accessible through the Thomson Reuters Datastream.

Datastream is a global financial and macroeconomic data platform providing data on equities, stock market indices, currencies, company fundamentals, fixed income securities and key economic indicators for 175 countries and 60 markets. This database is developed and commercialized by Thomson Reuters, a multinational mass media and information firm.

For the price's momentum, the retrieved data from the database are the daily closing prices from 2008 to 2018 for the selected stocks.

The stocks were screened first by their industry classification according to ICB (Industry Classification Benchmark). The chosen filter was 9000 and it broafdly represents all stocks related to technological activities. The technology industry can be divided into two sectors: Software & Computer Services and Technology Hardware & Equipment, according to the ICB. The outcome of this filtration process was approximately 30,000 publicly traded firms. For each company, the stock prices were gathered daily for the period from January 2008 to January 2018, 10 years in total. This sample period length is in line with previous research; Jegadeesh and Titman (2001), for example, conducted an observation of an eight-year period from 1990 to 1998 to support their results.

However, the initial selection included stocks that were not listed during the entire studied period, so, in order to avoid missing values in the sample another refining process was performed, and the firms that were not listed in the full period were dropped, resulting in a smaller sub-sample of 745 firms.

Lastly, to avoid selecting non-liquid firms, stocks were controlled by the size, using market capitalization as a proxy, and the 200 biggest companies were selected as the sample for the study, is relevant to acknowledge that these 200 stocks are a quite small percentage in relation to the whole tech market. Consequently, it should be taken into account this fact when analyzing momentum returns, specially the losers' portfolios, since they may not be representative of the absolute worst performers within the market.

The market cap on Datastream is the share price multiplied by the number of ordinary shares outstanding. Excluding the dead stocks from the sample will influence the results. However, so possible survivorship bias should be taken into account when interpreting the results.

Stocks are delisted for several reasons. Grundy and Martin (2001) documented that winners are delisted due to a merger or takeover and the observed superior performance during the formation period is partly attributable to information about the acquisition. On the other hand, loser stocks are frequently delisted due to bankruptcy or other negative performances. It is unpredictable whether observations of the momentum effect will be biased upwards or downwards, given the survivorship bias.

In order to access trading strategies based on momentum in relation to a benchmark that allows for comparison and conclusion about the profitability of momentum strategies, NASDAQ 100 was used as a benchmark for tech market performance. It is assumed that if the investors are not actively trading, they can obtain market performance by allocating capital in an exchange-traded-fund (ETF). NASDAQ 100 is a traded index and contains 34 technology stocks.

The nature of momentum returns combined with the goal of the study make necessary a quantitative approach. Only a mathematical approach enables results comparison and unbiased conclusions.

## 3.2 Variables

Since the focus of this study is the profitability of momentum strategies, it was necessary to calculate the returns of the stocks in the sample. There are two possible methods to calculate the returns: discrete or continuous compounding. There is no significant mathematical difference between these two methods, although they each present different property. Empirical evidence has demonstrated that the difference in returns is usually minor (Raahauge, 2008). In this investigation, continuous compounding was used due to its mathematical advantages. Returns for several periods were obtained by addition instead of multiplication, which is easier to apply and offers statistical advantages (Koutmos, 1997).

Nonetheless, continuous compounding does have one disadvantage. The simple return of a portfolio is a weighted average between the asset's return and its relative weight; however, this is not the case for continuous compounding. This does not represent a problem in this study because the time-window is quite short. Studies in the past have used continuously compounded returns to study stocks (Koutmos, 1997).

