Robustness tests of residual momentum strategies

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For a Master's degree specialized in
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Abstract:

Contrary to conventional momentum, the literature treating the subject of residual momentum is very narrow. The aim of this thesis is to contribute to the literature, first by using pricing models that have been recently proposed and were not available at the time when previous researchers published their work. Secondly, by adopting the point of view of an investor who has limited access to the market and its instruments. Mainly, this investor would be unable to short sell stocks. This second choice is of particular interest for portfolio managers who sometimes have limited choices regarding the instruments they are allowed to use. Following the analysis, it appears that residual momentum outperforms its conventional counterpart in every aspect detailed in this research. It seems that there is no reason for an investor who is currently using a conventional momentum strategy not to switch, at least partially, to a residual momentum strategy.

Keywords: momentum, residual returns, risk factors, asset pricing, stock-specific returns.

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1. INTRODUCTION

"Common sense is the collection of prejudices acquired by age eighteen"
Einstein

In physics, "*The momentum of a body is defined as the product of its mass by its velocity*" (Semat & Katz, 1958, p.182) and is a basic concept, taught year after year to students. An interesting fact is that momentum doesn't change, unless there is net force acting on the system. This is equal to say that if no forces are applied to an object in motion, it can go on in the same direction forever.

However, in finance, price momentum, generally simply called "momentum", is seen as one of the most, if not the most, important documented anomaly (Novy-Marx, 2015). Still, everyone in the financial industry seems to have his or her personal definition, and sometimes explanation, about the momentum effect. On top of that, some researchers have found it useful to add different kinds of momentum: absolute momentum, relative momentum, dual momentum (Antonacci, 2014) or even residual moment (Blitz, Huij & Martens, 2011; Gutierrez & Pirinsky, 2006).

To ensure consistency with the reader, I will use Novy-Marx's definition of price momentum, which is: "the tendency of stocks that have performed well over the prior year to outperform, going forward, stocks that have performed poorly over the prior year." (Novy-Marx, 2015), and will generally refer to it as classic or conventional momentum. Of course, the looseness of this definition is subject to interpretation. For example, the S&P 1500 Positive Momentum Tilt Index primarily sorts stocks based on the 11-months total return ending on the month prior to the rebalance month (S&P Dow Jones Indices (Ed.), 2015). While MSCI is going as far as using measures such as Sharpe ratios in their rankings and still, they simply name the index "MSCI Momentum" (MSCI Research (Ed.), 2013).

Similarly to physics, in the real world, plenty different forces act upon the system, and in this case, the stocks returns' direction eventually changes. In what might be considered as the first paper on price momentum, Jegadeesh and Titman (1993) pointed out that volatility and market mean reversals are two forces that have a very negative effect on the momentum strategy’s profitability, identifying one of its biggest weaknesses. In spite of that, in many cases, researchers are not only trying to explain why such a strategy is generating abnormal return, but are tending to use their findings to draw conclusions on whether an even more discussed matter is correct or not: market efficiency. This issue generally revolves around one question: *are the results consistent with a risk-based explanation or are they showing some behavioral biases of investors?*

Hopefully, this thesis will bring its own answer to this question and fuel the controversy, but the focus and ambition, is more oriented towards the determination of whether or not a residual momentum strategy might be a viable and profitable, solution for investors. It is mainly built upon three publications, namely: *Momentum, reversal, and the trading behaviours of institutions* (Gutierrez & Pirinsky 2006), *Residual momentum* (Blitz et al., 2011), and *Purifying momentum* (Ma et al., 2015).

My meeting with Pascal Lebois has very much influenced the subject. He presented the paper *Purifying Momentum* from J.P Morgan (Ma et al., 2015), and asked me if a similar strategy could be implemented by his team and what were my thoughts about the risks. The paper was about residual momentum and directly piqued my interest, as I had never heard of it before. Sadly, like many documents published by non-academic institutions, I found important information was missing to answer Pascal’s questions. I am afraid those documents are crowded with high average return, low volatility, which translates into high Sharpe ratios and more importantly, graphs showing that the strategy outperforms a given index even if it has nothing to do with the discussed strategy in terms of risk exposure. Additionally, the writer told me I should carry on further research on the robustness of the strategy before implementing it.

This thesis has also a scientific motivation as it seeks to be a direct addition to the work done by Gutierrez and Pirinsky (2006) and Blitz et al. (2011). In their research they describe residual momentum as the ranking of stocks based on the residual factor that stems from a regression model. Yet, the only regression models they use are the CAPM and the Fama and French 3-factor model. The recent development of new models in the literature, including a revised model by Fama and French (2014) with 5 factors, raises the question of whether or not residual momentum is still effective while using those models. Moreover, I am personally concerned about data mining, whether it is done consciously or unconsciously. Having a complementary analysis of the subject, in which the results of different values for the variables are displayed, should give a better understanding of the sensitivity of the model to these variables. This in turn should show if the results are robust, or if, on the contrary, they are random and the product of unconscious data mining.

Taking all the aforementioned information into account, this research will try to answer the following question: *is a residual momentum strategy profitable, what are the risks associated with it, and how does it perform compare to a classic price momentum strategy?*

The rest of the thesis is organized as follows: section 2 presents a review of the literature, first looking at momentum in general, and then focusing on the pricing models that will be used thereafter. Section 3 details the methodology used and discusses some of the assumptions and choices that have been made. Section 4 shows the results and analyzes. Section 5 concludes.

2. LITERATURE REVIEW

"One hundred thousand lemmings cannot be wrong"
Graffiti

This section begins with a brief history of momentum, where it comes from, how it has evolved and where it is now. Then, the focus is set on the models used later on to do this research.

2.1. A brief history of the momentum effect

Georges Soros might be one of the first users of a momentum-like strategy. In *The Alchemy of Finance* (Soros, 1987) he presents a simple model to explain stock prices movement, in boom/bust scenarios, based on two hypotheses. The first one states that each market participant is always biased in one way or another. Their views mainly cancel each other out but there is a residual that is *the prevailing bias*. The second hypothesis evokes the idea that markets can impact future events based on what they predict. He also adds the concept of an *underlying trend* that is, more or less, a trend in a fundamental that impacts, or supports, the way stock prices move. The fundamental he uses to illustrate the model in action is the earning per share but it could be any other measure such as dividend, free cash flow, book value, etc.

The model is based on self-reinforcing processes between three components: stock prices, the prevailing bias and the trend based on a fundamental. Everything starts with an underlying fundamental trend that is not yet identified by the market. The trend is key because otherwise there is only the prevailing bias in action and it is likely to be rapidly corrected. When people identify the trend, that has, for example, manifested itself in the EPS of a company, expectations change and stock prices start to move. At this point doubt may arise, but if the trend survives the correction in stock prices, a positive bias flourishes and stock prices start rising again, accelerating the trend. So long as this cycle of self-reinforcement continues, market's anticipation will rise faster than stock prices. The more it goes on the more the stock prices influence the fundamental trend and these stock prices are themselves more and more influenced by the prevailing bias. This makes both the trend and the bias highly fragile and eventually, at one point, the rising stock prices can no longer sustain the expectations. At that moment, disappointment starts overrunning the market, which pushes down the prices. If the trend was overly dependent on those prices, a total reversal of the market is very likely to happen. In this case, a similar self-reinforcing process begins, but in a reversed fashion.

Of course, to feed this model there must be a misconception in how the market interprets the fundamentals. At the precise moment this misconception is disguised, the reversal takes place. If one wants to understand boom/bust scenarios, comprehending the misconception as well as how and when it happens are the important elements.

Soros started using his model for the first time in the late 60s during the conglomerate boom, and presents a couple other situations where he was successful using this strategy. Simply put, not to short in anticipation of the incoming collapse but, on the contrary, to buy ahead of further buying made by non-informed investors.

Soros's strategy is very similar to, and partly influenced the positive feedback investment strategy described by De Long, Shleifer, Summers and Waldmann (1998). The link with price momentum strategy jumps out with this simple definition from their paper: "*Positive feedback investors are those who buy securities when prices rise and sell when prices fall*" (De Long et al., 1998, p.379).

They highlight a few different situations, experimental and empirical, where people chase the trend if prices tend to rise or, on the other hand, expect a reversal to the mean when prices are flat. Basically people base their expectations on historical price changes. The most striking example presented is one related to recommendations issued by analysts on exchange rates in the mid-80s. The dollar had been rising for quite a long time without being supported by the fundamentals, namely a larger spread in the interest rate between the U.S. and the world and a growing trade deficit. Even though the forecasters were aware of this, they expected the dollar to continue to increase in the following months as well as a decline in the coming years due to the divergence with the fundamentals. To sum up, they were issuing a buy recommendation while acknowledging the fact that the dollar was already overpriced.

Following these observations, a mathematical model is presented. It shows why a rational investor can expect rising prices to continue their way up on a short-term horizon, but at the same time expect those prices to fall on a long-term horizon. They explain such a strategy is rational in the presence of positive feedback traders.

This conclusion will be used by Jegadeesh and Titman (1993), in their article *Returns to buying winners and selling losers: implications for stock market efficiency*, as a possible explanation for the pattern of return they identified. Even though the words *price momentum* only appears in a footnote of the document, it can be considered as its foundation. The authors present a strategy: buying stocks with a good past performance and selling ones with a poor past performance, which goes against some other research conducted earlier. Notably De Bondt and Thaler (1985) suggest prior losers outperform winners in a 3 to 5-year time frame.

They also present some empirical evidence for such a strategy to work. In particular, the fact that most successful mutual funds analyzed, by Grinblatt and Titman (1989, 1992), are more inclined to buy stocks that have performed well over the last quarter, as well as the somewhat predictive power of the Value Line ranking which is based mainly on past relative strength. The work of Levy (1967), who proposes to buy stocks with a relatively higher price than their 27-week average, is also rapidly discussed. However, as pointed out by Jensen and Benington (1970), Levy analyzed more than 60 different variations of this strategy and only a few were actually beating a buy-and-hold strategy. Thus, I would say the strategy he presented was just the outcome of data mining. For this reason, it does not bring any new knowledge on whether or not historical prices can be used to generate abnormal return.

The strategy Jegadeesh and Titman (1993) propose is the following one: with K being the holding period in months, J being the return period used to rank the stocks also in months, the sub-strategies are referred to as a J-month/K-month strategy. Every month *t*, stocks are ranked on their return over the past J months, in ascending order. Then, 10 equally weighted portfolios are constructed based on the decile of this ranking scheme, one portfolio for the first decile, one for the second and so on. Each month *t*, the strategy is to go long the top decile, the *winners*, and short the bottom one, the *losers*, and keep this position for K months as well as close the position initiated *t*-K months ago. So, every month, 1/K of the total portfolio is rebalanced.

They have examined the results using J and K equal to 3, 6, 9 and 12 months. They have also tried those same strategies with a one week lag between the portfolio formation period and the holding period. Giving a total of 32 strategies.

Out of those strategies every zero-cost portfolio produces positive and significant return, except for the 3-month/3-month strategy that is insignificant. Do note the best strategy out of all these is the 12-month/3-month with one-week lag. The authors conclude what they call *relative strength strategies* are profitable on average and analyze in more details the 6-month/6-month without lag strategy.

I would like to highlight two point of their analysis. The first one is the results of the back testing, which gave them results from 1927 to 1989. Fama and French (1988) pointed out the variance of the market was much higher from 1926 to 1940 than it was afterwards, from 1940 to 1985. During this period of strong price swing, Jegadeesh and Titman (1993) observed the returns of the strategy were substantially lower than during the following period. One reason of this poor performance was the tendency of the strategy to select high beta stocks following market increase and low beta stocks following market decrease. Of course, such an exposure performs badly during market reversal, which is exactly what happened more often during these years. The second point is linked to the earnings announcements. The long part of the portfolio, the "winners", have a tendency to significantly outperform the short part of the portfolio around the quarterly earnings announcements that are made in the first few months after the formation date.

