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Momentum in the U.S. Equity Market. A profitable or a decadent strategy?

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ABSTRACT

The unpredictability of the stock market has forced investors to seek active investing strategies to earn excess returns. Several theories conducted by financial academics explain the nature of stock returns. Factor investing strategies aim to outperform the market based on a risk factor. One of the most studied market anomalies is the momentum factor.

This paper tesst the persistence and profitability of the momentum factor in the U.S. Stock Market. Evidence presented by Jegadeesh and Titman (2001) shows the abnormally high returns of the momentum strategy in the first twelve-month holding period. Nevertheless, these returns decrease in the following thirty-month holding period. Additionally, the strategy experiences "momentum crashes" after bearish markets. These crashes are caused by the sensitivity of momentum to market volatility. The investment strategy tested in this paper is based on the "*dynamic momentum*" strategy proposed by Daniel and Markowitz in 2016. Following a "back-testing" technique between 2016 and 2021, the strategy uses the CBOE (Chicago Board Options Exchange) VIX index, the monthly returns of FedEx, and the TLT ETF to test the profitability of momentum-based rebalancing strategies.

Finally, the results of this paper show the abnormal returns of the rebalanced portfolio, which alternates a long position in FedEx and an investment on the TLT ETF when the VIX index level exceeds the "switching level" of the portfolio weights. These abnormal returns are higher than the excess returns of buying and holding the FedEx stock based on its positive momentum. This reflects the importance of rebalancing the portfolio based on volatility indicators to avoid crashes of the momentum strategy.

Key Words: Factor Investing, CAPM, Fama-French factor models, Carhart four-factor model, momentum, U.S. Equity Market, momentum crashes, dynamic momentum, volatility, "back-testing", rebalancing.

RESUMEN

La imprevisibilidad de los mercados financieros ha forzado a los inversores a buscar estrategias de inversión activas para alcanzar rendimientos altos. Varias teorías desarrolladas por académicos financieros explican el origen de estos altos rendimientos. El *Factor Investing* busca conseguir mejores retornos que el mercado basándose en un factor de riesgo. Una de las anomalías de mercado más estudiadas es el factor momentum.

Este trabajo pretende comprobar la persistencia y rentabilidad del factor momentum en el mercado financiero de Estados Unidos. Evidencias presentadas por Jegadeesh y Titman (2001) prueban los altos rendimientos de la estrategia basada en momentum durante el primer período de doce meses. Sin embargo, estos rendimientos disminuyen durante el siguiente período de treinta meses. Asimismo, la estrategia experimenta "momentum crashes" después de mercados bajistas. Estos crashes están causados por la alta sensibilidad del factor momentum a la volatilidad del mercado. La estrategia de inversión probada en este trabajo está basada en la estrategia de momentum dinámico propuesta por Daniel y Markowitz en 2016. Siguiendo la técnica de "back-testing" durante 2016 y 2021, la estrategia utiliza el índice VIX de la CBOE (Chicago Board Options Exhange), los rendimientos mensuales de FedEx y del TLT ETF para probar la rentabilidad de estrategias de reequilibrio basadas en momentum.

Finalmente, los resultados de este trabajo muestran los altos rendimientos de la cartera reequilibrada, que alterna posiciones en largo en FedEx e inversiones en el TLT ETF cuando el nivel del índice VIX excede el "nivel de cambio" de los pesos de la cartera. Estos rendimientos son mayores que los rendimientos obtenidos comprando y manteniendo las acciones de FedEx siguiendo su momentum positivo. Esto refleja la importancia de reequilibrar la cartera basándose en indicadores de volatilidad para prevenir crashes de la estrategia de momentmum.

Palabras clave: Factor Investing, CAPM, modelos de Fama-French, modelo de los cuatro factores de Carhart, momentum, mercado financiero de EE.UU, momentum crashes, momentm dinámico, volatilidad, "back-testing", reequilibrar.

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1. Introduction

1.1 Objectives

Factor Investing has become one of the hot topics in the current financial spheres. This investment strategy falls in the category of "active investing", as investors actively try to outperform the market by earning excess returns. The increasing competition, knowledge, and technology present in the stock market, have forced investors to seek alternative profitable strategies. A factor is "any characteristic relating a group of securities that is important in explaining their return and risk." (Bender, et al.,2013). Finance literature has tried to identify and define a wide variety of factors, discovering an enormous amount of them. Investors who follow this strategy will seek to earn excess returns by exposing to the risk of one of these factors. However, factor investing is not simple. The persistence of some risk premia is caused by complex explanations and origins of these risk factors. Investors who perform these strategies are aware factor risk premia may be arbitraged away in the future, having a 100% probability of losing against the market in some time periods.

This paper gives a theoretical framework of different models which try to explain stock returns. The Capital Asset Pricing Model (CAPM), the Fama French three and five-factor models, and the Carhart four-factor model are widely accepted by the finance community. Nevertheless, the reliability of these models is highly dependent on portfolio construction, timing, and geographical location.

After the theoretical explanation, a specific factor is chosen for further explanation. Momentum is one of the most studied factors, reflecting a strong relationship between excess returns and the strong past performance of a stock. Momentum has been strongly present in the U.S. Equity Market, earning sustainable and consistent returns over time. Moreover, the paper proposes a quantitative study of an investment strategy based on this factor. The sensitivity of factors to macroeconomic trends and behavioral biases have contributed to the persistency of factors for long periods. Nevertheless, this sensitivity to macroeconomic factor has caused the crash of the momentum strategy in a couple of periods over the last 100 years.

The *"buy winners and sell losers"* strategy experiences negative returns after bearish markets. Sudden recoveries of the market after severe economic crisis (The Great Depression, 2008 Financial Crisis) make losers outperform winners, resulting in negative returns of the strategy. Evidence on the Daniel and Moskowitz paper (2016a) about momentum crashes shows the strong relationship between increasing volatility and the underperformance of the strategy. Because of this, Daniel and Moskowitz (2016b) proposed a strategy based on a *"dynamic momentum"*.

1.2. Strategy and methodology.

Following the *"dynamic momentum"* logic, the strategy proposed on this paper expects to mitigate the negative effect of volatility in the returns of the strategy. For the empiric analysis, a "back-testing" methodology is used to test the strategy conducted on this paper. The mentioned strategy follows momentum tendencies by investing in the momentum of a single stock and switching the investment to cash or cash equivalents when market volatility is too high. The strategy uses the VIX index as a measure of market volatility.

2. The Capital Asset Pricing Model (CAPM)

The unpredictable behavior of financial markets and the drivers for these changes have always been an object of study for investors. This curiosity is captured in several models developed by economists and well-known finance scholars. These models try to explain the relationship between risk and expected returns. Moreover, the models provide useful tools for quantifying risk, predicting expected returns, determining the cost of equity, and security valuation.

The Capital Asset Pricing Model (CAPM) was proposed by the American economists William Sharpe and John Lintner and the Norwegian economist Jan Mossin in the 1960s. It is based on the Harry Markowitz Modern Portfolio Theory. The basic assumptions for this model are (Markowitz, 1952): 1.) Investors are rational (they seek to maximize returns while minimizing risk), 2.) Investors are only willing to accept higher amounts of risk if they are compensated by higher expected returns, 3.) Investors timely receive all pertinent information related to their investment decision, 4.) Investors can borrow or lend an unlimited amount of capital at a risk-free rate of interest, 5.) Markets are perfectly efficient, 6.) Markets do not include transaction costs or taxes, 7.) It is possible to select securities whose individual performance is independent of other portfolio investments. This theory aggregates the principles of diversification and covariance relationship between securities as the main pillars of its theoretical framework. Even though the CAPM is a widely recognized theory among the financial spheres, certain criticism arises due to its key assumptions. These assumptions are constantly noted as simplistic and unrealistic. However, they establish a clear and solid model which sets the path for developing new and more sophisticated models.

For a proper understanding of the CAPM model, it is important to understand the concept of risk. In the financial environment, the volatility of the stock price determines the risk of a given stock. It is measured as the standard deviation of the expected returns of a stock. Additionally, risk and expected returns are positively correlated. Investors hold a specific amount of risk, expecting a return subjected to this amount of risk. The higher the level of risk, the greater return investors will expect. Investors try to avoid risk through different techniques. The most popular one is diversification. Investors try to diffuse the risk by investing in different types of assets. When investors combine two or more assets on a portfolio, the expected return of the portfolio will be the weighted average of the expected returns of the underlying assets (Pérold, 2004a). Moreover, the calculation of the standard deviation of the portfolio follows the same logic. This means the standard deviation of the portfolio will be lower than the ones of the individual assets. Therefore, diversification allows investors to reduce the risk "without any sacrifice in expected returns" (Pérold, 2004b).

The risk factors which affect the different sets of assets are correlated. The correlation between risk factors is reflected in the expected returns of the stocks, building a common oscillation relationship between them. Reasonably, Markowitz (1952) assured not all risks can be diversified away because of the correlation between the risk factors and expected returns. The correlation coefficient can take values between 1 and -1. A correlation of 1 means returns are perfectly positively correlated. This type of correlation provides a highly strong predictive power of one stock's returns over the other, since not only do they fluctuate together but also respond to the same market changes. A correlation of -1 states the expected returns of two stocks vacillate in opposite directions, suggesting they respond differently to events in the market. A correlation of 0 shows the null predictive power of one stock returns over the other as they are not moved by the same drivers.

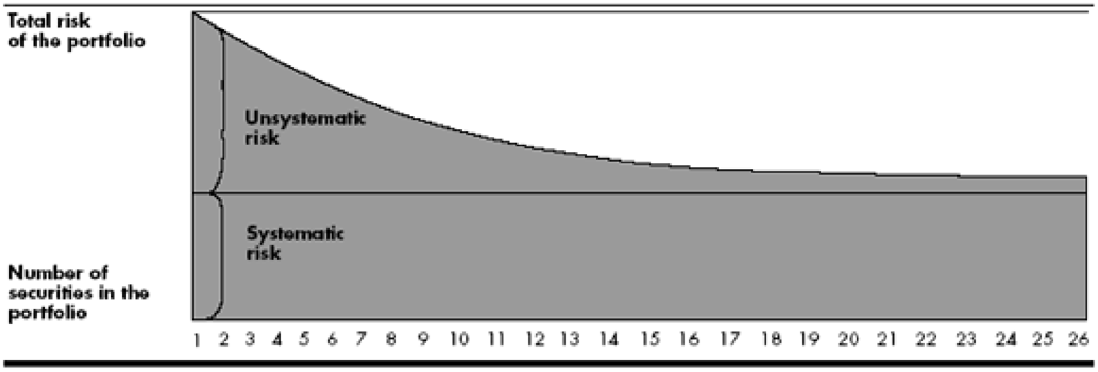
Investors can hold different combinations of assets within the same portfolio. By varying the weights allocations for each security, they get different expected returns for the same standard deviation and different levels of risk for a fixed expected return. These combinations lead the investors to optimize their weights allocations and compute the "efficient frontier". The "efficient frontier" shows all the optimal combinations of assets, providing investors with different options. Investors will choose among these options depending on their risk aversion.