The natural logarithmic return for a single-period for a given stock in time t is denoted as and defined as:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

$$\text{where } P_{i,t} = e^{r_{i,t}} \times P_{i,t-1}$$

Specifically, in this case, the single-period returns represent monthly returns (Platen & Sidorowicz, 2007). The compounded return for the momentum strategy with k periods is denoted by Cr and is defined as:

$$Cr_{i,t}(K) = \sum_{t=1}^{k} r_{i,t}$$

After this calculation, the ranking process began. Stocks were ranked based on their compounded returns $Cr_{i,t}(K)$ and the winner (W) and loser (L) portfolios were formed by the 10% best and worst performing assets, respectively (Platen & Sidorowicz, 2007). The equally weighted portfolios of *N* stocks have the following return calculation:

$$Cr_{P,t}(K) = \frac{1}{N}\sum_{t=1}^{k} Cr_{i,t}\,(K)$$

To calculate the return of the momentum strategy (M), it is necessary to subtract the loser portfolio from the winner:

$$Cr_{M,t}(K) = Cr_{W,t}(K) - Cr_{L,t}(K)$$

The average monthly return of the momentum strategy was calculated by dividing the average of all momentum portfolio during the sample period by the length of the holding period (H) (Platen & Sidorowicz, 2007). The monthly average return is denoted MR and calculated as follows:

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

## 3.3 Methodology

The chosen methodology for investigation of the momentum effect was drawn from Jegadeesh and Titman (1993). This makes the study comparable with past research, increasing its relevance in the field. The stock returns of the created portfolios were observed based on their past 6-month performance. This is referred to as the *formation period*, and the *holding period* will also be six months. The 6x6 window will be the only one used in this study in order to clarify the analysis. Additionally, the 6x6 window has often been studied on a standalone basis, giving it a central position in the spectrum of price momentum.

### 3.3.1 Portfolio Size

There are a variety of methods that can be applied to determine portfolio size. On the one hand, in the studies of Jegadeesh and Titman (1993) and Rouwenhorst (1998) stocks were grouped in ten decile portfolios. On the other hand, Asness et al. (2013) distributed stocks into the top third and bottom third. The stock's relative weight in each portfolio has implications for transaction costs and overall returns (Asness et al., 2013). Stocks are allocated into ten decile portfolios and, given the size of the sample, the result will be always 10 portfolios of 20 stocks each. In this way, the winner portfolio will comprise the top 10% of performers and the loser portfolio will comprise the worst 10%. This approach is similar to the one used by Jegadeesh and Titman (1993) and it resembles the portfolios created by individual investors.

(Campbell et al., 2001) documented an increase in firm-level volatility relative to the market. The highest levels of volatility imply that the correlation of the individual stock returns has decreased. Consequently, the volatility of the market portfolio remains the same even when the individual volatility of each stock has increased. This reflects the benefits of diversification, more now than ever. Thus, in order to reduce exposing the portfolios to idiosyncratic risk, the portfolios have a total of 20 stocks. This means that the strategies will be heavier in transaction costs, but the benefits of diversification will outweigh these costs.

### 3.3.2 Weighting

Looking at past studies, it is clear that the predominant stock weighting technique is the Equally Weighted approach. Equally weighted portfolios were used by several significant studies (Galariotis, 2010; Jegadeesh & Titman, 2011; Rouwenhorst, 1998). In contrast, the relatively weighted portfolios based on market capitalization or performance were used in Conrad and Kaul (1998). The advantage of a market cap weighting is that small stocks that are less liquid, hence more expensive to trade, have a relatively small weight in the portfolio (Swinkels, 2004). Nonetheless, within markets with large corporations, portfolios will heavily rely on these big firms.

In order to obtain comparable results with past studies, the portfolios were equally weighted, following the approach of Jegadeesh and Titman (1993; 2002). Since the sample is quite homogeneous in firm size and liquidity, there is no advantage to using relative weights.

### 3.3.3 Formation Periods

In terms of the formation and holding periods of time windows, the literature points to unanimous results. Initial findings suggested that momentum returns are positive and significant in the first 12 months after the formation period; however, the momentum effect reverses in the period of 13 and 60 months after formation (Jegadeesh & Titman, 2001). The standard approach in price momentum studies is utilizing three, six, nine, or 12 months for the formation and holding period. For the purposes of this study, the analysis only used the 6x6 strategy. In practice, stocks were sorted based on their performance over the last 6 months, and portfolios will be formed and, later, will be held for a period of 6-months. The WML (winner minus loser) portfolio was determined by taking a long position in the best-performing stocks and a short position in the worst performing stocks.