The first point is important for investors as it shows some of the risks involved in using such a strategy, while the second point gives the reader a foretaste of another way to explain the price momentum anomaly that will be discussed later on.

Of course, the anomaly attracted the attention of multiple researchers, some trying to prove it arises from investors' miss interpretation of information, for example Daniel, Hirshleifer and Subrahmanyam (1998) or Hong and Stein (1999). Some, on the contrary, are trying to prove the abnormal returns are in fact just a compensation for risk, for example Conrad and Kaul (1998).

Eight years after their publication, Jegadeesh and Titman (2001) continued their analysis of the momentum anomaly. First, they showed the strategy still works on the new 9 years of data available, even though investor could have adapted their strategy to the momentum effect. With some additional evidence, they came to the conclusion that it was a reasonable advocate against data mining issues, which contrasts with the small size and value stocks effects that, according to them, are no longer generating a statistically significant alpha on the period subsequent to their publication.[1] They also state investors have apparently not adapted their strategy to take advantage of the momentum effect. They conclude the Conrad and Kaul (1998) hypothesis, *momentum profit is due to cross-sectional differences in expected returns*, should be rejected. However, the behavioral models might be a partial explanation of the momentum effect, but definitely not the entire explanation in their proposed version. Mainly due to the negative post holding returns being dependent on the composition of the sample, its period, and whether or not the returns are risk-adjusted.

Some researchers also consider another perspective, notably Chordia and Shivakumar (2005), who argue earning momentum captures price momentum. The earnings momentum refers to the analysis that firms posting higher earnings than expected tend to outperform firms that post lower earnings than expected over a nine-month period. They found a zero-cost portfolio long the high earning surprise stocks and short the low earning surprise ones captures the price momentum effect, but the reverse does not hold true. They show the returns of the previously built portfolio are correlated with macroeconomic factors, and derive from this statement that price momentum should not be explained by idiosyncratic components of stocks returns.

Novy-Marx (2015) is following up on this research and shows Chorda and Shivakumar's (2005) conclusion holds in a broader variety of stocks, especially large ones. Basically, it means people who want to take advantage of the momentum effect should ignore the price momentum and focus their attention on the earnings momentum. Nevertheless, he goes further and shows price momentum negatively impacts earnings momentums. Investors could even use information on past performance to avoid price momentum stocks, when they build their earnings momentum portfolio, since they are only a source of volatility and drawdown. He also compares the earnings momentum strategy to volatility-managed momentum. Barroso and Santa-Clara (2013) identified price momentum tends to deliver high performance following low volatility markets and, on the contrary, delivers low performance following

[1] Jegadeesh and Titman (2001) say from 1982 to 1998 the average size factor returns -0.18% per month with a -1.01 t-stat, knowing the identification of the size premium was shown by Banz in 1981. Regarding the value effect, they found an average return of 0.12% per month with a 0.47 t-stat on the period from 1990 to 1998, which is subsequent to the period analyzed by Fama and French (1993).

high volatility which goes against the principle of higher risk, higher reward. It also translates into a very volatile Sharpe ratio, particularly high during calm periods but dramatically decreasing in highly volatile periods. Following this analysis, they developed volatility-managed momentum, which essentially targets a given level of volatility. To reach this target a forecasted volatility is calculated and used to determine how one should invest into the price momentum portfolio. For instance, when the target volatility equals the forecasted volatility the ratio is 1 and the volatility-managed momentum portfolio is the same as the conventional price momentum portfolio. However, if the forecasted volatility is twice the target volatility then the ratio drops to ½. Interestingly, Novy-Marx (2015) found earnings momentum was outperforming this volatility-managed momentum strategy, but using the same approach to manage volatility with earning momentum also improves the strategy.

Of course, such a persisting anomaly did not only attract the academic world but also the professionals. I would like to mention the work of Antonacci (2014) who won an award from the *National association of active investment managers*. The reviewing committee might not be as recognized as the one from well-known journals but a jury has nevertheless approved it. The author starts by differentiating absolute momentum from relative momentum, the former is looking at the excess performance of a given asset over a given period of time while the latter is comparing the performance of two assets over a given period.[2] The price momentum strategy of Jegadeesh and Titman (1993) described above was only concerned by relative momentum as they were building zero-cost portfolios, going long the relatively strong stocks and short the relatively weak ones. The dual momentum strategy Antonacci exposes uses four silos to get exposures to different risk factors, using one out of two potential assets, namely: equities (US vs. World ex-US), credit risk (High Yield vs. Credit Bond), REITs (Equity REIT vs. Mortgage REIT) and stress (Gold vs. Treasuries). The idea is to have two different alternatives in each silo plus the possibility to invest in T-Bill if neither is attractive. First, relative momentum is applied to the two assets to select the most attractive on, and then, if its absolute momentum is positive, it is selected. Otherwise, the T-Bill is taken instead. This procedure is done for the four silos and the full portfolio is built using the four selected assets

[2] The author suggests comparing the performance of an asset with the performance of T-Bill over the same one-year period to determine whether absolute momentum is positive or negative. However, I must raise concerns about some assumptions made by the author: first he expects T-Bill's return to be positive. Second, he expects an asset that is outperforming the T-Bill will continue on this trend *by virtue of the transitive property*, explaining that auto-covariance between an asset's excess return next month and its lagged one-year return is fairly high as shown by Moskowitz, Ooi and Perdersen (2011).

with an equal-weight scheme. The author claims this portfolio generates an annual Sharpe ratio of 1.07 over the period analyzed, 1974-2011. Sadly, this is done using indexes, and even using composite indexes for the World ex-US part of the equity silo as investments vehicles. He concludes using absolute momentum helps diminish the downside risk and allow investors to tame high volatility by taking advantage of the upside without the downside. Even though I think this research has a minor added value due to the flaws explained above, it nevertheless shows some potential usage of momentum. Perhaps a tripartite momentum will arise, though it would not be an easy task to understand the underlying forces driving such a strategy.

Index providers, such as the FTSE Rusell (Ed.) (2015), also provide investors analysis on the subject of momentum. Notably, they show a couple of different approaches used in practice when building indexes. They examine in more details five different versions: the classic strategy described in this introduction (that they call *return momentum*), a Sharpe ratio based one where the ratio is used instead of the total return for sorting stocks, the third one is based on what they call the CH Ratio which is calculated as the current stock price divided by the highest stock price over the past period, the fourth one is based on the alpha of regressions, and the last one is based on the error term of regressions. Then, an analysis of the different parameters is done, trying to highlight these parameters' sensitivity, for instance: the formation period, the holding period, the rebalancing month, so on and so forth. They conclude that the most robust strategies use a formation and holding period of 12 months / 12 months or 6 months / 12 months respectively and use a one-month formation lag. More interestingly, they identified that out of the three first strategies the classic one shows less industry or country effect than the second one and is less biased toward systematic risk than the third one. Additionally, these three strategies show varying exposure to systematic risk, which is the source of their momentum. The alpha and residual method, on the other hand, are not linked to systematic risk. The authors argue alpha could depict the stock specific returns, thus capturing stock specific momentum, while the residual technique would be linked to stock specific shocks, separating the noise from the news and taking advantage of the latter. Finally, they show there is a low correlation[3] between the alpha and the residual technique. Unfortunately, no information is given on the significance of this value. Nevertheless, it might open some room for multi-momentum strategies like the one described by Antonacci (2013).

[3] They report a correlation of 0.41 that, according to Calkins (2005), can be considered as low.

Coming back to the scientific literature, I would like to present in more details the residual based strategy used by the FTSE group in their analysis. It comes from the work of Gutierrez and Pirinsky (2006) where they expose another potential explanation for the price momentum effect. They found an agency-based[4] explanation related to money managers' incentives. To come up with this conclusion, and similarly to the work of Antonacci (2013) presented above, they split the momentum effect in two components: a relative one and a firm-specific one. However, Gutierrez and Pirinsky's approach of the stock-specific momentum is a little more elaborate and based on the residual of a CAPM-like regression, using the CRSP value-weighted index as the market portfolio proxy. For each stock, the sum of the monthly residuals over a J-month period ($\hat{\varepsilon}$) as well as the sum of the variance of the monthly residuals over the same J-month period ($\hat{\sigma}^2$) are calculated. The authors use these two amounts to identify winners and losers. Basically, a stock is a winner if $\hat{\varepsilon} > \hat{\sigma}$ and a loser if $\hat{\varepsilon} < -\hat{\sigma}$. According to them, using the variance to standardize the residuals allow for a better separation between return shocks that are actual news from those that are trivial noise. Nevertheless, they state their conclusion would not be affected if the variance factor was not taken into account. Contrary to relative momentum, they found firm-specific momentum does not exhibit a tendency to reverse in the long-term and show that they are two different phenomena. The former is in line with an overreaction of investors while the latter is in line with an underreaction. Their analyzes supports the idea that institutions have incentives to pursue relative returns, which contributes to overreactions, and in turn, partially explains the classic momentum performance. On the other hand, those same institutions are less interested by firm-specific abnormal returns, which contribute to underreactions, and in turn partially explains the firm-specific momentum performance.

To finish this brief history of momentum the work of Blitz et al. (2011) on residual momentum will be briefly discussed. Contrary to the work of Gutierrez and Pirinsky (2006), who advocate price-based strategies and residual-based strategies generate similar returns over the first year after the formation period, but differ dramatically during the one to five-year subsequent period, Blitz et al. (2011) found that even during the first year, the return of the residual momentum strategy, when adjusted for risks, is far superior. They found a residual based strategy is less affected by the time-varying exposures to the Fama and French

[4] Agency theory is the part of the financial economics research studying the conflicts of interest that exist between people with different interest in the same asset.

three factors than the price momentum. This characteristic allows achieving similar returns but with less volatility, which leads to higher risk-adjusted returns. Their construction of the residual momentum portfolio is slightly different from the one used by Gutierrez and Pirinsky (2006). Mainly, they use the Fama and French three factors model to do their regressions on a 36-month rolling window. Even though both papers note the alpha in the regressions have a role of general control for misspecification in the model of expected stock return, only Blitz et al. (2011) do not include it in their calculation of the residual. Next, they rank the stocks on the sum of their twelve last months' residual, adjusted by its standard deviation over the same period and excluding the most recent one.[5] The zero-cost portfolio is long the top decile and shorts the bottom one, using an equally weighted scheme in each decile. After performing many different tests, they present very illuminating conclusions: the residual momentum strategy generates higher long-term Sharpe ratio. Also, this strategy displays consistent performance in varying economic environment, even during multiple-year periods where classic momentum generates negative return. Third, the strategy is not specifically oriented toward small-cap stocks, which tend to carry higher transaction costs and higher firm-specific risk. Lastly, it is less affected by seasonal effects such as the January effect.

2.2. A brief review of asset pricing models

It is almost impossible to begin a review of asset pricing models without mentioning the capital asset pricing model (CAPM). It is the product of multiple researchers' work, notably but not exhaustively: Treynor (1962), Sharpe (1964) and Lintner (1965). I will briefly discuss it for the sake of completeness but the reader should focus on the other five models presented afterwards, as they represent a central piece of this research.

