UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

ANALYSING PORTFOLIOS OF HIGH-TECH AND LOW-TECH STOCKS USING A MODIFIED CARHART MODEL

Ljubljana, August 2022

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FED – the Federal Reserve System

U.S. – United States

CBOE – Chicago board options exchange

VIX – volatility index

ETP – exchange-traded products

ETF – exchange-traded fund

CAPM – capital asset pricing model

ICAPM – intertemporal capital asset pricing model

CCAPM – consumption capital asset pricing model

DCF – discounted cash flow

S&P 500 – Standard & Poor's 500 index

PEAD – post-earnings-announcement drift

NYSE – New York Stock Exchange

R&D – research and development

TRBC – the Refinitiv business classification

HML – high minus low

SMB – small minus big

PR1YR – previous year

PMN – positive minus negative

ERm – Rf – risk free rate

ER$_i$ – expected return

GRS – Gibbons Ross Shanken test

INTRODUCTION

Financial markets are deeply intertwined with every aspect of our lives. Asset prices, forming the very center of finance, indirectly influence the standard of living. The academic world has concluded a vast amount of research to determine a suitable asset pricing model. A model upon which prices could be determined to guarantee a sufficient return based on the qualities of a certain investment. The very first popularized model, the Capital Asset Pricing Model, was developed over 50 years ago and is still primarily used. The reason behind that lies in its simplicity and the failure of other, more advanced models. Through years of scholarly advancement, researchers tested various factors that could explain a sufficient amount of variance related to expected returns. In the late 1990s, momentum began to gain traction. The idea of using past price increases (decreases) to predict future returns seemed almost elementary. However, it worked. Thus, the Carhart asset pricing model was formed using the market premium, size, book value, and price momentum as the four factors.

In the later years, academics wanted to dissect price momentum thoroughly. The discovery of certain flaws, such as the inability to use momentum as a long-term strategy successfully decreased overall interest. Luckily, a suitable proxy for price momentum appeared. The base for momentum was no longer the past price increase but the past increase of earnings estimations set by analysts. The so-called earnings momentum did not experience price reversals and was superior in many other aspects. Therefore, the researchers turned to analyzing this new type of momentum. Most of the work focused on model refinement or expanding databases. Surprisingly, little focus was given to testing different types of stocks. Why should an investment manager use one model for all kinds of companies when there are countless differences between them? One possible division is between technological and non-technological stocks. The former group possesses specific qualities that make the split suitable. They are usually companies that have to spend a lot of money on research, which eventually drives the price up (assuming the endeavors are successful).

The need to tailor models to specified groups of stocks would make an interesting discovery for the users of sophisticated models or researchers willing to explore the topic further. That revelation (and goal) would complete the purpose of contributing to the refinement of asset allocation and investing. Building on the findings of the academic world, price, and earnings momentum are examined. The modified Carhart model is based on earnings momentum. For comparative reasons, the findings are compared to the standard Carhart model which is formed on price momentum. The findings are then applied to two datasets (low-tech and high-tech) consisting of ordinary shares listed on the New York Stock Exchange between 1990 and 2020. The intersection of four multiple regressions provides a definite answer to two hypotheses. Is momentum stronger in different types of stocks? Is earnings momentum superior to price momentum?

1 THE IMPORTANCE OF ASSET PRICING

The financial markets are ever-expanding. According to WorldBank (n. d.), the size of all market capitalizations of publicly listed companies in the United States of America exceeded $83.5 trillion in 2019, up from $1.1 trillion in 1975. As more money flows into the markets, the important role of asset pricing grows. Its primary role is to support the decision-making process by determining the required rate of return a specific investment should generate considering many different factors. Factor selection is determined by various asset pricing models which will be mentioned and described throughout the thesis. The focus of this chapter is to outline the importance and implications of asset pricing. Being present in the markets, there is no doubt that the financial landscape is changing drastically. Therefore, the notable changes in the past and future are also described in detail.

1.1 Implications of asset pricing

Alongside the growing prosperity of human civilization, the financial markets tend to expand. Driven by technological progress, the system is growing in connectivity. The 2008 financial crisis would not have been that bad (globally speaking) if the system had not already been interdependent. Right at the core of the financial world, you may find asset pricing. The force that drives inflows and outflows. This stimulates researchers to improve the currently available and massively used models. Nevertheless, most retail investors do not resort to them. However, retail investors represent an inferior percentage of the money invested. Davis (2009) discovered that in the 1950s they had a dominating position because they owned more than 90% of the publicly listed companies. That number has shrunk substantially. In 2009, they owned less than 30%. The data is still relevant in 2021 based on rumored information obtained from the two biggest market makers in the U.S. Assuming that the biggest financial institutions use carefully selected asset pricing models, a substantial amount of capital is at risk. That is the first major implication. Asset pricing indirectly affects money inflow and outflow. Furthermore, it can be used for portfolio holdings allocation. Sometimes it can be the sole reason behind a trade. The third implication is the fear of all asset managers. Asset pricing can actually be used to determine the success rate or skill of money managers. Does the importance of asset pricing also mean the models are perfected? When it comes to methods of risk quantification, perfect is never really achievable. In the following three paragraphs, the three major implications of asset pricing are dissected.

The 2008/09 financial crisis exhibited a close link between the financial sector and the real economy. Poterba, Samwick, Shleifer, and Shiller (1995) argue that asset prices are the leading indicators of economic activity. This leads to observed correlations between consumption and asset prices. In simple terms, where the money flows, the economy follows. This approach has been subject to a lot of criticism directed towards the various methods and approaches of analysis.

However, there is an undeniable link between the economy and the financial markets. At the very center lies asset pricing and its models. The results that derive from extensive calculations are often the driving force of money flow. A favorable model outcome just might lead an institution to invest a large sum of available funds. That investment will drive the asset price even higher, indirectly affect the performance of the company, and, thus, influence the real economy. The capital can also flow in the opposite direction. If the model outcome is unfavorable, the institution may divest. A slight hiccup in the model might therefore trigger improper money flow. The use of asset pricing also projects beyond the public markets. Funds that focus on companies that are still in the initial stages of development may use the models to upgrade their analysis. As the world grows in terms of connectivity and interdependence, the flow of capital cannot be halted. Institutions (and small investors) have access to global markets. Asset pricing should not be ignored due to its practicality and its influence on the real economy.

The desire of every investor is (or should be) to succeed in building a portfolio that perfectly balances risk and expected return. That is also the aim of asset pricing models. They play a vital part in determining the expected return a particular asset should provide based on the characteristics of the asset. The result that derives from the model is then used as the discount rate in various methods of valuing investments. A commonly used method is the Discounted Cash-Flow method.

$$DCF = \frac{CF_1}{(1+R)^1} + \frac{CF_2}{(1+R)^2} + \dots + \frac{CF_n}{(1+R)^n} \qquad (1)$$

As equation (1) shows, the discount rate (R) plays a pivotal role in determining the fair value that is the result of this calculation. If the current price of the asset on the market is below the fair value, the financial institution may find it attractive. The smallest mistake that stems from poor use of an asset pricing model could lead to massive losses. Naturally, this is a great incentive to further explore superior model construction. However, with the dynamic investment landscape and an ocean of influential factors, building a versatile model that could perfectly balance risk and expected return is strenuous.

Asset pricing models are known to be a fundamental part of investment analysis. Usually, the research is conducted before the investment which gives the money manager important insight. The results of the model reveal the expected return the investment under observation should have (given its characteristics). If it performs substantially better, the difference in return can be attributed to the skill of the money manager.

Carhart (1997) discovered that when considering stock-related factors, expenses, and transaction costs, most of the returns can be explained. The higher the percentage of returns explained by the asset pricing model, the less skill or luck is relevant. This poses a serious threat to money managers if the models drastically improve. Maybe then, the efficient market theory will fully hold and all assets will be priced to perfection.

1.2 Changes in the financial markets and their effect on asset pricing

The financial world is highly dependent on several different factors. As humanity prospers so does the business world. Nevertheless, all that prosperity would not have been possible without a substantial amount of change. The following paragraphs describe a few observed changes in the financial markets and how they directly or indirectly affected asset pricing.

The amount of capital in circulation is much larger than it was decades ago. Demirgüç-Kunt and Maksimovic (2002) discovered that the availability of long-term funding strongly affects the development of the securities markets. Nevertheless, long-term funding cannot be guaranteed everywhere. Usually, it requires a developed system. However, even a developed system might fail. That was observed at the height of the 2008/09 global financial crisis. However, banks have come a long way since then. After the formation of the Dodd-Frank act in the U.S., the banks are now required to have more stability. That also increases consumer faith in them. Li, Loutskina, and Strahan (2019) found evidence that the increase in deposits enhances the ability to extend long-term loans. It is an additional confirmation of the high interdependence observable in the financial markets. The ability to offer and extend long-term loans also has a strong impact on liquidity. Especially in high-tech-focused companies that usually require a big investment and an extensive amount of time to become cash flow stable. The more advanced a certain market is, the higher the liquidity which can impact certain asset pricing model factors like momentum.

As of the time of writing the stock market has fully recovered from the crash in March of 2020. All-time high prices are also visible in several total market valuation metrics. The Schiller P/E ratio is currently sitting on 38.42 in mid-July 2021 which is above the historical median of 15.85 (Multipl, n. d.).

The Buffett indicator (calculated by dividing the Wilshire 5000 Index by gross domestic product) is at 200% which is implying a highly overvalued market (Longtermtrends, n. d.). On the other hand, the VIX index (CBOE Volatility Index), which is used as a gauge of fear, does not seem high. Any number between 12 and 20 is considered normal and the index is currently 18.29 (Cboe, n. d.). The market seems to be habituated to higher valuations. The participants are freely paying steep premiums.

This occurrence has strong implications for some of the asset pricing models. The market capitalization of a certain asset affects the expected return. A $2T market capitalization stock will probably need more time to produce a 100% return on investment in comparison with a small-cap stock. The market price is also a component of the book/price ratio which is used to build a factor in the famous Fama-French three-factor model. The valuations imply that the assets should have lesser expected returns because the prices are already unreasonably high. In reality, however, it does not seem that way. Perhaps, the asset pricing models should adapt to higher valuations. Or a correction is due.

In 2020, as the COVID-19 crisis raged on, a record amount of U.S. dollars were printed. That increased the supply of money and prevented a financial disaster, thus saving many businesses and individuals from bankruptcy. The response from the FED (The Federal Reserve System) also caused the 10-year Treasury bond yield to go down. It was 0.498% on March the 9th 2020, down from 1.882% on January the 1st 2020 (CNBC, n. d.). A fundamental factor used in the models is the risk-free rate. Investors usually utilize the 10-year bond yield for it. The higher the yield the higher the required return on investment. The decrease in the yield, therefore, meant that the required return was lower. As a result, most growth stocks skyrocketed because they offered an adequate required return after the yield decreased. The amount of money in circulation is constantly growing. Bonds lose value and equity investments become the better alternative. Mishra, Parikh, and Spahr (2020) also found a connection between the monetary policies of the FED and stock market liquidity.

Many of the mentioned changes in the financial markets impact liquidity. A high level of liquidity facilitates opening and closing positions which results in a tighter bid-ask spread. If the market is illiquid the sellers and buyers have more trouble negotiating prices. The transaction costs are higher and usually, the settled-upon price is less favorable. A market participant should, therefore, require a higher expected return as the costs associated with it are higher. Chan and Faff (2003) find that liquidity has a negative correlation to investment returns. Keene and Peterson (2007) discovered that even after considering the factors of the Fama-French three-factor model, liquidity still plays an important role in determining the expected return.

Acharya and Pedersen (2005) developed a liquidity-adjusted CAPM (Capital asset pricing model) which proved the effect of liquidity on expected returns. A negative shock results in low short-term returns and high long-term returns on investment.

Arnott and Chaves (2012) found a strong connection between the demographics of a certain country and the market returns. Middle-aged adults add the most returns because they are in their prime age for investing. Market liquidity increases with a rising amount of representatives of that group.

As the global financial markets grow in terms of connectivity, the liquidity premium shrinks. Many publicly listed companies are listed on more than one exchange to give their shares a boost of liquidity. A higher level of liquidity would imply a lower expected return. However, the world is not yet fully connected which means that illiquid markets still exist. Considering the effect on investment returns, a liquidity factor could be a welcome addition to any asset pricing model.

1.3 Notable changes in the future

As the global financial world evolves, change is inevitable. This section reveals some potential changes in asset pricing that might refine the models or contribute to a more advanced financial world.

The majority of investing is conducted under the assumption that humans are rational beings. In a perfect world asset pricing perfection would be possible. However, there is a wave of new theoretical and empirical research that is arguing otherwise. Antony (2020) explains that the application of behavioral finance contributes to the design of an optimal portfolio. The troublesome part with behavioral finance is how to measure it, especially because of individual-specific attributes. Developing a model that could capture the subjectivity of every person is, therefore, a substantial challenge. Brunnermeier et al. (2021) are certain that the discovery of a model that captures the behavioral part holds promise to reveal some of the unknown parts of asset pricing.

Behavioral finance has not yet had a proper start. A few authors are trying to develop advanced models and incorporate emotions into their methodologies, although they are facing heavy opposition from the advocates of rationality. In the years to come, the financial world will eventually move forward and incorporate the "human" essence into investing. The difficult part is discovering an efficient way of measurement.

The global data analytics market is forecasted to grow at a rate of 25% annually until 2030 (Quince Market Insights, 2021). It will be a major surprise if the growing industry will not expand into the financial world.

Central banks and famous investment companies, such as Vanguard, have already progressed into data analytics. Their desire to better understand clients sparked an interest in developing better ways to collect, measure and analyze data.

Brunnermeier et al. (2021) emphasize the importance of many variables, such as income, macro-economic ratios, expectations, and stock return forecast which are used to develop a deeper sense of understanding.

The power of computers is increasing exponentially and, with it, the data analysis capabilities. In the future, data will play a central role in most (if not all) industries. The inclusion of big data analysis could lead to innovative asset pricing models.

The year 2020 is a fantastic example of how monetary policies affect the markets. Securities reacted strongly to any news related to central banks, inflation, interest rates, unemployment claims, etc. Nevertheless, there are just too many factors that influence market behavior. Proper empirical research is required to arrive at any sort of conclusion.

There is an abundance of research conducted in this field of study. The results, however, are mixed. Some authors argue that macroeconomic risk is intertwined with asset pricing. On the other hand, many argue otherwise. Brunnermeier et al. (2021) found little attention has been given to the understanding of the consequences of monetary policies regarding asset pricing.