### 3.3.4 Overlapping vs non-overlapping periods

Strategies can be studied with overlapping and non-overlapping periods. Notorious studies such as Rouwenhorst (1998) and Jegadeesh and Titman (1993, 2001) used overlapping holding periods. Overlapping holding periods result in a monthly revision of portfolios; for example, an initial investment in the top decile from January until June is followed by a similar position from February until July. The main advantage of this method is the enhanced power of the statistical tests due to an increased number of observations (Jegadeesh & Titman, 1993). In a non-overlapping method, a new portfolio is formed when the previous one has been liquidated. The major achievement of non-overlapping is that the investor only holds one portfolio at a time, engaging in less trading and supporting less trading costs.

Overlapping periods were used for comparison. Not only was this method widely in most comparable studies, but also it permits augmentation of the number of observations in the 10-year dataset. Therefore, robustness tests were stronger.

### 3.3.5 Statistical Significance

In order to determine if the results occurred by chance, statistical tests were executed. Since it is possible there will be positive returns in the loser portfolio and negative returns in the winner portfolio, a two-sided t-test is the most appropriate way to test the relevance of the results. For the two-sided t-test, the null hypothesis assumes the test value of zero. Consequently, rejecting the null hypothesis means that the results are statistically different from zero (Fisher & Box, 1987).

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

*Where: r is the mean value of the sample,* μ *is the value we are testing r against,* $\boldsymbol{\sigma}$ *is the standard deviation of the sample and n is the size of the sample.*

To determine if the results are statistically significant, the t-values were tested against the critical values given by the t-student distribution. Each t-value is tested at a 10%, 5%, and 1% significance level. Test values at the 10% level will be marked with 1 star (*), 5% significance level will be marked with 2 stars (**) and finally, 1%will be marked with 3 stars (***).

## 3.4 Software

Microsoft Excel was used to process data. Excel is a spreadsheet developed by Microsoft for Windows, macOS, Android, and iOS (de Levie, 2004). It features calculation, graphing tools, pivot tables, and a macro programming language called Visual Basic for Applications (Ravindra, 2008).

Since the dataset is extensive and the process is mechanical, the study required a resourceful technique to perform calculations. The output of this study included 210 different portfolios, which were analyzed separately. Excel capabilities enabled a faster process of portfolio creation

# Chapter 4

Chapter 4 presents an empirical analysis of the gathered data and the respective trading strategies built upon them. Initially, this chapter will focus on the performance of momentum portfolios with overlapping periods and time windows of 6 months for formation and holding. Subsequently, the market's performance is presented and properly compared to assess whether the momentum strategy is profitable or not.

## 4.1 Summary Statistics

| Statistic | **Winners Portfolio** | **Losers Portfolio** | **WML** |
|---|---|---|---|
| Median | 0,0959 | 0,0497 | 0,0334 |
| Average | 0,1117 | -0,0036 | 0,1153 |
| Monthly Average | 0,0186 | -0,0006 | 0,0192 |
| Standard Dev | 0,1938 | 0,2098 | 0,3063 |
| Maximum | 0,8566 | 0,4225 | 1,1046 |
| Minimum | -0,4479 | -0,8149 | -0,4479 |

*Table 1 Summary Statistics*

At a glance, these statistics (Table 1) demonstrate some unexpected outliers. Some of the winner portfolios delivered negative returns while some loser portfolios delivered positive returns. The rationale behind this is the fact that in January the returns of momentum trading strategies tendentially reverse.

Alternatively, the reversion of returns between Winner and Losers may be evidence of contrarian cycle within the stock market. Another unexpected fact is the positive median in Losers Returns, which may be explained by the restrict sample used in this study.