There are two types of risks: systematic and unsystematic risk. The systematic risk is the one implicit in the market performance. This type of risk impacts a wide variety of assets, which results in a generalized movement of stock prices. Some examples of systematic risk factors are the rise in interest rates or general geopolitical events. On the other hand, the unsystematic risk is subjected to a specific stock. These risk factors exclusively affect one stock or a small group of similar stocks. Internal financial and managerial issues affecting a specific company, or the increasing competition in a certain sector are unsystematic risk factors.

$$\textit{Total risk} = \textit{Systematic risk} + \textit{Unsystematic risk} \qquad (1)$$

Nevertheless, returns are not perfectly correlated, so the expected positive returns offset the negative ones, mitigating a portion of the overall risk. The portion which can be eliminated through diversification is the unsystematic risk. Investors holding perfectly well-diversified portfolios will reach the "minimum" level of possible risk. This "minimum" level of risk is systematic risk, which affects all assets and cannot be avoided. The following graph represents how risk is reduced through diversification and how investors are unable to avoid systematic risk.

Figure 1. Reduction of unsystematic risk through diversification



Source: Harvard Business Review

Once all the diversifiable risk is disseminated, investors expect to receive the risk-free rate. As investors are risk-averse, they will demand compensation for assuming systematic risk. US, notes, bonds, and Treasury bills are examples of risk-free assets, which will return investors the risk-free rate. In the perfect world of CAPM, markets are efficient. This assumption strongly suggests that all public information is reflected in stock prices. As investors are risk-averse and behave rationally, they will have the same expectations and hold the exact portfolios. The perfectly-diversified portfolio of all securities is called the market portfolio. Following the unrealistic stream of assumptions of the CAPM, this market value-weighted portfolio is comprised of all securities. As having a portfolio with all securities is impossible, marketers use different indexes as approximations to the market portfolio. The S&P 500 and the NASDAQ indexes are commonly used to approximate the market portfolio and set a benchmark for measuring the market risk.

The standard measure of systematic risk is *beta*. "One way to think of beta is as a gauge of a security's volatility relative to the market's volatility" (Mullins, 1982a). The *beta* of the market portfolio equals 1, which will be used as a benchmark for measuring the volatility of other stocks. If a security´s *beta* exceeds 1, the security is riskier than the market and it is highly sensitive to changes in the market. If a specific event occurs, either positive or negative, the stock will increase or fall in a greater amount than the index. A stock with a *beta* smaller than 1 will follow the same logic. The stock will be less sensitive, and inherently, less risky than the market index. Stocks with a *beta* equal to 1 will mostly replicate the market performance, showing no sensitivity to changes in the market. Additionally, some stocks have negative *betas*. These stocks are negatively correlated with the market performance, behaving upwardly when the market falls and vice versa.

As the basic assumptions of the CAPM model state, there is a relationship between risk and return. The return of a stock will be calculated based on its *beta*. If a stock has a higher *beta* than the market, its returns will be greater than the market. *Beta* is calculated as the covariance between the historical returns of the stock and the historical returns of the market index divided by the variance of the market returns.

Once *beta* is calculated, the relationship between risk and returns can be determined on basis of the systematic risk. This relationship entails the security market line (SML). The formula for calculating the expected returns of a stock is:

$$E(R_s - R_f) = \alpha_{iT} + \beta im\ (E\ (Rm) - Rf + \varepsilon_{it} \qquad (2)$$

Where:

Rs= Expected returns of the stock

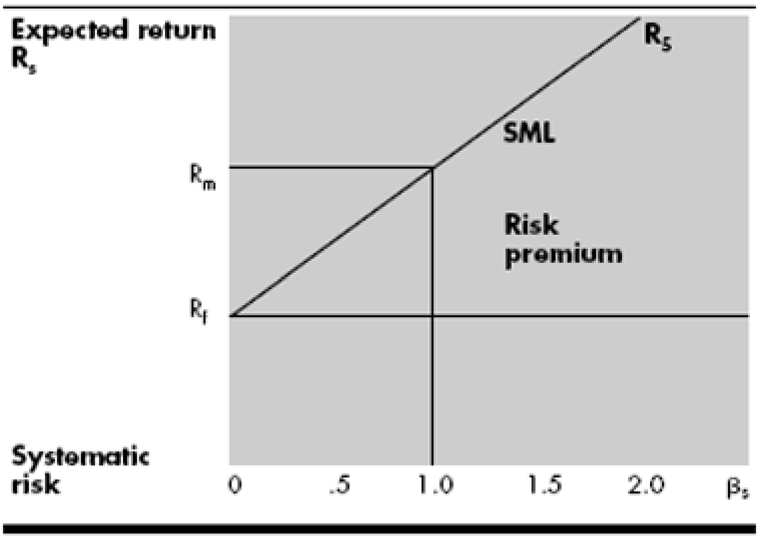
Rf= Risk-free rate

βs= stock's beta.

Rm-Rf= Market risk premium

The return of the stock equals the risk-free rate plus the market premium multiplied by the stock's *beta*. The market premium is the performance of the market over the risk-free rate. The SML is often represented graphically to attain a better insight into the relationship between *beta* (or systematic risk) and expected returns.

Figure 2. The Security Market Line



Source: Harvard Business Review, 1982

The intercept of the line is the risk-free rate and the slope is the risk premium. As the graph shows, the relationship between *beta* and expected returns is linear. Moreover, the upwardly sloping curve captures this direct relationship, where stocks with higher *betas* will have higher expected returns. This correlation is translated to portfolios as well. The *beta* of a portfolio is the weighted average of the *betas* of the securities comprising the portfolio.

The CAPM has several applications in corporate finance and investment management. Using the model for estimating a company's cost of equity is one of its most common applications. The company expects to earn the cost of equity as a return for its equity investments. If the company does not fulfill this requirement, the stock price will be adversely affected. As the cost of equity is related to the overall market conditions, it is extremely hard to estimate. An accurate prediction of the cost of equity is fundamental for budgeting management and an efficient capital structure of a company. The cost of equity will equal the expected return of a stock, therefore:

$$K_e = Rs = Rf + \beta s\ (Rm - Rf) \qquad (3)$$

This cost of equity will later be used for estimating the present value of a company. The discounted cash flow method is one of the most commonly used valuation techniques.

It estimates the present value of a company by discounting the future cash flows of the company at the cost of capital (WACC).

$$WACC= W_d*k_d + W_e*k_e \tag{4}$$

Where:

WACC= Weighted average cost of capital

W_d*= Weight of debt*

W_d*= Cost of debt*

W_e*= Weight of equity*

K_e*= Cost of debt*

Additionally, the cost of equity can be used in other valuation techniques. It is commonly used in the dividend discount model. This technique uses the cost of equity to calculate the current price per share of a company by the following equation:

$$Psp = \frac{Dps}{\mathrm{Ke{-}g}} \tag{5}$$

Where:

Pps= Price per share

Dps= Dividend per share

K_e*= Cost of equity.*

g= perpetuity growth rate in dividends per share.

Even though these two valuation models have limited assumptions, they are widely used in corporate finance. Both models require inputs such as perpetual growth rates and *betas,* which are extremely difficult to estimate. Scholars have conducted several studies trying to address the significance and applicability of CAPM (Fama French, 2003a). These studies have concluded the oversimplification of its assumptions, which can only apply to certain situations and companies. Nevertheless, it has been proven CAPM's scarcities are "no worse" than other model's assumptions (Mullins, 1982b). Consequently, finance erudites have developed more complex models based on CAPM.

3. <u>Factor Models</u>

In the perfect world of CAPM, investors can only obtain abnormal returns by holding a higher risk exposure than the market portfolio. Nevertheless, a broad sector of the finance literature has determined the existence of additional sources of systematic risk to which investors can be exposed. These sources are called market anomalies (otherwise called factors), which try to properly explain the abnormal returns obtained by investors.

Since the 1970s, several models have tried to identify, explain and prove the existence of these factors. A factor can be defined as "any characteristic relating a group of securities that is important in explaining their return and risk." (Bender, et.al, 2013a). Researchers have found a wide variety of factors that explain the long-term returns of a long-term equity portfolio. Some of the most studied ones are Value, Low Size, Low Volatility, Momentum, and Quality (Bender, et.al,2013b). The returns of these factors have been robust and consistent over the long term, which has enabled financial researchers to study them. Additionally, these factors have not been arbitraged away through time. This consistency is possibly caused by systematic errors (e.g., behavioral biases of investors) or by the cyclicality of their performance across long periods. Nevertheless, factors are still sensitive to changes in the overall market and macroeconomic trends.

3.1. <u>The Fama-French Three-Factor Model</u>

The first model which tries to explain abnormal returns through factors is the Fama-French Three-Factor Model. Proposed by Eugene Fama and Ken French in 1992, the model includes Value and Size as the principal explanatory sources of premium returns. It is presented as an alternative model for justifying the "cross-section of average returns on U.S. common stocks" (Fama; French, 1992).

The model argues portfolios of stocks with small capitalizations have greater excess returns than portfolios of stocks with large capitalizations. For capturing the risk inherent in firm size, the SMB (small minus big) risk factor is computed by calculating the monthly average return of the smallest stocks minus the average monthly return of the largest stocks (Womack; Zhang, 2003). The logic behind this factor relies upon the sensitivity of small companies to risk factors. Small firms are less liquid and have a reduced capacity of facing negative events. These facts suppose a higher risk for investors, and therefore, higher expected returns. A positive SMB indicates small stocks have outperformed large stocks.

Additionally, the model defends the stocks with higher book-to-market ratios have larger excess returns than stocks with lower book-to-market ratios. The HML (high minus low) risk factor expresses the difference between the monthly excess returns of a portfolio with high book-to-market (BV/MV) ratios and the monthly excess returns of a portfolio of stocks with low BV/MV. The HML factor is directly related to the expected future earnings of a company and studies the risk exposure of "value" firms (high BV/MV) and "growth" firms (low BV/MV). If a stock has a BV/MV ratio, the market value of a company decreases because of poor earnings expectations, increasing the risk exposure and the expected returns. A positive HML means high BV/MV stocks have outperformed low BV/MV stocks. Therefore, the excess returns of stock are explained by the following equation:

$$E(R_i - R_f) = \alpha_{iT} + \beta_{im}(E(R_m) - R_f) + \beta_{is} E(SMB) + \beta_{ih} E(HML) + \varepsilon_{it} \qquad (6)$$

Where:

R_i = Expected return of the stock.

R_f = Risk-free rate.

β_{im} = Market factor beta

R_m = Expected return of the market.

β_{is} = *Size factor beta.*

β_{ih} = *Value factor beta.*

For the *SMB* risk factor, stocks are split into two portfolios. One portfolio will be composed of the 50% smallest stocks, and the other portfolio will contain the 50% largest stocks. On the other hand, for constructing the *HML* portfolios, stocks will be divided into three different groups. The low group will be constructed with the stocks with the 30% lowest BV/MV ratios, the middle group entails the stocks with the 40% medium BV/MV, and the high group, composed of the stocks with the 30% highest BV/MV ratios. Each stock will belong to one of the groups of both categories.

For computing both risk factors, six portfolios are confounded S/L (small/low), S/M (small/medium), S/H (small/high), and B/L (big/low), B/M (big/medium) and B/H (big/high). The *HML* risk factor has stronger predictive power than the *SMB* risk factor. The *SMB* and *HML* risk factors will be derived from these portfolios where:

$$SMB = \frac{(R_{SmallLow} + R_{SmallMedium} + R_{SmallHigh})}{3} - \frac{(R_{BigLow} + R_{BigMedium} + R_{BigHigh})}{3} \tag{7}$$

$$HML = \frac{(R_{SmallHigh} + R_{BigHigh})}{3} - \frac{(R_{SmallLow} + R_{BigLow})}{3} \tag{8}$$

Therefore, the excess return of a portfolio of stocks will be estimated through the market risk factor, the *SMB*, and the *HML* risk factors in a time-series regression following the *OLS* (Ordinary Least Squares) method.