Looking at the long-term interest rate (FED funds rate) a pattern is visible. The rate declined from the highs of around 20% in 1981 to almost 0% in 2021 (MacroTrends, n. d.). The decline did not happen overnight. Nevertheless, the markets did not seem to notice or react strongly to it. That would imply that these reactions of the market are in fact short-lived. Further research would be required to fully reveal how monetary policies could be integrated into asset pricing models. After all, even a small adjustment could affect the risk premium which is a central part of any asset pricing model.

The financial world passes through a series of intermediaries that ensure smooth operations. These institutions are businesses that also need to generate revenue. Their costs are, therefore, usually rolled over to the consumer (investor). An investor is nothing more than a customer of assets.

The intermediaries that set prices, therefore, affect the real return through fees and commissions. More intermediaries between an investor and an asset lead to a lesser return. Imagine an individual that has the desire to invest. He goes to a bank (1^{st} intermediary). The bank runs a mutual fund (2^{nd} intermediary).

The mutual fund places trade at a broker (3^{rd} intermediary). The broker forwards the trades to a market maker (4^{th} intermediary) and the market maker delegates it to the exchange (5^{th} intermediary). There could be even more of them.

Brunnermeier et al. (2021) revealed a series of findings in this field. The inclusion of financial intermediaries in asset pricing models contributes to explaining price movements. Especially in asset classes with low barriers to entry. The effect of intermediaries is particularly visible in times of financial stress. However, the degree to which they contribute to the change is still unclear.

Intermediaries have an effect on the real return any investor earns. Most asset pricing models are focused on finding asset-specific factors and few of them mention other elements that affect expected return. Further research is required to determine the extent to which intermediaries influence expected return.

What comes next? The vast amount of unconsidered factors leaves enough room for further advancements. Furthermore, the number of potential factors tends to increase as new technology becomes available, thus increasing the complexity of the challenge.

For example, some believe that the social factor drives stock movements. The social factor measures how often a certain asset is found on social media, news, and TV. This was visible around the "meme stocks" mania around the start of 2021. Many companies became famous overnight because people on the social platform Reddit gave them a boost. In March 2021 one of the largest ETP (exchange-traded products) issuers released an ETF (exchange-traded fund) that tracks investor sentiment called VanEck Vectors Social Sentiment ETF (VanEck, n. d.). This is a serious move toward recognition of the impact of social media on assets.

The impact of social media is one of many examples of notable changes that will arise as asset pricing models evolve. With all this change. it is important not to neglect the models that are currently in use. In the following section, I will discuss the existing and well-known asset pricing models.

2 EVOLUTION OF ASSET PRICING AND THEIR DEFICIENCIES

The main concept behind any asset pricing model is that an investor should be compensated based on the time value of the invested money and the level of risk. The models define how much return you can expect (from a particular asset) based on the risk and the time component.

The time value aspect is more or less the same in most models and is represented as the risk-free rate (the return you could earn by investing in an investment with zero risk).

The big difference is in measuring the risk level which is a much bigger challenge due to an overload of potential factors that influence assets. Through the years, many different asset pricing models were formed. Sharpe (1964) developed the first model that had theoretical and practical implications. It is called the CAPM (capital asset pricing model) which was developed in the 1960s.

Since then researchers have been trying to improve this model or develop their own. However, few models actually became widely used. It is extremely demanding to find several factors that have enough explanatory power to be able to "predict" the expected return of an asset. In this section, four famous asset pricing models are described. Furthermore, their deficiencies are not ignored because they are the driving force behind further research.

2.1 The capital asset pricing model

The world-renowned CAPM model was the first (functional) asset pricing model developed over 50 years ago and it is still widely used in the financial sector. Usually, the CAPM is a cornerstone model learned at the university. The financial experts prefer to use it because of its simplicity. You can see the formula developed by Sharpe (1964) in equation 2.

$$ER_i = R_f + \beta_i \, (ER_m - R_f) \qquad (2)$$

The CAPM takes into account that money invested needs to have a sufficient return based on the time value of money (the first component) and the risk of the specific asset (the second component). The expected return (ER_i) equals the risk-free rate (R_f) plus the risk of a specific investment (β_i (ER_m – R_f)). The risk-free rate is the return you would have made if you invested in an asset without risk. Usually, the U.S. 10-year Treasury bond is used because there is almost a zero chance of the U.S. defaulting on its payments. The second component consists of the beta (β_i) of an investment multiplied by the excess return above the risk-free rate (also called market risk premium). The beta is a measure of volatility.

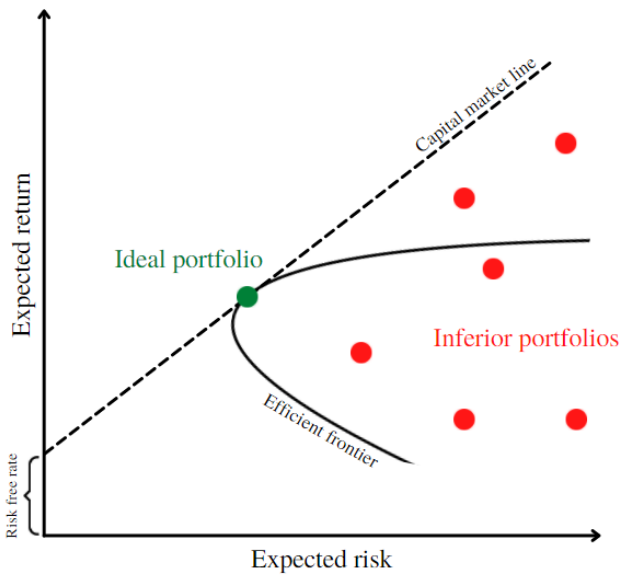
However, it is also used to determine the risk level. If the beta is larger than one, the investment is riskier than the overall market (usually referring to the S&P 500), thus requiring a higher expected return. If it is lower than one, the investment carries less risk than the market and the expected return is lower. The market risk premium (ER_m – R_f) is the expected return of the market subtracted by the risk-free rate. It is a measure of additional return that investors demand the extra risk.

The result of the CAPM is applied as the discount rate of an investment. It is an important element in the previously mentioned DCF analysis. An investment manager could look at the calculated number and compare that to the previous performance of that particular asset.

The model can also be used in portfolio optimization to balance out risk and return. If the optimization was perfect, the portfolio would lie on the so-called “efficient frontier”. The concept was developed by Markowitz (1952) and is based on the fundamentals of the modern portfolio theory.

Every potential investment in finance is a trade-off between expected return and expected risk. An increase in expected return, therefore, leads to increased risk. The capital market line in Figure 1 represents the area of balance. The efficient frontier rests on one very important assumption. The relationship between expected return and expected risk is not linear. Blindly adding risk does not increase the expected return by an equal amount. The ideal portfolio can be constructed at the intersection where the balanced expected return and risk meet the efficient frontier (where adding more risk only marginally improves the expected return). The theory was formed on many assumptions.

Figure 1: The efficient frontier



Source: Markowitz (1952).

The rationality of investors is one of them that is constantly under siege in modern articles. Markowitz (1952) also presumed that the investors had unlimited access to borrowing. The efficient frontier is very useful when it comes to theoretical work. In practice, it stumbles upon one very important truth. It is impossible to predict future results which makes it impossible to determine whether a portfolio is indeed on the efficient frontier.

Alongside Markowitz's theory, the CAPM also has some deficiencies which sparked an interest in many researchers. The cornerstone asset pricing model fails on many empirical tests. Fama and French (2004) made a major contribution when they mentioned a few areas of possible improvement.

The relation between the expected risk (often interpreted as beta) and return is flatter than the original authors proposed. Therefore, the cost of equity (discount rate) comes out too high for high beta stocks. Another observable flaw is the definition of the "market". In theory, the risk of a certain financial asset should be estimated relative to the "market portfolio". Does the market include only the traded financial assets? Or does it go beyond that? The difference appears minimal but the effect it has on the results is not to be neglected. Welch (2021) focused on another area where the theory is not consistent with data. According to the CAPM, high-beta stocks should have superior expected returns over low-beta stocks. That is due to increased risk. The data tells another story. The average rates of return have been higher for low-beta stocks. The model also assumes for the risk-free rate to remain constant and that the investors are always rational.

The researchers overcame the issues by either developing their own asset pricing models or by improving the standard CAMP. It resulted in the formation of many variations.

Black (1972) developed the Black CAPM which is empirically superior because it does not assume that a riskless asset exists. Merton (1973) built the Intertemporal Capital Asset Pricing Model (ICAPM) as another upgrade. The model is consumption-based which means that it takes investor behavior into account. It adds another variable (factor) that acknowledges that investors hedge against shortfalls in consumption. Lucas (1978) constructed the Consumption Capital Asset Pricing Model (CCAPM) as a great alternative to the classic CAPM. The model utilizes a consumption-based beta instead of the regular market beta. It is computed differently and assumes that the return required is also impacted by the risk that stems from consumer-driven volatility of the stock price.

Even though the CAPM has some obvious flaws, the financial world loves to use it. It is a simple model that makes investments easy to compare. Jacobs and Shivdasani (2012) interviewed many money managers on that topic. They discovered that the success of the CAPM depends on the approximations and adjustments the managers make. Simply adding a percentage point (or more) to calculations puts a lot of hope into the hands of an individual.

Decades have passed since all these variations came into existence. At some point, the research shifted from improving the CAPM to developing another model. The Fama-French three-factor model is a great example of a refined attempt to price assets.

2.2 Fama-French three-factor model

Another prominent model was developed in 1992 by two economists. Eugene Fama and Kenneth French (1993) realized that pricing assets solely on the risk coming from volatility are not enough. They added two more factors thus forming a three-factor model.

The model is not widely used due to a more complex structure than the CAPM. However, the two additional factors make it a better tool for explaining expected returns. Their model is presented in equation 3.

$$ER_i - R_f = \alpha_i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_2 (HML) + \varepsilon_I \qquad (3)$$

Common sense tells us that companies with a larger market capitalization need more time to grow in size than smaller businesses. Therefore, the annual expected return should be smaller which is exactly what Fama and French found out. Many investors believe value investing to be the superior strategy when compared to growth investing. It relies on a single dogma: buying stocks for less than they are worth. The approach has proven to be successful for many billionaires and also for the authors.

If we look at the CAPM, it is nothing more than a linear regression model. The Fama-French, however, is a multiple regression model with more explanatory power. The expected return of an investment (ER_i) subtracted by the risk-free rate (R_f) equals the constant (α_i) plus the three factors and the residual (ε_I). The first factor is the same as in the CAPM.

The market risk premium ($ER_m - R_f$)) tells an investor that the asset is more/less volatile (risky) than the average market and therefore deserves a higher/lower valuation. The second-factor SMB (small minus big) represents the size component. In simple words: small-cap stocks usually outperform large-cap stocks. A common way to distinguish value stocks from growth stocks is by looking at the price-book ratio. The third-factor HML (high minus low) is the value component. Value stocks tend to outperform growth stocks and that is exactly what the factor explains.

In theory, the results from the Fama-French model would yield a lower expected return than the results from the CAPM. It is because a part of the expected return is explained by the size and the value component making the model empirically superior. It means that by using the CAPM, you would expect a higher return for a certain asset. In reality, much of the return would be attributed to its size and a price-book ratio of it. Even though the model is finer than the standard CAPM, it is still not perfect. It has been susceptible to criticism. The creators pointed out a few possible improvements to the model.

Fama and French (1993) pointed out the need to show how the stochastic behavior of earnings affects the two new factors. The common variation in returns produced by profitability or another fundamental was also not included. Bhatt and Rajaram (2014) found the model has good explanatory power in times of market prosperity. In the event of a crisis, when it is even more important for the model to work, however, it fails. Especially the HML factor has lesser explanatory power during those periods. Blanco (2012) dissected the portfolio construction used in the original work. It was revealed as another area of concern. In the original work, the authors used the book-market ratio to distinguish value and growth stocks. However, that is not the only way to draw the line between the two types of stocks.

If the portfolios are constructed differently, the results are prone to change. Black (1993) mentioned the value premium (HML) factor could also be a derivative of sample-specific testing which means that it fails when tested on other data.

Furthermore, Kothari, Shanken, and Sloan (1995) indicate that the high explanatory power, attributed to the price-book ratio, stems from the mismeasurement of beta or due to survivorship bias.

The most relevant flaw is not in what is included in the model but rather in what is not. The financial world is so interconnected that there are millions of possible factors which could have asset-specific explanatory power. One of those factors is connected to earnings announcements. When a company reports its quarterly earnings the stock tends to move. If the reported results are better than expected, that indicates an increase in value and, therefore, the stock usually moves upward. If the results are disappointing, the price decreases. That is exactly what Jegadeesh and Titman (1993) discovered. They found a pattern that revolves around earnings announcements. That finding drove the research forward. It was a couple of years later when Mark Carhart introduced another prominent asset pricing model.

2.3 The Carhart model

The model was developed by Mark Carhart (1997) and is considered to be one of the best. The original development was not for estimating expected returns but rather to assess mutual fund performance. He claimed that the returns of funds had less to do with the skill of managers and more with asset-specific factors that could be anticipated. The model is an upgraded version of the Fama-French three-factor model. The fourth added momentum factor stands on the findings of Jegadeesh and Titman (1993). The model is presented in equation 4.

$$ER_i - R_f = \alpha_i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (PR1YR) + \varepsilon_I \quad (4)$$

The Carhart model is a multiple regression-based model that can explain an even larger amount of expected returns (variation). Carhart (1997) discovered low correlations between the factors and also with the market proxies as well.

The model is essentially a fusion of two important and often cited articles. The original "Common risk factors in the returns on bonds and stocks" was written by Fama and French (1993) and "Returns to buying winners and selling losers: Implications for stock market efficiency" by Jegadeesh and Titman (1993). The first article explains the development of the Fama-French three-factor model which is described in the previous chapter. The subsequent article focuses on capturing the one-year momentum anomaly. The strategy of selecting stocks based on their previous performance realized a sufficient return. Jegadeesh and Titman (1993) developed a model that selects stocks based on their previous 6-month returns and then holds them for 6 months.