Nonetheless, on average, the results are in line with those in the literature, which theorizes the tendential outperformance of winner's portfolio, meaning that Winners have a higher return than Losers. Consequently, the Zero-Cost Portfolio has majorly positive returns, as expected (Galariotis, 2010; Jegadeesh & Titman, 2011). This is equally in line with the fact that in absolute terms, winners present the highest maximum return and the higher minimum return (Galariotis, 2010; Jegadeesh & Titman, 2011).

US Tech returns are volatile, a fact that is corroborated by the high standard deviation. These values were expected due to the intrinsic characteristics of the tech stocks (Deng et al., 1999; Shynkevich, 2012).

Analyzing the returns considering market's and economy's recent development, it is clear that winners took advantage of the unprecedent growth observed during last decade. As stated, the expansionary policy imposed by the Federal Bank allied with the development of new technologies allowed for an impressive growth within the technological sector.

## 4.2 Raw Returns

The following table (Table 2) shows the returns of portfolios with overlapping periods for a 6x6 time-window. The portfolios were formed without a gap between formation and portfolio holding.

| 6x6 Time Window | **Raw Returns** |
|---|---|
| Winner | 0,019*** |
| p-value | 1,392 |
| Loser | -0,001*** |
| p-value | -0,042 |
| WML | 0,019*** |
| p-value | 0,909 |

***** p<0.01, ** p<0.05, * p<0.1**

*Table 2 Raw Returns*

The use of overlapping holding periods enabled an increase in the number of observations compared to using a non-overlapping period. In fact, for this particular sample and strategy, the number of portfolios grew from eight portfolios to 210. This approach strengthens the performed tests.

Winner portfolios generate, on average, a positive return of approximately 1,9% per month. Before the conducted analysis, the expectation was, in fact, a positive return, due to the fact that the relevant literature appoints 6x6 as a relatively profitable strategy in terms of price momentum. Realized gains by winner portfolios are significant at 10%, 5%, and 1% confidence levels which confirms the existence of momentum effect in Winners stocks. Consequently, within the selected sample, it is profitable to simply buy winner portfolios for the majority of sub-periods. At first glance, the results suggest that the U.S. tech Equity market does not efficiently incorporate information in the first 6 months. Therefore, simply buying the winners generates abnormal returns.

Analysis of the losers indicates that the results are negative and significantly different from zero at 10%, 5%, and 1% confidence levels. On average, a short position in Loser's portfolio would deliver 0,01% per month.

Alike to what was described for winners, this kind of data regarding losers confirms that momentum has not been arbitraged away in the equity capital markets. This aligns with the expected results according to the significant relevant literature (Geczy, 2015; Geczy & Samonov, 2016). Given that the 6x6 window is a short-term trading strategy, evidence of contrarian cycles in the stock market was not expected (Antoniou et al., 2006; Galariotis et al., 2007).

Zero-cost portfolio, the key strategy in the momentum field, is formed by jointly buying the winners while selling the losers. Given the above results, the WML (Winners minus Loser) portfolio returned positive of 1,9% per month. The results are, once again, statistically significant results for this sample at 10%, 5%, and 1% confidence levels. This outcome is in line with the relevant literature and was already expected due to the fertile environment within tech stocks for momentum phenomena (Deng et al., 1999; Shynkevich, 2012).

## 4.3 Momentum Returns in Excess of Market Returns

In order to obtain a closer perspective that is closer to the practical investment process it is required to compare the performance of the trading strategies with the market performance. Two benchmarks were chosen for this trading strategy, the Nasdaq 100 and S&P 500. S&P500 can be seen as a representation of the US Market as a whole, while Nasdaq 100 is a specific index for tech stocks. Although there is some overlap in the stocks of both Indexes, this comparison will also give insights about the relative performance of tech stocks over the market.