2.2.1 Capital asset pricing model

The CAPM is, to my knowledge, the first scientifically and professionally accepted explanation of the link between an investment's risk and its expected return. The model relies on the hypothesis that investors should not be rewarded for specific risk; the risk that can be

[5] The authors have also done research without standardizing the error factor and found it very slightly improves the measures. The example they give to illustrate this improvement only changes the Sharpe Ratio of the strategy from 0.89 to 0.9 by reducing both the return (from 11.88% to 11.2%) and the volatility (from 13.28% to 12.49%).

diversified away through a proper portfolio allocation. The CAPM is also based on the research done by Markowitz (1959) on portfolio choices, where he assumes investors are risk averse and optimize their portfolios based only on two factors: mean and variance. Two hypotheses are added in the CAPM: the first one assumes that actors of the market all agree on the joint distribution of asset returns for the period. The second presumes that there is a risk free rate at which everyone can borrow and lend money. Essentially, the first one is important to make sure every investor projects the same opportunities, and thus derives the same variance-minimizing frontier for risky assets. The second one allows investors to draw the same mean-variance efficient frontier that combines the risk free asset with the market portfolio (which is the portfolio at the point where one draws the tangent of the variance-minimizing frontier for risky assets that passes through the risk free rate point). More specifically the Sharpe-Linter CAPM equation is:

$$E(R^i) = R^f + [E(R^M) - R^f] * \beta_M^i$$

Where $E(R_i)$ is the expected return of asset I, M is the market portfolio, and $ß_{iM}$ is the market beta of asset i, the covariance of its return with the market return divided by the variance of the market return. (Fama & French, 2004)

2.2.2 Fama-French 3 factosr model

In *The Cross-Section of Expected Stock Returns*, Fama and French (1992) explore a variety of factors that the literature preceding their research highlights as other potential explanatory variables for stock returns. Specifically: size (market equity), leverage, earning-to-price ratio, and book-to-market equity (BE/ME, the value factor). They conclude that combining the size and value factors seem to capture the other effects in explaining the average stock returns. Finally, they found an intercept of almost 0 by regressing stock portfolios' returns using the three factors: market return in excess of the risk free rate, size, and value (Fama & French, 1993). This lead to the Fama-French 3-factor model:

$$R^i = R^f + [R^M - R^f] * \beta_M^i + R_{SMB} * \beta_{SMB}^i + R_{HML} * \beta_{HML}^i + \varepsilon$$

Where SMB is the size factor, HML is the value factor, ε is the error term, and the other variables are similar to the CAPM equation explained above.

An important note has to be made on the work of Carhart (1997) who built a four-factor model. It is based on Fama and French's 3-factor model plus an additional factor, UMD, deemed to capture the momentum effect described by Jegadeesh and Titman (1993).

2.2.3 Gross profitability premium factor

The contribution of Novy-Marx (2012) is based on the idea of a profitability ratio, measured by gross profit to assets. It has similar power predicting future returns to value ratio measured by book-to-market equity. He found that, when sorted by gross-profits-to-assets and controlling for book-to-market, profitable firms reach a materially higher average return than non-profitable ones. Interestingly, this is true even though, on average, the profitable firms tend to have lower book-to-market and higher market capitalization, which goes against the value and small size effects. As a matter of fact, a profitability strategy is very similar in principles to a value strategy: the former is selling unproductive assets to finance the acquisition of productive ones, while the latter is selling expensive assets to finance the acquisition of inexpensive ones. Nonetheless, at the end of the day the profitability strategy is really a growth strategy and this opposition makes it a very effective hedge for value strategy. Novy-Marx found that using both strategies doubles the exposure to risky assets while reducing the overall volatility so investors with a value strategy can seize the profitability premium without carrying on additional risks.

After analyzing multiple market anomalies, he came up with the following 4-factor model:

$$R^i = R^f + [R^M - R^f] * \beta^i_M + R_{HML^\diamond} * \beta^i_{HML^\diamond} + R_{UMD^\diamond} * \beta^i_{UMD^\diamond} + R_{PMU^\diamond} * \beta^i_{PMU^\diamond} + \varepsilon$$

Where $HML^\diamond$ is the value factor, $UMD^\diamond$ the momentum factor, and $PMU^\diamond$ the gross profitability factor. [6]

[6] The construction of the factors is similar to the one used in Fama and French (1993) for their HML factor. The $HML^\diamond$ is constructed based on log-book-to-market, $UMD^\diamond$ on cumulative returns over the first 11 months of the preceding year and $PMU^\diamond$ on gross profits-to-assets.

2.2.4 Quality minus junk factor

Asness, Frazzini and Pedersen (2014) look at the link between the quality of an asset and its price. First off, the quality of an asset is derived from Gordon's growth model and is composed of four aspects: profitability, growth, safety, and pay-out. They found profitability and growth to be undoubtedly linked with higher prices, safety to be mixed in this regard, and pay-out to be associated with lower prices. Overall higher quality is associated with higher prices, though explanatory power is somewhat limited. To understand this limited explanatory power they build a Quality-Minus-Junk (QMJ) factor. This factor generates highly significant risk-adjusted returns in the sample they studied. In fact, it takes advantage of flight to quality periods, benefiting from high returns during market crashes.[7] Controlling for quality also brings back the size effect that seems to have faded more recently (Jegadeesh and Titman, 2001).[8] The 5-factor model used by Asness, Frazzini and Pedersen is the following one:

$$R^i = R^f + \left[R^M - R^f\right] * \beta^i_M + R_{SMB} * \beta^i_{SMB} + R_{HMLD} * \beta^i_{HMLD} + R_{UMD} * \beta^i_{UMD} + R_{QMJ} * \beta^i_{QMJ} + \varepsilon$$

Where QMJ is the quality factor and $HMLD$ (for *HML Devil*[9]) is the value factor. The other factors are the same as for the models discussed above.

On a side note, they also identified this QMJ strategy, which is buying and selling depending on quality and not paying attention to stock prices, to be the opposite of the value strategy (the HML factor), which is buying and selling depending on stock prices without paying attention to quality. They are negatively correlated and the authors combined them in what they call *quality at a reasonable price* (QARP). Using the QARP, they show it has indeed a higher performance than either the value or the quality strategy alone.

[7] An analysis of the pricing of quality over time reveals it reached its lowest level in February 2000, just before the burst of the dot-com bubble. It was also very low right before 1987's crash and 2008's financial crisis.

[8] The SMB factor is only yielding an insignificant 13 basis points over their sample period without adjustments. However, when controlling for other standard factors, including QMJ, it jumps to a highly significant alpha of 64 basis points, with a t-statistic of 6.39.

[9] The HML Devil is an alternative construction of the HML factor proposed by Asness and Frazzini (2013). The main difference is the use of current price in the calculation of the B/P ratio. They also show the results of a monthly update of the portfolio compared to the yearly one proposed by Fama and French (1993). It is more effective and argue this approach to be even more impacting while paired with momentum.

2.2.5 Q-factor model

Hou, Xue and Zhang (2014) observe that the Fama and French 3-factor model, and the augmented version including the momentum factor UMD, fail to explain a large number of market anomalies, thus concluding a need for a better model. The model they present to try to explain more of these anomalies is composed of four factors: the market excess return, a size factor (ME), which is not constructed exactly like the SMB factor, an investment factor (I/A) and a profitability factor (ROE). The idea behind this construction follows the development of a theoretical economic model involving mainly two channels: the first being an investment channel where given expected cash flow and a higher (resp. lower) cost of capital translates into lower (resp. higher) net present value for new projects, thus lower (resp. higher) investment. The second being a profitability channel where high (resp. low) expected profitability paired with low (resp. high) investment has to translate into a high (resp. low) discount rate, otherwise the net present value of new projects would be high (resp. low) and the investment would be higher (resp. lower).[10]

Their q-factor model can be written, using the convention mentioned previously in the chapter, as:

$$R^i = R^f + [R^M - R^f] * \beta^i_M + R_{ME} * \beta^i_{ME} + R_{I/A} * \beta^i_{I/A} + R_{ROE} * \beta^i_{ROE} + \varepsilon$$

Even though it is derived from their economic model, the authors warn it is after all only an empirical model. Even if it might serve as a basis for future construction, it adds only little steps towards this direction.

Nevertheless, they conclude that many supposedly unrelated anomalies were in fact different demonstrations of the profitability or investment effect and the literature on those anomalies was overstated.

[10] They derive these conclusions from a 2-period economic model that yields the following equation: $E_O[r^S_{i1}] = \frac{E_0[\Pi_{i1}]}{1+a(\frac{I_{i0}}{A_{i0}})}$ where r^S_{i1} is the stock return of firm i at time 1, Π_{i1} is the profitability of firm i at time 1, $\frac{I_{i0}}{A_{i0}}$ is the investment of firm i at time 0, and a > 0 is a constant parameter.

2.2.6 Fama-French 5 factors model

Fama and French (2014) acknowledge the 3-factor model presented in Fama and French (1993) does not capture most of the variations in average return linked to profitability and investment. Similarly to Hou, Xue and Zhang (2014), Fama and French identify stocks' expected returns are dependent on three factors: price-to-book ratio, expected profitability, and investment. They base their analysis on an expanded version of the Gordon's growth model and came up with the following pricing model:

$$R^i = R^f + \left[R^M - R^f\right] * \beta_M^i + R_{SMB} * \beta_{SMB}^i + R_{HML} * \beta_{HML}^i + R_{RMW} * \beta_{RMW}^i + R_{CMA} * \beta_{CMA}^i + \varepsilon$$

Where RMW stands for *robust minus weak*, the profitability factor, and CMA stands for *conservative minus aggressive*, the investment factor.

The authors found the HML factor to be redundant and completely captured by the other four factors. Thus a 4-factor model, without the HML, should perform as well as the 5-factor in identifying abnormal return measured by the alpha of a regression. However, they propose an alternative version of the model using an orthogonalized version of the HML (HMLO) if the redundancy is an issue for the user.

They briefly discuss the work of Hou, Xue and Zhang (2014), which is very similar to theirs, pointing out the most important problem in asset pricing is small stocks, an issue Hou, Xue and Zhang somewhat fail to deal with, focusing on other matters.

3. METHODOLOGY

“I’d rather be lucky than good”
Leffy Gomez

This section will explain in detail the methodology used to carry on this research, presenting the choices that have been made and the reasons behind them. A sample of the VBA code used is shown in the Appendix 5, for the complete version refer to the excel files.[11]

3.1 Data

The sample is based on twenty years of monthly returns for stocks composing the S&P500 index, from 01/01/1996 to 31/12/2015. This choice is linked to personal limitation regarding access to data. A broader sample should be a priority in case additional research is made. Moreover, a quarterly list of the components of the S&P500 is also used to avoid survivorship bias during the formation of portfolios. Factors’ data was mainly available from authors’ websites[12] for the period analyzed, except for Novy-Marx’s factors that are available only until December 2012 and the Q-factor model that is available until December 2014.

3.2 Portfolio formation

The portfolios are created using a ranking system based on residualization. The models used are the ones described at the end of the literature review, namely: The Fama and French 3-factor model (FF3), their 5-factor model (FF5), the q-factor model (Qfact), the quality minus junk model (QMJ), and Novy-Marx’s model based on the gross profitability factor (Novy).

For every stock, on a given month, a regression of the monthly returns against the parameters of the chosen model is done using a J-month rolling window. It means the first portfolio is formed J months after January 1996, the first data point of the sample period. For each regression the *residual momentum score* (RMS) is measured by summing up the J/3 residuals of the past months excluding the most recent one. Skipping the last month should help avoid

[11] The files can be downloaded at: www.laurent-prunier.eu/mastersthesis
[12] I would like to thank the authors for making data freely available, especially Lu Zhang for granting me access to his google drive.

short-term reversal effects. Stocks are then ranked based on their RMS, the higher the better, and a long portfolio is formed using the K highest ranking stocks. Following DeMiguel, Garlappi and Uppal's (2007) conclusion, there is no consistent gain when using other weighting schemes rather than the equally weighted one, such as the mean-variance model, thus the securities inside the formed portfolio are equally weighted. Specifically, most of the gains from a more optimal diversification seem to be offset by estimation errors. The ranking procedure is repeated every month and portfolios are consequently also rebalanced on a monthly basis.