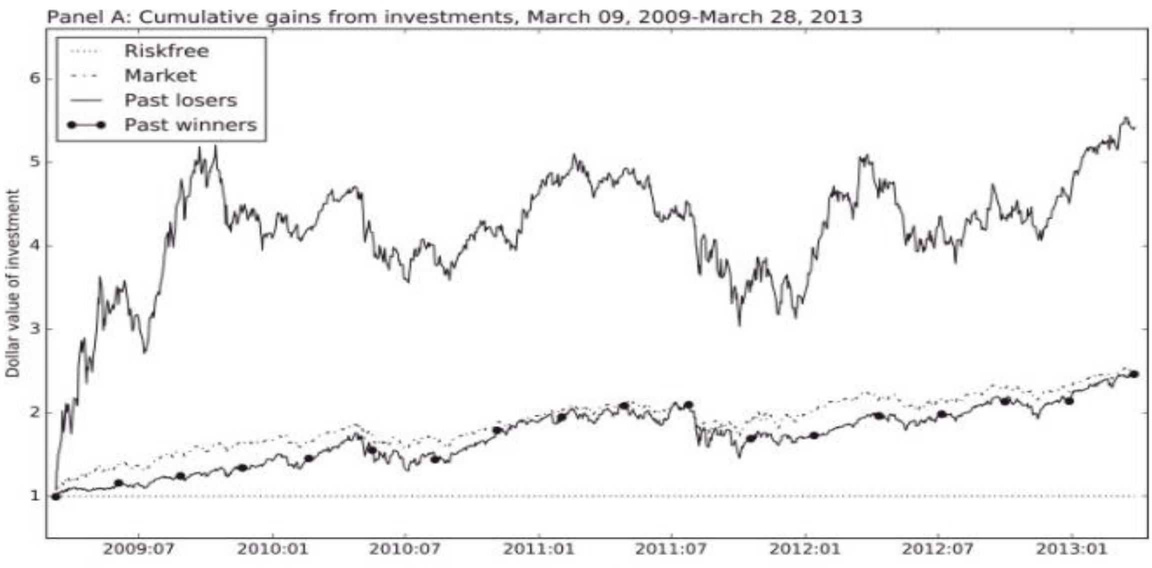
Winning portfolios (positive 6-month track record) have achieved superior returns that were attributed to an initial positive return following the earnings announcement. However, there is evidence of return reversal after a longer period.

Mark Carhart took these findings and merged them with the Fama-French three-factor model which lead to the development of the Carhart model. The impact of momentum was a rather new concept back then. Few authors have tried to explain the expected returns of assets using it. The momentum factor (PR1YR) was, therefore, a key finding in the academic world because it proved that past returns do affect future returns. In simple words: winners stay winners and losers stay losers. However, that only occurs in the short term. Carhart (1997) found that the fourth momentum factor improves the pricing errors that derive from previous models, such as the CAPM and the Fama-French three-factor model.

When you develop a model for more accurate measurements of portfolio returns, you will be subject to criticism, even more so if you base your research on mutual fund performance data. The model is prone to any comments that are directed towards the Fama-French three-factor model and also to any momentum critiques. Jegadeesh and Titman (1993) did not have any evidence-backed explanations for the observed return reversals.

This leaves enough room for analysis of investor behavior which is a currently popular topic of discussion. Daniel, Jagannathan, and Kim (2011) discovered that the momentum factor fails in times of panic, market declines, and high volatility. The term is referred to as "momentum crashes". Daniel and Moskowitz (2016) later uncovered that the previous losers do exceptionally better that the previous winners in times of market distress. The behavior of the winners and losers following the 2008 global financial crisis is presented in Figure 2.

Figure 2: The cumulative gains of past winners and past losers



Source: Daniel & Moskowitz (2016).

This proves the momentum factor to be inefficient in such times. With the rapid digitalization and information transfer, these types of shocks appear quite often and could have a large impact on returns. These are only a few of many issues regarding momentum.

If the momentum strategy was truly successful at all times, the need for further research would be obsolete. Nevertheless, academics have not stopped developing new models consisting of new (or improved old) factors. One example of this is the second model developed by Eugene Fama and Kenneth French which is called the five-factor model.

2.4 Fama-French five-factor model

Developed in 2015, the five-factor model is one of the youngest asset pricing formations. It was constructed by Eugene Fama and Kenneth French (2015) who are also the economists behind the widely known three-factor model. As mentioned before, their previous model was subject to a substantial amount of critique. Therefore, the need for an improved model had emerged. It stands on the foundation of their previous model and is improved with two additional factors. Their model is presented in equation 5.

$$ER_i - R_f = \alpha_i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (RMW) + \beta_5 (CMA) + \varepsilon_I \qquad (5)$$

In addition to criticism, two findings inspired the developers to create a more refined model. Novy-Marx (2013) found out that profitability has (more or less) the same explanatory power in predicting the average returns as the book-market ratio. The phenomenon is especially present in value investing strategies. Profitable firms can produce substantially higher returns than unprofitable firms.

The second finding that inspired them is connected to capital investments. Titman, Wei, and Xie (2004) indicate that companies that aggressively invest in growth projects tend to underperform the benchmark index. A possible explanation is that investors underreact to increased investment expenditures. Fama and French (2015) added these two important findings which made the model able to capture size, value, investment, and profitability variances.

This multiple regression model consists of five factors. The first three are the same as in the three-factor model. The fourth factor (robust versus weak) represents profitability. Profitable companies should be able to produce superior returns. There are many possible reasons behind that. Novy-Marx (2013) argues that the superiority stems from more stable cash flow, lower operating leverage, and a lesser impact of distress. According to Fama and French (2015), the RMW factor is calculated as the operating profits divided by book equity.

The fifth factor (conservative versus aggressive) is the investment measuring part of the new model. Companies with conservative investment expenditures have superior returns over companies with aggressive strategies. The logic might sound counterintuitive. Titman et al. (2004) suggest that there could be two explanations behind that finding.

The negative correlation between investing and stock return could be due to the increased risk of the new ventures. The second possible reason is connected to individual business characteristics. Whatever the true cause may be, there is a need for balance in such expenditures.

The market, therefore, tends not to reward businesses that are overspending on growth. Fama and French (2015) measured the CMA factor as the one-year change in total assets divided by current total assets.

Like all the mentioned models, the five-factor model is no exception when it comes to criticism and improvement suggestions. The authors themselves found one major flaw in the cornerstone model. Fama and French (2015) discovered that their model has issues in capturing returns on small stocks. Especially the low average returns that are similar to the returns of firms with high investment and low profitability. Another observation they made is directed at the usefulness of each factor.

They discovered that when adding profitability and investment the value factor becomes unnecessary. This finding is consistent with the research of Novy-Marx (2013). Fama and French (2017) later studied the model internationally and found the same setbacks. Experts employed by a large international asset management firm called Robeco also have a critical view of the Fama-French five-factor model.

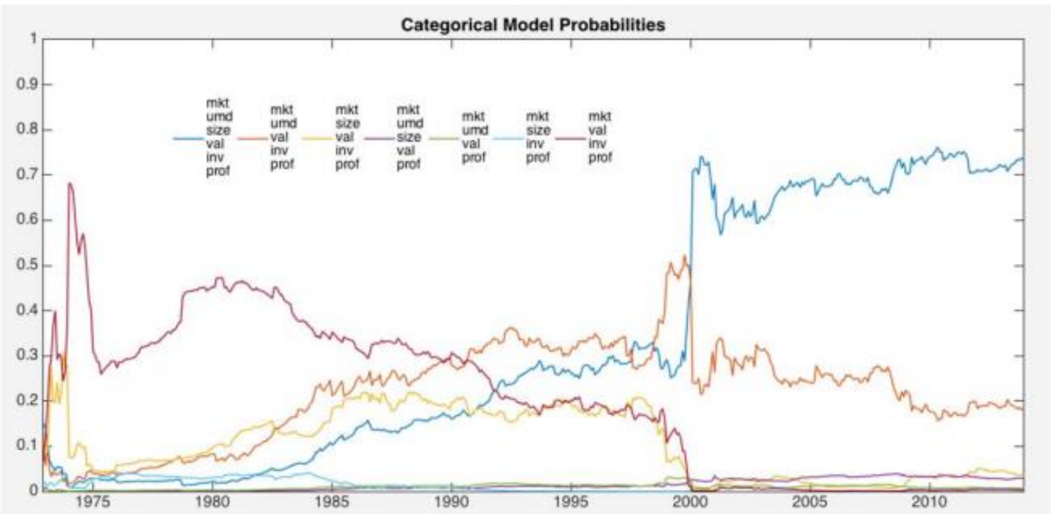
They pointed out that because the number of factors essentially doubled (excluding market risk) from the three-factor model, it is difficult to form results based on the cross-section of returns. Furthermore, they are surprised that the authors did not include the widely researched momentum and low volatility factors (Blitz, 2018). However, Fama and French (2017) mentioned that it would be interesting to add the momentum factor to the five-factor model.

Fama and French (2008) researched asset growth and profitability before they revealed the five-factor model. They discovered that these two anomalies are less robust. And then later they chose these exact factors and added them to form their new model. They do explain a sufficient amount of variation but the question remains. Were those the best factors to include? Furthermore, is the formula behind them the most suitable?

According to the Fama-French five-factor model, the most profitable investment would be in a company that is small in size, with a high book-market ratio, a robust profitable business model, and a conservative approach to investment expenditures. Figure 3 represents categorical model probabilities. A higher probability means a better model. The standard five-factor model (yellow line) comes in third which raises the question of whether the authors truly chose the best set of factors. UMD represents the momentum factor.

There is still a lot of room for further research. It is a difficult endeavor to find factors that can explain a lot of the variance.

Figure 3: Categorical model probabilities of various models

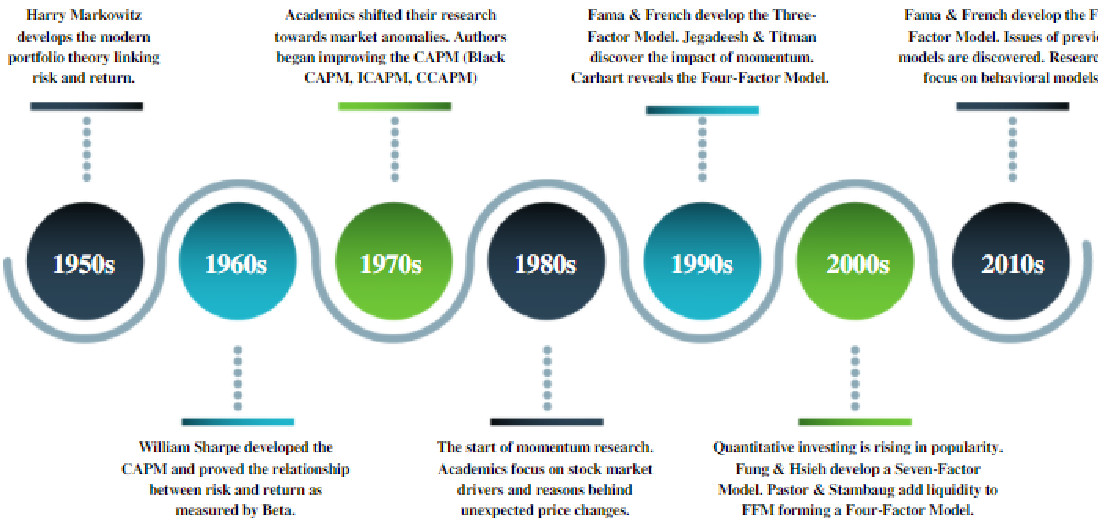


Source: Barillas & Shanken (2018).

2.5 Asset pricing models timeline

In this section, I have mentioned only the four most famous models. However, more models exist. In Figure 4 a timeline of various asset pricing innovations is presented.

Figure 4: Timeline of asset pricing



Source: Own work.

The models seem to be developing into more advanced and complex structures. I consider it a sign of progression. In the next section, I will discuss momentum as a whole.

The purpose of the thesis is to improve the Carhart model in which momentum is a central part. Therefore, a deep literature review on the subject will reveal the flaws and possible areas of improvement.

3 MOMENTUM IN THE 21ST CENTURY

Before the 1980s, researchers focusing on finance believed that stock movements follow the random walk theory. They had faith that the markets are indeed fully efficient and that past data could in no way be used to predict future price movements. Nevertheless, these last few decades of research revealed that certain market anomalies interfere with the efficient market theory. Among many observed anomalies, momentum has received the most attention. In this section, I will review the most popular and relevant literature on momentum and use it as a foundation for later empirical research.

3.1 Literature review on the momentum

Zaremba and Shemer (2018) describe momentum as the tendency for well-performing assets to continue outperforming and vice versa. Even though it has existed for centuries, the research conducted has been scarce until the last few decades.

Chabot, Ghysels, and Jagannathan (2008) discovered that because no capital gains taxes existed during the Victorian age, momentum investing proved to be a profitable strategy. However, the current financial landscape is more complex than it was between 1820 and 1914.

After the influential work of Jegadeesh and Titman (1993) was published, researchers truly began exploring the implications of momentum. The prominent work titled "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency" revealed that purchasing past winning assets and selling past losing assets could lead to a substantial profit. Chabot, Ghysels and Jagannathan (2008) discovered that the leading factors that drive equity market returns are systematic and not random. They are determined by an underlying pattern that stems from the effect of momentum. These two findings proved the profitability of the momentum investing strategy. However, more research was needed to fully understand this important anomaly.

Academics have been exploring the implications of momentum strategies on different markets and asset classes. Bianchi, Drew, and Fan (2015) performed numerous tests on commodity futures and found momentum investing to be a profitable approach. Menkhoff, Sarno, Schmeling and Schrimpf (2012) discovered significant excess returns on the currency markets.

Jegadeesh and Titman (1993) proved momentum to be profitable in the U.S. markets. Do the findings apply on a global scale?

Chui, Titman, and Wei (2010) uncovered that the strategy produces an even higher Sharpe ratio when global data is used. Asness, Moskowitz, and Pedersen (2013) tested the approach on eight diverse markets and asset classes and found a consistent momentum return premium. Academics covered a lot of groundwork on testing the strategies on various markets and assets. However, the real issue lies in understanding the origin.

The origin of momentum is exceptionally difficult to uncover. Authors first directed their focus on factors that are relatively easy to measure when compared to human-specific reasons. Cooper, Gutierrez, and Hameed (2004) claimed the state of the market to be a key determinant in the size of momentum profits. Lee and Swaminathan (2000) argue that past trading volume determines the persistence and magnitude of price momentum. Hong and Stein (1999) emphasized the importance of shocks connected to news about future fundamentals. These first momentum origin theories have not been kindly perceived.