The table below shows the summary statistics for each index.

| Statistic | **S&P 500** | **Nasdaq 100** |
|---|---|---|
| Median | 0,011 | 0,018 |
| Monthly Average | 0,006 | 0,010 |
| Standard Dev | 0,044 | 0,051 |
| Maximum | 0,102 | 0,123 |
| Minimum | -0,186 | -0,178 |

*Table 3 Summary Statistics: S&P500; Nasdaq100*

As expected, on average the tech stock outperformed the whole market. Additionally, the technological stock is more volatile than market's portfolio. These two facts are aligned with the literature: on the one hand, the S&P500 is a more diversified index which contains stocks from all sectors while On the other hand, Nasdaq 100 is a highly focused index, with specific tech stocks, consequently, not only this index is less diversified, but it is also focused on a growth sector characterized by high volatility. These numbers are in conformity with the literature that proves that technological stock has larger returns and volatility than the market portfolio (Deng et al., 1999; Shynkevich, 2012).

An interesting observation in this investigation is the comparison between winners' and losers' performance against the technological index (Nasdaq 100). The following table (Table 4) reports the returns adjusted to the market performance to clarify the profitability of the momentum. A comparison of the market's and the momentum performance is practically important for investing; investors may engage in active trading to exploit possible market inefficiencies or peg their performance to the market.

| 6x6 Time Window | **Excess Returns Over the Market** |
|---|---|
| Winner | 0,009*** |
| p-value | 1,392 |
| Loser | -0,010*** |
| p-value | -0,042 |
| WML | 0,019*** |
| p-value | 0,909 |

***** p<0.01, ** p<0.05, * p<0.1**

*Table 4 Excess Returns over the Market*

As expected, the returns in excess of the market's performance are lower than the raw results (Korajczyk & Sadka, 2004; Lesmond et al., 2004). This result is in agreement with the relevant literature since the market average performance was positive. However, the result did not revert itself, meaning that winner and WML outperformed the market and Loser portfolio underperformed. Winners contributed with 0,009% per month in excess returns while losers underperformed the market by 0,01%. It is worth noting that all the results are statistically significant at 10%, 5%, and 1% confidence levels.

The positive momentum returns in the zero-cost strategy are generated by a combination of the good performance of winners along with the bad performance of losers, who make an equivalent contribution for momentum returns. These results are aligned with those of Jegadeesh & Titman (2001), which suggest that the winner and loser portfolios contribute equivalently to the momentum profits. The excess of the returns over market's performance is supported by the sector's characteristics which makes them stocks with high potential for momentum observation. The rapidly advancing technology creates an environment of disruption, leading to investor's reliance on future expectations in relation with intangible factors, which in turn might increase investors reliance on future expectations related with intangible factors which might create a gap between price and intrinsic value (Deng et al., 1999; Shynkevich, 2012).

## 4.4 Comparison of the Empirical Results

| Publication | Average Monthly Returns | T Value | Sample | Market | Weight | Portfolio Size |
|---|---|---|---|---|---|---|
| Jegadeesh & Titman (1993) | 0,950 | 3,07 | 1965-1989 | The U.S. | EW | 10% |
| Conrad & Kaul (1998) | 0,360 | 4,55 | 1962-1989 | The U.S. | WRSS | N/A |
| Rouwenhorst (1998) | 1,160 | 4,02 | 1980-1995 | Europe | EW | 10% |
| Rouwenhorst (1999) | 0,390 | 2,68 | 1982-1997 | Emerging Markets | EW | 30% |
| Jegadeesh & Titman (2002) | 1,230 | 6,46 | 1965-1998 | U.S. | EW | 10% |
| Griffin et al. (2003) | 0,530 | 5,09 | 1975-1995 | Global | EW | 20% |
| Galariotis (2010) | 0,025 | 3,60 | 2000-2007 | Australia | EW | 5% |
| (Thesis) Dyachenko (2018) | 0,0192 | 0,909 | 2008-2018 | U.S. Tech | EW | 20% |