Financial scholars have conducted extensive research trying the prove the reliability and significance of this model. The Fama-French Three-Factor Model is a good and consistent predictor of excess returns (Fama; French, 1996a). Past research suggests the *HML* factor is reliable when explaining excess returns (Fama; French; 2014), as there is covariation between average returns and earnings (Chan and Chen, 1991). Moreover, the *SMB* risk factor also states a correlation between firm size and returns (Fama, French, 1996b).

Even the model is reliable in explaining excess returns of SMB and HML based portfolios, it fails to address other factors which are important for explaining a stock's performance. Because of this, the Fama-French Three-Factor Model has been expanded to capture these additional risks.

3.2. The Fama-French Five-Factor Model.

In 2014, Fama and French proposed the Fama-French Five-Factor model for extending the explanatory power and scope of their previous model. In 2012, some financial scholars like Novy- Marx, suggested the Three-Factor model fails to account for variation in average returns caused by profitability and investment factors. This new model incorporates profitability and investment as relevant factors for explaining excess returns.

According to Miller and Modigliani (1961), the total value of a firm's stock is determined by the earnings and investment of a stock. Fama and French based their theoretical valuation equation on this equation, therefore:

$$\frac{M_t}{B_t} = \frac{\sum_{t=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau}/(1+r)^{\tau}}{B_t} \tag{9}$$

Where:

M_t = Market value

B_t = Book value of equity

$Y_{t+\tau}$ = Earnings

$dB_{t+\tau}$ = Expected change in book equity (investment)

r= Expected stock returns

The equation draws several conclusions which explain the effects of both profitability and investment factors (Felix et al., 2020a). If everything is held constant except for future earnings ($Yt+\tau$) and expected return (r), higher expected earnings imply higher expected return, explaining the profitability premium. Additionally, if everything is held constant except for expected growth in book value of equity ($dBt+\tau$), and expected return (r), higher expected equity growth implies a lower expected return of the stock, explaining the investment premium (Felix at al., 2020b).

The profitability factor states that firms with higher profitability have higher expected returns (after controlling for investment and BV/MV). Profitability is measured based on the expected earnings of a stock. Typically, firms with higher expected earnings and valuation ratios are "growth" firms. These stocks place most of their cash flow in the future, increasing risk and expected returns (Swedroe, 2018a). For testing the significance of this factor, several studies evaluating different types of profitability measures (gross profitability, ROE, operating profitability, or cash profitability) have been conducted (Fama; French, 2018). All these studies have concluded the existence of a profitability premium in several international markets, stating the robustness of the factor (Swedroe, 2018b).

Therefore, the effect of profitability in stock average returns is captured by the *RMW* risk factor. This factor states the difference in monthly average returns of robust (high-profitability) portfolios and weak (low-profitability) portfolios. The portfolios for defining the *RMW* factor are constructed following the same procedure as *HML* based portfolios. Stocks will be divided into two robust portfolios and two weak portfolios, where:

$$RMW = \frac{(R_{SmallRobust} + R_{BigRobust})}{2} - \frac{(R_{SmallWeak} - R_{BigWeak})}{2} \qquad (11)$$

The change of the equity of a firm is captured by the investment risk factor *CMA*. This risk factor captures the difference between the monthly average returns of conservative (low investment) portfolios and aggressive (high investment) portfolios. Portfolios based on investment are constructed following the same procedures as the *HML* based portfolios. Therefore:

$$CMA = \frac{(R_{SmallConservative} + R_{BigConservative})}{2} - \frac{(R_{SmallAgressive} + R_{BigAgressive})}{2} \qquad (12)$$

Therefore, the monthly average excess return of a portfolio will be determined by the following equation:

$$E(R_i - R_f) = \alpha_{iT} + \beta_{im}(E(R_m) - R_f) + \beta_{is}E(SMB) + \beta_{ih}E(HML) + \beta_{ir}E(RMW) + \beta_{ic}E(CMA) + \varepsilon_{it} \qquad (13)$$

Where, β_{ir} is the beta for the RMW risk factor and β_{ic} is the beta for the *CMA* risk factor.

The main objective of the five-factor model is to increase the explanatory power of the three-factor model. According to Fama and French (2015a), their regressions showed significant statistics for both factors in North America and Europe. Their results suggested, “average returns for North America, Europe, and Asia Pacific increase with the book-to-market ratio (BV/MV) and profitability, and are negatively related to investment” (Fama, French, 2015b). Nevertheless, the average returns of Japanese portfolios showed a weak correlation with profitability and investment.

All models previously explained try to capture prominent patterns which explain excess returns. Even though these models are not capable of completely explaining the relation between factors and average returns, they entail a useful tool for understanding portfolio performance and behavior.

3.3. Carhart Four-Factor Model

Mark Carhart proposed his Four-Factor Model as an extension of the Fama-French Three-Factor Model. Carhart introduced this model in 1995, including momentum as the fourth factor. He used this model to explain the persistence of mutual fund returns (1997). He aimed to prove persistent returns in mutual funds were not caused by the stock-picking skills of fund managers but caused by a series of factors.

Mutual funds persistent returns have been an interesting topic for financial scholars. Several studies try to explain the causes of these abnormal returns. Elton, et al. (1996) determined the stock-picking skills of managers, and the informational differences between them predict stock returns for a five to ten-year period. Goetzmann and Ibbotson (1994) addressed funds abnormal returns to the “hot hands” effect. This effect is also reflected in the Jegadeesh and Titman (1993a) one-year momentum in stock returns.

Carhart’s results show evidence of this “hot-effect” in stock returns since, normally, funds are not able to repeat their past abnormal returns for long periods. On the other hand, Wermers (1996) suggests abnormal fund returns are caused by the managers successfully following momentum strategies. Carhart also concluded fund’s performance is significantly lower after transaction expenses are applied. This conclusion aligns with the evidence found by Glinblatt, et al. (1995), which states funds perform better before fees and transaction costs. Therefore, Carhart concludes “transaction costs consume the gains from following the momentum strategy in stocks”. The results presented trading fees decreased the funds' performance by 0.95%. Every fund has transactional expenses and charges management fees, but the percentages change from fund to fund. This may be one of the reasons for the persistence of mutual fund returns (Carhart, 1997a).

Furthermore, Carhart's study controls for survivor bias. The survivor bias in finance was addressed by Brown, et al. in 1992. In their paper, they suggested past fund performance can predict future performance. They concluded abnormal fund returns are biased as managers only take into account the returns of funds that have survived. Additionally, the persistence could also be explained by the degree to which "survivorship depends on past performance or whether there is any strategic risk management response on the part of surviving money managers" (Brown, et al., 1992).

Carhart acknowledges this bias and includes all survivor and non-survivor funds in his sample. His data is composed of "diversified equity funds monthly from July 1963 to December 1993" (Carhart, 1997b). He obtained the existent and not existing funds from several databases, primarily from Micropal/Investment Company Data (ICDI), United Babson Reports, and The Wall Street Journal. In his sample, funds are divided into aggressive growth, long-term growth, and growth-income categories. Carhart calculates stock returns as the total monthly return, addressing net asset value changes for capital gains and income distributions. This way of calculating returns mitigates the impact of a potential selection bias. He gets an average annual return estimate of 14.3%.

For his study, Carhart employed the CAPM and his four-factor model (1995) for measuring stock returns. These models evaluate quantitatively-managed portfolios listed in the NYSE, AMEX and Nasdaq indexes. Carhart included the one-year momentum described by Jegadeesh and Titman in 1993. The model can be interpreted as a "performance attribution model" (Carhart, 1997c), as it follows the fundamental strategies of small versus large-capitalization stocks, high BV/MV stocks versus low BV/MV stocks, and winner stocks versus loser stocks. The stock performance is estimated based on the CAPM, Fama-French three-factor model and Carhart four-factor model, where:

$$E(R_i - R_f) = \beta_{it} VWRF \qquad (14)$$

$$E(R_i - R_f) = \beta_{im} (E(R_m) - R_f) + \beta_{is} E(SMB) + \beta_{ih} E(HML) \qquad (15)$$

$$E(R_i - R_f) = \beta_{im} (E(R_m) - R_f) + \beta_{is} E(SMB) + \beta_{ih} E(HML) + \beta_{ip} PR1YR \qquad (16)$$

Where, β_{ip} represents momentum *beta* and *PR1YR* stands for the one-year momentum risk factor. The *PR1YR* captures the difference between winner portfolios returns and loser portfolios returns. Equation 4 expresses the excess return on the Center for Research in Security Prices (CRSP) value-weighted portfolio for all AMEX, Nasdaq and NYSE portfolios. The regression results are presented in Table 1.

Table 1. Performance Measurement Model Summary Statistics

Factor Portfolio	Monthly Excess Return	Std Dev	t-stat for Mean = 0	Cross-Correlations				
				VWRF	RMRF	SMB	HML	PR1YR
VWRF	0.44	4.39	1.93	1.00				
RMRF	0.47	4.43	2.01	1.00	1.00			
SMB	0.29	2.89	1.89	0.35	0.32	1.00		
HML	0.46	2.59	3.42	−0.36	−0.37	0.10	1.00	
PR1YR	0.82	3.49	4.46	0.01	0.01	−0.29	−0.16	1.00

Source: Carhart, 1997

The RMRF captures the excess returns on Fama-French (1993) market proxy. The table shows low cross-correlations between factors. Therefore, no multicollinearity affects the regression results. The monthly excess returns are substantially high, suggesting factors capture most of the cross-sectional variation in portfolio returns.

In 1997, Carhart further examined mutual fund portfolios formed based on lagged one-years returns following the methodology of Hendricks, et al. (1993). He sorted portfolios based on historical one-year returns every January between 1963 and 1993. Using reported returns net of the expense ratios and transactional costs, Carhart formed ten equally-weighted portfolios with a one-year holding period. At the end of the holding period, funds which disappeared through the year were excluded from the equally-weighted portfolios. Because of this, all portfolios were re-adjusted at the end of the holding period. The results showed a wider spread in mean returns of portfolios based on one-year lagged returns. Additionally, top funds appear to outperform bottom funds by 1% per month. The four-factor model has stronger predictive power than CAPM, capturing most of return variation under the *SMB* and *PR1YR* risk factors. Evidence show sensitivities to these factors are highly significant. This might be explained because top funds hold smaller stocks (Carhart, 1997d). Finally, Carhart concluded top fund returns are strongly correlated with one-year momentum coefficients. On the other hand, bottom fund returns showed a negative correlation with one-year momentum coefficients.

Carhart suggested the difference between top and bottom funds could be explained by the characteristics of the funds of each portfolio. According Carhart's results, expenses and turnover have an impact on performance. Higher average expense ratios and turnover seem to have a negative impact on portfolio average returns. On the other hand, fund age, size and load fees do not appear to explain much of the variation across average returns. Nevertheless, Carhart conducted further research on these fund's characteristics, concluding load fees, turnover, change in total net assets (TNA) and expense ratios. Table 2 shoes the estimates and t-statistics for these characteristics.