The portfolio following the aforementioned strategy is called *Full Portfolio*. Three other portfolios are built on subsets of the initial pool of stocks based on their market beta. Basically, before ranking stocks by RMS, they are ranked by their market beta, which is always the first beta in the pricing models used to run the regressions. The top third of the stocks is called the *HighBeta group*, the 1/3 to 2/3 is called the *MidBeta group*, and the lower third is called the *LowBeta group*. Next, stocks inside each group are ranked based on their RMS and a portfolio is constructed similarly to the Full Portfolio detailed above.[13]

Finally, a portfolio based on a conventional price momentum strategy is built to be able to compare the results. This portfolio is going long the K stocks with the highest return over the past twelve months, excluding the most recent one. The first date of formation is adjusted to the one of the residual momentum's date it is compared to, January 1996 + J months.

Do note, the portfolios are long only due to the motivation of the thesis itself, which is to determine how such a strategy would perform in the shoes of an individual investor or a portfolio manager that are most likely unable to invest into zero-cost portfolios. Even allowing them a 130/30 long-short strategy would certainly be an unrealistic hypothesis.

3.3 Results tables

The results of each portfolio are synthetized into tables displaying common measures such as average return, standard deviation, or value-at-risk. The goal is to provide useful information

[13] This split in three subsets is the reason why the variable K, the number of securities in each portfolio, is not above 70 on the analyzes. During determined periods, it is not possible to have enough data points to build portfolios using only the S&P500 stocks, especially when J is high.

on portfolio characteristics and a way to compare each strategy in term of performance, exposure to risks, and the type of investor it would most likely suit.

Every measure will not be detailed as it is assumed the reader is familiar with most of them. Nevertheless, the Farinelli and Tiblietti (2008) ratio (F-T ratio) will be presented, as it is a less common ratio. The idea is to divide the expected value of returns above a given threshold τ raised to the power p by the expected value of returns under the same threshold raised to the power q. This ratio can be tailored to match the investor's preferences. For instance, an investor who is risk-neutral below and above the threshold will have $p = 1$ and $q = 1$. However, if he is risk-averse (resp. risk-seeking) under the threshold, then $q > 1$ (resp. $0 < q < 1$). Finally, a risk-averse (resp. risk-seeking) investor above the threshold will exhibit a $0 < p < 1$ (resp. $p > 1$). Do note, the Omega ratio is a special case where $p = 1$ and $q = 1$ showing the preference of a risk-neutral investor, while the Upside potential ratio is the case where $p = 1$ and $q = 2$ representing a risk-averse investor in terms of loss, but neutral regarding gain above the threshold (Cogneau & Hübner, 2009).

According to the expected utility theory that may have been initiated by Daniel Bernouilli (1954), investors should be risk-averse above and under the threshold and are represented in the following analysis by $p = 0.75$ and $q = 1.25$ (Wiesinger, 2010). Regarding prospect theory (Kahneman & Tversky, 1979), the preference of an individual would be risk-seeking under the threshold and risk-averse above it, which is represented in the analysis by $p = 0.5$ and $q = 0.5$ (Wiesinger, 2010). According to Markowitz (1952) in *The utility of wealth*, people are risk-averse under a given threshold and risk-seeking above it. They will be represented by $p = 2$ and $q = 2$ (Wiesinger, 2010). Finally, for the sake of completeness, a fourth ratio is added using $p = 0.5$ and $q = 0.5$ and is deemed to represent an investor who would be risk-seeking under the threshold and risk-averse above it. However, no theory is supporting this behavior to my knowledge.

The returns of each portfolio are also regressed on the model used in the calculation of the RMS. The value, standard deviation, and p-value of the alpha and the different betas (3 to 5) as well as the adjusted r-square of the regression are displayed.

Some clarification regarding the calculation of the measures displayed: the average return is calculated per month in excess of the risk-free rate while the standard deviation is calculated per month on the portfolio's raw returns. The Sharpe ratio is based on those two measures and is thus also expressed in monthly terms. The maximum drawdown is also based on the portfolio's raw returns and the length is expressed in days. The VaR and CVaR are measured as well on the raw returns and monthly basis using the historical method. The different versions of the F-T ratio are all based on the raw returns but use the average risk free-rate of the period they cover as their threshold τ. These notes apply to all of the tables except if specified otherwise in its description.

4. RESULTS AND ANALYZES

"There ain't no such thing as a free lunch"
Robert Heinlein

The analysis is organized in two parts: the first one is a macro view of the strategies, focused on identifying the sensitivities of the strategy to its different parameters. The second one is a micro view of four particular strategies, each using a different pricing model for the RMS calculation to try to identify their characteristics.

4.1 First part - Macro view

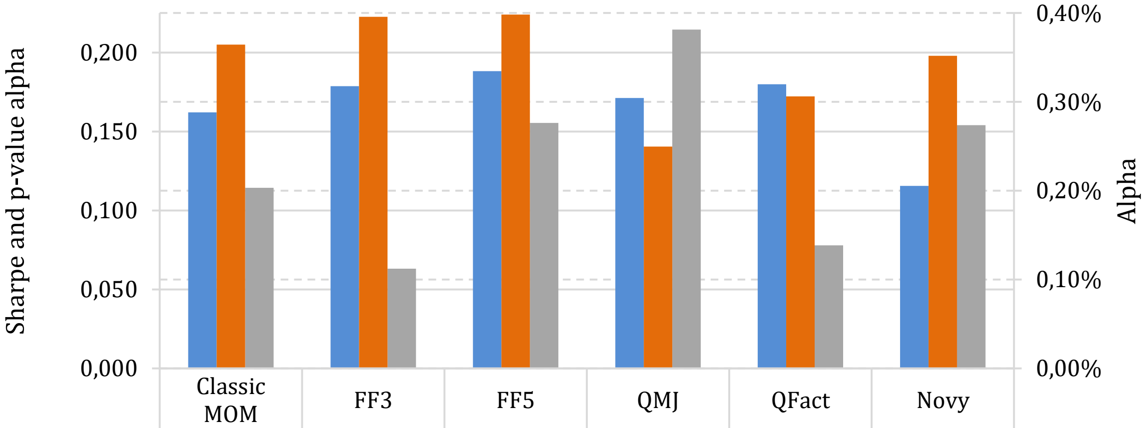
This part of the analysis is based on 50 different variations of the methodology explained in the previous section. The variables are: the model used as a basis for the RMS calculation, the length of the rolling window used in the RMS calculation, and the number of stocks in the portfolio formed. Appendix 1 displays a summary of each variation's average results (averaged per pricing model).

For these three variables, the results are presented using all of the 50 models' results followed by using only the results where the alpha is significant at a 95% confidence interval. However, one must notice the alpha, and its significance level, is obtained by regressing the residual momentum strategy on the pricing model used in this very same strategy. It means that the results of the strategies using the FF3 in their RMS calculation are regressed on the FF3 while the results of the strategies using the QMJ are regressed on the QMJ. In turn, this translates into a tougher test for the alpha, as more recent models have theoretically better identified the prices' drivers.

The analysis will mainly be based on two performance measures: the Sharpe ratio and the alpha plus its p-value. Regarding the classic momentum strategy, the results are based on the largest sample period, the same as the FF3, FF5, and QMJ models. Its alpha and p-value of alpha is found using the FF3 model. Finally, the classic strategy is not taken into account for the rolling window length nor the number of stocks analyzes because their goal is to show the sensitivity of the residual strategy. Otherwise, it would corrupt both analyzes.

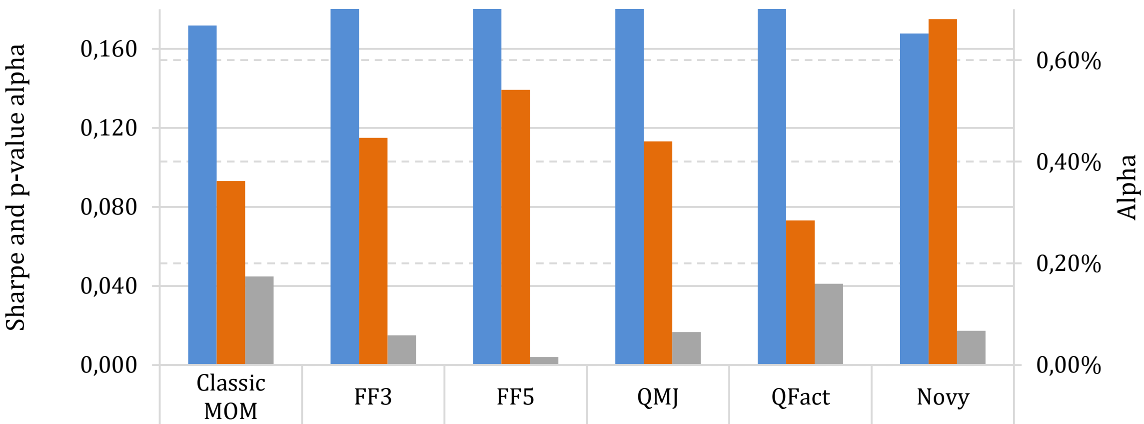
4.1.1 The choice of the pricing model

Graph 1: Comparison between models
(using average values)



	Classic MOM	FF3	FF5	QMJ	QFact	Novy
Sharpe	0,162	0,179	0,188	0,171	0,180	0,116
p-Val alpha	0,114	0,063	0,155	0,214	0,078	0,154
Alpha	0,36%	0,40%	0,40%	0,25%	0,31%	0,35%

Graph 2: Comparison between models
(using average values and only p-val alpha < 5%)



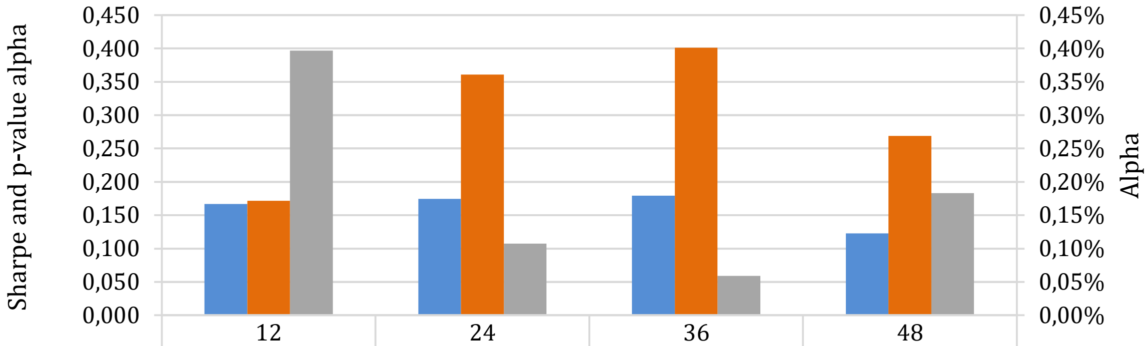
	Classic MOM	FF3	FF5	QMJ	QFact	Novy
Sharpe	0,172	0,183	0,199	0,199	0,182	0,168
p-Val alpha	0,045	0,015	0,004	0,017	0,041	0,017
Alpha	0,36%	0,45%	0,54%	0,44%	0,28%	0,68%

Comparing the classic strategy with the FF3, we can see a slightly higher Sharpe ratio (+0.17 / +0.11) and alpha (+0.04%/+0.09%) in favor of the residual momentum. The other residual strategies also outperform the classic momentum, except for Novy, but this may be due to the truncated sample period and needs further analysis. This is developed in the second part of this section.

