What is the best way to invest in public FinTech companies?

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Abstract

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The FinTech industry is becoming more attractive and is seen as a rising sector. Data shows that, in 2021, private investment vehicles, such as private equity firms, are investing more than ever in FinTech companies.

The objective of this research is to determine if it is profitable to invest in FinTech stocks, and what the best strategy. Research demonstrates the profitability of different investment strategies across different markets and sectors, and yet there is no evidence and no studies applied to publicly traded FinTech companies.

Based on the review of the literature on portfolio theory and market anomalies, the investment strategies chosen were value, momentum, and Combo. A small number of companies were studied and a small time period was analysed, which was due to data unviability. The investment strategies were applied, and the results were separated into two different time frames to isolate the impact of pandemic. A transaction cost analysis was done to access the portfolios' persistence and the bootstrap method was applied to the mean excess return with the purpose of having more robust conclusions.

The results indicate that, for the pre-pandemic period, investing in FinTech stocks using the momentum strategy is profitable. This strategy is even able to beat the market, producing a Sharpe ratio of 1.69. For the post-pandemic period, all the strategies employed turned out to be unprofitable and their results were quite inferior to the market.

Abstract (Portuguese Version)

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A indústria FinTech está em crescimento e é cada vez mais atrativa. Dados comprovam que, em 2021, veículos de investimento privado, como empresas de "private equity" , estão a investir mais que nunca em empresas desta indústria.

Esta tese tem como objetivo determinar se é rentável investir em ações de empresas FinTech e qual é a melhor estratégia para o fazer. Existem vários estudos sobre a rentabilidade de diferentes estratégias de investimento aplicadas a inúmeros setores e mercados financeiros, contudo não há qualquer análise nem resultados sobre estas estratégias aplicadas a ações de empresas FinTech.

Tendo como base a revisão de literatura sobre portefólios e anomalias de mercado, as estratégias de investimento escolhidas foram "value", "momentum" e Combo.

Devido à falta de dados, foi analisado um número reduzido de empresas e durante um curto espaço temporal.

As estratégias de investimento foram aplicadas e os resultados foram analisados em dois períodos diferentes, com o propósito de isolar o impacto da pandemia. Para examinar a persistência dos portefólios, uma análise de custos de transação foi elaborada. De forma a ter resultados mais robustos, o método "Bootstrap" foi usado para o retorno médio em excesso.

Os resultados indicam que, no período pré-pandémico, o investimento em ações FinTech usando a estratégia de "momentum" é rentável e acima do mercado, tendo esta estratégia um índice de Sharpe de 1.69. Para o período que inclui a pandemia, nenhuma das estratégias usadas é rentável e todas têm uma performance bastante abaixo do mercado.

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1. Introduction

The FinTech industry is becoming more popular and attractive to invest in. Chuen and Teo (2015) state that Fintech will model and transform the future of the financial sector, while also being recognised as one of the most promising and innovative industries today (Chishti and Barberis, 2016).

Private investors seem to believe in the success and profitability of this area. According to KPMG ("Pulse of Fintech H1'21", 2021), FinTech investment levels across Venture Capital, Private Equity and M&A in 2021 are, in some cases, at near-record levels and a recovery from the impact of COVID-19 can clearly be identified. Although most of the capital being put in the industry is from private investors, FinTech is gradually becoming more easily accessible for common investors.

In 2019, Ark Invest, a global investment fund, created an exchange traded fund (ETF) specializing on the FinTech industry, which gave common investors the opportunity to be exposed to this sector. More recently, in 2021, major players in FinTech such as Robinhood, Wise and Coinbase have gone public, bringing the attention and curiosity of investors to publicly traded FinTech companies and searching for promising stocks in the industry. Different investment vehicles and opportunities are being created to invest in FinTech, and one of the questions that arises is: How can an investor take part in this rising and promising industry?

Having in mind the record investment levels seen in the industry and the popular IPOs from FinTech companies that recently occurred, one of the research questions I will try to answer in this dissertation is: What is the best strategy to invest in FinTech publicly traded companies and is it profitable?

There is a great deal of literature and empirical studies on different investment strategies and market anomalies (Chui, 2003; Blittz et al., 2011; Asness et al., 2013; Barroso and Santa-Clara, 2015; Jegadeesh and Titman, 1993; Fama and French, 1998). And yet, there are no studies on the profitability and efficiency of these investment strategies applied to financial technology stocks.

In this thesis, I will place myself in the role of an investor who wants to be exposed to FinTech in order to participate in this revolutionary sector and must decide what are the best vehicles and strategies to apply and create a profitable investment strategy.

Two different investment "styles" will be expanded on and compared. First, I will talk about momentum investing, an investing style that relies on trends. The efficiency of this strategy has already been studied and its effectiveness has been proved for different time frames and different samples (Chui, 2003; Blittz et al., 2011; Asness et al., 2013; Jegadeesh and Titman, 1993).

Then, I will talk about value investing, an investment style which has the ambition of finding securities that trade at a discount when compared to their intrinsic value. For this strategy, multiple studies have also been conducted and its efficiency has been proved (Fama and French, 1998; Fama and French, 1992, 1993; Lakonishok et al., 1994; Asness et al., 2013).

Complementing the investment strategies described above, I will analyse the "Combo" strategy, which was proposed by Asness et al. (2013) and combines value and momentum investing.

2. Literature Review

In this section, I present the existing relevant literature around FinTech, the possible definitions for FinTech companies, and I examine the industry's investment landscape. Then, I present relevant research on portfolio theory and risk factors. In subsections 2.4 and 2.5, I present the literature on momentum and value investing to support the investment strategies employed in this dissertation. Finally, I present the performance metrics used to describe and quantify the investment strategies' results.

2.1. FinTech

FinTech, which stands for Financial Technology, is a field shaped by innovation and transformation. It has been growing due to factors like the sharing economy, information technology and favourable regulation (Lee and Shin, 2018). Despite its connection to today's era and modernity, the FinTech term can be traced to the early 1990s (Arner et al., 2015).

From a general standpoint, Arner et al. (2015) define FinTech as the usage of technology in Finance. The industry is not exclusively related to financing and banking; it is related to the entire scope in which the financial services industry operates and where it is present, giving the FinTech landscape a global and transversal “image” (Arner et al., 2015).

Gomber et al. (2017) propose another definition and clearer “lines” for what FinTech companies are, stating that these companies usually rethink the existent business models or create new solutions in the financial markets, having a disruptor factor associated with them.

There is not a single widely accepted definition in academia for what a FinTech company, or even FinTech itself, is. For this thesis, the FinTech term will be interpreted as the usage of technology in Finance, as proposed by Arner et al. (2015), and a FinTech company will be perceived as a disruptor company, which creates solutions or rethinks the existent business models in the financial sector through the usage of innovative technology (Gomber et al., 2017).

KPMG (“Pulse of Fintech H1’21”, 2021), a widely and respected report on the state of the FinTech environment, identifies five different segments in the sector: Payments, InsurTech, RegTech, WealthTech, Blockchain/Cryptocurrency, and Cybersecurity.

InsurTech (insurance technology) is a segment in which companies use technology in the insurance sector. They simplify processes, with some being purely digital companies. An example are chatbots, computer programs that simulate a real person interacting with a client.

RegTech (regulatory technology) is used to manage regulatory processes in the financial industry through technology. This sector uses artificial intelligence and machine learning to automate tasks that are done by compliance departments.

WealthTech aims for the wealth management and investment services to become more digital and efficient. This segment provides an alternative to traditional wealth management services by using innovative and modern technologies like Big Data and artificial intelligence.

2.2. FinTech Investment

FinTech is already considered as a rising and gifted industry. The power of this sector is driven by a huge number of innovative start-ups that offer services which were, in the past, exclusively attributed to banks (Chishti and Barberis, 2016).

According to KPMG ("Pulse of Fintech H1'21", 2021), the 2021 global investment levels in FinTech assumed a V-shaped format when compared to 2020 levels, showing a clearly strong response to the pandemic effects. This report also shows that in the first half of 2021, venture capital investments reached similar levels to the annual record of $54 billion achieved in 2018. In the private equity field, these firms invested, in the first half of 2021 alone, more than the yearly record established in 2018. (KPMG, 2021 "Pulse of Fintech H1'21).

Early investment vehicles, such as venture capital and private equity firms, seem to believe in the profitability and positive evolution of this sector.

2.3. Portfolio Management

In the literature of portfolio theory there are two distinct approaches and points of view on the subject of portfolio management. The most recent and widely debated today are the Modern Portfolio Theory (Markowitz, 1952) and the Random Walk Theory (Fama, 1965; Samuelson, 1965).

The Random Walk Theory defends that stock prices follow a random walk, implying that these cannot be predicted (Fama, 1965; Samuelson, 1965). This theory is rejected by several authors, who defend and put forward methods to predict stock prices, denying the randomness and unpredictability behind the theory (Cowles and Jones, 1937; Fama and French, 1988; Lo and MacKinlay, 1988, 1990a). Because this theory defends that neither fundamental nor technical analysis can lead to successful investment strategies and taking into consideration the purpose of this dissertation – which is to study different investment strategies applied to FinTech stocks –, the focus of the research will be on the Modern Portfolio Theory and its implications.