That is because most conventional strategies failed miserably during the 2008 global financial crisis. Demirer and Zhang (2019) attributed the losses to the “herding effect”.

They also implied that by analyzing behavioral patterns, the profits could be increased. Daniel and Moskowitz (2016) found strings of negative returns that can be persistent and infrequent. Fan, Li, and Liu (2018) recommend using an alternative way of ranking winners and losers to avoid this issue. Despite the common perception of beating the market with momentum strategies, many issues that continue to corrode excess returns appear to be.

Because of these setbacks, the authors focused heavily on improving the performance of momentum strategies. Blitz, Huij, and Martens (2011) discovered that by ranking stocks according to their residual returns instead of total returns, momentum returns are twice as large. Residual returns are the returns of stock after adjusting for Fama-French factors. These findings have been tested and proved in the Chinese (Lin, 2019) and Japanese (Chang, Ko, Nakano & Rhee, 2018) markets. Moskowitz, Ooi, and Pedersen (2012) revealed that time-series momentum strategies produce better returns and have little exposure to standard asset pricing factors. Furthermore, this approach performs well during extreme market conditions. Time-series momentum selects financial assets based on their past performance and ignores the other assets. A major risk of momentum investing is the so-called momentum crash. Barroso and Santa-Clara (2015) made a major discovery when they proved that momentum can be predicted. Their study suggests using volatility scaling to avoid huge losses. On the other hand, Daniel and Moskowitz (2016) recommend using dynamic volatility scaling. Fan, Li, and Liu (2018) compared these two strategies and discovered that dynamic volatility scaling is the better option. Researchers also put a lot of emphasis on uncovering firm and market-specific factors that could enhance the explanatory power or profit-generating ability of momentum.

3.1.1 Firm-specific factors enhancement

Firm-specific factors are nothing more than characteristics of companies that prove to contribute to momentum. Commonly observed factors, such as turnover, size, volatility, and investment often appear in science journals. Lee and Swaminathan (2000) emphasize the importance of past trading volume as a determinant of momentum persistence and magnitude. Furthermore, they discovered that value stocks have lower turnover ratios and also earn higher future returns. Their findings also point towards the direction of behavioral origins of momentum. Avramov, Chordia, Jostova, and Philipov (2007) discovered a strong connection between credit ratings and momentum profits. They proved momentum to be profitable among low-grade firms. However, profitability disappeared in high-grade firms. Sagi and Seasholes (2007) observed momentum drivers and found that firms with low costs, higher revenue growth volatility, or options for growth outperform the standard strategies.

Arena, Haggard, and Yan (2008) found higher momentum returns among stocks with high idiosyncratic volatility. Asem (2009) revealed that dividend-paying companies experience lesser momentum profits.

The results are consistent with behavioral explanations of momentum emergence. Jiang, Li, and Li (2012) attribute higher momentum profits to firms with large capital investments. Nyberg and Pöyry (2014) went one step further and revealed that asset expansion is responsible for higher returns. Booth, Fung, and Leung (2016) found the strategy to be profitable only in small-cap stocks. An abundance of possible factors makes this topic particularly interesting to research. However, the market-specific factors also have an impact on momentum.

3.1.2 Market-specific factors enhancement

When compared to firm-specific factors, these factors apply to a wider range of assets. Nevertheless, that does not make them any less important or influential. Literature often points out market state, sentiment, market liquidity, and political risk as strong factors. Chordia and Shivakumar (2002) uncovered that a set of macroeconomic variables related to business cycles can explain momentum profits. Cooper, Gutierrez and Hameed (2004) explain momentum profits differently. According to their work, the market is the driver of momentum. If it is going up, the momentum profits follow and vice versa. The success of strategies, therefore, depends on the state of the market. Asem and Tian (2010) explored further and discovered that the momentum profits are larger when the market remains in the same state for a longer time. They emphasized the role of investor confidence regarding momentum payoffs. Stambaugh, Yu, and Yuan (2012) found more evidence of investor sentiment leading to optimism-based pricing which leads to higher momentum profits. Antoniou, Doukas, and Subrahmanyam (2013) present similar findings with momentum being stronger in times of full market optimism. Han and Li (2017) expanded the research by testing investor sentiment in China and found similar evidence.

Investor sentiment is not the only important factor under observation. Sadka (2006) revealed a connection between momentum returns and market-wide liquidity.

Liu and Zhang (2008) used a standard macroeconomic factor called “the growth rate of industrial production”. They found evidence of a link between the factor and momentum profits. Garcia-Feijoo, Jensen, and Jensen (2018) discovered the importance of the funding environment. In states with restrictive funding, momentum profits tend to be higher. Filippou, Gozluklu, and Taylor (2018) revealed political risk as an influential factor. However, their research was tied to momentum in the currency markets. Market-specific factors do not seem any less influential when compared to firm-specific factors.

The amount of progress is visible and researchers have been closing in on fully understanding this important anomaly. However, there are still many issues with momentum investing and also with the momentum factors included in asset pricing models.

3.2 Issues of momentum

Singh and Walia (2020) divide the literature review on the momentum into four clusters: testing the profitability, sources, improvement of traditional strategies, and Asia-Pacific market testing. Researchers have been progressing in all four categories. In the following section, the most troublesome flaws of momentum are discussed.

3.2.1 Origin

The origin of momentum refers to the drivers behind it. Researchers do not seem to fully agree on the forces that make momentum a profitable strategy. The academics are separated into two groups. The rationalists and behaviorists.

The first group believes that momentum profits stem from the fact that traders take on additional risk and deserve a higher return. Johnson (2002) believes the expected growth rate shocks to be responsible for immediate price movements. Ruenzi and Weigert (2018) also provide a risk-based explanation of the famous anomaly. However, they do not exclude the possibility of additional behavioral explanations. Li (2018) attributes the price continuation effect (momentum) to short-term productivity concerning winner stocks. All are plausible explanations. However, in recent years, the research has shifted towards behavioral theories of momentum origin.

The advocates of behavioral finance have other explanations. Singh and Walia (2020) split them into three subgroups. The first possible behavioral explanation is initial underreaction. Investors tend to underreact which allows the price to deviate from the fundamental value thus resulting in high returns. Da, Gurun, and Warachka (2014) discovered that the speed of information received is very relevant.

A small continuous burst of information results in low levels of attention which leads to smaller returns. Chen and Lu (2017) built a whole trading strategy around the information diffusion speed. The concept relies on the findings of Hong and Stein (1999) who revealed the link between momentum profits and information diffusion. The faster the information diffuses into the market, the lower the returns. Docherty and Hurst (2018) ascribe the price continuation effect to investor myopia. That short-sightedness leads to the gradual diffusion of fundamental news.

The contrary explanation focuses on price overreaction. Investors push the stock price way above the intrinsic value which leads to short-term momentum profits.

Daniel, Hirshleifer, and Subrahmanyam (2005) discovered that the cause behind it is mainly investor overconfidence. However, the returns tend to reverse in the long run. Hillert, Jacobs, and Müller (2014) found the same long-run reversal but attributed the price overreaction to media coverage. The work of Adebambo and Yan (2016) confirms both findings.

The third and final subgroup according to Singh and Walia (2020) is the disposition effect group. The new research aims to uncover what the internal drivers of momentum are. Disposition could be described as a collection of biases. It is a common anomaly in behavioral finance. The tendency to sell winners before they have reached their potential and the desire to hold losers because of hope are two prominent examples of this anomaly. It is extremely difficult to measure, analyze, and research investor behavior. It is even harder to utilize that behavioral research to predict future returns. Grinblatt and Han (2005) divided investors into two groups.

Disposition investors (first group) tend to create a spread between fair value and the market price. The rational investors (second group) then take advantage of these spreads using a long or short position which produces momentum. Hur, Pritamani, and Sharma (2010) went one step further and proved that the momentum induced by the disposition effect is indeed larger for stocks largely held by individual investors. Hur and Singh (2019) added another bias to the equation. They found that the anchoring bias reinforces the disposition effect, thus resulting in a stronger momentum effect.

The origin of momentum remains to be a divided section of the momentum. However, I find that you cannot fully understand a subject until you have a solid foundation.

3.2.2 Liquidity risk and momentum crashes

Liquidity can be perceived in two ways. The market-wide liquidity focuses on factors that influence the whole market, such as inflow and outflow, number of transactions, the efficiency of trades, etc. Asset-specific liquidity is more subtle and in short means volatility and volume. Chordia, Roll, and Subrahmanyam (2000) discovered that liquidity remains an important factor to consider. It affects momentum profits in a specific way. Sadka (2005) implied that liquidity could be strongly related to transaction costs.

Transaction costs usually lower the expected returns of momentum trading. Jang, Keun Koo, Liu, and Loewenstein (2007) revealed that transaction costs are indeed linked to the liquidity premia. Anthonisz and Putniņš (2017) indicate that investors holding assets with higher liquidity risk should be compensated for that.

Usually, when the liquidity is low, the risk is higher because trade orders cannot be executed quickly and for the desired price. Hou, Xiong, and Peng (2006) proved price momentum to be stronger among stocks with a high volume. Lesmond, Schill, and Zhou (2004) emphasize the importance of high turnover for momentum strategies to be profitable.

Acharya and Pedersen (2004) uncovered that a persistent negative shock to liquidity leads to low short-term and high long-term returns. Wu (2019) tested the connection between liquidity risk and return. The results proved that high liquidity risk assets earned a higher average return than the bottom quintile. The effect of this specific risk type on expected returns is visible.

However, Li, Novy-Marx, and Velikov (2019) recently revealed that there is not enough compelling evidence to suggest liquidity has a direct impact on expected returns. The evidence is mixed and suggests the need for further research. Especially because of the emergence of commission-free brokers and enhanced global financial connectivity.

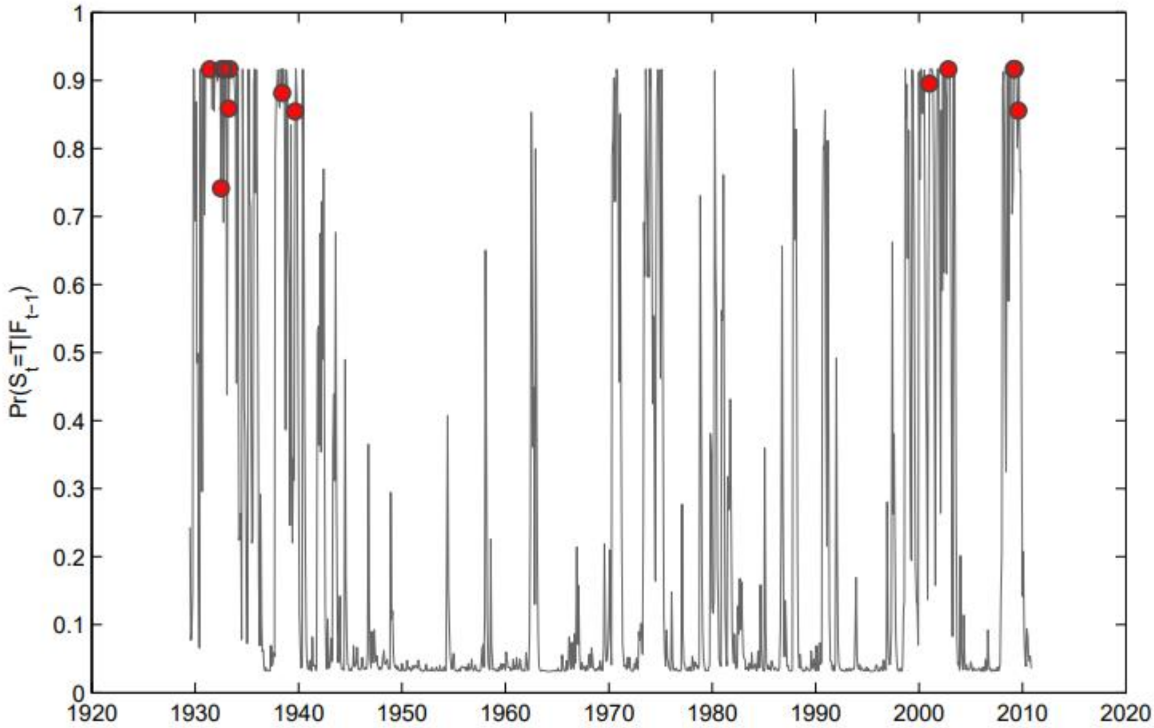
Momentum is not as perfect as it seems. While it may produce superior returns in prosperous times, the strategy fails in turbulent times. Ruenzi and Weigert (2018) unveiled a possible explanation of momentum profits. They argued that the profitability of this strategy is actually (at least partly) compensation for crash risk exposure. Daniel et al. (2011) conducted a wide analysis on this topic.

Out of 978 observed months, 13 of them exceeded losses of 20% or more. The line in Figure 5 shows the probability of the market is in a turbulent state hence the increased risk for a crash. The red dots represent momentum crashes resulting in a drop larger than 20%.

That kind of decline could be responsible for erasing a large amount of produced positive returns. Furthermore, a 20% drop requires a 25% return to break even again. Therefore, researchers have been trying to mitigate that risk. Han, Zhou, and Zhu (2014) proposed a simple stop loss strategy to minimize the downside risk. Daniel and Moskowitz (2016) described these momentum crashes as quite persistent. Furthermore, they made a key addition when they discovered they can be partly forecasted.

That opened up a whole new area of research. Butt and Virk (2020) documented liquidity as an important determinant in predicting momentum crashes. Lin, Yang, Chou, and Ko (2021) propose a timing momentum strategy where the signals of moving averages are incorporated into the price momentum. While these approaches may be successful, there is an even better way. Novy-Marx (2015) discovered that using earnings momentum instead of the standard price momentum decreases the volatility. Furthermore, it eliminates the crashes without decreasing the average returns. Zhang and Bao (2017) added that the success of earnings momentum during crashes depends on the method used to measure momentum.

Figure 5: Turbulent market state probability and momentum crashes



Source: Daniel, Jagannathan & Kim (2011).

Both liquidity and momentum crashes have a strong impact on momentum. Literature offers a substantial amount of solutions that can improve the average returns. These findings can be used to enhance the momentum factor in any asset pricing model.