Controlling for alpha significance improves performances across all strategies (except for the alpha of the QMJ) and reduces the divergence between models for the Sharpe ratio. The same slight outperformance is also identified and the Novy model continues to exhibit a different behavior. Its Sharpe ratio is now in line with the other models but its alpha is clearly above all of the other results.

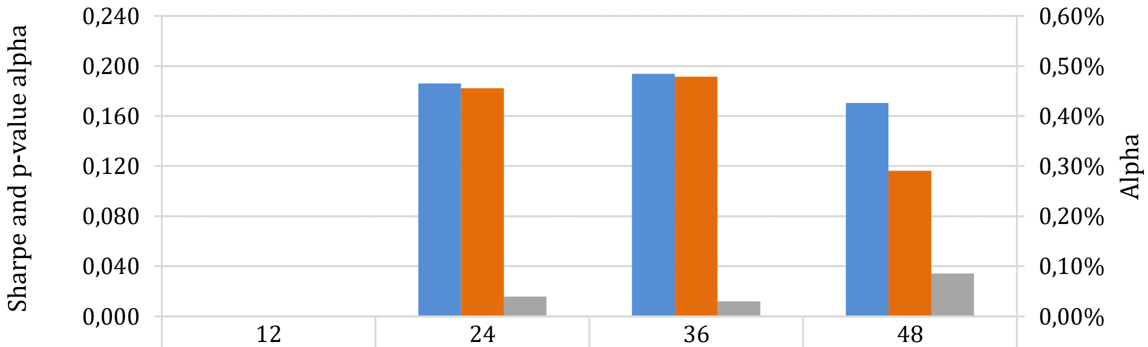
4.1.2 The choice of the rolling window length

Graph 3: Comparison between rolling windows length
(excl.Classic MOM, using average values)



	12	24	36	48
Sharpe	0,167	0,175	0,179	0,123
p-Val alpha	0,397	0,107	0,059	0,183
Alpha	0,17%	0,36%	0,40%	0,27%

Graph 4: Comparison between rolling windows length
(excl.Classic MOM, using average values, and only p-val alpha < 5%)

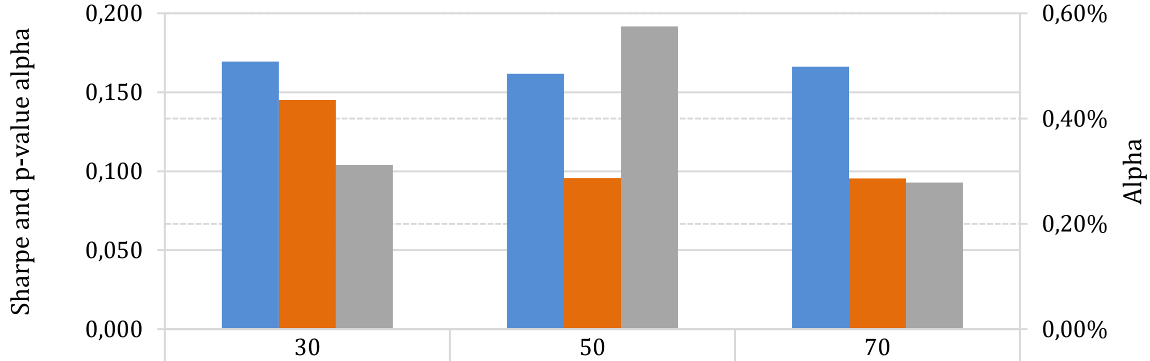


	12	24	36	48
Sharpe		0,186	0,194	0,170
p-Val alpha		0,016	0,012	0,034
Alpha		0,46%	0,48%	0,29%

Looking at Graph 3 it seems the 36-month rolling window is the best solution for the residual momentum strategy, both in terms of performance and significance. Graph 4 shows there is no strategy with a significant alpha at the very short rolling window of 12-month. It also confirms the 36-month looks like the sweet spot for this strategy. This may be the reason why it is the length used by Blitz et al. (2011). Nevertheless, there are only small differences between the 24 and the 36 windows, which is not the case for the 48 window that is being outperformed by the previous two. Therefore, choosing windows between 24 and 36-month could be an option but one should bear in mind it would involve potential calendar effects.

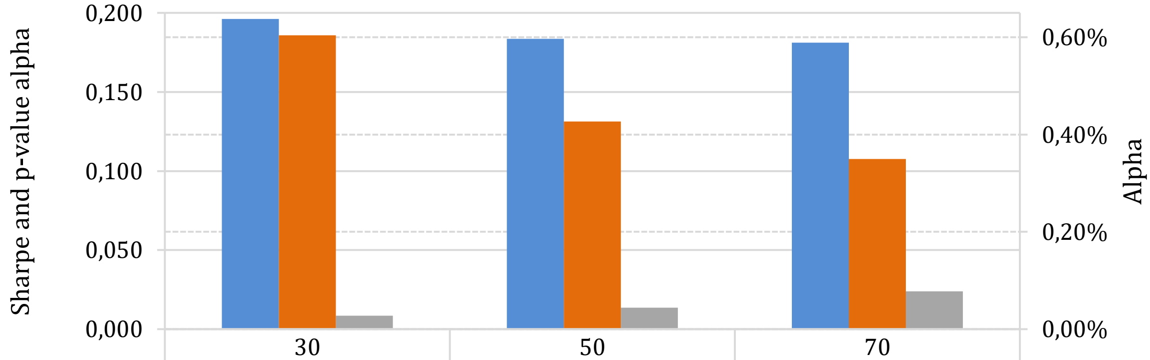
4.1.3 The choice of the number of stocks

Graph 5: Comparison between number of stocks picked
(excl. Classic MOM and using average values)



	30	50	70
Sharpe	0,169	0,162	0,166
p-Val alpha	0,104	0,192	0,093
Alpha	0,44%	0,29%	0,29%

Graph 6: Comparison between number of stocks picked
(excl. Classic MOM, using average values, and only p-val < 5%)



	30	50	70
Sharpe	0,196	0,184	0,181
p-Val alpha	0,009	0,014	0,024
Alpha	0,60%	0,43%	0,35%

Without controlling for alpha's significance, it does not seem to have a clear trend between performance and the number of stocks picked, 50 picks being the worst choice between the three options presented and the 30-stock portfolios being the top performers. However, when controlling for alpha's significance, an inverse relationship between the number of stocks in the portfolios and its performance can be identified. This goes against the principle of diversification but could mean the RMS is, as stated by Gutierrez and Pirinsky (2006), correctly identifying stock-specific momentum. Diversification being deemed to reduce stock-specific risks, it counteracts the benefits of identifying stock-specific momentum and could be the explanation of the outperformance of more concentrated portfolios.

4.1.4 Macro overview conclusion

The first point of this analysis confirms there is a real interest in pushing it further even though whether it will be a good substitute to the classic momentum approach or a potential addition to it remains unknown. Before going into a more detailed analysis of the strategies, some choices have to be made regarding the values given to the different variables. Concerning the rolling window length, the value 36 will be selected due to the little differences there is between 24 and 36 and the fact that previous researchers have also used this value. In regards to the number of stocks in the portfolios, the value 50 will be selected. In a way, this choice to use more or less the top decile is similar to the one adopted by other researchers, which in the case of the S&P500, rounds around 50 stocks[14]. Moreover, it is also motivated by the point of view adopted by this research, the portfolio of a somewhat common investor, which means going over 50 lines seems unlikely due to transaction costs but restricting the portfolio to only 30 might look a little too concentrated for some people.

Finally, only the FF5, QMJ, Qfact, and Novy models will be analyzed in more details for it is the real addition of this research to the work done by Gutierrez and Pirinsky (2006) and Blitz et al. (2011) who focused on the CAPM and FF3.

4.2 Second part - Micro view

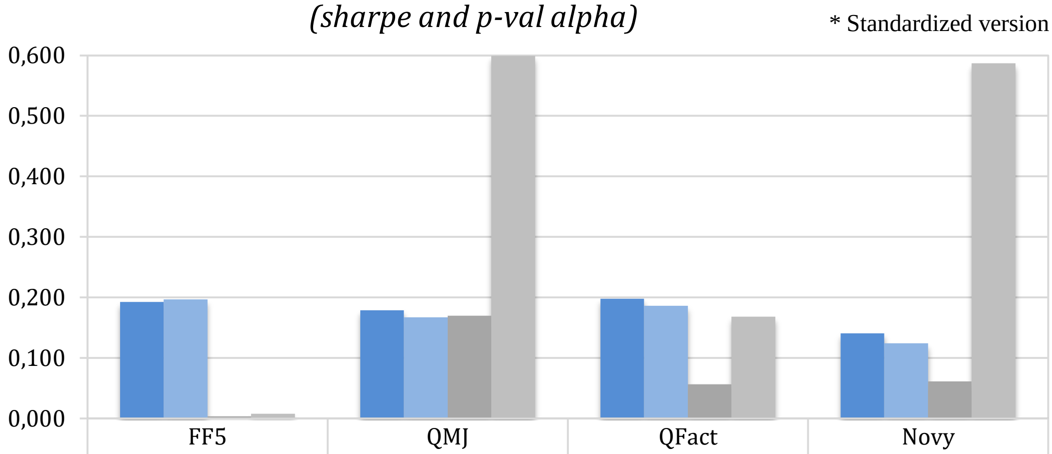
For this second part of the analysis, the models have been rerun using a slight modification to the calculation of the RMS. Similarly to Blitz et al. (2011), the error term is standardized by its standard deviation over the period it is calculated on. According to them, it helps drive apart actual information from mere noise which, in turn, slightly improves the performance. Appendix 2 shows the complete results for each model.

[14] Even though the S&P500 is composed of 500 stocks on average, the need to have at least 3 years of historical prices to be eligible for the calculation of the RMS (when using a 36-month window) means selecting 50 stocks is actually investing in more than only the top decile.

Do note, regressions' results are displayed for both the pricing model used in the calculations of the RMS, and the FF3 model. When no indication is given, it is based on the RMS's model otherwise *(FF3)* will be written after the measure.

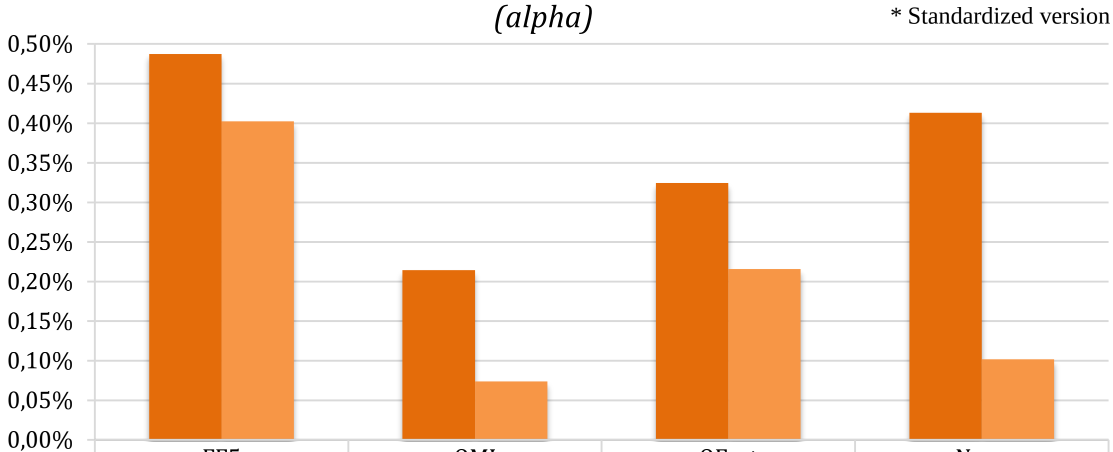
4.2.1 Standardizing the RMS

Graph 7: Standardization comparison
(sharpe and p-val alpha)



	FF5	QMJ	QFact	Novy
Sharpe	0,192	0,179	0,198	0,141
Sharpe*	0,197	0,167	0,186	0,124
p-Val alpha	0,004	0,170	0,057	0,061
p-Val alpha*	0,008	0,599	0,168	0,587

Graph 8: Standardization difference
(alpha)



	FF5	QMJ	QFact	Novy
Alpha	0,49%	0,21%	0,32%	0,41%
Alpha*	0,40%	0,07%	0,22%	0,10%

Except for the Sharpe ratio of the FF5 strategy, it appears standardizing the RMS calculations is not improving the performance. As a matter of fact, the opposite effect is observed as the alpha is lower for all the models and, more importantly, is less significant. The Sharpe ratio is not affected as much but remains lower in three cases out of four.