The Modern Portfolio Theory, introduced by Markowitz (1952), is a mathematical framework designed for creating a portfolio in which the returns are maximised for a certain level of risk.

The model is a “tool” to find out the most efficient portfolio given a set of securities with a certain level of risk (Markowitz, 1952).

Markowitz (1952) proposes that the most efficient portfolio comes from this optimization problem, in which, by changing the weights of the securities present in the portfolio, the risk is minimised for a specific level of return. The efficient frontier of mean-variance optimised portfolios comes from this interactive process.

Markowitz’s (1952) approach is a trade-off between risk and return. It can be used by investors in two ways: to maximise the highest return for a certain level of risk or to obtain the lowest risk for a certain level of return. Returns are measured by the mean of the expected returns and the risk is measured by the variance of the expected returns (Markowitz, 1952).

Building on Markowitz’s (1952) work, Sharpe (1964) and Lintner (1965) developed the Capital Asset Pricing Model, known as CAPM. The model is as follows:

$$E(r_i) = r_f + \beta_i[E(r_M) - rf] + e_i \tag{1}$$

This model allows for the calculation of a theoretical rate of return on an asset, taking into consideration the level of non-diversifiable risk. The non-diversifiable risk is also known as the market risk.

The expected return on an asset $E(r_i)$ is composed by the risk-free rate r_f, a risk premium and an error term. The risk premium is the result of the multiplication of β_i, which is a measure of the volatility of the asset compared to the market, by the market excess return $[E(r_M) - rf]$. The error term e_i is the stock specific risk, with a mean of zero.

This model implies that the only source of return uncorrelated to the market is the risk-free return, suggesting that the only risk present is the market risk (non-diversifiable). The model has been criticised for having just one source of risk – the market risk –, which implies that there cannot exist any portfolio that produces excess returns which are not explained and are correlated to the market.

Ross (1976) proposes a new model: the Arbitrage Pricing Theory, also known as APT. The APT model adds to the CAPM flexibility, enabling different risk factors “weighted” by their respective sensitivity. The model introduces the idea that investors consider different risk domains besides the market risk:

$$E(r_i) = r_f + \beta_{i,k} F_{i,k} + e_i \tag{2}$$

In the APT model, returns are measured by a vector of sensitivities (the different β_k) towards systematic risk factors F_k. In this model, there can be different risk factors, including the market risk pointed out in the CAPM.

Ross (1976) does not identify possible risk factors. Later on, several authors propose possible risk factors, which originated other pricing models still being used today.

Fama and French (1993) developed the three-factor asset pricing model as a response to the CAPM single risk-factor focus and the APT model's lack of specification for any risk factors. They discovered that two different portfolios – apart from the market portfolio present in the CAPM model – can explain stock returns: the portfolio Small Minus Big (SMB), which accounts for company "size" based on firm respected market value of equity; and High Minus Low (HML), constructed on the companies' book-to-market equity, which is also known as value. This can explain stock returns being independent from market risk.

Fama and French (1992, 1993) argue that SMB and HML are proxies to risk factors. They add specificity to Ross's (1976) work by pointing out identifiable risk factors, giving origin to the FF3 model which includes size, value, and market risk. The FF3 model is as follows:

$$R_{i,t} - r_f = \alpha_i + \beta_1 MRP + \beta_2 SMB + \beta_3 HML + e_{i,t} \tag{3}$$

The weighted excess return ($R_{i,t} - r_f$) on the portfolio at time t is explained by three risk factors: the market risk premium, the size risk factor (SMB), and the value factor (HML).

Other authors identify and propose different risk factors, originating other models such as the Carhart four factor-model (Carhart, 1997), which includes a risk factor for capturing the momentum phenomenon; the five-factor model, also known as FF5 (Fama and French, 2015); the five-factor APT (Chen et al., 1986); and, more recently, Asness et al. (2019) has proposed a factor for measuring quality.

2.4. Momentum Strategies

The momentum strategy gained value and attention after the influential work of Jegadeesh and Titman (1993). In their work, the authors noticed that, on one hand, stocks with superior past returns will continue to have superior returns during 3-12 months holding periods, and on the other hand, stocks with low cumulative returns show lower future returns during those same holding periods.

The strategy employed in Jegadeesh and Titman (1993) was the following: buying past "winners" (assuming a long position in stocks with recently high cumulative returns) and selling past "losers" (assuming a short position in stocks with recently low cumulative returns). To study the effectiveness of the strategy, Jegadeesh and Titman (1993) constructed 16 different portfolios based on collecting past returns on 1, 2, 3, and 4 quarters and having holding periods of the same length. They prove that momentum achieves significant statistical excess returns, and that the profitability of the momentum strategy is not due to systematic risk or the reaction of delayed stock prices to common risk factors. The momentum strategy is also recognised as WML, which stands for Winners Minus Losers.

Momentum strategies suffered some criticism after being studied and employed during and after the subprime crisis[1]. The strategies' efficiency and profitability were questioned as several authors demonstrated their bad performance in high volatility scenarios, panic states, and market declines (Daniel and Moskowitz, 2016; Demirer and Zhang, 2019). The efficiency of momentum investing during the COVID-19 pandemic has not yet been studied.

Years after the influential work of Jegadeesh and Titman (1993), other authors studied the efficiency of momentum strategies for different markets and asset classes and confirming their validity, with some even adapting and managing the strategy (Chui, 2003; Blittz et al, 2011; Asness et al., 2013; Barroso and Santa-Clara, 2015).

Carhart (1997), in a study on mutual fund returns, combined the FF3 model (Fama and French; 1992, 1993) with the momentum anomaly, creating a new factor model known as the Carhart four-factor model, which includes the factor WML (Winners Minus Losers) – the proxy for the momentum risk factor.

[1] The subprime crisis occurred between 2007 and 2010.

2.5. Value investing

Value investing strategies seek to find securities that trade at a discount when compared to their intrinsic value. They are known for buying stocks that have low prices relative to earnings, dividends, historical prices, and book assets (Lakonishok et al, 1994).

Numerous authors studied different value strategies for different stock markets – with a special focus on U.S and Japanese markets –, confirming its validity and efficiency (Lakonishok et al., 1994).

Chan et al. (1991) studied four variables that represent value investing proxies on the Japanese market. They concluded that: earnings yield, size, book-to-market ratio, and cash flow yield can predict stock returns. They also found a risk premium for value in the Japanese stock market.

One of the most well-known and employed strategies among academics for measuring value is based on the book-to-market ratio – BE/ME. It was tested and proved to beat the market for different time frames (Fama and French, 1992, 1993; Lakonishok et al., 1994; Asness et al., 2013).

Despite the book-to-market ratio strategy being the most employed and studied measure for value investing, there are other predictive measures which proved to be effective (Lakonishok et al., 1994; Piotroski, 2000).

Fama and French (1998) contributed to the value investing effectiveness study by reporting a risk premium for value portfolio in 12 of the 13 stock markets accessed in their study.

2.6. Value and momentum strategies combined

Asness et al. (2013) highlight that value and momentum studies focus mainly on U.S. equities and usually examine the two anomalies separately. In the rare studies performed outside of the U.S., the two anomalies were also separately studied.

In the work “Value and Momentum Everywhere” (Asness et al., 2013), the joint effect and correlation of value and momentum market anomalies are accessed and explored for the first time. Asness et al. (2013) find that value and momentum are negatively correlated among and for different asset classes.

With value and momentum anomalies being negatively correlated, it allows for an investor to diversify and diminish his risk, even with short-selling constraints.

Asness et al. (2013) propose a beneficiating strategy by: value and momentum being negatively correlated and from its independent positive return. The investment strategy proposed, titled "Combo", is the following:

$$r_{Combo}{=}0.5_{R_t}Value + 0.5_{R_t}Momentum \tag{4}$$

The Combo strategy creates an equal-weighted portfolio that allocates one half to the value and the other half to the momentum portfolio.

2.7. Investment performance measures

The following measures helped to access and compare the profitability of the portfolios assembled to replicate the investment strategies.

The portfolio's mean excess return (which is the portfolio holding period return) subtracted by the risk-free rate is a simple metric to access and compare the profitability for different portfolios. Despite this being an easy way to compare results, risk is not taken into consideration. There are measures that consider risk, namely risk-adjusted performance measures. To measure risk, the simplest metric is the standard deviation.

The Sharpe ratio, proposed by Sharpe (1994), is one of the most taught risk-adjusted measures which combines risk and return:

$$Sharpe\ ratio = \frac{(r_{p-}r_f)}{\sigma_p} \tag{5}$$

The Sharpe ratio allows for the calculus of the portfolio's mean excess return $(r_{p-}r_f)$ divided by the portfolio's volatility (its total risk), which is measured by the standard deviation of the portfolio σ_p and takes into account the portfolio's excess returns and "controls" by its risk.

Modigliani and Modigliani (1997) introduced the M-squared, or M^2, measure. The M^2 accesses the return of a portfolio, adjusted for the risk of a benchmark. This way, the returns of a portfolio that take into consideration other levels of risk and different benchmarks, such as other portfolios or indices, are easily accessible.

$$M^2 = Sharpe\ Ratio * \sigma_{benchmark} + r_f \tag{6}$$

The M^2 measure is easier to interpret when compared to other risk-adjusted measures, as it is represented in units of percentage return.