Table 2. Fund Characteristics Estimates

Independent Variables (Coefficients × 100)	Estimate	*t*-statistic
Expense ratio (t)	−1.54	(−5.99)
Turnover (t) (Mturn)	−0.95	(−2.36)
ln TNA (t-1)	−0.05	(−0.66)
Maximum Load (t-1)	−0.11	(−3.55)
Buy turnover (t)	−0.43	(−1.16)
Sell turnover (t)	−1.26	(−3.00)

Source: Carhart, 1997

Table 2 shows a strong relationship between performance and load fees, sell turnover, and expense ratios. All variables show a negative relationship with the dependent variable, which is the monthly excess returns from the four-factor model. His results show expense ratios and turnover reduce performance by more than 1% and 0.95% respectively.

Carhart suggests two possible explanations for evaluating past-winners mutual fund performance. He stated funds grouped in the same decile may be "relatively consistent with strategies through time", earning abnormal returns because fund managers continuously follow these strategies. Moreover, he stated funds grouped in the same decile hold stocks with similar characteristics and hold them from one to two years.

Finally, in his study of the persistence on mutual funds returns (1997), Carhart concluded that by following the strategy of buying last-year top decile funds and shorting last-year bottom-decile funds, investors will earn a return of 8% per year. Differences in market value and momentum account for 4.6% of the variance in average monthly returns. Additionally, the spread in mean returns can be explained by the expense ratios and transaction costs. which capture 0.7% and 1% of this spread respectively. Nevertheless, the model has strong explanatory power for one-year horizons, losing this predictability for longer periods. The unexplained spread in mean returns is mostly explained by the notable underperformance of bottom-decile funds (Carhart, 1997e). Mutual funds earning abnormal four-factor alphas are expected to earn abnormal returns and alphas for the subsequent periods. Nevertheless, evidence shows top-decile funds “earn back their investments expenses with higher gross returns” (Carhart, 1997f). Therefore, buying last year's winners captures Jegadeesh and Titman’s one-year momentum (1993) without transaction costs.

4. <u>Factor Analysis</u>

This section discusses the basis of momentum strategies and possible causes of momentum profits. Moreover, this section presents evidence of the consistency of momentum strategies in different international markets. Momentum has been one of the most studied anomalies in the past decades, where numerous strategies have been developed to capture the “momentum-effect”. This effect has been remarkably significant in the U.S. and European markets, suggesting the long-term horizon and persistence of momentum.

Even though the momentum effect has been consistent over time, the investment strategies based on momentum have experienced negative returns in a couple of time periods. These negative returns are called “momentum crashes”. This phenomenon, was studied by Kent and Moskowitz (2016c) in their paper “Momentum crashes”. Finally, the paper proposes an investment strategy based in the mitigation of the negative effect of market volatility in strategies trading in the momentum of a stock.

4.1. <u>Momentum background</u>

Finance erudites have conducted extensive research on momentum strategies, presenting strong evidence supporting the hypothesis winners (stocks with the best performance) in the past twelve-month period will continue to perform well for the following three to twelve-month period (Jegadeesh, Titman, 2001a). Additionally, the worst performers in the last twelve-month period will continue to perform poorly for the following three to twelve-month period. Evidence exhibits winners do not tend to be riskier than losers.

The existence of a momentum premium has been extremely difficult to explain through traditional risk-adjusted models like CAPM and Fama French three and five-factor models (Jegadeesh and Titman, 2001b). Both authors examined the relationship of cross-sectional differences in expected returns and momentum profits through the Fama-French three-factor model. They formed momentum portfolios based on the NYSE size decile rankings, ordered by increasing size. As the smallest stocks are less liquid, they experience higher volatility, placing them in both extreme winner and loser portfolios. Evidence showed losers are more sensitive to the *HML* and *SMB* risk factors, suggesting losers are riskier stocks. Following the Fama-French risk-adjusted logic, riskier stocks should earn higher expected returns. Because of this, momentum profits cannot be explained by the Fama-French three-factor model. The risk-adjusted logic goes against the momentum effect, which defends winners will earn higher expected returns.

Therefore, price and earnings momentum are defined as “alpha signals” (Bender, at al., 2013c). These signals capture the risk which is not explained by the model-defined risk factors but they fail to define this risk. The “alpha signals” may be the prelude for identifying new anomalies. Nevertheless, anomalies should be defined with a theoretical framework and be persistent over time.

Portfolio formation is highly important in anomaly testing. In 1993, Jegadeesh and Titman tested the performance of buying losers and selling winners strategies in the NYSE and AMEX listed stocks between 1965 and 1989. They studied the results of the tree to twelve-month formation and holding periods. For constructing the portfolios, they select stocks based on their returns in the past J months and subsequently, hold them for K months (Jegadeesh, Titman;2001c). Stocks are ranked based on their past returns, forming ten equally weighted decile portfolios. The stocks in the P1 decile are the winners and, and the stocks in the P10 decile are the losers.

Table 3 shows all strategies earn abnormal positive returns. All strategies have significant statistics except the three-month/three-month strategy of Panel A. Panel A presents the strategies which immediately hold the portfolios after the formation period. Panel B presents the strategies which wait a week between the formation period and the measurement of the lagged returns of the portfolio. This “intermediate” period seeks to mitigate the effects of the bid-ask spread and price pressure arisen from portfolio formation. According to Jegadeesh and Titman (2001d), the most successful strategy is based on the returns over the past twelve months for subsequently holding these stocks for three months, yielding a 1.31% return per month (Panel A).

Table 3. Returns of Relative Strength Portfolios

		Panel A				Panel B			
J		*K*= 3	6	9	12	*K*= 3	6	9	12
3	Sell	0.0108	0.0091	0.0092	0.0087	0.0083	0.0079	0.0084	0.0083
		(2.16)	(1.87)	(1.92)	(1.87)	(1.67)	(1.64)	(1.77)	(1.79)
3	Buy	0.0140	0.0149	0.0152	.0156	0.0156	0.0158	0.0158	0.0160
		(3.57)	(3.78)	(3.83)	(3.89)	(3.95)	(3.98)	(3.96)	(3.98)
3	Buy-sell	0.0032	0.0058	0.0061	0.0069	0.0073	0.0078	0.0074	0.0077
		(1.10)	(2.29)	(2.69)	(3.53)	(2.61)	(3.16)	(3.36)	(4.00)
6	Sell	0.0087	0.0079	0.0072	0.0080	0.0066	0.0068	0.0067	0.0076
		(1.67)	(1.56)	(1.48)	(1.66)	(1.28)	(1.35)	(1.38)	(1.58)
6	Buy	0.0171	0.0174	0.0174	0.0166	0.0179	0.0178	0.0175	0.0166
		(4.28)	(4.33)	(4.31)	(4.13	(4.47)	(4.41)	(4.32)	(4.13)
6	Buy-Sell	0.0084	0.0095	0.0102	0.0086	0.0114	0.0110	0.0108	0.0090
		(2.44)	(3.07)	(3.76)	(3.36)	(3.37)	(3.61)	(4.01)	(3.54)
9	Sell	0.0077	0.0065	0.0071	0.0082	0.0058	0.0058	0.0066	0.0078
		(1.47)	(1.29)	(1.43)	(1.66)	(1.13)	(1.15)	(1.34)	(1.59)
9	Buy	0.0186	0.0186	0.0176	0.0164	0.0193	0.0188	0.0176	0.0164
		(4.56)	(4.53)	(4.30)	(4.03)	(4.72)	(4.56)	(4.30)	(4.04)
9	Buy-Sell	0.0109	0.0121	0.0105	0.0082	0.0135	0.0130	0.0109	0.0085
		(3.03)	(3.78)	(3.47)	(2.89)	(3.85)	(4.09)	(3.67)	(3.04)
12	Sell	0.0060	0.0065	0.0075	0.0087	0.0048	0.0058	0.0070	0.0085
		(1.17)	(1.29)	(1.48)	(1.74)	(0.93)	(1.15)	(1.40)	(1.71)
12	Buy	0.0192	0.0179	0.0168	0.0155	0.0196	0.0179	0.0167	0.0154
		(4.63)	(4.36)	(4.10)	(3.81)	(4.73)	(4.36)	(4.09)	(3.79)
12	Buy-Sell	0.0131	0.0114	0.0093	0.0068	0.0149	0.0121	0.0096	0.0069
		(3.74)	(3.40)	(2.95)	(2.25)	(4.28)	(3.65)	(3.09)	(2.31)

Source: Jegadeesh and Titman, 1993.

Factors have been screened over long periods. This has permitted researchers to observe cyclical and seasonal patterns. Momentum shows an interesting seasonality in January. Jegadeesh and Titman (2001e) sampled different portfolios and strategies to test for this seasonal pattern. For this study, they added Nasdaq listed stocks to their NYSE and AMEX formed portfolios. Additionally, they excluded small capitalization (less than $5 stocks) stocks with low liquidity. They excluded small-cap firms as they concentrate most of the January return reversals. They obtained a negative return of -1.55% in January, in contrast with the positive returns obtained every other month. This negative return damages the momentum effect, preventing investors to engage in momentum strategies. This reluctance has contributed to the persistence of momentum premia.

4.2 <u>Sources of momentum profits.</u>

Momentum is one of the most complex anomalies. Because of this, researchers have difficulties in explaining the potential sources of momentum profits. In 2020, Anginer, et al. suggested mispricing is a consistent source of anomalies. This statement was also contemplated in Jegadeesh and Tilman's (2001f) paper. The reactivity of stock prices to new information will be fundamental for determining future prices. If stocks do not fully reflect new information, prices will defer from their fundamental values, altering future prices. The underreaction of stock price to new releases of information will generate future profits. Additionally, Jegadeesh and Tilman (2001g) suggested cross-sectional dispersion in expected returns will impact future return expectations. Because of this, high realized returns will entail high returns in the following period. Factor portfolio returns will follow the same logic as expected returns. Higher realized factor realization will generate higher factor realizations in the future. Another source of momentum profits could be the "serial covariance of the idiosyncratic components of security returns" (Jegadeesh, Tilman;2001h). They found a negative correlation of -0.0028 for the 6-month return equally weighted index. Momentum will only get beneficiated from the positive correlation between serial covariances of returns. Therefore, they concluded serial covariance is not a source of momentum profits.

The time factor is extremely important for explaining momentum. Delayed price reaction to factors may trigger momentum profits. As it was explained before, if factor realization impulses future returns and prices do not fully react to newly released information, investors will be able to predict expected returns (Jegadeesh, Tillman; 2001i). Lagged market returns impact stock returns. Moreover, when the correlation is greater than 0, investors will get beneficiated from this lag effect. The lagged stock beta also has an impact on stock returns and profits. Stocks with large contemporaneous betas will closely replicate the market when it goes up, but not as much as they should because of the lagged beta effect. This delayed reaction enables investors to follow a momentum strategy that buys high beta stocks when the market goes up and consequently, earns momentum profits in the next period.

In 1999, Moskowitz and Grinblatt presented strong evidence of industry momentum explaining individual stock returns. According to their study, "industry portfolios exhibit significant momentum, even after controlling for size, book-to-market equity (BE/ME), individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences" (Moskowitz, Grinblatt; 1999). After proving their "random industry strategy", they concluded that buying past industry winners and selling past industry losers earns persistent and sustainable profits. Additionally, they stated industry momentum is more profitable than individual stock momentum, especially in the short-term horizon. Llewellyn (2001), also supports the importance of industry momentum. The author concluded industry momentum outperforms individual stock momentum because of the "lead-lag" component of momentum returns.