I can see three potential explanations for this phenomenon: *(a)* first, it might be that what Blitz et al. (2011) thought to be noise in the error term is in fact actual information. *(b)* Second, it might be that the pricing models already capture all the information and the error term only contains noise. This would mean the non-standardized version working better is only arbitrary and, pushing the argument to its limit, the whole strategy may just be random in itself. *(c)* Third, the standardization process is simply not effectively reducing the noise contained in the error and an alternative process should be developed to enhance it. Answering this question is out of the scope of this research but hopefully whether *b* is correct or not will appear throughout the subsequent analysis.

4.2.2 Risks and rewards of the strategies

Table 1: Performance and risk measures

This table presents key measures for each model as explained in the methodology section. To make comparison easier, the results for the classic momentum strategy is displayed for the three different sample period.

	Sample till 12/2015			Sample till 12/2014		Sample till 12/2012	
	Classic MOM	FF5	QMJ	Classic MOM	Qfact	Classic MOM	Novy
Avg return (m)	0,75%	0,93%	0,78%	0,78%	0,88%	0,66%	0,66%
Std dev (m)	0,053	0,047	0,047	0,054	0,047	0,056	0,053
Max DD	-54,7%	-43,4%	-48,4%	-54,7%	-52,3%	-54,7%	-52,7%
Max DD length (d)	273	273	273	273	641	273	641
VaR (95)	-8,8%	-6,8%	-6,2%	-9,5%	-7,2%	-9,9%	-8,7%
CVaR (95)	-11,7%	-10,5%	-11,3%	-11,9%	-11,0%	-12,2%	-12,9%
VaR (99)	-12,2%	-11,6%	-12,7%	-12,8%	-12,6%	-12,8%	-14,4%
CVaR (99)	-15,7%	-16,3%	-16,1%	-18,5%	-22,5%	-18,5%	-21,5%
Sharpe R	0,141	0,197	0,167	0,144	0,186	0,117	0,124
Avg return (annualized)	9,42%	11,73%	9,76%	9,76%	11,11%	8,18%	8,19%
Std dev (annualized)	0,185	0,164	0,161	0,188	0,164	0,195	0,184
Sharpe (annualized)	0,510	0,717	0,605	0,519	0,678	0,420	0,446

Anew the residual momentum strategies are a little bit better in term of performance than the classic momentum, it being in terms of return, volatility, or Sharpe ratio. Regarding extreme risk, the residual momentum strategies are also outperforming the classic one, except for Novy, which is once again the outlier. This is highlighted by the maximum drawdown, and the monthly VaR and CVaR at a 95% threshold not being as high as for the conventional momentum, especially in the case of the FF5 model. However, the length of the drawdown is similar in the classic, FF5, and QMJ, but looks higher in the case of Qfact and Novy. Nevertheless, this number must be taken into account with care, as there is almost a flat period in terms of portfolio value of one year before the real drop in 2008. These two strategies spike right before the flat period, leading to a higher max drawdown length. This feature shows a similar behavior between the conventional and residual momentum during market turmoil.

The reader could argue that classic momentum is actually doing better during extreme events by looking at the VaR and CVaR at the 99% threshold. However, these numbers being calculated using historical data, the sample seems much too small to draw any meaningful conclusion.[15]

Table 2: Exposure to FF3 factors

P-values are displayed underneath coefficient estimates between brackets. Numbers in bold are significant at a 95% confidence level.

	Classic MOM	FF5	QMJ	Qfact	Novy
Alpha *(FF3)*	0,25%	**0,48%**	**0,31%**	**0,39%**	0,30%
	(0,251)	(0,001)	(0,021)	(0,013)	(0,091)
β Mkt *(FF3)*	**0,91**	**0,96**	**0,95**	**0,93**	**1,00**
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
β SMB (FF3)	**0,29**	0,00	0,03	0,07	**0,14**
	(0,000)	(0,921)	(0,514)	(0,129)	(0,007)
β HML (FF3)	0,13	**0,28**	**0,36**	**0,30**	**0,22**
	(0,060)	(0,000)	(0,000)	(0,000)	(0,000)

Table 2 shows residual momentum is generating significant alpha, contrary to the classic strategy. The exposure is also different as residual momentum is taking advantage of the value premium and is not exposed to the size effect which, according to Jegadeesh and Titman (2001), is not producing above average returns anymore. Both strategies are highly exposed to the market, though the classic one a little less. These features could be the explanation of the higher extreme risk associated with the classic momentum: it is more exposed to the size effect, that is generally more affected during market distress, and residual momentum is more exposed to value stocks that are performing better during those bad periods.

Novy is once again showing a different trend with the highest exposure to the market but the lowest exposure to the HML. Also, it is the only one showing a significant exposure to the

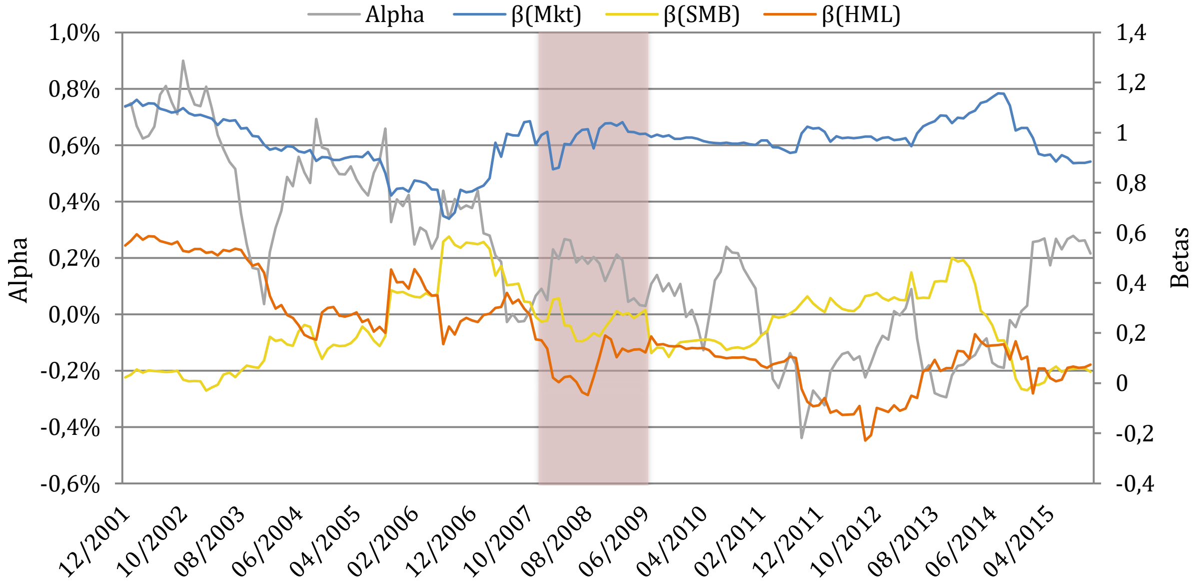
[15] There is only 203 data points for the FF5 and QMJ models, 193 for the Qfact, and 169 for Novy, which means the VaR and CVaR at 99% are only based on 1 or 2 points.

SML. Additionally, it is the most similar to the classic strategy in terms of exposure.

4.2.3 Risks and rewards of the strategies over time

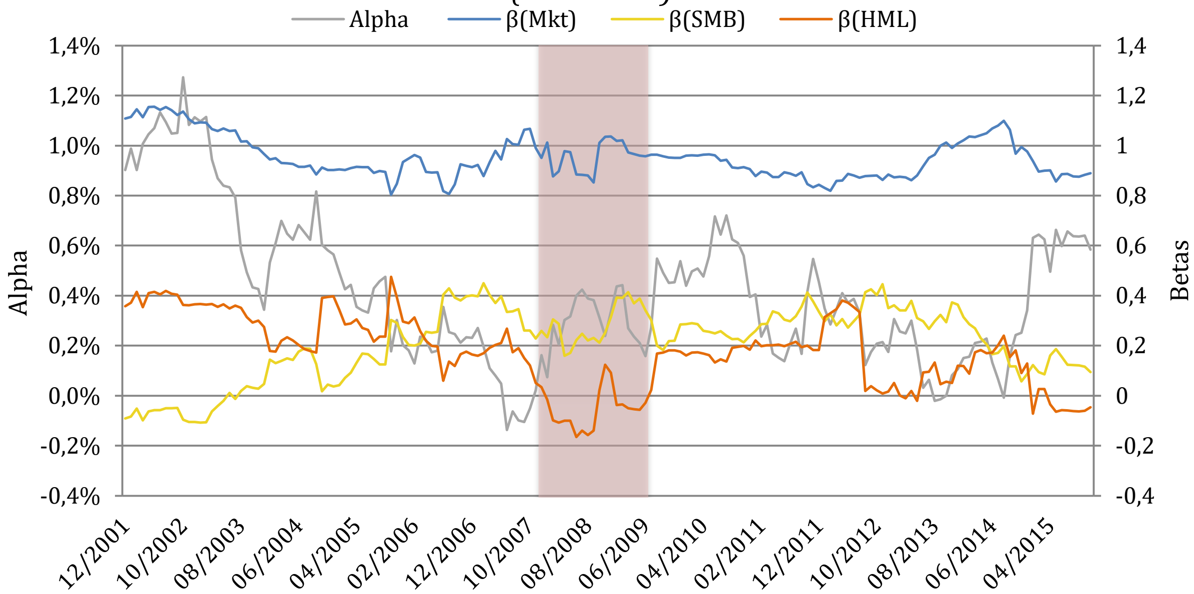
Graph 9: Exposures to FF3 factors

(QMJ model)



Graph 10: Exposures to FF3 factors

(FF5 model)



The two graphs above show the evolution of the estimated alphas and betas against the FF3 factors across time, using a 36-month rolling window for the QMJ and FF5 models. The red area represents the recession period determined by the National Bureau of Economic Research (2015). Additional information on the models' exposures is available in appendix 3.

An interesting feature of the strategy is the more or less constant exposure to market risk, especially after 2008's crisis. It ranges between 0,8 and 1,2 most of the time for every model except Novy. On the other hand, the exposure to size and value is more dynamic, being sometimes positive, sometimes negative, and not always going in the same direction. This dynamic exposure could be the source of alpha for the residual momentum. Comparing Novy to the other three models, it appears its market beta is the most volatile as shown in table 4, but at the same time, its SMB beta is the least volatile and its HML beta volatility is under the average of the four models (0.19). This shows a less dynamic exposure to these two premia and, once again, might be a reason for its underperformance.

Looking at the recession period, the stability in exposures is more pronounced with reduced standard deviation of betas, sometimes the half or the third of the value over the full sample period. This contrasts with the known tendency of the classic momentum strategy to exhibit drastic swing between favorable and unfavorable market periods (Jegadeesh & Titman 1993). It is certainly the reason behind residual momentum's reduced risk in term of maximum drawdown and value-at-risk.

Another catching point is the difference in alphas' level before and after the crisis, which clearly appears in the following table.