Among investors, "beating the market" is an often-heard expression, normally attributed to skill and a good stock picking. The aim of an investor is to create a portfolio in which the positive excess returns are dissociated from the market and its variation.

The Jensen alpha, proposed by Jensen (1968), accesses the returns that are not explained by the market:

$$Alpha: \alpha_p = r_p - r_f - \beta_p(r_m - r_f) \tag{7}$$

The Jensen Alpha, α_p, is obtained with a regression, having the portfolio's excess return $(r_p - r_f\ )$ as the dependent variable and the market's excess return $(r_m - r_f)$ as the independent variable. The market beta, β_p, also retrieved from this regression, measures the portfolio's volatility towards the market. The Jensen alpha is the excess return of a portfolio controlling for the market risk. It can also be interpreted as the average return on a portfolio above or below the capital asset pricing model (CAPM).

In accordance with the literature on portfolio management, investors and researchers usually test the validity of a portfolio's excess returns while considering other risk factors apart from the market risk. Controlling for value and size as risk factors is also common, with the FF3 alpha being a fitting solution to measure this (Fama and French, 1992, 1993). The FF3 alpha is the portfolio's excess return controlling for market, value, and size risk factors. The measure is as follows:

$$FF3\ alpha: \alpha_p = r_p - r_f - \beta_{p,M}(r_m - r_f) - \beta_{p,V} r_{HML} - \beta_{p,S} r_{SMB} \quad (8)$$

The regression of the excess returns of the portfolio ($r_p - r_f$) over the three risk factors results on three betas ($\beta_{p,M}, \beta_{p,V}, \beta_{p,S}$) and the FF3 alpha α_p.

Fama (1965) rejects the hypothesis proposed by Osborne (1959) that logarithmic price changes follow a normal distribution. Instead, Fama (1965) finds that stock price changes are leptokurtic – flatter-tailed distributions that have a higher chance of extreme events. To understand the data and the characteristics of the series, I decided to include the third and fourth moments of the distribution: skewness and excess kurtosis of the portfolio's returns, respectively. Skewness measures symmetry in a distribution. If the distribution curve is shifted to the left or to the right, the distribution is said to be skewed. The kurtosis measures the extreme values present in the tails of the distribution.

3. Data and Methodology

The financial technology industry is not present in the most well-known industry classification systems, as opposed to other sectors. NAICS and ISIC[2], for example, don't have a code for financial technology or FinTech.

An extensive research was conducted to set a tailored list of publicly listed FinTech companies. Several online lists were consulted and considered, but some problems were encountered. The number of companies available in these lists was too low, and the prevalence of private companies in the constituents, which are not the focus of the research, was also common. An example of this is a list of the largest FinTech companies constructed by the CFTE[3], which, as of 08/11/2021, only had 28 listed companies from a universe of 226 FinTech firms.

To set a group of FinTech public listed companies, three different FinTech ETFs were identified and chosen to form a primary list. These ETFs were chosen based on their prospectus and information provided on how FinTech is defined and the purpose of the funds.

[2] NAICS (North American Industry Classification System) and ISIC (International Standard of Industrial Classification) are classification systems designed to identify what industry a company belongs to. NAICS is a classification adopted and used by the U.S., while ISIC is the United Nations classification system.
[3] CFTE's (Centre for Finance, Technology and Entrepreneurship) list of the Largest Fintech Companies by Market Valuation, as of 08/11/2021, had 226 constituents, with 28 of those being listed companies.

The following ETFs were chosen:

- Ark FinTech Innovation ETF (ARKF)[4]. They define FinTech innovation in their website as the "introduction of a technologically enabled new product or service that potentially changes the way the financial sector works". This ETF was chosen because their definition of FinTech is similar to the one proposed for this research.
- FinTech ETF (FINX)[5]. This ETF seeks to be exposed to companies that provide financial technology solutions, stating in its website that:

  > *"... is designed to track the performance of companies listed in developed markets that are offering technology-driven financial services which are disrupting existing business models in the financial services and banking sectors".*

  This ETF's definition of FinTech is similar to the one proposed in this thesis and it was chosen to set the initial list.

- ETFMG Prime Mobile Payments ETF (IPAY)[6]. This ETF is designed to provide a benchmark for the payments segment within FinTech. I acknowledge that one of the segments within FinTech is payments, which is what made me choose this fund to be part of the pool choice of ETFs.

Having identified these three ETFs, their holdings were retrieved on 04/11/2021. To set an initial list of public FinTech companies, the constituents of the three ETFs described above were used to create the first draft of the list of companies. The purpose of this thesis is to understand how to successfully invest in FinTech stocks and what the best strategy to do that is. Thus, picking companies that form different ETFs holdings seems like a reasonable first step for an investor to consider.

To guarantee that the companies retrieved from the ETFs' holdings were indeed from the financial technology sector, two different classifications were constructed. I classified all 122 companies one by one in the first draft of the initial list.

In Appendix 1, the classification of the companies can be consulted. For the first category – "Business" –, the companies' core business was consulted, through the Thomson Reuters

[4] https://ark-funds.com/funds/arkf/
[5] https://www.globalxetfs.com/funds/finx/
[6] https://etfmg.com/funds/ipay/

terminal, and their business summary was analysed. If the description mentioned a firm exposure to financial services using technology – the FinTech definition proposed in this thesis –, the company was classified with a "Yes" for the category "Business".

For instance, the business summary for the company Bill.com, retrieved from the Thomson Reuters terminal, reads: "Bill.com Holdings Inc. provides a cloud-based software for back-office financial operations for small and midsize businesses (SMBs)", which shows exposure to the financial sector and usage of technology in their business, originating a positive classification for "Business". Another example is Snap.inc. In this case, the business summary did not reflect any connection to the financial services industry:

> *"Snap Inc. is a camera company. The Company's flagship product, Snapchat, is a camera application that helps people to communicate through short videos and images known as a Snap. Snapchat contains of five tabs: Camera, Communication, Snap Map, Stories and Spotlight. Camera is the starting point for creation in Snapchat. Snapchat opens directly to the Camera, helping to create a Snap and send it to friends".*

Therefore, this company was classified with a "No" for the category "Business".

A second classification was arranged for companies with a classification of "No" for "Business". Past mergers and acquisitions were consulted for those companies, and if a past merge or acquisition wasa FinTech company, the category "Mergers and Acquisitions" was marked with a "Yes". A company with a negative classification for "Business" and "Mergers and Acquisitions" was taken out of the list. Therefore, the list was composed by companies with a classification of "Yes" for either "Business" or for "Mergers and Acquisitions".

The list was initially comprised of 122 companies. After this filtering process, 8 companies were excluded, leaving the final list with 114 companies.

To understand where these companies were being traded, I built a map in Power BI (Figure 1) identifying the location of the exchanges where the companies who were part of the list were being traded. In Appendix 2, a table showing the location (by country or city) of the exchanges and its representativeness in the dataset can be consulted.

Figure 1: Exchanges' location of the securities present in the final dataset

The exchanges' location with more representativeness in the dataset is North America. NASDAQ and NYSE represent more than 70% of the exchanges' location in the list of FinTech companies.

To set the time frame for this thesis, two important aspects were considered. First, I accessed when FinTech IPOs started to increase in number and amount on a global level, aiming to understand when these companies started to be available to public investors. FT Partners[7] develops research with a focus on the FinTech landscape, trends, and environment. This research also focuses strongly on the environment of IPOs in the U.S. and globally. By analysing the Q2 2021 report, it is notable that the market of FinTech IPOs, in the U.S and internationally, started to become more active from 2015 onwards. Another important point considered to set the time frame was the data availability for the companies in the list. I calculated the average year in which these companies started to be traded on their respective exchange. That year turned out to be 2015. Therefore, taking these two aspects into consideration, the period of research was established to begin in 2015 and end in 2021[8].

Regarding the extraction of the data, it was retrieved from Datastream: the daily stock prices, which were used to compute returns and the momentum predictor; the monthly market value of equity and common equity, used to form the value predictor. To ensure homogeneity and because most of the securities were traded in U.S. exchanges (around 71% of the securities, as can be seen in Appendix 2), the last two variables were downloaded currency adjusted to the U.S. dollar.

[7] https://www.ftpartners.com/fintech-research/almanac
[8] The data was retrieved up until October 2021.

It is important to understand what kind of dataset was constructed. Although it was decided to start the analysis in the beginning of 2015, some of the companies entered the market later. Furthermore, some companies in the dataset only have data information on prices and market value of equity and common equity for 2021, since that was the year they entered the market. Consequently, the minimum number of companies in the dataset that were being traded on a monthly basis is 63.

Common value of equity can be negative. There are several reasons why this can happen, such as leverage or negative results. As the dataset is composed by recently formed companies and start-ups, which normally are not profitable at the start of their "life", several data points for common value of equity are negative.