3.2.3 Cultural dimensions

The world may be connecting but there are still large cultural gaps that make it difficult to form a strategy with global applications. Singh and Walia (2020) conducted an extensive review of topics on momentum investing. Most of the research is conducted with developed market data. However, recently academics shift their interests toward emerging markets where many opportunities can be found. Chui et al. (2010) based their research on the famous work of Geert Hofstede. He researched cultural dimensions. They discovered momentum to be riskier in the U.S. and Europe when compared to Japan and East Asia. The proposed explanation behind that lies in different interpretations of information which form behavioral biases. Galariotis and Karagiannis (2021) discovered that there is a solid link between Hofstede's cultural dimensions, economic policies, and momentum profits. Furthermore, that link is not influenced by global variables. Such important factors should be taken into account when forming momentum strategies. Nedev and Bogdanova (2019) tested many different strategies over 20 years. They found momentum to be stronger in the U.S. market when compared to Chinese markets. Cultural differences can affect the returns of momentum strategies in different ways.

Bornholt, Dou, Malin, Truong, and Veeraraghavan (2011) discovered that the profitability of momentum strategies is negatively correlated with individualism. Investors that satisfy their wants and needs experience fewer momentum profits. Hong, Lee, and Swaminathan (2003) concluded that high corruption markets experience weak momentum. Beracha, Fedenia, and Skiba (2014) found evidence of a lower frequency of trades as the cultural distance between a company and the investor grows.

Cheema and Nartea (2014) did not find information uncertainty to affect momentum profits in China. The situation is different in Europe and the U.S. Leippold and Lohre (2012) found more pronounced momentum profits in high uncertainty markets.

There are many differences between cultures that echo in the financial world. This poses a serious challenge for developing a profitable momentum strategy (or a viable asset pricing model) that could be applied on a global scale. Because most cultural differences originate from a deeply embedded behavioral background, this is no easy task.

3.2.4 Trading costs

Momentum strategies require a lot of buying and selling. To ensure a smooth order flow, the financial system is intertwined with intermediaries. Each is responsible for their part in the system which is the foundation on which trading costs are formed.

Singh and Walia (2020) discovered that few research articles have tested the profitability of momentum strategies and also considered trading costs. In reality, these costs can decrease the profits by a hefty amount. Furthermore, they found brokerage commissions to be higher in emerging markets, a rising area of interest.

Larger institutions tend to have contracts in place with many intermediaries thus reducing their trading fees per trade. That would imply momentum trading to be exclusive. Siganos (2010) discovered that even smaller investors can exploit the momentum anomaly. The finding largely increases the area of applicability. However, the extent to which trading costs influence profitability is foggy. Badreddine, Galariotis, and Holmes (2012) find that momentum profits disappear after considering trading costs. They also suggest that the holding period strongly affects these profits. On the other hand, Korajczyk and Sadka (2004) argue that in some cases momentum remains a profitable strategy. Nevertheless, they pointed out that the transaction costs cannot fully explain the persistence of returns. Abbes, Boujelbène, and Bouri (2008) concurred and added that the trading costs are superior when handling “loser portfolios”. The findings may not be consistent but there is evidence of momentum profitability decreasing. Chordia, Subrahmanyam, and Tong (2014) discovered that the decimalization of stocks halved the average returns. The reason is in a tighter bid-ask spread. Nevertheless, transaction costs remain an important factor.

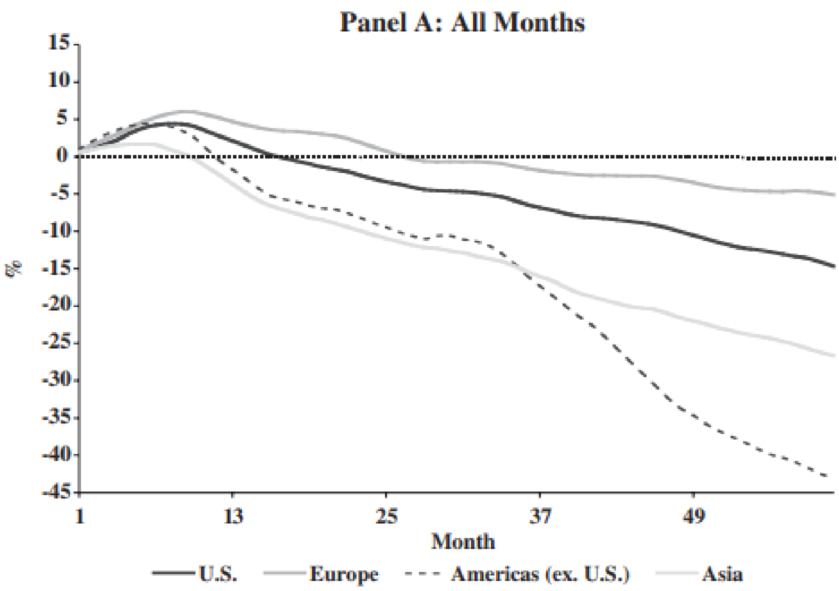
Frazzini, Israel, and Moskowitz (2014) emphasize the cost reduction approach to boost profitability without affecting style drift. Li, Brooks, and Miffre (2009) suggest shortlisting stocks based on transaction fees.

Strong evidence appears to be scarce. Especially since researchers usually assume trading costs do not exist. However, that belief might lead to false results which do not apply to real-life situations. It is also important to note that the rising popularity of commission-free brokers could eradicate the need to analyze the effect of (direct) trading costs on momentum profitability.

3.2.5 Price reversal

The most important and widely documented flaw of momentum investing is price reversal. When researchers measure momentum they are usually referring to price momentum. The speed and velocity of price change are their main interest. According to Leippold and Lohre (2012) momentum (when not backed by fundamentals) is nothing more than price overreaction. The fact that fundamentals are the backbone of long-term returns sparked interest among researchers. Ahmed and Safdar (2018) discovered that past price performance can either be driven by fundamentals or other reasons. Inconsistency between past price performance and fundamentals leads to reversals. It is a major flaw that has been widely documented. Price reversal was first mentioned by Jegadeesh and Titman (1993). Long-term price reversal is visible in Figure 6. The abnormal momentum returns from the first 3-12 months are erased in the following year or two.

Figure 6: Performance of price momentum by region



Source: Griffin, Ji & Martin (2003).

Hou et al. (2006) proved price momentum profits to be larger in high volume stocks and up markets. However, they are still subject to reversal. Hur and Singh (2019) discovered that the reversal is even stronger when behavioral forces, such as the disposition effect and anchoring bias, are in place. The findings go beyond the standard stock markets. Bianchi et al. (2015) described and analyzed price reversals in the commodity markets.

The pattern prevents conventional look-back or holds strategies. The reversals could stem from various observations.

Bloomfield, Tayler, and Zhou (2009) suggest that information is the root of it all. Uninformed traders are responsible for long-term price reversals. That is because their contrarian approach lingers beyond the momentum generated by informed traders. Another prominent explanation is linked to skepticism. Luo, Subrahmanyam, and Titman (2021) attributed short-term momentum to informed traders who cause price underreaction. Skeptical investors then follow the lead. They invest based on stale information causing some momentum and eventually reversals. There are a few instances where price momentum does not reverse. Booth et al. (2016) discovered that the profits from small market capitalization stocks are not reversed in the long run. Conrad and Yavuz (2017) uncovered the possibility of distinguishing stocks that experience reversal and stocks that do not.

Price reversal remains an important aspect of momentum investing. Many institutions and individual traders find themselves chasing the trend which in its essence is nothing more than momentum investing. More research is needed to fully understand the opportunities, dangers, and limitations of momentum investing. However, there is a possible solution that overcomes many of the mentioned issues.

3.3 A possible solution

The issues of price momentum commonly documented in science journals are not small nor are they neglectable. They may hinder the profit-generating ability of most strategies. Even the most advanced methods have been exposed to these observed flaws. After the most dangerous issue was revealed (long-term profit reversal), the academic research split into two subgroups of momentum testing. Some insisted to improve the price momentum strategies. The other branch focused on the so-called earnings momentum.

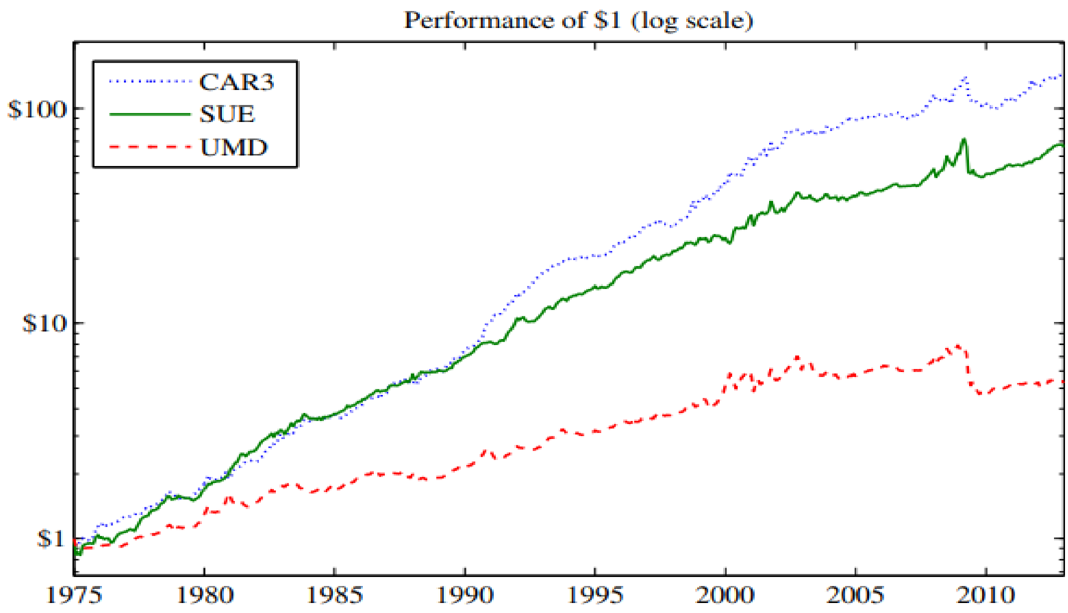
Increasing earnings momentum means that the rate of profits (or earnings per share) is increasing each year or quarter. Usually, when a company announces higher earnings, the investors believe the stock to be worth more, thus pushing the price up. The first thing researchers had to do was to prove that price and earnings momentum are equal in terms of explanatory power. Chordia and Shivakumar (2006) discovered that price momentum can indeed be captured by earnings momentum. Leippold and Lohre (2012) acknowledged earnings momentum to be the force behind price momentum. Hong et al. (2003) proved earnings momentum to exist only in those markets where price momentum is profitable.

Hou et al. (2006) found earnings momentum to be larger among low-volume stocks and in down markets. They also revealed that price momentum increases with rapid investor attention growth while earnings momentum decreases. Earnings momentum could be regarded as a viable proxy for price momentum.

Furthermore, there are a few extra advantages that overcome the previously mentioned issues. Daniel, Hirshleifer, and Sun (2020) developed a short horizon factor that is based on earnings surprises. It is motivated by the inattention of investors and can capture all the short-term anomalies. Mao and Wei (2014) revealed that the past discount rate news does not affect earnings momentum. This makes earnings momentum less prone to the opinions of analytics. Regarding cultural dimensions, Hong et al. (2003) found earnings momentum to be profitable in countries where the investor protection laws are stringent. Another difficulty of price momentum is the previously mentioned momentum crash. They appear around critical times and wipe out years of returns. Zhang and Bao (2017) discovered that earnings momentum does not crash as much when a specific method of calculation is implemented. They used standardized unexpected returns (SUE) as a measure of earnings.

Probably the most convincing evidence of earnings momentum overpowering price momentum is presented in Figure 7. The SUE and CAR3 are both earnings momentum factors while UMD represents the price momentum factor. SUE (standardized unexpected earnings) uses the most recent year-over-year changes in earnings per share. CAR3 (cumulative three-day abnormal returns) measures the excess return above the market over three days by the asset. UMD (up minus down) represents the average return of two winner momentum portfolios minus two loser momentum portfolios (Novy-Marx, 2015).

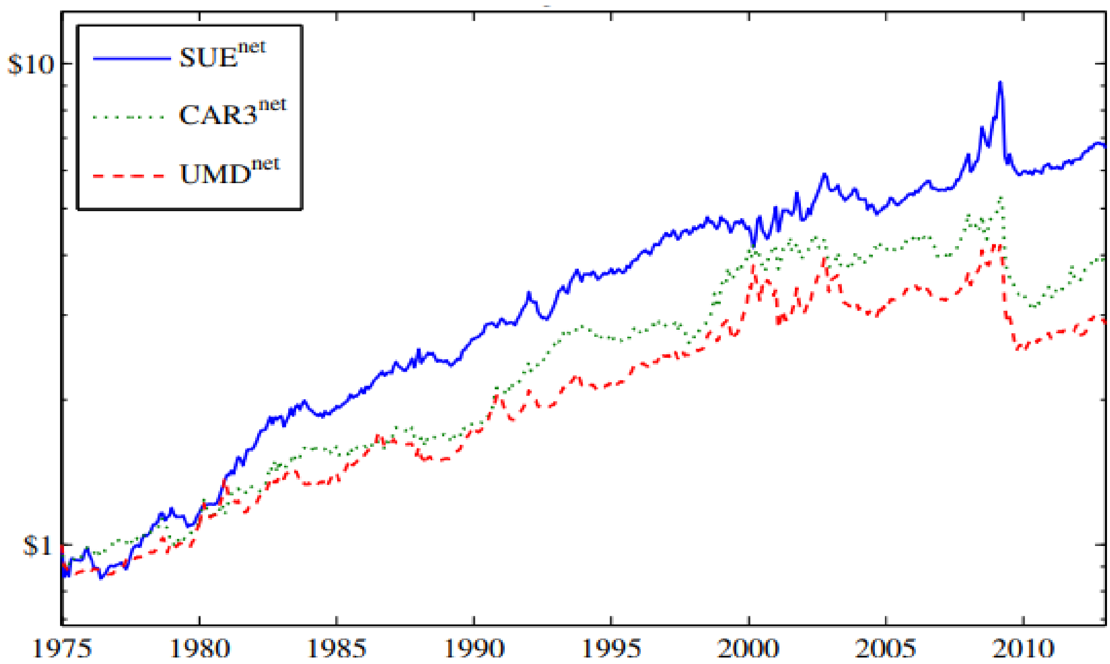
Figure 7: Value of $1 using various momentum factor methods



Source: Novy-Marx (2015).

You might look at the chart and wonder how trading costs affect these strategies. Is earnings momentum still superior after they are considered? The difference between overall profitability based on the methods of measuring momentum is visible in Figure 8.

Figure 8: Value of $1 after transaction costs



Source: Novy-Marx (2015).