The last possible explanation of momentum profits arises from behavioral models. The difficulties in explaining excess returns experienced by rational risk-adjusted models and by the Arbitrage Pricing Theory have motivated researchers to look for alternative explanations (Frieder, 2003). Delong, et al. (1990a) studied how irrational strategies affected stock returns. Their "positive feedback trading strategy" was followed by investors because of behavioral biases. These behavioral models and theories use behavioral biases to give a rationale to price patterns. Barberis, et al. (1998a) attributed the momentum effect to the conservatism bias. This bias states investors tend to partially react to new releases of information, causing an initial price underreaction. Edwards (1968), suggested investors "underweight new information" and prices will gradually adjust to the new information. This underreaction generates abnormal returns in the holding period and normal returns in the subsequent period (Jegadeesh, Tilman, 2001j).

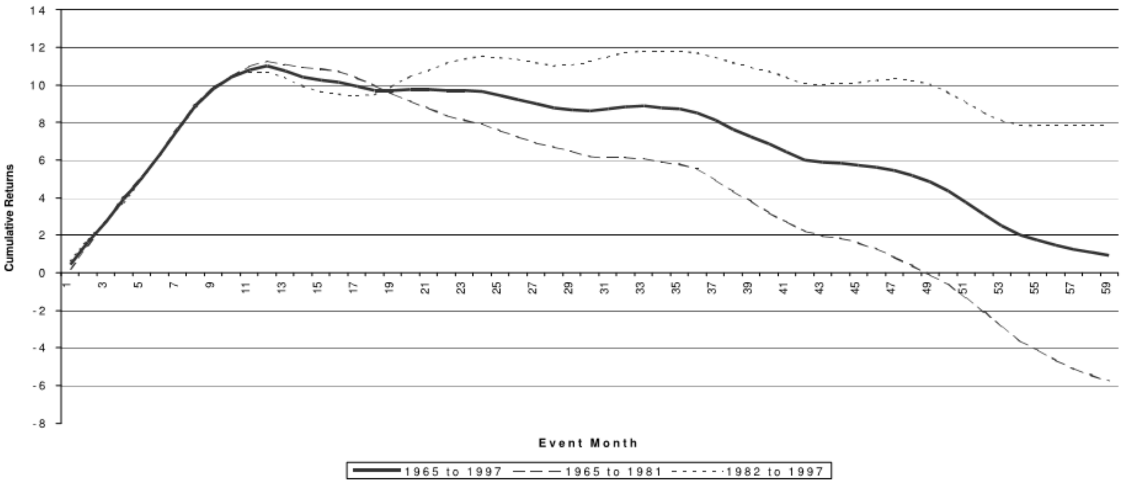
Based on the Kahneman and Tversky (1974a) definition of "representative heuristic", Barberis, et al. (1998b) suggested investors are subjected to this effect while identifying patterns. Representativeness heuristics have a big impact on decision-making as they "reduce mental effort in decision making, potentially causing biases in judgment" (Tversky, Kahneman, 1974b). Tversky and Kahneman defined this type of heuristic as identifying "an uncertain event, or a sample, by the degree to which it is similar to the parent population". Additionally, they concluded the extrapolation bias affects investor behavior. Extrapolation means generalizing a population's future outcome after observing just a few individuals. Applying these biases to the financial context will lead investors to believe stocks with strong past performance will experience a similar performance in the future. Moreover, investors will tend to not treat extraordinary earnings growth as an isolated event and extrapolate those growth expectations to the future. Barberis, et al. (1998b) also observed both tendencies (conservatism bias and representativeness heuristics) together. They concluded both tendencies experienced at the same time could cause overreaction, deviating the prices from their fundamental values and generating negative returns in the long term.

Daniel, at al. (1998) make references to the “self-attribution bias” of investors for explaining short-term momentum returns and long-term reversals. When they receive positive information, they observe how stock prices reflect this information. If stocks perform well after reflecting the new information, investors tend to attribute this performance to their stock selecting and investing skills. Nevertheless, if stocks perform poorly, they attribute this performance to bad luck or external causes. This cognitive bias is counter-productive, as it generates imaginary overconfidence when selecting winners and it misinterprets the drivers of stock prices. This overconfidence places additional pressure on stock prices, moving the price away from their fundamental value. Following the momentum long-term return reversal, the delayed overreaction will then be followed by normal returns when prices go back to their fundamental value.

Also related to information reaction and interpretation, Hong and Stein (1999) divided investors into two groups: “informed” investors and the “technical traders”. The first group “obtain signals about future cash flows but ignore information in the history of prices” (Jegadeesh, Tilman; 2001k). On the other hand, “technical traders” only take into account the winner’s historical prices, placing additional pressure on the stock price. This pressure will deviate the price from its fundamental value, exposing the stock to long-term return reversals. Even it is not a specific bias, both investors behave irrationally as they do not use all available information. As it was stated before, if prices do not fully reflect information, mispricing arises.

The “positive feedback trading strategy” mentioned at the beginning of this section, generates the momentum effect caused by either underreaction or overreaction to information. This reaction causes abnormal returns during the holding periods but diminishing returns in the long term. Jegadeesh and Tilman (2001l) try to address the effect of positive feedback on traders in return reversals. These traders are highly optimistic regarding the winner future performance of past winners. They examined winner-loser portfolios in three time periods. Figure 3 shows the cumulative momentum profits and their evolution through time. The portfolios are constructed with stocks trading in the Nasdaq, AMEX, and NYSE, excluding the small-cap firms of the NYSE trading at less than $5 per share.

Figure 3. Cumulative Momentum Profits



Source: Jegadeesh and Titman, 2001

Figure 3 shows incredibly high abnormal returns for the twelve-month holding period. During this period, returns reach almost 12% but decline to 6% in the thirty-month holding period of the 1965 to 1981 period. The evidence shows the strategy is profitable for the twelve-month holding period but profits decline for the sixty-month holding period decline for every subperiod. This proves positive feedback traders generate momentum for the twelve-month holding period. After this period, the slow adaptation of prices to information and long-term return reversals will decrease momentum profits.

5. Momentum in the U.S Equity Market

5.1 U.S. Equity Market Background

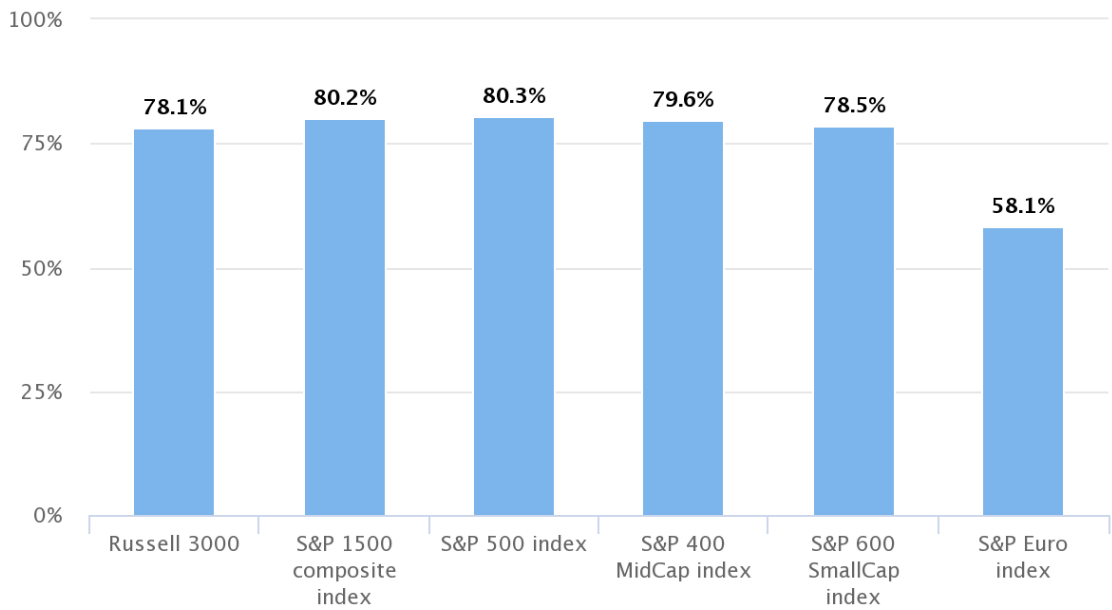
The U.S. equity market has remarkably changed in the last 25 years. The enormous technological developments and information processing systems have forced dealers to enhance electronic trading strategies, changing the traditional dynamic of stock exchanges. Before the year 2000, the U.S. market was exclusively dominated by the NASDAQ and the NYSE. Currently, the market is controlled by 13 exchanges, 33 equity

ATCs and OTC venues. This fragmentation of the stock market has promoted the electronification of the market and the implementation of extensive regulation.

Representing more than 40% of the $97 trillion global equity market cap, the U.S. capital market is the largest in the world (SIFMA Insights, 2021a). The U.S. equity market is 3.7x larger than the Chinese market and 4.22x larger than the European market. In October 2020, the average traded share volume stood at 10.5 billion, increasing until an average volume of 16.2 billion shares traded in March 2021. According to the WFE (World Focus Exchanges, 2021), in January 2021, the number of companies listed in the NASDAQ amounted to 2.987. Moreover, the number of companies listed in the NYSE stood at 2.873 in the same period. The market capitalization of all companies listed in the NASDAQ, NYSE and OTCQX U.S. Market in March 31, 2021 was $149,107,685.7 million (Siblis Research, 2021a).

The largest public companies in the U.S. have clear domination over the stock market, driving the performance of the major indexes. The market capitalization of the top 500 U.S. public companies totals $35,385.262.3 million (Siblis Research.2021b) accounting for 72.1% of the total market capitalization of the stock market. The U.S. stock market is extensively held by institutions. These institutions hold an average of 80% of the market capitalization of all of the major indexes in the country. Institutions also hold an average of 80% of the largest companies in the U.S. Figure 4 shows the institutional ownership percentages of the most important indexes across the U.S.

Figure 4. Index Institutional Ownership, 2017



Source: Bloomberg, April 24 2017

The U.S. equity market is incredibly liquid, transparent, efficient, and competitive. Moreover, investors get beneficiated from low bid-ask spreads and low transaction costs. All these advantages create price improvement opportunities, especially for retailers (SIFMA Insights, 2021b). The historical success of the U.S. capital markets has been boosted by its regulatory framework. This framework is continuously changing, always protecting the interests of investors and enhancing transparency. The stimulus packages granted by the U.S. Congress after the COVID-19 pandemic have contributed to maintain liquidity and mitigate the extremely high levels of volatility. The way investors choose to invest and engage with the companies is changing as well. The Environmental, Social, and Governance (ESG) standards are shaping investor's selection of companies, forcing them to engage in more sustainable and socially responsible practices.

The U.S. capital market plays a fundamental role in the American economy. Higher investment and efficient capital allocation are two key drivers of GDP per capita. Therefore, higher GDP per capita means more disposable income and more economic opportunities for the population. It is important to highlight the financing role of capital markets. "Capital markets fuel the economies" (SIFMA Insights, 2021c) as they drive economic growth and financial equilibrium. In the U.S, 72% of the economic activity is financed by the stock market. Bank lending is not the main source of financing, standing at only 20%. Non-financial corporations use debt capital markets as their major source of financing, reaching almost 80% in the U.S. (SIFMA Insights, 2021d).