I downloaded the Fama/French 3 factors monthly data for the U.S. from Kenneth R. French Data Library[9]. The decision to choose U.S. data was made because most of the companies in the dataset are traded in U.S. stock exchanges. Hence, four series were downloaded. The risk-free rate is the "30-day U.S. T-Bills", which is the risk-free proxy used in this dissertation. The excess return on the market is the value-weighted returns of all firms on CRSP from the U.S. who are traded in the NYSE, NASDAQ and AMEX[10] and it is the proxy to the market portfolio used in this research. The factors SMB (Small Minus Big) and HML (High Minus Low) are the average return of an investment strategy for size and value, respectively. The Fama/French 3 factors was chosen as it is used to calculate some risk-adjusted performance measures.

To calculate the M^2 (the reasons for its usage are explained in section 2), I downloaded the variable price for the ETFs chosen to set the initial dataset from Datastream: the Ark FinTech innovation ETF, the FinTech ETF and the ETFMG Prime Mobile Payments ETF. For these ETFs, the monthly logarithmic returns and the monthly volatility were calculated.

All the data was downloaded into an Excel sheet and the construction and strategies of the portfolios were conducted in Python. In Appendix 3, a part of the script used to create the investment strategies is shown. The performance results were assembled and calculated in Excel.

[9] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html
[10] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

3.1. Investing strategies/Portfolio construction

3.1.1. Momentum

For the construction of the momentum strategy, the most common and adopted methodology was followed. I calculated the last twelve months' logarithmic returns on the asset, skipping the last month (Jegadeesh and Titman, 1993; Asness et al., 2013). Skipping the most recent month is common in momentum literature and is done to avoid the one-month reversal in the returns, which empirical research attributes to liquidity or microstructure issues (Jegadeesh, 1990; Lo and MacKinlay, 1990; Boudoukh et al., 1994; Asness., 1994; Grinblatt and Moskowitz, 2004).

The predictor was calculated as follows:

$$Momentum_{i,t} = \sum_{l=t-12}^{t-2} r_{i,j} \tag{9}$$

This way, the momentum predictor for a stock i at time t is its cumulative return from t-2 to t-12.

Having the predictors for the different securities at different points in time, I accessed the "winner" and "loser" stocks by creating quintiles. In statistics, quintiles divide a sample into 5 different groups, each composed by 20% of the sample. The quintiles were used to divide the universe of stocks into 5 equally sized portfolios. The highest quintile, number 4, indicates the "winner" stocks, which are the stocks that have the highest cumulative returns. The lowest quintile, number 0, indicates the "loser" stocks, the ones with the lowest cumulative returns. To create the momentum strategy (WML), a portfolio with a long position in the "winner" subportfolio and with a short position in the "loser" subportfolio was created.

3.1.2. Value

To build the value portfolio, the most standard and recognised approach present in the literature was used: the book-to-market ratio, as a signal to form value portfolios. To build the portfolio, the previous month's book-to-market ratio of the stock's universe was calculated (Fama and French, 1992, 1993; Lakonishok et al., 1994).

The predictor was calculated in the following manner:

$$Value_{i,t} = \frac{Common\ Equity_{i,t-7}}{Market\ Value\ of\ Equity_{i,t-1}} \tag{10}$$

This way, the value predictor for stock i at time t is its book-to-market ratio at $(t-1)$. The common equity variable has a lag of six months to avoid data unavailability. The stocks were divided into 5 ranked portfolios, in a way similar to the momentum strategy. The highest quintile (the "high" portfolio), number 4, represents stocks with a high book-to-market ratio, while the quintile number 0 (the "low" portfolio) represents stocks with a low ratio. To create the value strategy (HML), a portfolio with a long position in the "high" subportfolio and with a short position in the "low" subportfolio was created.

I decided to create equally weighted portfolios for the value and momentum measure as this is one of the simplest ways to balance a portfolio, while also following the literature on momentum and value (Jegadeesh and Titman, 1993; Fama and French, 1992). Thus, to calculate the portfolios' returns, the following formula was used:

$$r_{p,t} = \sum_{i=1}^{n} \frac{r_{i,t}}{n_{p,t}} \tag{11}$$

Hence, the portfolio's returns at time t is the sum of the securities' returns in the portfolio divided by the size of the portfolio at time t, $n_{p,t}$.

There are other ways of weighting portfolios, with value-weight portfolios being an example (Asness et al., 2013). Nonetheless, equally weighted portfolios are a reasonable way for a common investor to create his portfolios as it is simplest and most straightforward method.

3.1.3. Combo

The Combo portfolio was calculated by equal-weighting value and the momentum portfolios' returns at time t.

The investment strategy was calculated in the following manner:

$$r_{Combo} = 0.5_{R_t} Value + 0.5_{R_t} Momentum \quad (12)$$

4. Results

In this section, I analyse the results obtained from the investment strategies employed: value, momentum, and Combo.

The analysis of the results obtained from the portfolios' performance is divided into two different time periods. This separation was done for two main reasons: firstly, markets around the world reacted aggressively to the pandemic news and fears around March 2020, which originated great losses across all financial markets. Additionally, recovery levels also happened to be great and rather rapid in the following months, making this period incomparable to previous years and phases. Secondly, empirical evidence suggests that momentum strategies perform bad in highly volatile, panic-ridden scenarios (Daniel and Moskowitz, 2016; Demirer and Zhang, 2019). Taking these arguments into consideration, it was decided that the results from the investment strategies would be accessed in a pre-pandemic and then post-pandemic period.

Regarding the results, the first ones to be analysed were from 2015 until December 2019, which corresponds to the pre-pandemic period. Then, the period containing the effects of the pandemic, which I set to start in 2020[11] and end in 2021[12], was analysed.

In the subsequent subsections, for each of these periods, comments are made on the relevant investment performance measures and their meaning. Finally, the results of both periods are compared in order to understand the joint conclusions. In this analysis, the benchmark considered is the market portfolio. The M^2 for both of these periods is also presented, which introduces the comparative analysis performed on the ETFs used in the dissertation.

At the end of the results overview of both periods, a comparative analysis with the performance of the ETFs is carried out, as the initial dataset for the research is composed with their constituents, and, for an investor, these ETFs could represent another alternative to invest in

[11] From February 2020 until 2021, financial markets around had great volatility levels.
[12] October 2021.

FinTech. In this comparative analysis, I pick the best portfolio created using the strategies employed in the two periods of time studied and compare it with the performance of the three ETFs.

4.1. Performance of the investment strategies

In this subsection, I present the results from the investment strategies employed by accessing and interpreting the returns of the portfolios and subportfolios that come from their application. I show and comment on the relevant performance measures while comparing them with the market portfolio, which is the benchmark. I present the annualised mean excess return and standard deviation as a first and simple approach for measuring returns and risk. Using these two measures, I also use the Sharpe ratio, which easily compares performance among the different portfolios. Then, I show the annualised Jensen alpha and the annualised 3FF alpha. Regarding the portfolios' symmetry metrics, I also present the third and fourth moments of a distribution: skewness and excess kurtosis. To initialise the comparison of the results with the ETFs, the M^2 is used.

4.1.1. Analysis of results from the pre-pandemic period

Taking into consideration Table 1, it is clear that, during the pre-pandemic period, the better performance is achieved with momentum when compared to the combo and value strategies. For the momentum and Combo strategies, the mean excess return is positive and statistically significant. Both strategies have a mean excess return above the one achieved by the market portfolio (the benchmark), with the momentum portfolio's mean excess return being around four times higher and the Combo's being around two times higher.

For the momentum and Combo portfolios, the Sharpe ratio is above one, which, among investors, is considered to be a good score. These strategies also have a higher ratio when compared to the market portfolio, although, for these strategies, the excess kurtosis is much higher than the market, which represents a higher outlier risk. For the momentum and Combo strategies, the skewness is negative, which can represent bigger losses as the distributions have a fatter tail on the left.

Table 1: Investment strategies' results from the pre-pandemic period

In Table 1, the results for the value and momentum portfolios and their respective five subportfolios are shown. In the two last columns, the results from the Combo and market portfolios are shown. All returns are log normalised. In the first rows of the table, the mean excess return, standard deviation and Sharpe ratio are shown. In the middle of the table, the Jensen alpha, beta and 3FF alpha obtained with regressions are shown. At the end, the third and fourth moments of a distribution are shown: skewness and excess kurtosis. The mean excess return, standard deviation, Sharpe ratio and alphas are annualised values. The Sharpe ratio, beta, skewness, and excess kurtosis are dimensionless. All other measures are in percentages rounded to two decimal points. Some statistics are marked in bold if they are significant at a five percent level.