While earnings momentum might be superior to price momentum (in some ways), it is not without flaws. Jiang and Zhu (2017) argue that information shocks that stem from behavioral reasons are the driving force behind earnings momentum. That would make the earnings surprises a shadow of investor sentiment which makes it no different than price momentum. Earnings momentum also has issues in international markets. Bron, Ghosh, and Petrova (2018) found earnings momentum to be inferior in European markets. Another issue of earnings momentum is the commonly observed post-earnings-announcement drift. Kausar (2018) believes that the earnings-based trading strategies are more or less an artifact of PEAD. Fink (2020) observed the difficulty of accurately processing earnings announcements. If something is difficult to process, it is usually also difficult to predict. There is also a tested alternative that produced better results. Barroso and Santa-Clara (2015) made a breakthrough when they discovered that momentum risk could be predicted. That eliminates the crash exposure and enlarges the Sharpe ratio. The robustness of their method is stronger at the expense of higher transaction costs. There are some cases where price and earnings momentum are equal. In both strategies, academics have a broad range of possible explanations of origin. Both also suffer under the weight of transaction costs which are a derivative of the high turnover needed for momentum strategies. The foggiest area of research belongs to cultural dimensions of momentum where it is still not yet certain where, why, and which momentum works better.

However, the success of earnings momentum in some areas appears to overshadow price momentum. It has proven to be superior in withstanding momentum crashes. Most importantly, long-term profits do not reverse.

There is still enough room for further research on this topic. I have noticed that there is an area where academics have not often wandered. Most focus on distinguishing various momentum strategies and enhancements and how they affect the overall market. Few center on how a certain momentum strategy affects various types of assets.

3.4 Momentum in high-tech and low-tech stocks

No company is the same. Logic reasoning would imply that therefore, no stock is the same. Academics have conducted countless tests and investigated many possible factors that should be able to explain a sufficient amount of variation. Seeking a "one size fits all" model seems like a utopia-seeking endeavor. Each of the mentioned models, strategies, and alternatives has proven to have its flaws. Most are built on assumptions that do not mimic real-life situations. Maybe another angle of clarification would be welcome. Maybe it is time we try to develop asset pricing models that are suitable for specific types of stocks. By narrowing the applicability, the models should be stronger in their designated field.

A possible type of division is between high-tech and low-tech stocks. This split makes sense because the first group is responsible for a significant amount of the total market. In the United States of America, the renowned S&P 500 index represents around 80% of total publicly listed stocks. Information technology accounted for 27.9% of the index on August the 31st 2021 (S&P Global, 2021). This is based on the division provided by the Global Industry Classification Standard. However, it is not the only possible way to draw the line between groups. High-tech stocks tend to have certain characteristics. They usually do not pay out a dividend, invest heavily in expansion and growth, trade at higher multiples, build a competitive advantage through intangible assets, etc. A company that is not classified as a technology company could still be a high-tech stock. Amazon, Facebook, Uber, and Airbnb for example, are not classified as information technology stocks. However, they are high-tech stocks. This calls for a better method of division. Borah, Pan, Park, and Shao (2018) found out that the average R&D and advertising costs represent 16.85% of total sales in high-tech stocks. On the other hand, low-tech stocks spend only 1.75% of total sales. Brown, Martinsson, and Petersen (2017) found similar evidence. A division based on R&D expenses should be superior in forming two distinct groups.

Here is why. Asem (2009) discovered that non-dividend stocks experience stronger price momentum. Kothari, Laguerre, and Leone (2002) revealed stronger future benefits that stem from R&D expenses when compared to benefits deriving from capital expenditures. Furthermore, the level of uncertainty is higher. According to Borah et al. (2018), the environments of high-tech stocks change rapidly which makes it difficult to compose accurate forecasts. This increases the level of risk.

It is consistent with the dogma of finance: higher risk should lead to a higher potential reward. Aboody and Lev (2000) found a strong connection between R&D expenses and insider gains. Larger expenses directed towards the future lead to large insider returns. While this may be subject to insider information exploitation, the evidence of a higher degree of uncertainty in high-tech stocks is hard to ignore. The business world is changing. Modern businesses are taking the lead with their low-cost scalable business models. Bagella, Becchetti, and Adriani (2005) noticed the increasing amount of intangible assets in the U.S. and Europe. All these findings provide substantial evidence that the division between high-tech and low-tech stocks is a viable option.

Although many researchers focused on the difference between high-tech and low-tech stocks, Ahmed and Alhadab (2020) were the first to test how momentum investing performs in these two groups. They discovered that high-tech stocks produce superior momentum profits. A part of that is attributed to the price reaction to the news. In high-tech stocks, volatility responds symmetrically to all types of news (good and bad). The situation for low-tech stocks is the exact opposite. The volatility responds asymmetrically. These findings have major implications, especially in the derivatives markets where volatility is used to determine option prices. In their research, they used price momentum to measure momentum profits.

However, price momentum has certain flaws that make it inferior when compared to earnings momentum. This opens up a new area of research which is also the main focus of this thesis. Is earnings momentum superior in generating momentum profits in high-tech and low-tech stocks?

4 RESEARCH FRAMEWORK AND METHODOLOGY

Underneath a particular stock, there is always a business. In certain cases, however, that direct connection becomes lofty, especially during short periods of market irrationality. Attentive investors may take advantage of the gap between stock price and business performance resulting in profits that are essentially a product of momentum. Carhart (1997) designed the four-factor model to emphasize the effect of momentum on the performance of stocks.

Researchers have been trying to test that model over many different time frames and data sets. However, they have rarely tried to test the model over many different types of stocks. Ahmed and Alhadab (2020) discovered that the gap that translates to momentum profits is not the same for all stocks. High-tech stocks produce a superior price momentum effect. Their analysis stemmed from the use of price momentum which possesses certain drawbacks that carve into sustainable profit making. Chordia and Shivakumar (2006), Mao and Wei (2014), Zhang and Bao (2017), and other academics favor earnings momentum over price momentum because of the robustness it offers.

Building on their findings, I modify one of the most renowned asset pricing models, the Carhart model. The modified model is then tested against the standard model on different data sets. The findings should give a clearer picture of the need to apply different asset pricing models to different types of stocks.

This section is designed to explain the research process with the development of the key research questions. Furthermore, a description of the used data sets is attached. The next part outlines the system of factor and portfolio construction. In total, five different factors are used in the analysis. In the end, the research findings are outlined and discussed.

4.1 Research purpose and design

The purpose of this research is to contribute to the refinement of asset allocation and the performance appraisal of fund managers. Furthermore, the academics could use the findings as a starting point for new research.

Since the invention of the CAPM model, there have been various breakthroughs in the field of asset pricing. Interestingly, very few online sources report on the usage of refined and improved models. The utilization of simpler models appears to have taken over the complex yet substantially better models. Perhaps, there are a few quant funds that operate on the backbone of models, such as the Carhart model or the Fama-French five-factor model. Another possible reason for avoidance is the documented flaws. In recent years, academics have slowly progressed into uncovering different market drivers, such as biases and momentum. Their mission is to build asset pricing models by finding quality factors that could explain the behavior of the stock market. Many factors failed on the robustness checks while others just did not have enough explanatory power. Maybe, the issue is not so much in the type of factor used but more in the type of stocks upon which the factors are applied. Ahmed and Alhadab (2020) were the first to test how momentum investing performs in these two different groups of stocks. They discovered that high-tech stocks produce superior momentum profits when compared to low-tech stocks. There are millions of businesses worldwide and each one has certain characteristics that make it unique. The application of contrasting models on different types of stocks is, therefore, a logical solution to refine the models.

Through the literary review, I find the Carhart four-factor model to be the best fit for the challenge. These four factors have been tested by various other researchers and have delivered the best results in terms of explanatory power. However, the standard Carhart model uses price momentum as the fourth factor. That type of momentum has shown to have certain flaws that decrease the long-term success and stability of the model. Scholars have introduced a collection of possible substitutions among which only earnings momentum stood out. The new type of momentum, which is a proxy for price momentum, has more explanatory power and is less prone to long-term price reversals or momentum crashes.

To summarize. Firstly, asset pricing models should be tailored to the stock upon which they are applied. Secondly, the Carhart model is the best fit to build an asset pricing model. Thirdly, the price momentum in the Carhart model is inferior to earnings momentum. From that collection of discoveries, I have developed one key objective. The goal of the research is to discover essentially if asset pricing models have better explanatory power when they are tailored to the various types of stocks (assuming a sophisticated asset pricing model). Following the style of Ahmed and Alhadab (2020), I split the data set into high-tech and low-tech stocks due to several key differences discovered by the authors. To reach my goal, I develop four different regression analyses. A standard Carhart model (price momentum) executed on high-tech and low-tech stocks. And a modified Carhart model (earnings momentum) executed on high-tech and low-tech stocks.

The design of this research is as follows. Firstly, I assemble four hypotheses, two for each research question. That adds a certain amount of direction to the whole research. The next phase covers the process of data assembly. Historical data includes more than 7782 stocks listed on the New York Stock Exchange. The next step is identifying the correct process and calculation for the factors. The first three factors of the model are gathered from the Kenneth French website. The price momentum and earnings momentum factors are built and calculated independently following the process described by the authors. In the following phase, six monthly rebalanced value-weighted portfolios are constructed (per factor) which are used to build the two momentum factors. In the end, the collected factors from the Kenneth French website and the calculated factors (price and earnings momentum) are merged into a list organized by month over 30 years. These factors are then imported into the Stata software where the regression models are executed showing the success rate of the research. In the next sections, each of the mentioned steps is thoroughly dissected.

4.2 Research questions development

As indicated, the main goal of the research is to essentially discover if asset pricing models have better explanatory power when they are tailored to the various types of stocks (assuming a sophisticated asset pricing model). The objective can be captured by two research questions.

The first one is focused on whether the two models react differently to different types of stocks. From this research question, I form two hypotheses. The models are better at explaining returns in high-tech stocks. The models are suitable to explain returns in low-tech stocks. I expect both of these hypotheses to be accepted. The first one is because the momentum factor tends to be stronger in high-tech stocks. The second one is due to the credibility of the Carhart and the modified Carhart model. This first research question shows if there is a difference in explanatory power when the model is applied to different data sets (different types of stocks).

The results stem from comparing a standard Carhart model executed on a high-tech stocks data set with a standard Carhart model executed on a low-tech stocks data set. The findings are additionally tested by comparing a modified Carhart model executed on a high-tech stocks data set with a modified Carhart model executed on a low-tech stocks data set.

The second research question is revolving around earnings-based momentum. Is the modified Carhart model better than the standard Carhart model? Out of this research question, I form two hypotheses. The modified Carhart model offers greater explanatory power over the standard Carhart model in high-tech stocks. Earnings-based momentum is better at explaining results in low-tech stocks. I expect that these two will prove to be correct because of pre-existing evidence of earnings-based momentum superiority. The second research question reveals if the earnings momentum-based models are superior or inferior. The results are obtained by comparing the results of the standard Carhart model with the results of the modified Carhart model.

4.3 Data assembly

The needed numerical data is collected through the Refinitiv Eikon system, which is the successor of Datastream. As mentioned before, the first three factors of the Carhart model are collected in their final form through the Kenneth French website. However, price and earnings momentum factors require additional data, such as monthly returns, market capitalization, anticipated earnings per share, and stock price. The complete data set includes 7782 ordinary stocks listed on the New York Stock Exchange over 30 years (from January 1990 until December 2020). From those 7782, 1340 were classified as high-tech. To avoid survivorship bias, all the stocks that were once active on the NYSE are included. Not only the currently actively listed ones. However, some of the stocks are removed due to the lack of complete data which could negatively affect the analysis.

Because the analysis requires two different data sets, the collected information is split into two subgroups: high-tech stocks and low-tech stocks. The first group includes information technology, telecommunications, and pharmaceutical companies. The reason behind that is the excessive need for research and development expenses which usually result in favorable outcomes, thus creating a stronger momentum effect in the market. The second group contains all the remaining sectors. The split is made using the Refinitiv Business Classification (TRBC) classification system in the Eikon software.

To avoid misunderstanding over the details of the data collected, I describe the collected variables in detail in table 1.

Table 1: Data variable description

Variable	Description
Monthly returns	Incorporates the price change and any relevant dividends for the last month.
Market capitalization	The sum of market value for all relevant issue level share types. The market capitalization is calculated by multiplying the number of shares outstanding by the latest close price.
Earnings per share	The statistical average of all broker EPS estimates is to be determined on the majority accounting basis.
Stock close price	The latest available closing price. If there are no trades for the most recent completed tradable day, the most recent prior tradable day is used.

Source: Own work.

Monthly returns and market capitalization are used to construct the price momentum factor for the standard Carhart model. Earnings per share and stock price are used to construct the earnings momentum factor for the modified Carhart model.

4.4 Factor and portfolio construction

For factor construction, I follow the standard approach of Fama & French (1993) for the first three factors. $ER_m - R_f$ (excess return over the market), HML (the value component), and the SMB (the size component) are all imported from the Kenneth French website. PR1YR (price momentum) and PMN (earnings momentum) are constructed independently with careful consideration to compare with the data of the other three factors. The first portfolio was formed in September 1990 and the last portfolio for December 2020.

For the construction of the price momentum factor, I follow the approach of Carhart (1997). Firstly, the list of stocks is split on the median market value of equity. In the next step, the stocks in each of the two batches are ranked according to their trailing eleven-month return lagged one month. Stocks without data for the previous twelve months use a shorter period of past returns (minimal eight months). I construct six portfolios (S/W, S/N, S/L, B/W, B/N, B/L) from the intersection of market equity and return using 30% breakpoints. That means that the top 30% of stocks are positioned in the winner portfolio while the bottom 30% are positioned in the loser portfolio. For example, the S/W portfolio contains stocks that are smaller in size and show strong (winning) momentum. The portfolios are rebalanced (reformed) monthly to capture the dynamics of the market.

For each portfolio, I report buy-and-hold value-weighted returns for the next month following the date of the portfolio formation. The sort month is usually skipped in momentum testing. This yields a time series of monthly returns from 1990 till 2020. In the final step, the price momentum factor (PR1YR), which represents the winning versus the losing momentum stocks, is calculated for each month following equation 6.

$$PR1YR = \frac{(S/W-S/L)\text{t}+(B/W-B/L)\text{t}}{2} \qquad (6)$$

S/W is the portfolio consisting of smaller companies that were recording stronger momentum (winning when compared to other companies) while S/L are smaller companies with weaker momentum (losing when compared to other companies). B/W is the portfolio of larger companies with stronger momentum while B/L are larger companies with weaker momentum.