*Table 5 Summary: Empirical Results*

The above table shows the comparison between the results across different papers and this thesis. As it is possible to see, the momentum returns of the thesis are the lowest when compared with relevant literature. This may suggest that the market is more efficient regarding information incorporation. Nonetheless, it is important to take into account that this thesis has the smallest sample since it only covers the U.S. Stock Market, more specifically, the 200 biggest listed tech stocks. Consequently, losers' portfolios are not comprised by the worst performers in the market which may be one of the reasons behind lower returns of the zero-cost portfolio. In terms of weighting and portfolio size the different papers do not differ substantially, hence this thesis goes in line with the relevant literature (Griffin et al., 2003; Jegadeesh & Titman, 1993).

## 4.5 Hypothesis Validation

At the light of the attained results it is clear that H0 should be rejected. Hence, H1 accepted. Momentum trading strategies applied within the US Tech stocks are significantly profitable and statistically different from zero.

The goal of this study was to test, empirically, whether the momentum returns are statistical or not. As it is observable in the tables above, momentum present significant returns in this sample. As expected, the winner's portfolio's presented on average, positive returns (Galariotis et al., 2007; Jegadeesh & Titman, 1993). Losers, correspondently, delivered negative returns and, consequently, the zero-cost portfolio had positive returns. These numbers are fully confirmed by the relevant literature (Galariotis et al., 2007; Jegadeesh & Titman, 1993).

In a practical point of view of the investment, where the investor may either invest active or inactively, momentum return was compared to the market performance. This gives an insight into the difference between actively engaging and passively holding the market's portfolio. In this comparison, as expected, the winner outperformed the market, losers underperformed it. Collectively, the WML outperformed the market, providing positive and significant returns. These returns are lower than raw returns due to the positive market performance.

Nonetheless, these portfolios are evidence of momentum strategies profitability. Momentum effect was already covered, globally (Geczy, 2015; Geczy & Samonov, 2016).

The results of this thesis are lower than the gathered studies in the table above (Table 5). Although it may seem that the momentum effect lost its magnitude through the years, it is relevant to recall that the sample for this dissertation includes the 200 biggest US Tech Companies, contrastingly, other studies included the whole market (Galariotis et al., 2007; Jegadeesh & Titman, 1993). This fact impacts the results because in this small samples the losers are not quite the worst absolute performers of the market since the studied sample is comprised of tech stock which is characterized by its growth (Carpenter & Petersen, 2002).

Is possible that even within the refereed samples the losers are not as bad as losers when the market is studied in its total size (Galariotis, 2010). It is not less important to bear in mind the characteristics of the tech stock market, more specifically in terms of performance. Not only tech stocks have the potential for great performance (Deng et al., 1999; Shynkevich, 2012), but also the winner kept winning for the last ten years. This can explain the lower magnitude between winners and losers when compared with other studies.

In terms of momentum, observation is possible to analyze in the light of Behavioral Financial Theory. The manifestation of momentum in the US Tech market can be explained by investor's biases (Barberis et al., 1997; Ritter, 2003). It is safe to assume that by the time the studied period began, in 2008, the markets were at its bottom, and it was in that exact same year that the longest bull market in history has begun.

Similarly, in 2008, the Dotcom speculative bubble was already forgotten by newly arrived market participants. These two facts backed the environment for the observation of momentum phenomena. Additionally, strong economic growth influenced investors by enhancing their confidence. This way the identified heuristics such as representativeness, overconfidence and overreacting were experienced among investors' community (Lam et al., 2010; Schmeling, 2009).

This is evidenced by the rise of market's capitalizations of technological companies, as of 2018, the top five companies by market capitalization are tech stocks, which shows the profile and investor's confidence in this sector.