Sample Period: 2015-12 to 2019-12

	Value Portfolios						Momentum Portfolios							
	P4 (High)	P3	P2	P1	P0 (Low)	HML	P4 (Win)	P3	P2	P1	P0 (Lose)	WML	Combo	MKT-Rf
Mean excess returns	11.79	10.15	10.66	11.73	12.02	-1.42	**26.97**	16.13	22.07	8.76	-16.04	**45.33**	**21.19**	12.31
p-value	*0.19*	*0.31*	*0.34*	*0.29*	*0.34*	*0.82*	*0.03*	*0.04*	*0.00*	*0.35*	*0.15*	*0.00*	*0.01*	*0.05*
St.Dev	16.26	18.38	20.22	19.46	24.70	23.27	25.79	15.76	15.34	17.86	26.32	26.75	16.77	12.20
Sharpe	0.73	0.55	0.53	0.60	0.49	-0.06	1.05	1.02	1.44	0.49	-0.61	1.69	1.26	1.01
Alpha	9.25	13.76	10.62	10.53	12.71	-4.65	**28.30**	14.67	**23.35**	10.50	-16.21	**43.30**	**20.53**	0.00
p-value	*0.28*	*0.15*	*0.33*	*0.31*	*0.34*	*0.71*	*0.04*	*0.08*	*0.01*	*0.27*	*0.24*	*0.00*	*0.02*	*1.00*
Market beta	0.11	-0.36	-0.07	-0.03	-0.06	0.17	-0.02	0.13	-0.12	-0.17	-0.21	0.19	0.18	1.00
p-value	*0.57*	*0.10*	*0.78*	*0.90*	*0.85*	*0.55*	*0.95*	*0.49*	*0.53*	*0.44*	*0.50*	*0.55*	*0.37*	*0.00*
3FF alpha	11.25	16.30	13.09	13.92	15.68	-5.59	**29.52**	15.89	**25.34**	13.28	-12.03	43.75	**18.35**	-
p-value	*0.20*	*0.09*	*0.23*	*0.19*	*0.24*	*0.66*	*0.04*	*0.06*	*0.00*	*0.16*	*0.40*	*0.00*	*0.05*	-
Skewness	-0.47	0.08	-0.45	-0.33	0.54	-0.65	0.18	-0.77	-0.23	-0.08	0.37	-0.21	-0.89	0.43
Excess kurtosis	0.98	0.76	-0.01	0.77	1.26	0.54	1.33	1.40	1.01	2.71	-0.33	0.86	1.68	0.05

The Combo strategy from Asness et al. (2013) beneficiates from the value and momentum strategies being negatively correlated and from its independent positive return. I find that, for this time frame and with this dataset, the first premise is true, as the standard deviation for the portfolios HML (High Minus Low) and WML (Winners Minus Losers) is 23.27 % and 26.75% respectively, while for the Combo portfolio it is 16.77%.

When accessing a portfolio's returns, it is normal to comprehend which part of the returns are explained by exposure to the different risk factors. To access this, I first regressed the portfolios' returns over the market model, also known as CAPM. In this process, I obtained the Jensen alphas (the reasons for the usage of this metric are explained in subsection 2.6).

All subportfolios derived from the application of the value and momentum strategies produce positive Jensen alphas. However, it is only for momentum subportfolios and for the strategy itself (WML) that the alphas are statistically significant. For the Combo strategy, a statistically significant Jensen alpha was also produced. The market beta, which was also retrieved from the CAPM regression, is very low (near 0) or negative for all subportfolios and portfolios. The market beta is not statistically significant for any of the portfolios, which can imply that the market does not explain the portfolios' returns.

I regressed the results over the 3FF model (this model is expanded on in subsection 2.6) to understand if the 3FF alphas were also positive and statistically significant for the investment strategies identified above, as two other risk factors are introduced in this regression: proxy for size and value. The portfolios and subportfolios with significant Jensen alphas also have a positive and significant 3FF alpha.

Table 2: M^2 results for the pre-pandemic period considering the 3 ETFs

Sample Period: 2015-12 to 2019-12

	Value Portfolios						Momentum Portfolios						
	P4 (High)	P3	P2	P1	P0 (Low)	HML	P4 (Win)	P3	P2	P1	P0 (Lose)	WML	Combo
M squared (ARKF)	22,31	19,36	18,94	20,23	18,25	89,54	27,78	27,40	34,48	18,31	-0,43	38,84	31,49
M squared (FINX)	23,17	20,01	19,56	20,94	18,82	8,85	29,01	28,60	36,17	18,89	-1,15	40,83	32,97
M squared (IPAY)	22,53	19,53	19,10	20,41	18,40	8,90	28,09	27,71	34,91	18,46	-0,61	39,34	31,86

In Table 2, the M^2 measure for the value and momentum portfolios and subportfolios is shown, together with the measure for the Combo strategy. The three ETFs' risk (standard deviation) is used to compute the respective measures. All values are in percentages.

The M^2 measure accesses the return of a portfolio adjusted for its risk compared to a benchmark. Three ETFs utilised in this dissertation are used as benchmarks with the objective of exploring if the momentum and Combo portfolios – which are the overall best strategies in terms of performance for the pre-pandemic period, adjusted for the benchmark risk – still perform well and within similar levels to the ones shown with their own risk.

According to Table 2, for the momentum and Combo strategies, the performance of their subportfolios is lower when adjusted for the ETFs' risk. Regardless of that, the M^2 for these portfolios is close to their mean excess return, which could imply that the performance of the portfolios would be lower, but still good, if they had the same risk as the ETFs. For instance, the momentum portfolio's M^2 is around 40%. Although this measure includes the risk-free rate, its performance is relatively similar to the original mean excess return of 45%.

It is important to understand that some of these ETFs started trading after December 2015, which is the beginning of the pre-pandemic period. Still, it was decided that a comparison of the strategies with the three ETFs would be done. The momentum strategy, being the one with the best performance, was chosen to be compared with the ETFs in terms of mean excess return and Sharpe ratio.

Table 3: Performance measures results of the ETFs and the best portfolio

Sample Period: 2015-12 to 2019-12

	ARKF	FINX	IPAY	The best strategy (Momentum WML)
Mean excess return	12.19	19.26	14.16	**45.33**
p-value	*0.60*	*0.06*	*0.07*	*0.00*
St. Dev	20.40	17.97	15.54	26.75
Sharpe	0.60	1.07	0.91	1.69

In Table 3, the annualised mean excess return, standard deviation, and Sharpe ratio for both the ETFs and the best performing strategy during the pre-pandemic period are displayed. Apart from the Sharpe ratio, all other values are in percentages. Some statistics are marked in bold if they are significant at a five percent level.

The mean excess return is not significant for any of the ETFs, the standard deviation of the best performing strategy (momentum (WML)) is higher when compared with the volatility of the ETFs, and the Sharpe ratio for the momentum strategy beats the three funds for the pre-pandemic period.

4.1.2. Analysis of results for the post-pandemic period

For the post-pandemic period (the results can be consulted in Table 4), the mean excess return is not significant for any of the portfolios, which can be explained by the small sample size of this period, with only 19 months being analysed. The mean excess return for the value subportfolios is near zero. Regarding the momentum subportfolios, the mean excess return is positive and generally high, though the “loser” portfolio – which, in the case of the momentum strategy (WML), is shorted – has a positive return, originating a bad performance.

Table 4: Investment strategies results' from the post-pandemic period

In Table 4, the results for the value and momentum portfolios and their respective five subportfolios are shown. In the two last columns, the results from the Combo and market portfolios are shown. All returns are log normalised. In the first rows of the table, the mean excess return, standard deviation and Sharpe ratio are shown. In the middle of the table, the Jensen alpha, beta and 3FF alpha obtained with regressions are shown. At the end, the third and fourth moments of a distribution are shown: skewness and excess kurtosis. The mean excess return, standard deviation, Sharpe ratio and alphas are annualised values. The Sharpe ratio, beta, skewness, and excess kurtosis are dimensionless. All other measures are in percentages rounded to two decimal points. Some statistics are marked in bold if they are significant at a five percent level.

Sample Period: 2020-01 to 2021-07

	Value Porfolios						Momentum Porfolios							
	P4 (High)	P3	P2	P1	P0 (Low)	HML	P4 (Win)	P3	P2	P1	P0 (Lose)	WML	Combo	Mkt - Rf
Mean excess returns	0.30	0.02	-0.10	0.01	0.10	-0.08	43.55	29.91	13.36	30.90	52.86	-9.56	-4.82	25.21
p-value	*0.48*	*0.95*	*0.78*	*0.97*	*0.81*	*0.81*	*0.24*	*0.23*	*0.60*	*0.30*	*0.22*	*0.71*	*0.71*	*0.15*
St.Dev	0.53	0.48	0.46	0.42	0.49	0.41	46.52	31.50	32.22	37.51	54.46	32.24	16.02	21.93
Sharpe	0.56	0.05	-0.23	0.03	0.20	-0.20	0.94	0.95	0.41	0.82	0.97	-0.30	-0.30	1.15
Alpha	0.11	-0.16	-0.29	-0.14	0.00	-0.27	39.54	19.51	3.93	29.40	51.14	-11.96	-5.72	0.00
p-value	*0.81*	*0.68*	*0.45*	*0.70*	*0.97*	*0.42*	*0.34*	*0.46*	*0.89*	*0.38*	*0.29*	*0.67*	*0.68*	*1.00*
Market beta	0.01	0.01	0.01	0.01	0.00	0.01	0.16	0.41	0.37	0.06	0.07	0.10	0.05	1.00
p-value	*0.20*	*0.16*	*0.14*	*0.20*	*0.41*	*0.09*	*0.76*	*0.23*	*0.29*	*0.89*	*0.91*	*0.79*	*0.79*	*0.00*
3FF alpha	0.15	-0.09	-0.27	-0.13	0.00	-0.01	27.27	16.10	3.72	30.98	48.46	-21.49	-10.83	-
p-value	*0.75*	*0.83*	*0.52*	*0.75*	*11.75*	*6.93*	*0.55*	*0.59*	*0.91*	*0.41*	*0.37*	*0.48*	*0.48*	-
Skewness	0.28	-0.82	-0.62	-0.34	-0.57	1.15	-0.55	-0.84	-1.26	0.14	-0.39	-0.46	-0.46	-0.52
Excess kurtosis	2.51	1.33	1.91	1.05	1.55	2.83	0.82	0.97	3.27	2.59	1.35	-1.33	-1.32	1.28

The market portfolio beats every strategy if we take into consideration the different measures presented in Table 4. The Jensen and 3FF alpha are not statistically significant for any of the portfolios, which can be due to the sample size, as referred above.