Table 3: Average exposure to FF3 before and after recession

The data of this table is calculated similarly to what is done for table 4. The sample before recession starts in December 2001 and the after recession sample ends in the same date as the sample size detailed in the methodology section.

	Before recession				After recession			
	QMJ	FF5	Qfact	Novy	QMJ	FF5	Qfact	Novy
Alpha *(FF3)*	0,44%	0,52%	0,60%	0,40%	-0,04%	0,35%	-0,13%	-0,17%
β Mkt *(FF3)*	0,94	0,98	0,91	0,96	0,99	0,93	0,97	0,99
β SMB (FF3)	0,22	0,14	0,26	0,31	0,23	0,26	0,30	0,24
β HML (FF3)	0,37	0,27	0,33	0,35	0,05	0,13	-0,02	0,08

Except for FF5, the alphas are positive before the crisis, though downward trending. However, they are negative after the crisis, but upward trending on the last months of the analysis. These differences show it would be interesting to analyze the strategies on a longer sample Nevertheless, FF5 is delivering alpha more consistently than the other models, and without surprise, it goes in pair with having the lowest alpha's standard deviation (0.295%).

Table 4: Exposure to FF3 factors across time

This table presents key measures for the results of the rolling regressions over the models' returns per period. The rolling window is 36 months for both the models' return regression and the RMS calculation, which is using the standardized method, and portfolios composed of 50 stocks. The recession period starts on December 2007 and ends on June 2007 as identified by the National Bureaux of Economic Research. It also means the recession analysis is only based on 18 data points.

	QMJ						**FF5**					
	Full period			Recession			Full period			Recession		
	Avg	Std dev.	Min / Max	Avg	Std dev.	Min / Max	Avg	Std dev.	Min / Max	Avg	Std dev.	Min / Max
Alpha *(FF3)*	0,2%	0,3%	-0,44% / 0,9%	0,2%	0,1%	0,03% / 0,27%	0,4%	0,3%	-0,14% / 1,27%	0,3%	0,1%	0,07% / 0,44%
β Mkt *(FF3)*	0,96	0,10	0,66 / 1,16	0,99	0,05	0,85 / 1,04	0,95	0,08	0,8 / 1,16	0,96	0,06	0,85 / 1,04
β SMB (FF3)	0,22	0,15	-0,03 / 0,59	0,25	0,05	0,17 / 0,34	0,21	0,14	-0,11 / 0,45	0,28	0,08	0,16 / 0,41
β HML (FF3)	0,19	0,20	-0,23 / 0,59	0,08	0,07	-0,05 / 0,19	0,17	0,15	-0,17 / 0,47	-0,05	0,08	-0,17 / 0,12

	Qfact						**Novy**					
	Full period			Recession			Full period			Recession		
	Avg	Std dev.	Min / Max	Avg	Std dev.	Min / Max	Avg	Std dev.	Min / Max	Avg	Std dev.	Min / Max
Alpha *(FF3)*	0,2%	0,6%	-0,56% / 1,76%	-0,1%	0,1%	-0,36% / 0,08%	0,2%	0,4%	-0,54% / 1,43%	0,2%	0,1%	-0,12% / 0,25%
β Mkt *(FF3)*	0,95	0,09	0,73 / 1,14	1,01	0,06	0,93 / 1,11	0,97	0,15	0,55 / 1,3	0,97	0,07	0,86 / 1,07
β SMB (FF3)	0,28	0,14	0 / 0,62	0,32	0,06	0,24 / 0,42	0,28	0,11	0,11 / 0,65	0,23	0,05	0,15 / 0,3
β HML (FF3)	0,14	0,23	-0,23 / 0,62	-0,02	0,09	-0,14 / 0,16	0,23	0,17	-0,09 / 0,59	0,09	0,09	-0,09 / 0,24

Graphs in appendix 4 show the evolution of the Sharpe ratio and its components. Interestingly, the Sharpe ratio reaches its highest more than one year before the recession. Following that high, it starts declining. First, driven by lower returns and second, by higher volatility. It drops until about four months before the end of the recession and, at that point, starts to climb back up until the end of the sample period. This behavior is in line with the market beta of the strategy being around one in any market condition. Even if it is not specially a searched-for characteristic from an absolute performance point of view, it can be very desired by portfolio managers or investors looking for relative performance.

4.2.4 Risks and rewards in subsets

Table 5: Comparison between beta subsets

This table presents key measures for the results of the models after splitting into three beta subset, namely: low, mid and high. The standard model, without restriction, is referred to as "Full". The rolling window is 36 months for the RMS calculation, which is using the standardized method, and portfolios are composed of 50 stocks. Average returns and Sharpe ratio are on a monthly basis

	QMJ				**FF5**			
	Full	Low	Mid	High	Full	Low	Mid	High
Avg return	0,78%	0,71%	0,90%	0,88%	0,93%	0,80%	0,77%	1,08%
Sharpe	0,17	0,17	0,21	0,16	0,20	0,20	0,18	0,18
Alpha *(FF3)*	0,31%	0,26%	0,47%	0,30%	0,48%	0,42%	0,32%	0,45%
P-val alpha *(FF3)*	0,02	0,04	0,00	0,04	0,00	0,00	0,00	0,01
	Qfact				**Novy**			
	Full	Low	Mid	High	Full	Low	Mid	High
Avg return	0,88%	0,78%	0,84%	0,86%	0,66%	0,47%	0,55%	0,96%
Sharpe	0,19	0,19	0,20	0,15	0,12	0,11	0,11	0,15
Alpha *(FF3)*	0,39%	0,33%	0,38%	0,24%	0,30%	0,17%	0,19%	0,52%
P-val alpha *(FF3)*	0,01	0,02	0,00	0,15	0,09	0,28	0,14	0,01

Looking at table 5, it appears the alphas are significant at a 95% confidence interval across all subsets for the QMJ and FF5 models. For the Qfact, it is only insignificant for the high beta subset, while it is the only subset where it is significant for the Novy. This is a solid argument in favor of both the QMJ and FF5 being robust strategies.

Overall, there is no clear trend on whether one subset is performing better than another, although Novy is the only one where the Sharpe ratio is highest in the high beta subset, showing once again a different behavior. Interestingly, for FF5 and Qfact, the full strategy is performing better than their subsets in terms of Alpha and in terms of Sharpe ratio for FF5.

Table 6: Comparison between beta subsets

This table presents the correlations between the Full model's returns and all the subset models' returns, namely: low, mid and high.

	QMJ				FF5		
	Low	Mid	High		Low	Mid	High
Full	0,94	0,94	0,93	Full	0,92	0,92	0,91
Low		0,89	0,86	Low		0,86	0,79
Mid			0,93	Mid			0,92
	Qfact				**Novy**		
	Low	Mid	High		Low	Mid	High
Full	0,92	0,93	0,90	Full	0,91	0,91	0,91
Low		0,90	0,81	Low		0,89	0,83
Mid			0,91	Mid			0,92

It has previously been highlighted that the strategies have a market beta around one and tend to stay close to this number over time, which means the full strategy should, in theory, be similar to the mid one. In line with this statement, the alpha of the mid strategy for QMJ, FF5 and Qfact has the lowest p-value across all subsets, still being significant at a 99.5% level. Table 6 also somewhat confirms this theory as the correlation between the full and the mid strategy is always the highest among the three subsets, though it is by a very low margin. In the same logic, the lowest correlation is between the low and high portfolio.

Table 7: Correlation with classic momentum

This table presents the correlations between the Full model's returns and the classic momentum's returns.

	QMJ	FF5	Qfact	Novy
Classic	0,74	0,72	0,71	0,78

Finally, table 7 shows correlations are at the limit between highly and moderately correlated, which according to Calkins is 0.7 (2005), and confirms residual momentum and classic momentum strategies are different from each other. Additionally, there might be some potential for increased performance by combining both approaches, especially for the FF5 and Qfact that have the least correlation.

4.2.5 Does it suit you?

Looking at the F-T ratios in table 8, every type of investor is better off selecting the residual momentum strategy over the classic one, except for the Novy model. This means the residual strategies are doing better above and under the risk-free rate, which is the selected threshold, than the classic one. The good performance under the threshold was already highlighted by the extreme risk measures presented earlier. The fact that the residual is also performing better above the risk-free rate is an additional very desirable feature in favor of the residual momentum.

Table 8: Determine investors preferences

This table shows the different F-T ratio based ratios for each standardized strategies and the corresponding classic momentum strategy (in term of sample period). The risk free rate calculated using Fama and French's data has been used as the threshold for the ratios.

	QMJ	FF5	Classic	Qfact	Classic	Novy	Classic
Omage R	1,565	1,675	1,448	1,642	1,456	1,394	1,361
Upside potential R	9,715	10,577	9,755	9,861	9,524	8,191	8,428
F-T R (0.5, 0.5)	2,715	2,939	2,152	2,829	2,229	2,258	2,024
F-T R (0.75, 1.25)	15,616	16,972	14,570	16,080	14,253	12,653	12,317
F-T R (1.25, 0.75)	0,168	0,177	0,151	0,179	0,157	0,163	0,158
F-T R (2, 2)	1,103	1,181	1,133	1,137	1,131	1,046	1,092

Finally, table 9 partially confirms these preferences, as QMJ and FF5 are favored over the classic strategy most of the time by any type of investor. This fact, however, does not hold true for the Qfact and, in the case of Novy, is actually the opposite.

Table 9: Comparison of F-T ratio over time

This table shows the proportion of time when the F-T ratio of the given residual momentum strategy is superior to the same ratio for the classic momentum strategy. The given F-T ratio is calculated using a 36-month rolling window and the average risk free rate over the rolling period as the threshold.

	QMJ	FF5	Qfact	Novy
F-T R (0.75, 1.25)	79,8%	90,5%	51,0%	29,3%
F-T R (0.5, 0.5)	79,8%	82,7%	51,0%	30,1%
F-T R (2, 2)	56,5%	76,2%	47,1%	31,6%

Overall, risk-averse investors, those following the expected utility theory represented by F-T R (0.75, 1.25), as well as investors following the prospect theory, risk-seeking under the threshold and risk-averse above it represented by F-T R (0.5, 0.5), will both have a preference for the FF5 and the QMJ strategies. For those following Markowitz's theory, stating that people are risk-averse under a threshold and risk-seeking above it, represented by F-T R (2, 2), the choice is a bit less appealing. They would definitely prefer the FF5 strategy but it is less pronounced then the other two types of investors. The fact that the Novy strategy would not appeal to any investors over the classic momentum strategy confirms the different caveats found throughout this analysis.

4.2.6 Raise your standards

Table 10: Comparison between standardised and non-standardised models' results

This table shows the results for the models with and without standardisation, using a 36-month rolling window and picking 50 stocks in the portfolios. The model with standardisation is asterisked (*). The best value between both versions is highlighted in bold.