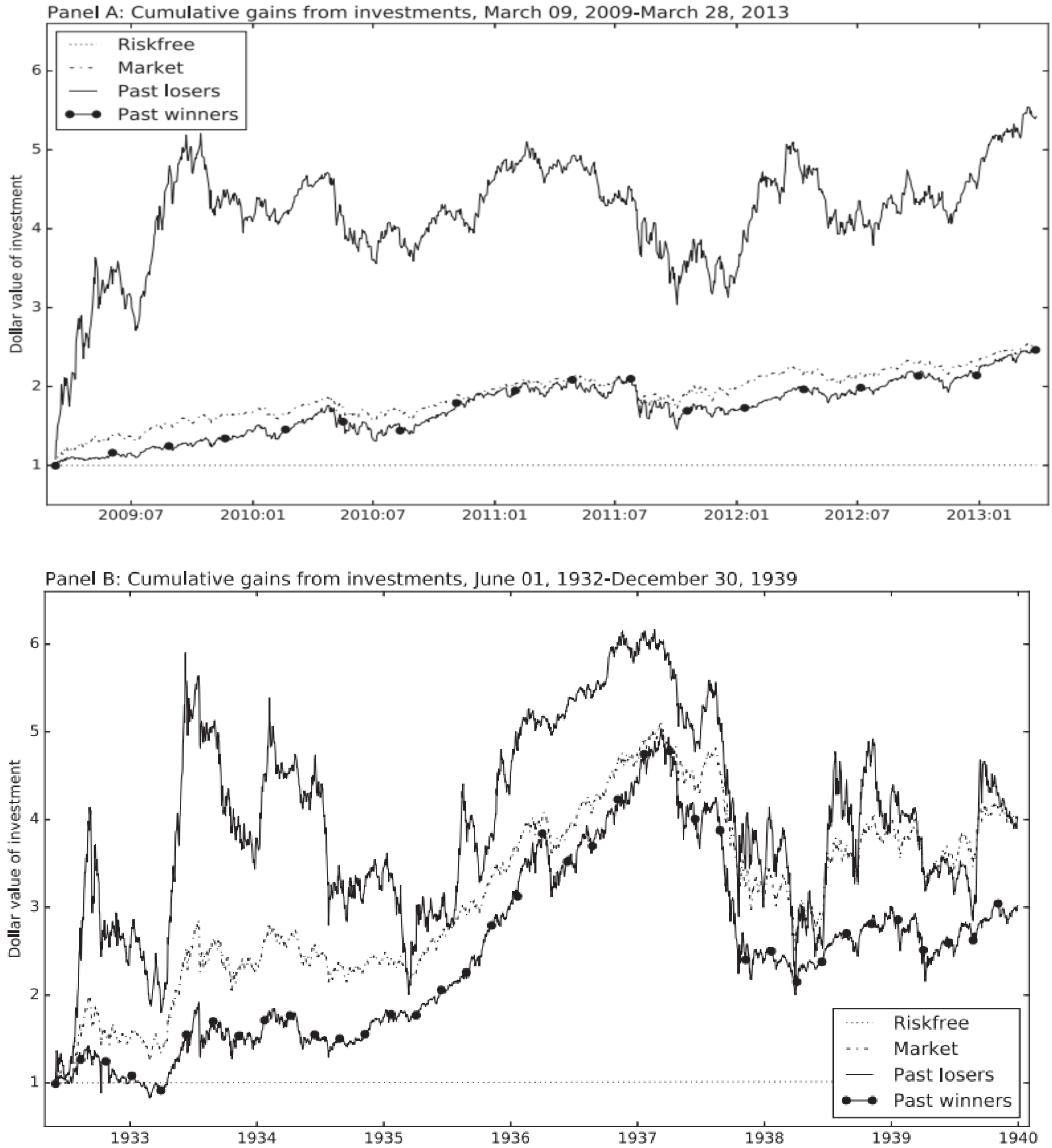
5.2 Momentum crushes and macroeconomic factors.

The momentum strategy accumulates positive and consistent returns over time. It offers investors a pervasive performance, giving them the opportunity of achieving significant gains. The momentum strategy has been consistent during long periods, markets, and asset classes. Nevertheless, the strategy collapses when certain macroeconomic conditions take place. In bear markets and high volatility periods, the strategy strongly underperforms (Daniel, Moskowitz, 2016a). Blinded trust in factor investing and stationary strategies focused on one single factor leading to strategy collapses. Because of this, for obtaining long-term consistent returns, it is crucial to engage in dynamic and multi-factor strategies (García, 2020). Kent and Moskowitz proposed an alternative strategy that predicts and prevents momentum crashes. They applied a "dynamic momentum" strategy which outperformed the traditional momentum strategy.

Even though momentum is one of the most exploited factors in the financial markets, it is highly vulnerable to macroeconomic factors and the overall economic situation. Events generating uncertain and high-volatility periods lead to momentum crashes. These crashes have been observed across different markets and asset classes. Political uncertainty, wars, pandemics, and climate catastrophes generate uncertainty and untrusty environments for investors. Moreover, momentum is especially sensitive to sudden recoveries of the market because of its *"buy winners and short losers"* strategy. Therefore, momentum crashes arise from sudden market recoveries after a bear market period.

In their 2016 paper, Daniel and Moskowitz studied these crashes with a sample of the U.S. equity market between 1927 and 2013. For their study, Kent and Moskowitz obtained the data from the Center of Research of Security Prices value-weighted index. They utilized companies listed in the Nasdaq, NYSE, or Amex at the time of portfolio formation and computed daily and monthly decile momentum portfolios, with a one-month holding period, rebalanced at the end of each month. They focused on two periods: July-August of 1932 and March-May 2009. Under these periods, the momentum strategy collapsed as past losses earned higher returns than past winners. Between July and August of 1932, the loser decile portfolio obtained a 232% return in contrast with the 32% return of the winner deciles portfolio. Between March and May of 2009, the loser decile portfolio earned a 163% return and the winner decile portfolio only rose by 8% (Daniel; Moskowitz, 2016). Both periods were preceded by an extremely severe financial crisis. The Crash of 1929 and the Financial Crisis of 2008 generated bear market periods followed by a dramatic market recovery, crashing the momentum strategy in 1932 and 2009.

Figure 5. Momentum crashes in 1932 and 2009



Source: Daniel and Moskowitz, 2016

Figure 5 shows the cumulative gains from investments in momentum strategies. Panel A represents the cumulative gains between March 2009 and March 2013. Panel B represents the cumulative gains between June 1932 and December 1939. Past losers clearly outperform past winners in both periods. The worst months of momentum returns take place when "the lagged two-year return is negative" (Daniel, Moskowitz, 2016b) and when markets experience a dramatic rise. Additionally, extreme returns occur in the most extreme top and bottom portfolios as they are more sensitive to high volatility periods.

This behavior has two explanations. The traditional momentum strategy of *"buy winners and short losers"* behaves like a written call option. Following this strategy, the investor has a long position in past winners and a short position in past losers. When markets go down, the option writer (short losers) wins as he is bearing the market will go down. Losers get beneficiated with down markets, earning higher returns than winners. The other explanation is the correlation between the returns obtained with this strategy and volatility exposure. The beta coefficient of the past-loser decile portfolios is more volatile than the coefficient of past-winner decile portfolios. At a bear market and extremely volatile situations, betas of past-loser portfolios can rise over 3, in contrast to the betas of past-winner portfolios, which can drop below 0.5. This difference generates a negative beta for the overall momentum portfolio, leading to the collapse of the strategy.

Evidence in Daniel and Moskowitz (2016c) shows statistically significant negative betas for the *WML* (winner minus loser) portfolio in distressed market situations. In their regression, they introduced an ex-ante bear market indicator ($I_{B,\,t-1}$) to forecast the mean and variance of the *WML* strategy. This indicator would be equal to 1 when the returns of the past two years were negative and 0 if this condition is not fulfilled. Additionally, they introduced a not ex-ante contemporaneous bull market indicator ($\tilde{I}_{U,\,t}$) which would be equal to 1 when the return of the value-weighted index is greater than the risk-free rate for the given month and 0 if this condition is not achieved. When both conditions are fulfilled, the beta of the *WML* portfolio is -1.796. This negative beta reflects the underperformance of the momentum strategy when the market goes up after a bearish period.

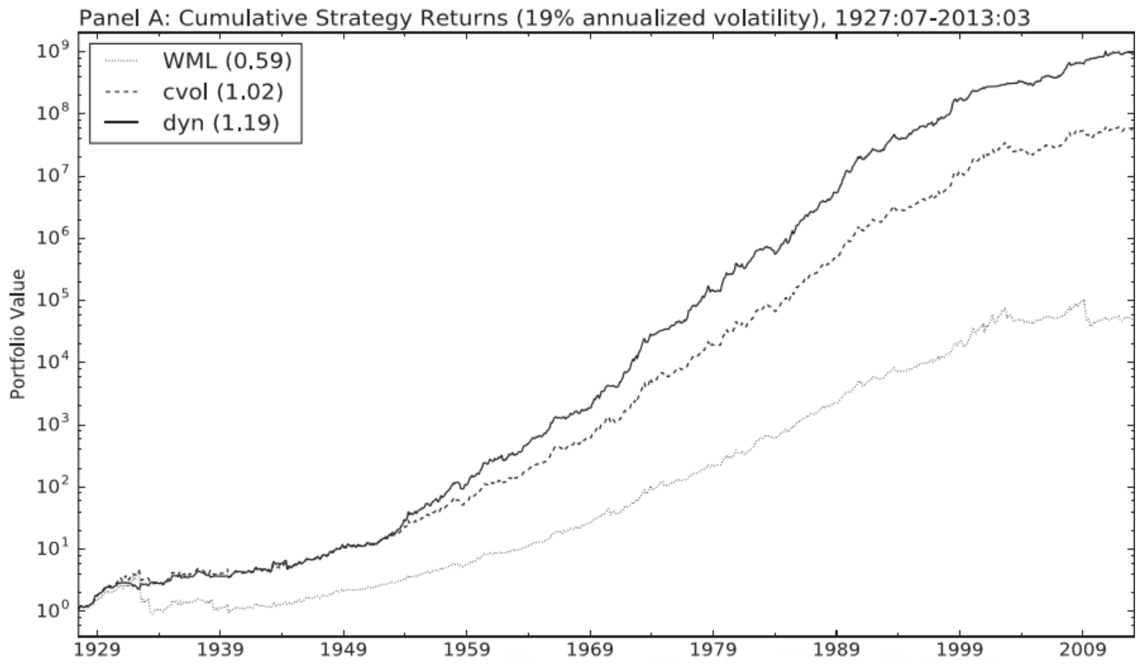
5.2.1 Dynamic Momentum

Because of the relationship of momentum portfolio return with time-varying volatility, Daniel and Moskowitz (2016d) proposed a "dynamic momentum" strategy. Expanding the insights obtained from the constant volatility momentum strategy used by Barroso and Santa Clara in 2015, they addressed the time-variant feature of volatility.