For the momentum (WML) and Combo portfolios, the worst performers in terms of mean excess return and Sharpe ratio, that poor performance can be explained by their distribution series: both have negative skewness, which implies a higher probability of higher losses, and negative excess kurtosis, which means bigger tails than what is expected in a normal distribution series.

Table 5: M^2 results for the post-pandemic period considering the three ETFs

Sample Period: 2020-01 to 2021-07

	Value Porfolios						Momentum Porfolios						
	P4 (High)	P3	P2	P1	P0 (Low)	HML	P4 (Win)	P3	P2	P1	P0 (Lose)	WML	Combo
M squared (FINX)	21,36	3,96	-5,28	3,22	9,03	-4,26	34,14	34,59	16,44	30,32	35,31	-7,69	-7,84
M squared (IPAY)	21,57	3,98	-5,37	3,23	9,10	-4,34	34,50	34,95	16,60	30,63	35,68	-7,80	-7,95
M squared (ARKF)	22,44	4,05	-5,71	3,27	9,40	-4,64	35,94	36,41	17,24	31,90	37,18	-8,26	-8,42

In table 5, the M^2 for the value and momentum portfolios and subportfolios is shown, together with the measure for the Combo strategy. The three ETFs' risk (standard deviation) is used to compute the respetive measures. All values are in percentage to the U.S. dollar.

The portfolios' adjusted returns for the ETFs' risk, accessed thanks to the M^2 measure, are generally better when compared to the "original" returns, with the portfolios' own risk, as shown in Table 5.

For the value strategy, the difference within its subportfolios is very high. Their volatility during the post-pandemic period was near zero and, when adjusted for higher benchmark risks, their returns increase. For the momentum and combo portfolios, the adjusted returns are slightly better, as the ETFs in the post-pandemic period carry more risk than these strategies[13].

In Table 6, a similar table to the one presented for the analysis of the pre-pandemic period is shown, with the goal of comparing the performance of the three ETFs with the best portfolio or subportfolio from the post-pandemic period. For this period, Ark FinTech Innovation ETF (ARKF) beats the best subportfolio if we take into consideration the mean excess return and the Sharpe ratio. Although subportfolio P4, from the momentum strategy, has a positive and high

[13] The ETFs' risk can be accessed in Table 6 thought the standard deviation. Their risk, with the exception of two subportfolios, is higher than any other metrics.

mean excess return, its standard deviation is equally high, originating a Sharpe ratio below one, which is not considered to be good.

Table 6: Comparison between the "winner" portfolio from the momentum strategy and the three ETFs

Sample Period: 2020-01 to 2021-07

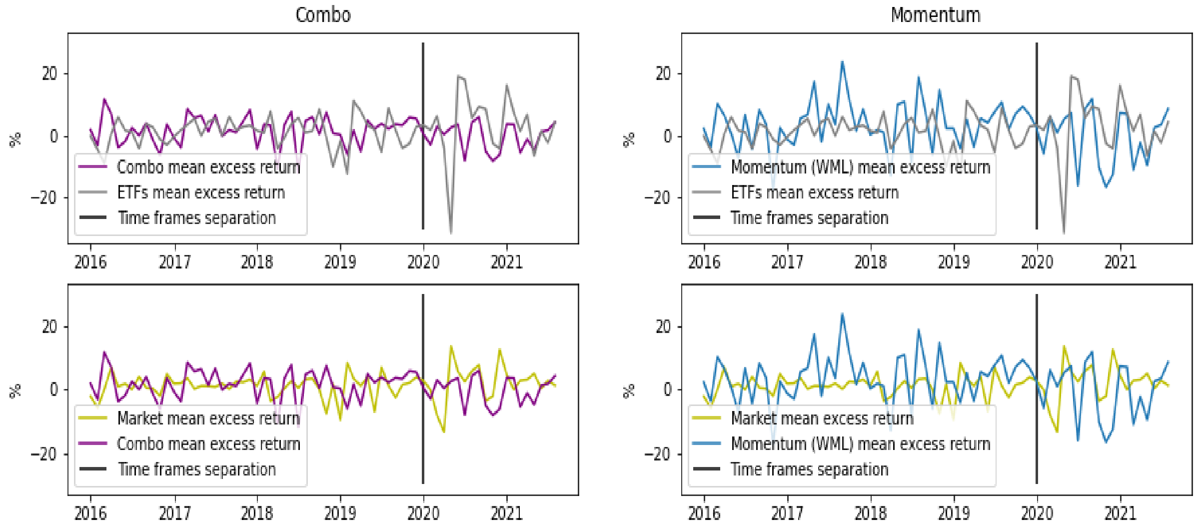
	ARKF	FINX	IPAY	The best sub portfolio (Momentum P4)
Mean excess return	51.56	0.29	29.41	43.55
p-value	*0.09*	*0.33*	*0.33*	*0.24*
St. Dev	38.01	37.92	41.65	46.52
Sharpe	1.36	0.01	0.71	0.94

Table 6 shows the mean excess return, standard deviation and Sharpe ratio for the three ETFs used in the dissertation and the best performing subportfolio ("winner" momentum portfolio) during the post-pandemic period.

4.1.3. General conclusions regarding the two periods

Regarding the momentum and Combo portfolios, both these strategies produce significant statistics and beat the market portfolio for the pre-pandemic period. However, when it comes to the post-pandemic period, the superiority of these strategies in relation to the market is no longer true and the returns are not positive for either of the three portfolios: value, momentum and Combo. In Figure 2, the momentum and Combo strategies are visually compared with the market portfolio and the mean return of the three ETFs. Three main conclusions can be extracted from the analysis of the results performed above and visually confirmed in Figure 2: for the pre-pandemic period, momentum and Combo strategies perform better while having the market and the three ETFs as benchmarks; in the post-pandemic period, the strategies perform worse than the market; finally, the overall best strategy employed in this dissertation is the momentum strategy.

Figure 2: Mean excess return for the Combo and momentum portfolios and an average of the three ETFs time series.



In Figure 2, four graphs are displayed. On the left side, in purple, the Combo mean excess return time series is represented. On the right side, in blue, the momentum excess return time series is represented. In the top two graphs, a time series composed of the average of the three ETFs' mean excess return is drawn in grey. In the bottom two graphs, in yellow, is a time series representing the market's mean excess return. The time series are in percentages.

5. Transaction costs

In this dissertation, the performances of the investment strategies proposed and of the ETFs, which are a passive investment vehicle, are often compared. The strategies accessed and studied in this research are actively managed and require that an investor balances and trades to create the portfolios in the different months. In this section, I evaluate if the composition of the portfolios' constituents is persistent over time. This approach is an alternative to evaluating transaction costs, as the less changes are made in the composition of a portfolio, the less trades an investor does and, ultimately, the cheaper the investment strategies are to implement.

In section 4, the reasoning beyond separating the analysis of the investment strategies' performance into two different periods of time is explained. In this transaction cost analysis, the same periods of time will be used, and the results will be analysed separately.

To access the persistence of the portfolios, the portfolios' turnover rates are calculated in the following manner:

$$Turnover_t = \frac{[(stocks\ in\ Q_{t-1} \cap Not\ (Stock\ in\ Q_t)) \cup ((Stocks\ in\ Q\ _t \cap Not\ (Stock\ in\ Q_{t-1})]}{Number\ of\ stocks\ in\ Q_t} \quad (13)$$

[14]

The portfolio turnover measures how frequently the stocks in the portfolio are bought or sold over some time. To calculate this metric, the portfolio composition on months t and $t-1$ is compared and the "differences" are added. This way, the stocks that were bought and sold from one month to another are accounted for. Having the sum of the bought and sold stocks from one month to another, that sum is divided by the size of the portfolio at time t.

Table 7: Momentum and value portfolios' mean and variation turnover rates

		Momentum		Value	
		P4 (Winner)	P0 (Loser)	P4 (High)	P0 (Low)
1st time frame	**Mean**	11,50	14,20	5,95	7,54
	St.Dev	4,53	7,77	4,23	4,26
2nd time frame	**Mean**	17,39	19,48	12,93	12,47
	St.Dev	6,62	8,76	17,44	17,00

Table 7 shows the mean and standard deviation of the turnover rates from the momentum and value strategies composed by the long-short portfolios, namely WML and HML. The first and third rows show the mean turnover and the second and fourth rows show the standard deviation. The results are separated according to the two different periods of time proposed in this dissertation. The results are displayed in percentages and rounded to two decimal points.