As for the last constructed factor, I follow the approach of Chan, Jegadeesh, and Lakonishok (1996) for the earnings momentum factor. Firstly, the list of stocks is split on the median market value of equity. Then, the stocks are ranked according to a special measure of earnings news that stems from analyst revisions. Analysts do not necessarily revise their earnings predictions every month. Therefore, a six-month moving average of cumulative revisions is used (equation 7). It captures the earnings per share revisions.

$$REV6_{it} = \sum_{j=0}^{6} \frac{(f\,it-j) - (f\,it-j-1)}{p\,it-j-1} \qquad (7)$$

The $f$it is the consensus estimate of earnings per share in month t of firm i. The difference in the revisions is then scaled by the stock price in the prior month. In the next step, the companies are ranked, based on $REV6_{it}$ and market equity, in six portfolios (S/P, S/N, S/Ne, B/P, B/N, B/Ne) using 30% breakpoints. The portfolios are rebalanced monthly. For each portfolio, I report buy-and-hold value-weighted returns for the next month following the date of the portfolio formation. This yields a time series of monthly returns from 1991 to 2020. In the final step, the earnings momentum factor (PMN) which represents the positive minus the negative earnings revisions is calculated following equation 8. The factor is calculated monthly.

$$PMN = \frac{(S/P-S/Ne)\text{t}+(B/P-B/Ne)\text{t}}{2} \qquad (8)$$

S/P is the portfolio consisting of smaller companies that were receiving positive earnings revisions while S/Ne are smaller companies with negative earnings revisions. B/P is the portfolio of larger companies that were receiving positive earnings revisions while B/Ne are larger companies that were receiving negative earnings revisions.

The monthly calculations of the factors allow a time series regression to analyze the explanatory power of each factor. Table 2 exhibits the five different factors used in the regression analysis.

Table 2: A list of regression factors

Factor	Description
$ER_m - R_f$	Captures the risk attributed to equity investments.
HML	Represents the extra risk growth stocks carry.
SMB	Expresses the extra risk attributable to smaller companies.
PR1YR	Captures the price momentum effect.
PMN	Captures the earnings momentum effect.

Source: Own work.

4.5 Regression analyses

To assess earnings momentum superiority in different types of stocks, four multiple regression analyses are carried out. To add to the robustness of the test, I also test the alphas using the GRS test (Gibbons Ross Shanken). The number of regression analyses, the data set, and the used model are exhibited in table 3.

Table 3: Time-series regression models

Number	Data set	Used model
1	High-tech stocks	$ER_i - R_f = \alpha_i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (PR1YR) + \varepsilon_I$
2	Low-tech stocks	$ER_i - R_f = \alpha_i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (PR1YR) + \varepsilon_I$
3	High-tech stocks	$ER_i - R_f = \alpha_i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (PMN) + \varepsilon_I$
4	Low-tech stocks	$ER_i - R_f = \alpha_i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (PMN) + \varepsilon_I$

Source: Own work.

The expected excess return of an investment (dependent variable) is, therefore, determined by four different factors (independent variables). Regressions number one and two are aimed toward the discovery of the contrast in asset pricing between different types of stocks. Regressions number three and four tests the same thing. Instead of the standard price momentum, the models are modified with an earnings momentum factor. The results of the comparisons should provide a clear answer to the first research question.

By comparing regression one with three and two with four, the explanatory power of earnings momentum is revealed. The results should confirm or reject the two hypotheses that stem from the second research question. Is earnings momentum superior when compared to price momentum?

5 RESEARCH FINDINGS

The findings of my research revealed a few surprising and counterintuitive discoveries. All the tested regression models can explain a sufficient amount of the variance, which makes them applicable to real-life scenarios. The models proved to be robust after alpha testing with the GRS test. There were no observable collinearity issues with the factors.

5.1 Testing on different types of stocks and different types of models

Technological stocks tend to have stronger price movements. That would imply that you should be able to capture a larger portion of returns following various momentum strategies. The first research question, which aimed to discover the applicability of different asset pricing models on different types of stocks, revealed the opposite. Table 4 shows the regression results with the usage of price momentum as the fourth factor of the Carhart asset pricing model.

There is a substantial difference in the explanatory power between high-tech and low-tech stocks. The average R^2 for high-tech portfolios is 0.678 while the average for low-tech portfolios sits at 0.8288. One note here. The price momentum factor (β_4) was calculated using absolute return, which makes it vulnerable to extreme values. The standard error was not calculated in the process to detect that. “Black swan” events do occur in reality but are not considered here. That could be the reason behind the unusually high R^2.

The standard Carhart model which is based on price momentum can explain a sufficient amount of variance for both types of stocks. The price momentum factor (PR1YR) seems to be significant ($p < 0.05$) in most portfolios, except for large companies with neutral momentum. Around the time of hypothesis formation, I assumed the model would better fit rapidly growing technological stocks. The results portray the exact opposite. Low-tech stocks which usually move slower in the market, seem to be better suited for the use of the standard Carhart model.

The reason could be connected with lower expectations that do not inflate the valuations. This confirms my first research question. Different models should be used for different types of stocks. This observation is further supported by the regression results of the second model.

Table 4: Regression results for the standard Carhart model (1990 to 2020)

	Testing the explanatory model of a standard Carhart model on high-tech and low-tech stocks. The table presents the coefficients (t statistics in parenthesis) and the R^2 of the multiple regression for each portfolio whose monthly returns were regressed according to: $ER_i - R_f = \alpha i + \beta_1 (ER_m - R_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (PR1YR) + \varepsilon_I$						
	Portfolio	α	β_1	β_2	β_3	β_4	R^2
High-tech data	S/W	2.6687 (11.02)	1.037 (18.01)	0.6047 (7.59)	0.1047 (1.30)	0.3695 (8.60)	0.6022
	S/N	2.2647 (10.35)	0.8562 (16.45)	0.6245 (8.68)	0.2440 (3.36)	-0.0830 (-2.14)	0.5643
	S/L	2.8423 (11.70)	1.1232 (19.45)	0.9767 (12.23)	0.0911 (1.13)	-0.8212 (-19.06)	0.7638
	B/W	1.1411 (7.36)	0.8968 (24.33)	0.2024 (3.97)	-0.2370 (-4.61)	0.4315 (15.69)	0.7333
	B/N	0.6907 (5.69)	0.8069 (27.96)	-0.3130 (-7.84)	-0.0660 (-1.64)	0.0431 (2.00)	0.6919
	B/L	0.9674 (6.23)	0.8106 (21.96)	-0.1695 (-3.32)	-0.2235 (-4.34)	-0.3777 (-13.71)	0.6990
Low-tech data	S/W	1.8723 (9.87)	1.1276 (24.73)	0.7781 (12.56)	0.8821 (13.81)	.3309 (7.53)	0.7350
	S/N	1.3922 (11.57)	0.8526 (29.47)	0.5850 (14.89)	0.6735 (16.62)	-0.1493 (-5.35)	0.8224
	S/L	2.0077 (11.21)	1.1761 (27.33)	0.7857 (13.44)	0.7410 (12.29)	-0.8660 (-20.89)	0.8541
	B/W	0.7196 (6.98)	1.0136 (40.92)	-0.0753 (-2.24)	0.3559 (10.25)	0.3968 (16.62)	0.8327
	B/N	0.5981 (7.49)	0.8509 (44.34)	-0.1739 (-6.67)	0.3609 (13.42)	.03168 (1.71)	0.8572
	B/L	0.5841 (5.62)	0.9650 (38.60)	-0.0828 (-2.44)	0.4969 (14.19)	-0.4063 (-16.87)	0.8717

Source: Own work.

Table 5 shows the regression results with the usage of earnings momentum as the fourth factor of the modified Carhart asset pricing model. Again, there is an evident gap in the explanatory power of high-tech and low-tech stocks. The average R^2 for high-tech portfolios is 0.6032 while the average for low-tech portfolios sits at 0.8164. However, as in the previous regression, uncommon extreme values are not considered.

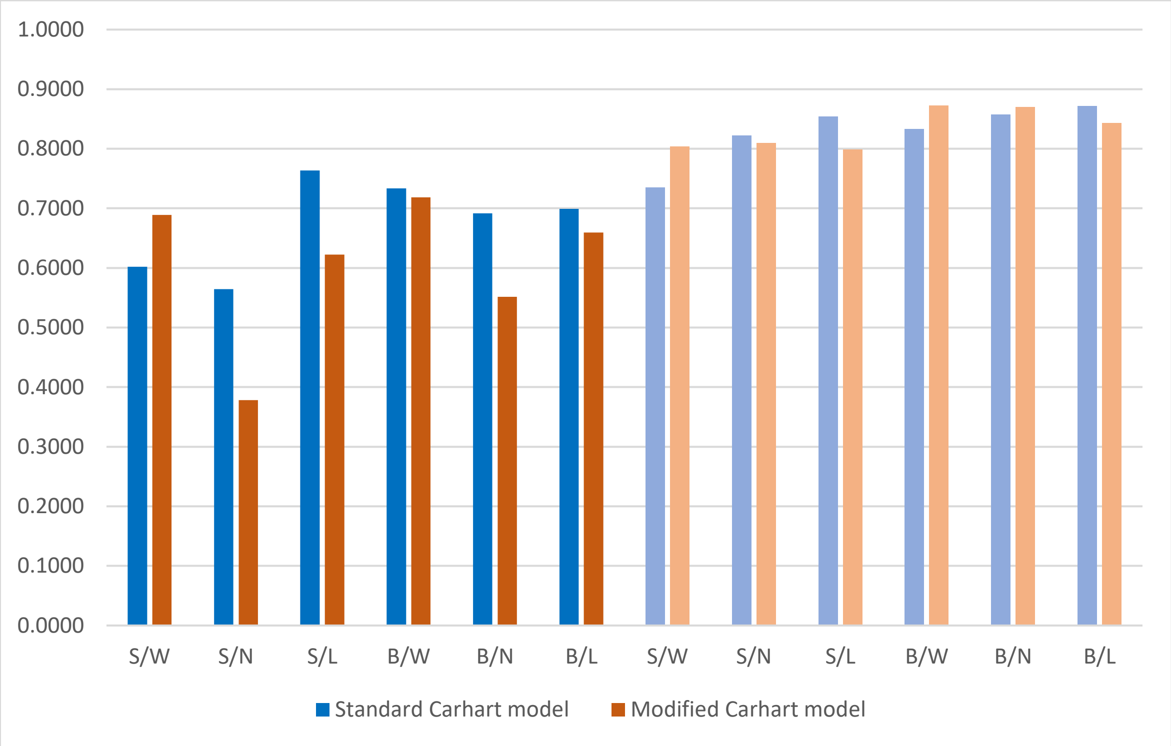
Table 5: Regression results for the modified Carhart model (1990 to 2020)

	Testing the explanatory model of a modified Carhart model on high-tech and low-tech stocks. The table presents the coefficients (t statistics in parenthesis) and the R^2 of the multiple regression for each portfolio whose monthly returns were regressed according to: $ER_i - Rf = \alpha i + \beta 1\ (ER_m - Rf) + \beta 2\ (SMB) + \beta 3\ (HML) + \beta 4\ (PMN) + \varepsilon_I$						
High-tech data	Portfolio	α	β1	β2	β3	β4	R^2
	S/P	2.8558 (11.30)	1.0058 (16.91)	0.7257 (8.75)	0.2781 (3.36)	0.8090 (12.90)	0.6888
	S/N	1.2844 (6.54)	0.5363 (11.60)	0.2930 (4.55)	0.0221 (0.34)	0.0971 (1.99)	0.3782
	S/Ne	2.5093 (10.93)	1.0311 (19.07)	0.7990 (10.60)	0.2640 (3.51)	-0.5207 (-9.14)	0.6223
	B/P	0.8026 (5.08)	0.8932 (24.00)	-0.0783 (-1.51)	-0.1727 (-3.34)	0.4485 (11.44)	0.7185
	B/N	0.5951 (4.99)	0.5296 (18.86)	-0.1662 (-4.25)	-0.2081 (-5.34)	0.0873 (2.95)	0.5517
	B/Ne	1.1490 (8.06)	0.8679 (25.86)	-0.1516 (-3.24)	-0.1586 (-3.40)	-0.2217 (-6.27)	0.6596
Low-tech data	S/P	2.1815 (10.40)	1.2270 (25.19)	0.8472 (12.55)	0.9024 (13.21)	0.8295 (13.89)	0.8033
	S/N	1.1268 (7.79)	0.9942 (29.61)	0.6338 (13.62)	0.8139 (17.28)	0.1008 (2.45)	0.8094
	S/Ne	1.7996 (10.83)	1.1465 (29.73)	0.7607 (14.23)	0.8821 (16.31)	-0.3458 (-7.31)	0.7990
	B/P	0.5977 (5.98)	0.9545 (41.15)	-0.0736 (-2.29)	0.4432 (13.62)	0.4813 (16.92)	0.8727
	B/N	0.4601 (5.41)	0.9327 (47.24)	-0.2024 (-7.40)	0.3283 (11.86)	0.0362 (1.49)	0.8699
	B/Ne	0.9796 (9.18)	1.0349 (41.77)	0.0129 (0.38)	0.4635 (13.34)	-0.3434 (11.30)	0.8427

Source: Own work.

Is the modified Carhart model better than the standard Carhart model? At first sight, the two models appear to have similar explanatory power with significance levels of $p < 0.05$. Surprisingly, as with price momentum, the earnings momentum factor (PMN) is not significant in big companies with neutral momentum. The literature review suggested that earnings momentum could be a good proxy for price momentum. It can be. However, the explanatory power is inferior. That finding applies to high-tech and low-tech stocks. A possible reason behind it could be the psychological component that comes from analyst revisions. These results reject my second research question. The modified Carhart model, as it appears, is not superior to the standard Carhart model. The R^2 of all the portfolios is visible in figure 9.

Figure 9: A comparison of R^2 between the standard and modified Carhart model



Source: Own work.