This strategy “dynamically adjusts the weight on the *WML* momentum strategy using the forecasted return and variance of the strategy” (Daniel, Moskovitz, 2016e). The returns of the *WML* portfolio are negatively related to expected volatility. As previously stated, momentum does not have a constant relationship between expected return and volatility. Thus, the expected optimal Sharpe ratio varies through time and will reach its minimum level with high expected volatility. Using the VIX (volatility index) as a reference, investors can determine when to change the weights of their momentum portfolios. When forecasted volatility reaches high levels, investors will increase the weight on the loser decile portfolio and decrease the weight on the winner decile portfolio. Daniel and Moskowitz used the traditional momentum strategy as a baseline. The baseline strategy has a constant weight of 1. Moreover, they used the constant volatility strategy of Barroso and Santa Clara to a better insight into the impact on their strategy. The weights for both constant and dynamic volatility strategies are not equal to 1. The weights for the dynamic strategy are 3.6x more volatile than the weights of the constant strategy and they can reach negative levels. A negative weight implies higher usage of leverage than in other strategies.

Figure 6 shows the relative performance of the dynamic strategy relative to the traditional and constant momentum strategies between July 1927 and March 2013.

Figure 6. Cumulative Strategy Returns



Source: Daniel and Moskowitz, 2016

Figure 6 clearly shows the outperformance of the dynamic momentum strategy over the traditional and constant momentum strategies. The graph shows a persistent and sustained outperformance of the strategy, which has a Sharpe ratio of 1.19. This Sharpe ratio is four times larger than the Sharpe ratio of the traditional *WML* strategy, which stands at 0.59. They found this strategy was consistent across several international markets, periods and, asset classes. Finally, even their empirical findings were robust, they suggested momentum crashes might have a behavioral explanation as well, blaming the extensive focus of investors on losses instead of focusing on probabilities.

6. Investing strategy and methodology.

6.1 Strategy proposal. Momentum in practice.

As mentioned in this paper, momentum strategies crush after bearish markets. The momentum factor is extremely sensitive to market volatility. Because of this, market volatility is a key factor in the investing strategy proposed in this paper. Additionally, the strategy tested in this paper is based on the "dynamic momentum" strategy proposed by Daniel and Markowitz (2016e).

The strategy consists of investing in the momentum of one single stock trading in the S&P 500 and, simultaneously, changing the portfolio weights and investing in cash and cash equivalents when the momentum of the stock is negative or the volatility is too high. The CBOE VIX index gives the "switching level" (to be determined in the implementation section) in which a divesture of the stock is made and an investment in cash or bonds takes place to offset the losses. Similarly, the portfolio weights are switched back again towards a long position in the selected stock when the VIX level goes below the "switching level".

The changes of the portfolio weights (if necessary) are made every month. This aspect is important for the strategy because changing the portfolio weights too often would substantially increase transaction costs and decreasing returns. On the other hand, not changing the portfolio weights regularly would suppose missing momentum signals, increasing the losses of the portfolio. First, the strategy tests the final five-year return an investor would have if he/she switched the 100% of his/her portfolio weights towards the TLT ETF when the market volatility is above the benchmark and switch the 100% of his/her portfolio weights back to the stock when the volatility is below the benchmark. The stock studied in this paper is FedEx. The company has experienced a positive momentum for the last five years. The strategy studies the returns of the company in the last 5-year period and how they can be maximized following it.

To quantify the market volatility, the CBOE Volatility Index (VIX) will be used. This index gives a measure of the 30-day expected volatility of the stocks trading in the S&P 500. It is calculated in real-time, based on the price oscillations of the S&P 500 put and call options. Emulating the strategy developed by Daniel and Markowitz (2016), the VIX will be the baseline for changing the weights of the portfolio. Currently, a value above 20 in the VIX index means high volatility. High levels of volatility imply fear in the capital markets and uncertainty for investors.

6.2 Methodology

For testing the strategy, a "back-testing" technique will be used. With this technique, a hypothesis is proposed. In this case, the hypothesis reads as follows: "On June 1, 2021, the five-year returns of the rebalanced portfolio (composed by a long position in a stock and temporary investments in cash or cash equivalents when volatility is too high) are higher than the five-year returns of the buy and hold portfolio (composed by a long position in FedEx)".

Data is gathered from Yahoo Finance. FedEx monthly prices for the last five years are collected. Additionally, the last five-year monthly prices of the iShares20 + Year Treasury Bond ETF (TLT) are gathered. The TLT is a weighted index of the debt issued by the U.S. Treasury with maturities of more than 20 years. As it is a combination of various fixed income securities, it gives an accurate proxy of the risk-free rate. Finally, monthly and daily VIX data are collected. Both daily and monthly data are gathered to have a better insight into the relationship between the level of volatility and FedEx returns. Moreover, no transaction costs are assumed when rebalancing the portfolio.

The next step for testing the strategy is computing the monthly returns of FedEx, the TLT ETF, and the changes of the VIX Index. The returns of FEDEX, the VIX Index, and the TLT ETF are calculated by applying the following formula:

$$E(r) = Ln\left(\frac{P1}{P0}\right) \tag{17}$$

The natural logarithm of the return is taken to "denormalized" the distribution of prices and volatility levels for achieving a more accurate measure of the stock's return.

To determine the "switching level" of the VIX index, it is important to address the 60-day moving average of the VIX index. At the beginning of every month, instead of looking at the exact value of the index, the 60-day moving average is taken into account. By doing this, abrupt changes in volatility from month to month are avoided. The moving average of the index enables the investor to have a more accurate and realistic insight into the volatility behavior during the given month. Therefore, at the beginning of every month, if the 60-day moving average is above the "switching level" (to be determined in the implementation section), the 100% invested in the long position in Amazon will be invested in the TLT ETF. The procedure is exactly the same for the 60 periods.

Finally, on June 1, 2021, the returns of the strategy will be calculated. Similarly, the return of the strategy is compared with the return of just buying and holding FedEx. Additionally, the Sharpe ratio of both strategies will be calculated for an adjusted comparison between risk and return.

6.3 Implementation and results.

FedEx has performed well for the past five years. The changes in consumer behavior towards online purchases and the increasing number of national and international shipments have boosted its operations and stock price. Moreover, the COVID-19 pandemic has beneficiated its operations even more. The closure of physical retailers and the extremely huge capacity of FedEx's online platform has placed the company as one of the “winners” after the explosion of the COVID-19 pandemic in February 2020.

The company has experienced a positive momentum for the last five years. On June 1, 2016, FedEx's stock price stood at $143.005. On June 1, 2021, FedEx's stock price reached $302.580, experiencing an increase of 119.59%. Nevertheless, the stock has suffered a couple of major price declines in the last quarter of 2018 and during the explosion of the COVID-19 pandemic. Additionally, FedEx's stock price rose dramatically between July 2020 and December 2020. The strategy aims to test whether the FedEx return could have been maximized by switching the long position investment in FedEx to cash following the increasing volatility signals in the last quarter of 2018 and in February 2020.

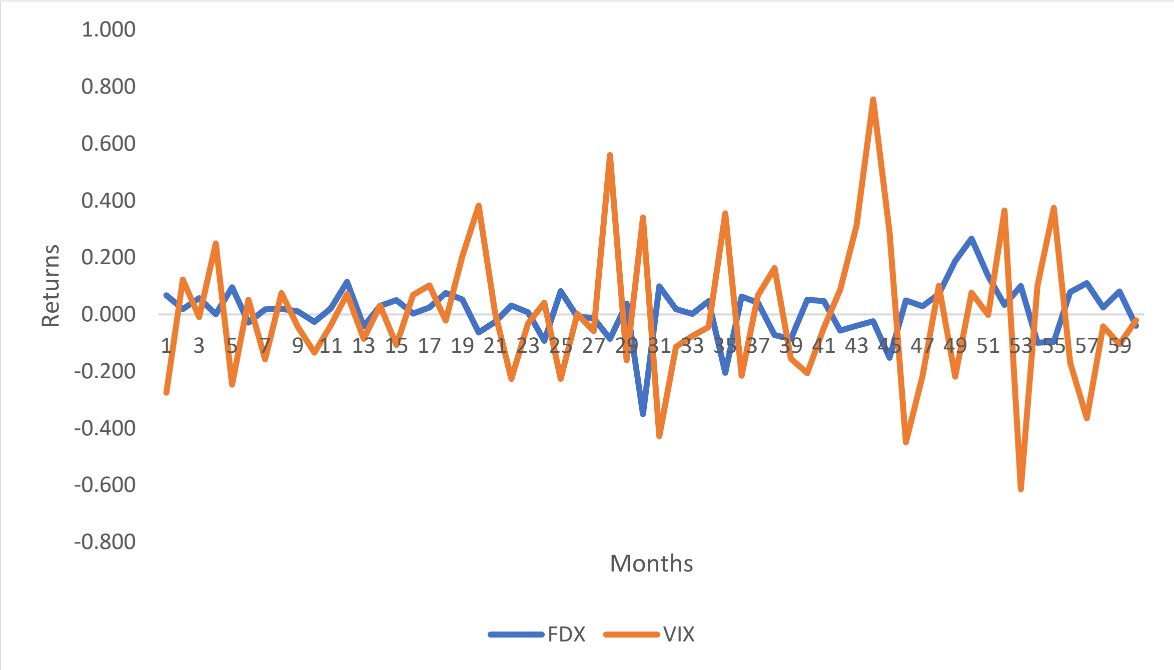
Figure 7. FedEx monthly prices for the last five years

Source: Yahoo Finance

Figure 7 shows the evolution of FedEx prices and the positive momentum for the past five years.

First, addressing the relationship between FedEx returns and the VIX index is key for determining the "switching level". Figure 8 shows the relationship between the company's returns and the VIX returns during the past 5-year period.

Figure 8. FDX 5-y V.S. VIX monthly returns



Source: Yahoo Finance

Figure 8 represents the negative relationship between the VIX index and Amazon returns. The correlation coefficient of both returns stands at -0.5. The coefficient suggests there is not an excessively strong correlation between FedEx prices and VIX levels. This implies FedEx is not remarkably sensitive to market volatility. The initial assumption stated that it is more accurate to use the 60-day moving average of the VIX index for a more precise measure of volatility. After testing this assumption, the results show a negative correlation of -0.09 between FedEx returns and the 60-day moving average of the VIX index. These results suggest FedEx returns are more correlated with drastic changes of month-to-month volatility. Because of this, the monthly level of the VIX index is used to set the benchmark to change the portfolio weights.

The standard level of the VIX index stands at a level of 20. Above this standard level, expected volatility is considered too risky for investors. As FedEx returns are not extremely sensitive to the VIX index, the portfolio can tolerate higher levels of volatility. Therefore, the "switching level" is higher than 20 for this specific company. Taking into account the extremely high levels of the index during the boom of the COVID-19 pandemic (when FedEx price fell the most), level 20 is multiplied by 1.5 to reach a 30-level benchmark for switching the portfolio weights. It is important to highlight that this assumption is merely illustrative. The benchmark changes from stock to stock, depending on the stock sensitivity towards the VIX index.

At the beginning of every month, if the VIX level is above 30, 100% of the investment is rebalanced into the TLT ETF. Table 4 shows the results of the back-testing.