Biases arose due to the fast evolution in technologies and the inadaptability of investors to properly value it. During the last years, technologies experienced an unprecedented change, from 2000-2009 the major trends were developments in mobility, cloud, big data, machine learning. During the 2009-2015 era, new products were created along with the development of artificial intelligence, drones, blockchain and 3D printing.

Some future evolutionary trends might be related to self-driving vehicles, hyperloop transportation and solar-powered cities. Sectors such as banking or financial and insurance services have adopted mobile digitization, enabling mobile banking. Retail industry has embraced e-Commerce and with respect to Healthcare, a rise in digital solutions should be noticed. The fast-paced evolution of technology led to products that were unimaginable some years ago and consequently the conditions for the momentum effect were met (Deng et al., 1999; Shynkevich, 2012). Some of the investors behind these companies rely heavily on intangible assets with low salvage value also the investors do not know how to properly value these technologies which are continuously changing (Carpenter & Petersen, 2002).

# Chapter 5

## 5.1 Conclusion

The main goal of this thesis was to research if the price momentum effect can be observed in the U.S. tech market. The methodology used was taken from Jegadeesh and Titman (1993) and applied to the sample period 2008-2018. The studied time-window comprises 6 months for portfolio creation and 6 months for holding. The results suggested that momentum trading strategies based on going long in the winners' portfolio and shorting the losers' portfolio generated significant and abnormal returns in the sample comprising the 200 biggest tech companies listed from 2008 to 2018. Considering these results is possible to conclude that a trading strategy based on a 6x6 time-window is significantly profitable and more advantageous than holding the market portfolio. Looking separately at winners' and losers' portfolios allowed the assessment to determine that both winners and losers contribute equally to momentum returns.

So, there are three possible strategies to take advantage of the observed phenomena, investors can either buy winners, short losers, or combine both into a zero-cost portfolio. These strategies are possible due to the characteristics of the market and specifically of this sector (Jegadeesh & Titman, 2011). As already stated, the technological market potentiates the price drift creating a gap between value and price. This type of situation is justified by the high reliability of the sector in intangible assets and the inability of investors to properly valuing it. Additionally, the results suggest the existence of some biases in the investor's behaviors. The continuous winning state in the whole sector indicates overconfidence and representativeness, also, the steep growth of some stocks may be evidence of herding trading (Demirer et al., 2015).

This dissertation unveils new empirical information regarding price momentum which reinforces the academic knowledge in this field. This work is focused on price momentum within the technological sector, clarifying the dynamics in this specific sector. Awareness on price dynamics for this particular market is extremely relevant given the major importance of technology in the evolutionary process. This information is useful for a wide range of market participants such as regulators, investors and managers.

## 5.2 Practical Implications

For active investors and fund administrators, is relevant and useful to be aware that momentum dynamics are significant in the tech sector and that there are opportunities to obtain abnormal returns.

Analyzing the obtained results combined with the information provided in the relevant literature is possible to obtain relevant insights regarding the possible trading strategies that can be performed in the technological sector. Given the returns table set above, there are three ways to exploit momentum to obtain abnormal returns. Is possible to buy winners, sell losers or create a zero-cost portfolio. A long position in winner's portfolio enables the capitalization of the enthusiasm and confidence of the market that the good performance will perpetuate itself into the future, this strategy would deliver positive returns over the studied time-frame, however this strategy cannot be the best when applied for linger time-windows due to the risk of occurrence of contrarian cycles in the markets.

Alternatively, investors can also obtain superior returns solely by shorting losers' portfolio, hence exploit the continuation of the bad performance of certain stocks, this strategy would deliver positive returns within this sample and time-frame. Nevertheless, the investor would be exposed to the risk of contrarian cycles on the longer time-windows.