Three main conclusions can be extracted from Table 7. Firstly, the mean and variation turnover rates for value subportfolios are lower when compared to momentum subportfolios.

Secondly, between the first and second periods of time, the turnover rates average and standard deviation increase for both strategies. For value, in the "High" subportfolio, the average more than doubles from one period to another.

The third conclusion is that, overall, the transaction costs for both strategies, accessed with the portfolios' turnover, are low. This conclusion is based on the following rationale: If we take into consideration the number of stocks in the dataset (114) and the fact that the portfolios were constructed with quintiles, which represent 20% of a population, and assuming that, on average, 114 companies are being considered to assemble the investment strategies each month, a subportfolio would be composed of 22 stocks. If we were to consider a 14% turnover, around three stocks would have to be traded each month, which represents a very low transaction cost.

[14] Q stands for quintile, which, in statistics, is a representation of 20% of a given population.

6. Bootstrap

In statistics, bootstrapping consists of resampling an original dataset with a replacement, creating numerous simulated datasets to recreate its entire population (Frost, 2018).

In this process, every datapoint has an equal probability of being chosen to be included in the resampled datasets. As the process of resampling with a replacement is executed, the same datapoint can be chosen more than once. This process results in resampled datasets with the same size of the original sample (Frost, 2018).

One of the advantages of the bootstrapping method is that it does not assume any type of distribution in the data, contrary to traditional statistics, which normally assume that data is normally distributed or that it follows a particular distribution.

Considering that the period analysed in this dissertation is relatively low – less than six years are evaluated in terms of the strategies' returns –, the bootstrap method was applied with the objective of resampling the mean excess return from the momentum, Combo, and market portfolios. This was done in order to achieve more robust conclusions.

In this research, the "sample" size – the one to be bootstrapped and from which the replicate samples were drawn – is composed of 68 datapoints, which are the different monthly excess returns. The bootstrap consisted of randomly producing samples with a size of 68 entries for 10,000 times. Because of the method's resampling with a replacement, it is possible that, inside one random sample, the one-month excess return for January 2020, for example, appears twice, while not appearing at all in another sample.

Each random sample has its own statistics, such as mean and standard deviation. From this process, the mean Sharpe ratio was calculated using the 10,000 mean excess return samples from the momentum, Combo, and market portfolios. The value portfolio was not used because of its consistent underperformance, as shown in section 4.

The mean excess return is resampled considering the entire data frame, although this process was also done only taking into consideration the pre-pandemic period in order to exclude the negative results caused by the pandemic from the portfolios' returns.

In Table 8, the mean Sharpe ratio retrieved from the bootstrap process is shown.

Table 8: Bootstrapped Sharpe ratios

		Sharpe ratio
Entire time frame	Momentum	0.62
	Combo	0.50
	Market	0.62

		Sharpe ratio
1st time frame	Momentum	1.03
	Combo	1.77
	Market	0.64

In Table 8, the bootstrapped Sharpe ratios for the momentum and Combo strategies, together with the market portfolio, are shown. The results of the bootstrap take into consideration the entire time frame and, then, only the pre-pandemic period. The Sharpe ratios are rounded to two decimal points, and they are unidimensional.

Taking into consideration Table 8, it is surprising that, for the pre-pandemic period, the Combo strategy is the one with the highest Sharpe ratio, which is not the same conclusion retrieved in section 4, as the momentum strategy was the best performer across all metrics.

The bootstrap results for the entire data frame show that the market and momentum portfolios both have a similar bootstrapped Sharpe ratio and the Combo strategy has slightly worse results when compared to other portfolios.

The bootstrap method helped to understand and state more vigorously that, for the pre-pandemic period, the Combo and momentum strategies beat the market. However, if the entire time frame is taken into consideration, the momentum and market portfolios are similar in terms of performance.

7. Limitations and further investigation

This research is limited and affected by three main points. Firstly, the way FinTech is defined in this dissertation is subjective and very singular, which originates a posterior choice of certain ETFs and, consequently, the incorporation of their holdings to set a primary list. If a different set of companies was to be selected to establish and construct the dataset, the results could possibly be different and other conclusions could be extracted.

Secondly, the size of the time frame (in terms of the number of months being analysed) is also a constraint, with 69 months' worth of data on strategies' returns and a maximum of 114 companies being examined. Other studies on the effectiveness of investment strategies normally use larger amounts of historical data and study indices or samples from larger companies. Since this analysis was done on a rather small time frame, inconclusive and non-significant results can emerge, which was the case for the analysis on the post-pandemic period.

Finally, the pandemic had a huge impact on the behaviour and returns of both the strategies and the market during the post-pandemic period. The conclusions from the first and second periods are distinct, making the scenario of the pandemic not happening an astonishingly interesting one. That would allow a comprehension of the investment performance evolution and its results, as the different conclusions and results between the two periods, shown in sections 4, 5, and 6, are rather evident.

I sincerely hope that this thesis actively contributes to the development of new studies and research on the returns of FinTech public companies. This is a new and unexplored field that would beneficiate from and be enriched by the study of different investment strategies applied to the field; some more quantitative, some more naïve and simpler. Future studies could focus on periods of time different from the ones in this research, study the next months and years to analyse this or apply other investment strategies to these FinTech stocks.

To test the validity of the investment strategies analysed in this research, enlarging the dataset in terms of samples studied would be valuable. This can be easily accomplished as a large amount of FinTech companies tend to become publicly traded.

8. Conclusion

In this thesis, three different investment strategies were applied to FinTech stocks. Their efficiency and profitability were studied, seeking to understand how an investor can be exposed to this sector and what the best investment strategy is. The strategies studied were: value, momentum, and Combo. These strategies were previously studied and identified as profitable and efficient for different time frames and datasets (Chui, 2003; Blittz et al., 2011; Asness, 2013; Jegadeesh and Titman, 1993; Fama and French, 1998; Fama and French, 1992, 1993; Lakonishok, Shleifer and Vishny, 1994; Asness et al., 2013).

For FinTech public companies, the value strategy seems to be unprofitable and not worth implementing. The value portfolio proved to be unprofitable for the time frames accessed and does not produce excess returns. This portfolio also does not have a risk premium associated with it.

Another market anomaly studied in this dissertation is the momentum strategy. Considering the analysis done, this strategy seems to be the most profitable and the one with the best performance in most of the metrics accessed. From 2015 to 2020, the momentum portfolio beat the market and achieved positive alphas according to the CAPM and the 3FF model.

Despite being the most profitable strategy, this active management approach is suited for investors who have great risk tolerance. The momentum strategy shows high levels of volatility and the probability of extreme events and their impact is also cause for concern, as the strategy has negative skewness and positive excess kurtosis.

The momentum results allow me to agree with Daniel and Moskowitz (2016) and Demirer and Zhang (2019), as the strategy proved to perform bad in high volatility and panic-ridden scenarios. From 2020 to 2021 – the period of time in which the market has a mean excess return of around 25% –, the WML strategy showed negative results.

The last investment strategy studied was Combo (Asness et al., 2013), with interesting results emerging from the Sharpe ratio bootstrap. For the period between 2015 and 2020, the higher bootstrapped Sharpe ratio among the Combo, momentum and market portfolios is achieved with this strategy. Value and momentum anomalies are negatively correlated, which allows an investor to diversify and diminish his risk (Asness et al., 2013). The risk profile of this strategy proved to be much lower when compared to momentum and value, which was one of the keys for the good Sharpe ratio.

In this dissertation, a comparison of the performance of the three investment strategies described above with three Fintech ETFs is also done. From 2015 until 2020, an active management style, like the momentum strategy, is preferable and a better choice for an investor. For the period between 2020 and 2021, a more conservative and lower risk investment vehicle seems to be more profitable, with ARKF beating the strategies employed.