Table 4. Monthly Portfolio Returns

FEDEX						
Date	Adj Close	HPR	HPR TLT	VIX	Change weights	Portfolio Return
01/06/2016	143.005					
01/07/2016	152.921	0.067	0.021	11.870	N/a	0.067
01/08/2016	155.783	0.019	-0.010	13.420	N/a	0.019
01/09/2016	164.992	0.057	-0.015	13.290	N/a	0.057
01/10/2016	165.052	0.000	-0.045	17.060	N/a	0.000
01/11/2016	181.480	0.095	-0.086	13.330	N/a	0.095
01/12/2016	176.300	-0.029	-0.007	14.040	N/a	-0.029
01/01/2017	179.421	0.018	0.013	11.990	N/a	0.018
01/02/2017	183.093	0.020	0.014	12.920	N/a	0.020
01/03/2017	185.151	0.011	-0.006	12.370	N/a	0.011
01/04/2017	180.355	-0.026	0.015	10.820	N/a	-0.026
01/05/2017	184.291	0.022	0.019	10.410	N/a	0.022
01/06/2017	206.623	0.114	0.008	11.180	N/a	0.114
01/07/2017	198.251	-0.041	-0.007	10.260	N/a	-0.041
01/08/2017	204.303	0.030	0.033	10.590	N/a	0.030
01/09/2017	214.976	0.051	-0.023	9.510	N/a	0.051
01/10/2017	215.700	0.003	0.000	10.180	N/a	0.003
01/11/2017	221.098	0.025	0.007	11.280	N/a	0.025
01/12/2017	238.368	0.075	0.016	11.040	N/a	0.075
01/01/2018	251.254	0.053	-0.029	13.540	N/a	0.053
01/02/2018	235.871	-0.063	-0.033	19.850	N/a	-0.063
01/03/2018	229.841	-0.026	0.028	19.970	N/a	-0.026
01/04/2018	237.120	0.031	-0.021	15.930	N/a	0.031
01/05/2018	238.962	0.008	0.020	15.430	N/a	0.008
01/06/2018	217.801	-0.093	0.006	16.090	N/a	-0.093
01/07/2018	236.468	0.082	-0.014	12.830	N/a	0.082
01/08/2018	234.621	-0.008	0.013	12.860	N/a	-0.008
01/09/2018	231.582	-0.013	-0.029	12.120	N/a	-0.013
01/10/2018	212.475	-0.086	-0.030	21.230	N/a	-0.086
01/11/2018	220.826	0.039	0.018	18.070	N/a	0.039
01/12/2018	155.571	-0.350	0.055	25.420	N/a	-0.350
01/01/2019	171.751	0.099	0.008	16.570	N/a	0.099
01/02/2019	175.068	0.019	-0.016	14.780	N/a	0.019
01/03/2019	175.465	0.002	0.054	13.710	N/a	0.002
01/04/2019	183.943	0.047	-0.020	13.120	N/a	0.047

01/05/2019	149.787	-0.205	0.066	18.710	N/a	-0.205
01/06/2019	159.409	0.062	0.010	15.080	N/a	0.062
01/07/2019	166.205	0.042	0.003	16.120	N/a	0.042
01/08/2019	154.587	-0.072	0.105	18.980	N/a	-0.072
01/09/2019	141.878	-0.086	-0.027	16.240	N/a	-0.086
01/10/2019	149.379	0.052	-0.011	13.220	N/a	0.052
01/11/2019	156.610	0.047	-0.004	12.620	N/a	0.047
01/12/2019	147.960	-0.057	-0.034	13.780	N/a	-0.057
01/01/2020	142.131	-0.040	0.077	18.840	N/a	-0.040
01/02/2020	138.722	-0.024	0.063	40.110	CHANGE	0.063
01/03/2020	119.157	-0.152	0.062	53.540	CHANGE	0.062
01/04/2020	125.198	0.049	0.012	34.150	CHANGE	0.012
01/05/2020	128.941	0.029	-0.018	27.510	N/a	0.029
01/06/2020	138.481	0.071	0.003	30.430	CHANGE	0.003
01/07/2020	167.109	0.188	0.044	24.460	N/a	0.188
01/08/2020	218.155	0.267	-0.052	26.410	N/a	0.267
01/09/2020	249.592	0.135	0.008	26.370	N/a	0.135
01/10/2020	258.218	0.034	-0.034	38.020	CHANGE	-0.034
01/11/2020	285.197	0.099	0.016	20.570	N/a	0.099
01/12/2020	258.367	-0.099	-0.013	22.750	N/a	-0.099
01/01/2021	234.729	-0.096	-0.035	33.090	CHANGE	-0.035
01/02/2021	253.839	0.078	-0.060	27.950	N/a	0.078
01/03/2021	283.302	0.110	-0.054	19.400	N/a	0.110
01/04/2021	290.310	0.024	0.024	18.610	N/a	0.024
01/05/2021	314.810	0.081	0.000	16.760	N/a	0.081
01/06/2021	302.580	-0.040	0.012	16.420	N/a	-0.040

Source: Yahoo Finance

Table 4 shows the HPR (holding period rate) of both FedEx and the TLF ETF calculated with the formula stated in the methodology section. Moreover, column 5 reflects the VIX level for the beginning of the month. Column 6 contains the decision of changing 100% of the investment to the TLT ETF. “N/a” means not changing the portfolio weights and keeping the long position in FedEx, and “CHANGE” means switching the portfolio weights to the TLT ETF. The months in which the weights change to the ETF match the surge of the COVID-19, which caused extremely high levels of uncertainty. Therefore, the returns of the portfolio for those periods correspond to the returns of the TLR ETF.

The cumulative return of the five-year period is calculated with the following formula:

$$Portfolio\ Return = (1 + r1) * (1 + r2) \ldots (1 + r60) - 1 \qquad (18)$$

The five-year returns of the long position in FedEx without rebalancing amount to 62.62%. On the other hand, the five-year returns of the rebalanced portfolio stand at 115.89%. The rebalancing strategy beats the simple buying and holding strategy as it offsets the losses of FedEx in highly volatile periods.

As Table 4 shows, there are just a few rebalances of the portfolio. The profitability of the strategy is the result of avoiding highly volatile periods, just like the "dynamic momentum" strategy of Daniel and Markowitz (2016f).

Table 5. Statistics

	Buy and hold Portfolio	Rebalanced Portfolio
SD	0.090	0.087
SD (annualized)	0.312	0.300
Expected monthly return	1.25%	1.56%
Annualized return	16.06%	20.45%
Sharpe ratio	0.476	0.642

Source: Yahoo Finance

Table 5 shows the key statistics of the strategy results. The standard deviation (SD) of the monthly returns of the rebalanced portfolio is slightly lower than the standard deviation of the buy and hold portfolio, proving the effectiveness of the rebalancing strategy in reducing the volatility of the portfolio. Therefore, the annualized SD of the rebalanced portfolio is lower than the SD of the buy and hold portfolio. The annualized SD is calculated as:

$$Annualized\ SD = SD * \sqrt{12} \tag{19}$$

The expected monthly return is calculated doing a simple average of the five-year monthly returns, and it is annualized following the formula:

$$Annualized\ return = \left(1 + E(r)\right)^{12} - 1 \tag{20}$$

The annualized return for the rebalanced portfolio is 20.45%, 4.39% higher than the annualized return of the buy and hold portfolio. The Sharpe ratio of both portfolios is calculated as:

$$Sharpe\ ratio = \frac{\mathrm{E(r) - rfr}}{\sigma} \tag{21}$$

As the strategy uses the TLT ETF return as the risk-free rate, this return is subtracted from the annualized expected return of each portfolio. The Sharpe ratio on June 1, 2021, of the rebalanced portfolio (0.642) is higher than the Sharpe ratio of the buy and hold portfolio (0.476). This means that for every additional unit of volatility (measured as the SD), the rebalanced portfolio gives higher excess returns than the buy and hold portfolio.

Even though the strategy is profitable in this study, the results are not extrapolatable to the stock universe or other historical periods. This practice is focused on a specific short-term period and in a concrete company. The strategy aims to test the exposure of the momentum factor to market volatility and how to prevent momentum crashes. For extrapolating this strategy to the U.S. equity market, a further study should be conducted. Additionally, to refine the strategy, more advanced and complex indicators can be taken into account. In this study, FedEx is less sensitive to volatility than other stocks.

For testing this strategy with other stocks, the "switching level" of the VIX index can be adjusted based on the sensitivity of each stock with the VIX index. It is important to identify the main drivers of the returns of a stock and trade based on those drivers. Moreover, another alternative to this strategy is not changing the 100% of the portfolio weights towards the risk-free rate. For example, establishing a 25% weight on the risk-free and a 75% weight on the stock when market volatility exceeds a specific level can be an alternative to this strategy.

7. Conclusion

The persistence of risk factors has been an object of discussion in the financial environment. The profitability of factor investing strategies has also been questioned by investors and finance academics. To answer this question, determining the drivers of each factor's performance is extremely important. The exposure to macroeconomic conditions fluctuates across factors, influencing the way investors structure their portfolios. The momentum factor has been widely studied, and its persistence in the U.S. equity market was proved by Jegadeesh and Titman in 2001. The strategy proposed in this paper proves the profitability of momentum-based strategies and the importance of portfolio rebalancing.

Jegadeesh and Titman (2001) stated momentum returns cannot be explained by traditional risk-adjusted models like the CAPM the Fama-French factor models. In their

2001 paper, the researchers proved the factor gave abnormally high excess returns for the twelve-month holding period after portfolio formation. Nevertheless, these high excess returns declined in the thirty-month holding period because of the slow price adaptations to new information (Jegadeesh, Titman; 2001m). The mispricing theory for explaining momentum returns was supported by Anginer et al. in 2020(b). Other possible explanations for momentum returns are industry momentum (Moskowitz, Grinblatt, 1999) and behavioral theories studied by Delong, et al. (1990b) and Barberis et al. (1998c).

As Daniel and Moskowitz concluded in 2016, momentum strategy crashes after bearish market periods. Their study was centered on analyzing stock returns after a severe economic crisis. The returns of past losers outperformed the returns of past winners because of the high volatility after bear markets. Therefore, the momentum factor is highly sensitive to market volatility. To try to mitigate the damaging effect of volatility on factor returns, they proposed a “dynamic momentum” strategy in 2016. The results show this strategy maximizes factor returns by avoiding highly volatile periods.

The “back-testing” technique used in this paper gives a similar conclusion as the strategy proposed by Daniel and Moskowitz in 2016. Data between June 2016 and June 2021, the strategy alternates a long position in FedEx and an investment in cash and cash equivalents when volatility is too high. Using the CBOE VIX index as an indicator of market volatility, a value of 30 is set as the “switching level” of the investment. The study compares the returns of merely following the FedEx momentum for the last five years or following the rebalancing strategy. The results show a cumulative return of 115.89% for the rebalanced portfolio against a 62.62% return for the buy and hold position in FedEx. Additionally, the annualized return of the rebalanced portfolio reaches 20.45%, in contrast with the buy and hold portfolio annualized return, standing at 16.06%.

The Sharpe ratio also suggests that rebalancing the portfolio increases the profitability for investors. The strategy tests the persistence of the momentum factor and the exposure of the factor to market volatility. Moreover, taking into account the overall economic situation and the stock-specific characteristics is key for the success of the strategy. The rebalancing strategy is successful in preventing crushes of the momentum strategy and avoiding negative returns based on a market volatility indicator. Finally, even though the strategy is profitable and the initial hypothesis is fulfilled, the results cannot be applied to other stocks, markets or historical periods.

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