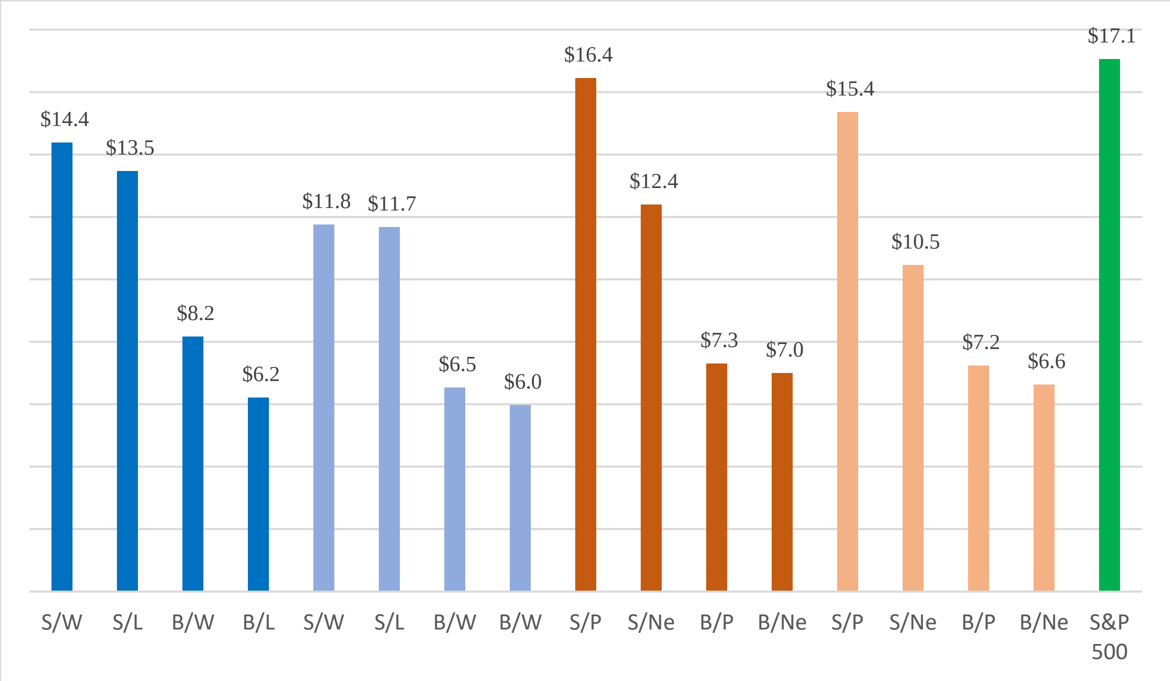
The standard Carhart model came ahead in nine out of twelve portfolios. The darker colors represent high-tech portfolios and the lighter colors exhibit low-tech. Figure 9 highlights the results for both research questions. Firstly, different models should be used for different types of stocks. That is evident in the higher R^2 of light-colored low-tech portfolios. Secondly, the modified Carhart model (using earning momentum) is not superior to the standard Carhart model (using price momentum). One can notice that by comparing the blue-colored portfolios with the orange ones.

The modified model may be inferior but does that mean the earnings momentum strategy returns are too?

5.2 Is earnings momentum superior?

From a perspective of explanatory power, earnings momentum delivered inferior results when compared to price momentum. The models can explain a smaller amount of expected return variance. Basing the momentum factor on analyst earnings revisions does not have the same power as simple past price movements. Stemming from that reality, one would assume that earnings momentum-based investing strategies would deliver lesser returns. That was not the case. In figure 10, the total returns under different momentum strategies are presented.

Figure 10: The value of $1 invested in September 1990



Source: Own work.

Blue portfolios follow the price momentum strategy and orange portfolios utilize the earnings momentum strategy. The darker colors represent high-tech portfolios and the lighter colors exhibit low-tech. The portfolios are rebalanced monthly and held until December 2020. Fees and commissions are ignored.

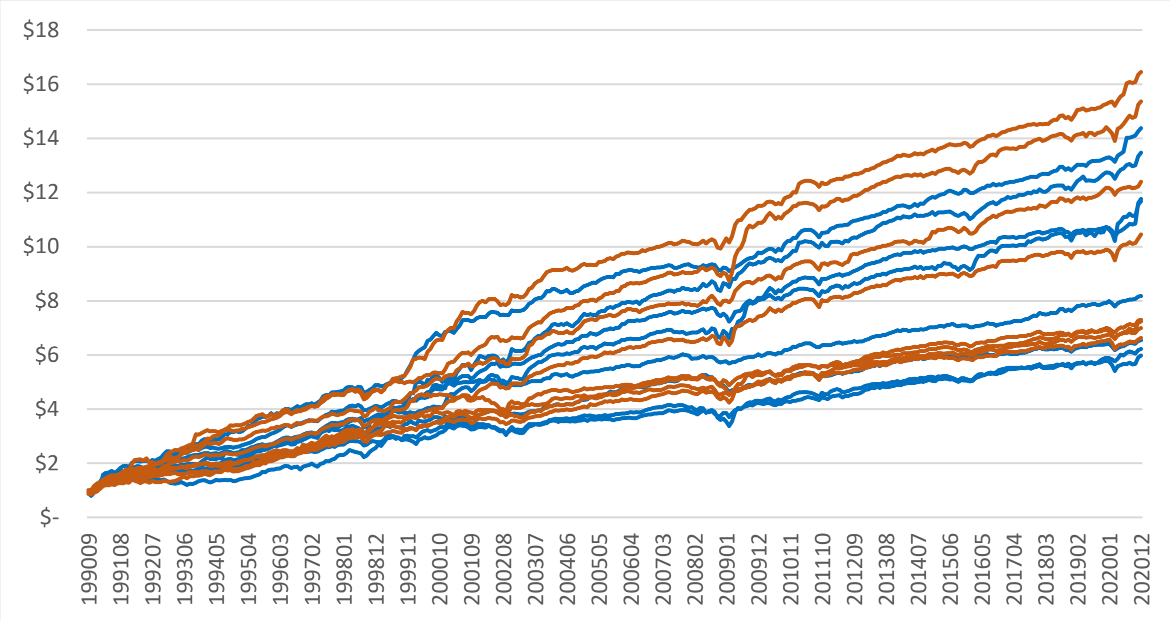
The observable difference between the success of earnings momentum and price momentum is the puzzling part. How can price momentum be superior in predicting the expected return of a security and inferior when employed as an investment strategy? One possible explanation is linked to the explanatory power of the models. Earnings momentum left a larger portion of variance unexplained. It is plausible that one or more impactful events are contributing to superior returns. Such events were not included in the earnings momentum factor (PMN). This suggests the need for further refinement of the momentum factors. Figure 10 also includes the simple S&P 500 index as a benchmark.

It is a widely recognized strategy for sustainable long-term returns. The index is bought and the distributions are reinvested as soon as they are paid out. This involves minimal effort and minimal costs. Nevertheless, the strategy still outperformed all the other momentum-based portfolios. However, by employing the earnings momentum strategy in technological stocks with improving earnings revisions, the return came very close.

Momentum strategies are often associated with high volatility, momentum crashes, and other unexpected events. The momentum reversals are also a noticeable occurrence in strategies that are based on durations longer than one year.

However, because the portfolios are rebalanced monthly, no shocks are evident. The performance of the utilized models and portfolios is visible in Figure 11.

Figure 11: The value of $1 (price and earnings momentum) invested in Sep. 1990



Source: Own work.

Most momentum strategies fail when transaction costs are included. My research does not include fees and commissions in the calculations. Because the portfolios are rebalanced monthly, fees would substantially decrease the return on investment. Commission-free brokers did not exist in 1991, which is when my first portfolio is formed.

The first company with this breakthrough idea launched in March 2015. Therefore, the momentum investing strategies were not as successful in the past as they were from 2015 onwards. It would make sense to compare momentum investing returns in the new-age investment world. Figure 12 shows the value of one dollar invested from March 2015 to December 2020. This implies the returns are net of fees. The colors represent the same portfolios as in Figure 9.

Harnessing the power of momentum allowed eleven out of sixteen portfolios to outperform the benchmark. Since the returns are net of fees, this provides a successful strategy to utilize. In theory, everything always seems implementable. However, the markets are governed by psychology. Is this approach applicable to real-life situations?

Figure 12: The value of $1 invested in March 2015

Source: Own work.

5.3 Discussion and implications

Momentum investing requires constant position monitoring and a high tolerance for risk. The portfolios often reported monthly price swings of over ten percent. Large institutions probably would not opt-in for such an approach. Insurance companies or retirement funds even less so. Smaller quant funds, however, may express more interest. It is nearly impossible for manual implementation of the suggested approach to succeed. Luckily, the emergence of trading bots and data sciences made it possible for such high turnover strategies to appear. Commission-free trading also gave them an edge.

Quant funds focusing on quantitative data analysis are not always successful. In fact, few succeed over a longer period. There are numerous reasons behind that. A common issue is predicting the direction and intensity of the market. The markets are often influenced by psychology and sentiment. Therefore, it is very difficult to build successful models or pick winning stocks. If a fund was able to capture a large amount of variance that stems from sentiment, it could outperform the market by a large margin. That is also the direction in which most of the academic work is heading. The idea to capture the psychological component in a quantitative model is extremely difficult and an endlessly fruitful endeavor.

The usage of my model is not easily implementable by the masses. However, retail investors can adjust their portfolios to a certain extent from the findings of this study.

Firstly, they could monitor previous earnings revisions that imply (but do not guarantee) stronger momentum. If analysts are consistently increasing their predictions, that is a stronger signal for future growth than the past price increase.

Secondly, momentum returns are larger in technological stocks. It would make sense for short-term investors to stick to faster-growing companies. Thirdly, the two models can be used to calculate the adequate discount rate, which determines the fair value of an investment. However, I believe asset pricing models are not commonly used by investors with relatively smaller portfolios.

The built models are far from perfect. It would be interesting to see the model results on stock markets beyond the United States. A sufficient amount of variance is also still left unexplained which implies further refinement is needed. In the research, I split the data set into high-tech and low-tech stocks. Maybe it would make sense to form other groups of stocks. Splitting the data per sector would be a fascinating start.

CONCLUSION

Momentum investing has its moments. Technological stocks tend to be more volatile. That would imply the possibility of harnessing that volatility to produce superior returns. However, it is not reflected in the results of the regression. The amount of explained variance in the expected returns is much larger in low-tech stocks. That finding is confirmed in both price and earnings momentum models. Although, black swan events are not considered. Different asset pricing models should be used on different types of stocks. Concerning the second research question, earnings momentum proved to be inferior to price momentum. Despite the benefits emphasized in the existing literature. The difference, however, is minimal.

The surprising part of the research is the dissonance between the regression results and total return. How can earnings momentum be inferior in predicting the expected return of a security and superior when employed as an investment strategy? One possible explanation revolves around the unexpected events that the regression could not explain. Nevertheless, all fee-neglecting momentum strategies failed to compete with the benchmark S&P 500 index. This suggests the need for further refinement. Especially now when commission-free brokers have emerged which allow high-turnover strategies to flourish.

The findings can be compressed into two sentences. Use different models on different types of stocks. Use earnings momentum but expect the unexpected.

If any of the readers should implement this approach in the future, it is important to note that with each user, the success of momentum investing weakens. In the words of legendary quant fund manager Jim Simons: “There's no such thing as the goose that lays the golden egg forever.”

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APPENDIX

Appendix 1: Summary in the Slovenian language

Svet investicij se čedalje bolj prepleta z našim vsakdanjikom. Glavno določilo veličine finančnih trgov v večji meri določa cena. Izhodišče cene pa je pogosto pogojeno z modeli vrednotenja sredstev. V poznih devetdesetih letih prejšnjega stoletja je Carhart razvil poseben model, ki je vključeval tako imenovani zagon (angl. momentum). Koncept določanja donosa glede na predhodno gibanje cene je sicer enostaven, vendar delujoč. Carhartov model kot glavne faktorje modela uporablja tržno premijo, velikost delnice, knjigovodsko vrednost in cenovni zagon. Presenetljivo malo poudarka je bilo na testiranju različnih vrst delnic. Zakaj bi upravljavec naložb uporabljal en model za vse vrste podjetij, ko pa je med njimi nešteto razlik? Ena od možnih delitev je med visoko tehnološke in nizko tehnološke delnice. Tehnološke delnice so običajno podjetja, ki morajo porabiti veliko denarja za raziskave, kar sčasoma dvigne ceno (ob predpostavki, da so prizadevanja uspešna). Potreba po prilagajanju modelov določenim skupinam delnic je zanimivo odkritje za uporabnike sofisticiranih modelov ali raziskovalce, ki so pripravljeni globlje raziskati temo. To razkritje (in cilj) dopolnjuje namen prispevanja k izboljšanju razporejanja sredstev in vlaganja. Na podlagi ugotovitev akademskega sveta zgradim dva multipla regresijska modela, ki ju uporabim na visoko in nizko tehnoloških delnicah. Presečišče štirih multiplih regresij daje dokončen odgovor na dve glavni raziskovalni vprašanji. Ali je razlika v zagonu med različnimi vrstami delnic? Je dobičkovni zagon boljši od cenovnega?

Regresijski modeli se veliko bolj prilegajo nizko-tehnološkim delnicam. To ugotovitev potrjujeta oba modela. Različne vrste delnic torej zahtevajo različne vrste modelov. Glede na ugotovitve obstoječih znanstvenih del bi bilo pričakovati, da bo dobičkovni zagon prevladal. Izkazalo se je, da je običajni, cenovni zagon boljši napovedovalec pričakovanih donosov. Razlika je sicer minimalna, vendar signifikantna. Presenetljiv del raziskave je neskladje med rezultati regresije in skupnim donosom. Kako je lahko dobičkovni zagon slabši pri napovedovanju pričakovanega donosa vrednostnega papirja in boljši, če se uporablja kot naložbena strategija? Morda je vzrok v nepričakovanih dogodkih, ki se skrivajo v delu nepojasnjene variance. Kljub uspešnosti investicijskih strategij, ki temeljijo na zagonu, je dolgoročno prevladal S&P 500 indeks. To nakazuje potrebo po dodatni izpopolnitvi. Predvsem bi bilo zanimivo videti drugačne vrste delitev delnic. Sektorska primerjava ter prileganje regresijskih znotraj le-teh je le ena od možnih nadgraditev te raziskave.

Glavne ugotovitve je možno strniti v dve povedi. Uporaba različnih modelov na različnih vrstah delnic je priporočljiva. Dobičkovni zagon je kot investicijska strategija superioren, vendar nepredvidljiv.

Če bi bralec v prihodnosti uveljavil ta pristop, je pomembno omeniti, da z vsakim uporabnikom uspeh zagonskega vlaganja slabi. Z besedami legendarnega upravitelja kvantnega sklada Jima Simonsa: "Ne obstaja gos, ki bi večno nosila zlata jajca."