Appendix:

Appendix 1: **List of companies used in this dissertation and respective classification for the “Business” and “Mergers and Acquisitions” categories**

Company Name	**Business**	**Mergers and Acquisitions**
SQUARE INC - A	Yes	
COINBASE GLOBAL INC -CLASS A	Yes	
SHOPIFY INC - CLASS A	Yes	
TWILIO INC – A	No	Yes
TELADOC HEALTH INC	No	No
ADYEN NV	Yes	
UIPATH INC - CLASS A	Yes	
ZILLOW GROUP INC - C	Yes	
SEA LTD-ADR	Yes	
SILVERGATE CAPITAL CORP-CL A	Yes	
OPENDOOR TECHNOLOGIES INC	Yes	
LENDINGCLUB CORP	Yes	
MERCADOLIBRE INC	Yes	
PAYPAL HOLDINGS INC	Yes	
JD.COM INC-ADR	Yes	
ROBINHOOD MARKETS INC - A	Yes	
DOCUSIGN INC	Yes	
ETSY INC	Yes	
TCS GROUP HOLDING-GDR REG S	Yes	
DRAFTKINGS INC - CL A	Yes	
WORKDAY INC-CLASS A	Yes	
META PLATFORMS INC	No	No
INTERCONTINENTAL EXCHANGE IN	Yes	
INTUIT INC	Yes	
DISCOVERY LTD	Yes	
PINDUODUO INC-ADR	Yes	
BILL.COM HOLDINGS INC	Yes	
STONECO LTD-A	Yes	
Z HOLDINGS CORP	Yes	
TENCENT HOLDINGS LTD-UNS ADR	Yes	

FARFETCH LTD-CLASS A	No	No
AMAZON.COM INC	Yes	
PALANTIR TECHNOLOGIES INC-A	No	No
SNAP INC – A	No	No
JSC KASPI.KZ GDR-REG S	No	No
PAGSEGURO DIGITAL LTD-CL A	Yes	
TOAST INC-CLASS A	Yes	
PINTEREST INC- CLASS A	No	No
SOUTH AFRICAN RAND	No	No
ADYEN NV	Yes	
FISERV INC	Yes	
UPSTART HOLDINGS INC	Yes	
AFFIRM HOLDINGS INC	Yes	
FIDELITY NATIONA	Yes	
AFTERPAY LTD	Yes	
SS&C TECHNOLOGIE	Yes	
XERO LTD	Yes	
TEMENOS AG - REG	Yes	
LUFAX HOLDING LTD-ADR	Yes	
BLACK KNIGHT INC	Yes	
NEXI SPA	Yes	
GUIDEWIRE SOFTWARE INC	Yes	
NCINO INC	Yes	
NUVEI CORP-SUB V	Yes	
MARATHON DIGITAL	Yes	
HUT 8 MINING CORP	Yes	
HEALTHEQUITY INC	Yes	
SIMCORP A/S	Yes	
ENVESTNET INC	Yes	
HYPOPORT SE	Yes	
OPEN LENDING CORP - CL A	Yes	
VIRTU FINANCIA-A	Yes	
RIOT BLOCKCHAIN INC	Yes	
GREENSKY INC-CLASS A	Yes	
ZIP CO LTD	Yes	

HIVE BLOCKCHAIN	Yes	
SHIFT4 PAYMENT-A	Yes	
BIT DIGITAL INC	Yes	
BITFARMS LTD/CANADA	Yes	
BOTTOMLINE TECH	Yes	
LENDINGTREE INC	Yes	
SAPIENS INTL	Yes	
IRESS LTD	Yes	
BOKU INC	Yes	
LEONTEQ AG	Yes	
HUB24 LTD	Yes	
YEAHKA LTD	Yes	
MITEK SYSTEMS INC	Yes	
BLUCORA INC	Yes	
VERTEX INC - CLASS A	Yes	
WEALTHNAVI INC	Yes	
TRITERRAS INC-CLASS A	Yes	
QIWI PLC-SPONSORED ADR	Yes	
MAKUAKE INC	Yes	
GREENBOX POS	Yes	
AMERICAN EXPRESS CO	Yes	
MASTERCARD INCORPORATED	Yes	
VISA INC	Yes	
GLOBAL PMTS INC	Yes	
DISCOVER FINL SVCS	Yes	
MARQETA INC	Yes	
FLEETCOR TECHNOLOGIES INC	Yes	
WORLDLINE	Yes	
GMO PAYMENT GATEWA	Yes	
DLOCAL LTD	Yes	
WISE PLC	Yes	
NCR CORP NEW	Yes	
WESTERN UN CO	Yes	
WEX INC	Yes	
FLYWIRE CORPORATION	Yes	

EURONET WORLDWIDE INC	Yes	
ACI WORLDWIDE INC	Yes	
EVERTEC INC	Yes	
EVO PMTS INC	Yes	
GREEN DOT CORP	Yes	
NETWORK INTL HLDGS	Yes	
CIELO SA	Yes	
PAYONEER GLOBAL INC	Yes	
EML PAYMENTS LTD	Yes	
PAX GLOBAL TECHNOL	Yes	
GMO FINANCIAL GATE	Yes	
CANTALOUPE INC	Yes	
JACCS CO LTD	Yes	
INTERNATIONAL MNY EXPRESS INC COM	Yes	
SEZZLE INC	Yes	
I3 VERTICALS INC	Yes	
NET 1 UEPS TECHNOLOGIES INC	Yes	
PAYPOINT	Yes	
MONEYGRAM INTL INC	Yes	
PAYSIGN INC	Yes	
INTELLIGENT WAVE	Yes	

Appendix 2: Location and distribution of exchanges

Exchanges location	Firms traded in the exchange	%
United States	82	71%
Tokyo	9	8%
Australia	8	7%
London	5	4%
Canada	4	3%
Amsterdam	2	2%
Singapure	1	1%
Switzerland	1	1%
Italy	1	1%
Denmark	1	1%
Germany	1	1%
Paris	1	1%

In appendix 2, I show the number of firms traded in countries and cities exchanges' and it's percentage.

Appendix 3: Python script used to form the momentum strategy

```
def Momentum_function(formation):
    end_measurement = formation - MonthEnd(1)
# go to the last 11 month returns of all firms
    signal_MOM = momentum_11_month_ret.loc[end_measurement]
#giving other name
    signal_MOM = signal_MOM.reset_index(name="11_M_returns")
# returns that are 0 are form the ones that were not traded at that date so exclude
    signal_MOM = signal_MOM[signal_MOM["11_M_returns"]!=0]
#Create 5 deciles, 0 for the losers and 4 for the winner
    signal_MOM["decile"] = pd.qcut(signal_MOM.iloc[:,1],5,labels=False,duplicates = "drop")
# portfolio 4
    Mom4_portfolio_MOM = signal_MOM[signal_MOM.decile == 4]
# portfolio 3
    Mom3_portfolio_MOM = signal_MOM[signal_MOM.decile == 3]
# portfolio 2
    Mom2_portfolio_MOM = signal_MOM[signal_MOM.decile == 2]
# portfolio 1
    Mom1_portfolio_MOM = signal_MOM[signal_MOM.decile == 1]
#loser portfolio
    Mom0_portfolio_MOM = signal_MOM[signal_MOM.decile == 0]
# returns from the portfolio 4
    Mom4_returns = comulative_monthly_ret.loc[formation + MonthEnd(1), comulative_monthly_ret.columns.isin(Mom4_portfolio_MOM["index"])]
# returns from the portfolio 3
    Mom3_returns = comulative_monthly_ret.loc[formation + MonthEnd(1), comulative_monthly_ret.columns.isin(Mom3_portfolio_MOM["index"])]
# returns from the portfolio 2
    Mom2_returns = comulative_monthly_ret.loc[formation + MonthEnd(1), comulative_monthly_ret.columns.isin(Mom2_portfolio_MOM["index"])]
# returns from the portfolio 1
    Mom1_returns = comulative_monthly_ret.loc[formation + MonthEnd(1), comulative_monthly_ret.columns.isin(Mom1_portfolio_MOM["index"])]
# returns from the portfolio 0
    Mom0_returns = comulative_monthly_ret.loc[formation + MonthEnd(1), comulative_monthly_ret.columns.isin(Mom0_portfolio_MOM["index"])]

    portfolio_mom_4_returns =  Mom4_returns.mean()
    portfolio_mom_3_returns =  Mom3_returns.mean()
    portfolio_mom_2_returns =  Mom2_returns.mean()
    portfolio_mom_1_returns =  Mom1_returns.mean()
    portfolio_mom_0_returns =  Mom0_returns.mean()
    wml_returns = Mom4_returns.mean() - Mom0_returns.mean()
    return wml_returns,portfolio_mom_4_returns,portfolio_mom_3_returns,portfolio_mom_2_returns,portfolio_mom_1_returns,portfolio_mom_0_r
```

Appendix 4: Python script used to perform the Bootstrap analysis

Bootstrap

```
mean_excess = pd.read_excel("tables thesis.xlsx",sheet_name="bootstrap")
```

```
combo = mean_excess.Combo
wml = mean_excess["Wml "]
market = mean_excess["Market"]
```

```
# Defining bootstrap function
def bootstrap(wml,combo,market, N = 10000):

    #create a sample composed by multiple samples with the same size of the original data
    index = np.arange(len(wml))

    # create an array without initializing its entries
    Sharpe_wml = np.empty(N)
    Sharpe_combo = np.empty(N)
    Sharpe_market = np.empty(N)

    #
    for i in range(N):
    # choose a random number in an array which contains the exat number of the series datapoints
        random = np.random.choice(index, size = len(index))
        Iwml = wml[random]
        Icombo = combo[random]
        Imarket = market[random]
        Sharpe_wml = np.mean(Iwml)/np.std(Iwml)
        Sharpe_combo = np.mean(Icombo)/np.std(Icombo)
        Sharpe_market = np.mean(Imarket)/np.std(Imarket)
        return Sharpe_wml, Sharpe_combo, Sharpe_market
```

```
sr_combo= []
sr_market = []
```

```
for i in range(len(wml)):
    w,y,q = bootstrap(wml,combo,market, N = 10000)
    sr_wml.append(w)
    sr_combo.append(y)
    sr_market.append(q)
    SR = np.mean(sr_wml)
    SRq = np.mean(sr_market)
```

```
    return wml_returns,portfolio_mom_4_returns,portfolio_mom_3_returns,
    portfolio_mom_2_returns,portfolio_mom_1_returns,portfolio_mom_0_returns
```

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