Additionally, an unhedged short position can provide, in practice, infinite losses for the investor. Finally, one of the best ways to take advantage of the observed momentum effect is by composing a zero-cost portfolio (Galariotis, 2010; Jegadeesh & Titman, 2011). Zero-cost trading strategy involves a simultaneous purchase of winners and sale of losers such as that both costs cancel each other. Likewise, this strategy would also deliver superior returns to investors in the studied time-frame and sample, with the advantages of efficiency gains and cost reduction. This strategy is theoretically an optimized way to capitalize on momentum although in the long-term there is exposure to contrarian cycles, a fact that would require investors to rebalance the portfolios with some frequency.

For the SEC, this information can be useful to understand that the market dynamics still present a gap between value and price. This fact is important from a regulatory point of view given the threats of speculative bubbles in tech stocks. A speculative bubble is a situation of investor's enthusiasm triggered by news of price increases. This sentiment is spread by psychological contagion, thus attracts several classes of investors. The Dotcom bubble and crash is an example of a speculative bubble created by the over-enthusiasm of internet firms which shows how far can go the investor's sentiment in some cases. Because bubbles can be categorized as a social-psychological phenomenon, they are, by nature, difficult to control. Regulatory changes applied after the financial crisis may diminish future speculative events. An integrated rather than entity-based approach to regulate equity markets is necessary to stabilize the financial cycle across the financial system as a whole. Regulating leverage would help to prevent misallocation of resources from asset bubbles.

This said, SEC (Security Exchange Commission) can use momentum indicators to measure market sentiment and intervene in the markets. These interventions may be simply demanding more transparency on Technological Equity capital markets to avoid the destructive event in the markets and clarify the investors about the real prospects of the firms or issue warnings about groups of firms that may be in risk overvaluation due to a high level of momentum.

Finally, for the academic community, this work represents additional empirical evidence of momentum that defies the EMH. This is relevant for the understanding of the technological sector and investor's behavior regarding the market.

## 5.3 Limitations

The momentum effect has been observed in several asset classes including equity, debt, currency, and commodities. This thesis focused exclusively on equity—it is the most studied asset class in terms of momentum.

Additionally, the conducted study was confined to the U.S. tech sector. Momentum may be exploited by the use of several strategies. The most relevant types of momentum are related to price, earnings, and industry. This thesis only covered price momentum strategies. On the other hand, it was limited to the approach pioneered by Jegadeesh and Titman (1993).

The methodology of this study only uses solely the 6x6 time window, which does not translate to an understanding of the profitability of momentum in other possible time-horizons. It is also impossible to evaluate and observe contrarian cycles in the stock market because of the short-term nature of the studied time-window. Also, it should not be disregarded that adjustments were not made for the January effect observed by Jegadeesh and Titman (1993). January, normally, represents an inversion in momentum effect, losers outperform winners, creating negative returns in the zero-cost portfolio. This said, momentum returns might be lower than the ones presented in past studies due to the absence of this adjustment.

Empirical evidence shows that transaction, commission brokerage costs and income taxes lower the profitability of momentum trading strategies, this thesis does not adjust the returns for these costs fact which constitutes a limitation. Finally, (Jegadeesh and Titman, 1993) showed that exists a bid-ask spread which lowers trading profitability, this thesis does not adjust for this spread. Literature suggested a gap of a month between the formation and the holding period. (Griffin, 2010) documented that this gap mitigates microstructure distortions; namely, price pressure, lagged reactions, and bid-ask spread.

## 5.4 Recommendations for the future

Although since the first discovery of Jegadeesh and Titman, some extensive work was done. Nevertheless, this work has raised significant questions that may be answered in future studies. For example, this analysis can be extended to other types of momentum and to different time-windows that were not covered in this work. Additionally, an empirical study that evaluates the extent to which intangible assets influence momentum across different sectors would be a great addition to the literature. From a behavioral standpoint, it would be useful to determine which generations of investors tendentially behave inefficiently and/or irrationally and study what is really the rationality and irrationality within financial markets. Ultimately, studies should be made to find a discernible cause for the momentum phenomena. Momentum and reversals are already a well-established empirical fact but for a deeper understanding it is required a test for the causes behind it.

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