	FF5	FF5*	QMJ	QMJ*	Qfact	Qfact*	Novy	Novy*
Avg return (m)	**1,1%**	0,9%	**1,0%**	0,8%	**1,1%**	0,9%	**0,9%**	0,7%
Std dev (m)	5,6%	**4,7%**	5,4%	**4,7%**	5,4%	**4,7%**	6,3%	**5,3%**
Max DD	-48,4%	**-43,4%**	-51,7%	**-48,4%**	-55,1%	**-52,3%**	-55,2%	**-52,7%**
Max DD length (d)	273	273	639	273	641	641	641	641
VaR (95)	-8,2%	**-6,8%**	-7,7%	**-6,2%**	-7,9%	**-7,2%**	-9,7%	**-8,7%**
CVaR (95)	-11,8%	**-10,5%**	-12,1%	**-11,3%**	-12,0%	**-11,0%**	-14,5%	**-12,9%**
VaR (99)	-13,2%	**-11,6%**	-14,1%	**-12,7%**	-14,8%	**-12,6%**	-16,6%	**-14,4%**
CVaR (99)	-18,5%	**-16,3%**	-18,6%	**-16,1%**	**-20,8%**	-22,5%	-22,2%	**-21,5%**
Sharpe R	0,192	**0,197**	**0,179**	0,167	**0,198**	0,186	**0,141**	0,124
Omage R	1,667	**1,675**	**1,611**	1,565	**1,677**	1,642	**1,454**	1,394
Upside potential R	**10,80**	10,58	10,27	**9,72**	**10,48**	9,86	**8,82**	8,19
F-T R (Rf, 0.5, 0.5)	2,660	**2,939**	2,488	**2,715**	2,657	**2,829**	2,138	**2,258**
F-T R (Rf, 0.75, 1,25)	16,80	**16,97**	**16,12**	15,62	**16,46**	16,08	**13,22**	12,65
F-T R (Rf, 1.25, 0.75)	0,175	**0,177**	**0,169**	0,168	**0,180**	0,179	**0,168**	0,163
F-T R (Rf, 2, 2)	**1,251**	1,181	**1,181**	1,103	**1,210**	1,137	**1,143**	1,046

Point 2.1 of the analysis section raised the question of whether standardisation was improving the performance of the strategy or not. Table 10 shows the answer is not totally straightforward, but one trend is clearly identified: standardized version is less risky, whether it is in terms of volatility, max drawdown, or value-at-risk, but generates less returns in exchange. This trend materialized into a mixed answer while looking at the Sharpe ratio, which is higher for the FF5* but in all other instances is higher for non-standardized version of the model.

Looking at the F-T ratios it looks like the investors following the prospect theory would prefer the standardized version while those following Markowitz's theory would always go for the non-standardized one. On the other hand, the risk-averse investor, following the expected utility theory, is mixed, showing three times out of four a preference for the non-standardized version. This could go against the fact that the standardized version is less risky than its counterpart, but it actually simply means the returns under the risk-free rate show a less spiky pattern than the ones above it.

5. CONCLUSION

"The opera ain't over until the fat lady sings."
Dan Cook

This section starts with a formal answer to the question that has motivated this research based on the analysis developed in it. Then, the limitations of this answer as well as suggestions for potential further research are discussed. Finally a few words about the whole process of writing this thesis will conclude it.

5.1 Answer to the research question

As a reminder, the research question given in the introduction was: *does a residual momentum strategy is profitable, what are the risks associated with it and how does it perform compare to a classic price momentum strategy?* with a focus on a standard investor or portfolio manager's point of view.

First, regarding profitability, the residual momentum strategy is profitable. It is verified using a large variety of values for the different variables, notably the pricing model and the rolling window length of the regressions, using both the standardized and non-standardized method.

Secondly, concerning the risks. A non-analyzed risk of the strategy is of course model risk as it involves manipulating a somewhat consequent amount of data. Nevertheless, it should be addressed with little difficulty as the underlying mathematics are manageable. Undoubtedly, market risk is involved while using this strategy as shown by its market beta varying around 1. However, this same feature reduces the relative performance risk as well. Additionally, compared to the market, the strategy works well and a better Sharpe ratio and reduced extreme risks prove it.[16] The exposure to other common risk premia, such as size or value, fluctuates over time and could be the source of the strategy's outperformance.

Also, with regard to the classic momentum strategy, residual momentum outperforms it in

[16] The QMJ/FF5/S&P500 have an annualized Sharpe of 0.61/0.72/0.31, maximum drawdown of -48.4%/-43.4%/-52.8% and a VaR(95%) of -6.2%/-6.8%/-8.0% over the sample period. Calculation for the S&P500 is based on monthly opening prices retrieved from Yahoo!Finance using the ^GSPC ticker.

every aspect mentioned above. It generates higher returns with lower volatility, lower maximum drawdown, and lower value-at-risk (at least at a 95% level). Moreover, it has a fairly constant market beta as opposed to the classic strategy, which is known to exhibit a volatile exposure to market.

In the introduction, I mentioned that most authors use their research to draw conclusions on the market's efficiency. However, I do not wish to infer in any direction since the analyzes I have performed are not oriented toward answering this question. Nevertheless, Novy-Marx said: "*Price momentum… is often regarded as the most important financial anomaly*" (2015, p.1) and the fact that residual momentum outperforms conventional momentum only adds to the importance of the anomaly.

Finally, point 2.1 of the analysis section raised some concerns on whether standardizing the error term improves the performance or not. Contrary to Blitz et al. (2011), I found no clear evidence that one solution outperforms the other. This may be the result of the long only position of the portfolios analyzed in the context of this thesis. In turn, it would signify that being able to split the noise from the actual information contained into the error term on the short side of the portfolios has a greater impact on the strategy's performance.

5.2 Limitations and suggestions

Obviously every research goes in pair with some limitations. The first one I would like to raise is linked to the access of data which translated into a limited sample. Therefore, the first suggestion would be to extend the sample period, and to carry similar analyzes using various indexes in order to observe how the strategy is performing when access to smaller firms or other countries is allowed. Similarly, it could be quiet interesting to follow the strategy's behavior on different asset classes such as bond or real estate. Do note that extending the sample period would require to calculate the value of factors for some of the models, especially for the Q-factor and Novy-Marx's pricing models.

The second limitation is related to the choice of methodology. Some researchers, such as Gutierrez and Pirinsky (2006) or Blitz et al. (2011), form portfolios every month but contrary to what is done here, hold them during a certain number of month. Clearly, analyzing the effect of the holding period after formation could be a great addition to the other axes already analyzed in this research. Nevertheless, one should keep in mind that this work has been done with a long only investment policy. Consequently, it could prove delicate to choose an appropriate solution to deal with the investment's size of the various portfolios or to interpret the respective portfolios' returns. In addition, this difference of approach would also make the comparison with previous research a little approximated while it offers an additional point of view to the literature.

Following on the answer to the research question, it might be interesting especially from an academic point of view, to deepen the analysis toward the efficiency of the market and the importance of the residual momentum as an anomaly in this regard.

Still following the answer formulated above, it could be interesting to have a better understanding of the effect of standardizing the error term on the residual momentum strategy.

5.3 Closing words

To conduct research was a totally new experience and it did not go without some period of doubt and uncertainty. Nevertheless, it was overall a very good experience and in addition to the financial knowledge acquired, it allowed me to develop and improve a variety of skills. Mainly, I am now more confident in dealing with the whole process of researching a subject: managing multiple data sources, planning the different steps, organizing my work, dealing with computer linked matters, researching what has already been done on the subject, etc.

Moreover, looking at the limitations and suggestions mentioned above, as well as the literature on the subject, it seems there are still numerous areas that can be researched and numerous improvement that can be brought. This fact paired with my enjoyment of the writing of this thesis might really motivate me to continue working on the residual momentum in the future.

I would like to end with the following story, which, in my opinion, should be kept in mind while working on subjects like the one discussed in this thesis:

It is 1953. Freeman Dyson questions Fermi in Chicago to discuss with him his own results for the meson-proton distribution. Fermi was however visibly unimpressed by the results and asks Dyson, how many selectable parameters he had used for the calculations. Dyson answers that he had used four parameters. Fermi's retort: "I remember how my friend John von Neumann used to say, with four parameters I can adjust an elephant, and with five I can make him wiggle his trunk." (Intalus, 2014)

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APPENDICES

Appendix 1: Average of results' tables for the non-standardized models.

The following tables present an average of the results for the FF3, FF5, QMJ, Qfact, and Novy models used in the calculation of the RMS without standardizing the error term.

Average of results using the FF3 factors model

	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	1,0%	0,7%	0,8%	1,1%
Std dev (m)	5,7%	4,1%	4,5%	6,7%
Max DD	-55,8%	-54,2%	-46,9%	-55,8%
Max DD length (d)	340	514	550	431
VaR (95)	-8,1%	-6,7%	-7,2%	-9,3%
CVaR (95)	-12,8%	-9,9%	-10,2%	-14,4%
VaR (99)	-14,7%	-10,5%	-11,2%	-15,9%
CVaR (99)	-18,5%	-15,2%	-16,0%	-20,9%
Sharpe R	0,148	0,129	0,132	0,135
Omage R	1,625	1,581	1,560	1,552
Upside potential R	10,70	9,86	10,31	10,57
F-T R (Rf, 0.5, 0.5)	2,501	2,967	2,625	2,228
F-T R (Rf, 0.75, 1,25)	16,58	16,28	16,26	15,88
F-T R (Rf, 1.25, 0.75)	0,168	0,166	0,160	0,159
F-T R (Rf, 2, 2)	1,256	1,066	1,136	1,277

Regression of Full portfolio

Adj R2	0,802		
	Value	Std Err	P-value
Intercept	0,004	0,002	0,067
Mkt-RF	1,124	0,040	0,000
SMB	0,076	0,054	0,229
HML	0,464	0,056	0,000

Regression of LowBeta portfolio

Adj R2	0,780		
	Value	Std Err	P-value
Intercept	0,003	0,001	0,092
Mkt-RF	0,785	0,030	0,000
SMB	0,017	0,040	0,440
HML	0,362	0,042	0,000

Regression of MidBeta portfolio

Adj R2	0,864		
	Value	Std Err	P-value
Intercept	0,003	0,001	0,071
Mkt-RF	0,932	0,026	0,000
SMB	-0,067	0,035	0,152
HML	0,402	0,036	0,000

Regression of HighBeta portfolio

Adj R2	0,831		
	Value	Std Err	P-value
Intercept	0,003	0,002	0,142
Mkt-RF	1,333	0,043	0,000
SMB	0,081	0,058	0,315
HML	0,544	0,060	0,000

Average of results using the FF5 factors model

	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	1,1%	0,8%	0,8%	1,1%
Std dev (m)	5,7%	4,2%	4,5%	6,5%
Max DD	-51,0%	-49,6%	-48,1%	-51,9%
Max DD length (d)	375	525	517	478
VaR (95)	-7,8%	-6,5%	-6,9%	-9,4%
CVaR (95)	-12,3%	-9,9%	-10,5%	-13,6%
VaR (99)	-14,3%	-10,9%	-11,1%	-14,3%
CVaR (99)	-18,4%	-15,2%	-16,1%	-20,2%
Sharpe R	0,163	0,149	0,135	0,144
Omage R	1,683	1,648	1,572	1,587
Upside potential R	11,02	10,32	10,17	10,70
F-T R (Rf, 0.5, 0.5)	2,625	3,000	2,646	2,307
F-T R (Rf, 0.75, 1,25)	17,14	16,91	16,24	16,10
F-T R (Rf, 1.25, 0.75)	0,174	0,173	0,162	0,164
F-T R (Rf, 2, 2)	1,284	1,121	1,127	1,287

Regression of Full portfolio

Adj R2	0,830		
	Value	Std Err	P-value
Intercept	0,004	0,002	0,113
Mkt-RF	1,142	0,044	0,000
SMB	0,158	0,059	0,014
HML	0,392	0,076	0,000
RMW	0,072	0,086	0,275
CMA	-0,042	0,102	0,241

Regression of LowBeta portfolio

Adj R2	0,788		
	Value	Std Err	P-value
Intercept	0,003	0,001	0,150
Mkt-RF	0,856	0,036	0,000
SMB	0,100	0,048	0,139
HML	0,215	0,061	0,012
RMW	0,179	0,070	0,085
CMA	0,087	0,083	0,195

Regression of MidBeta portfolio

Adj R2	0,868		
	Value	Std Err	P-value
Intercept	0,002	0,001	0,237
Mkt-RF	0,986	0,031	0,000
SMB	0,072	0,041	0,216
HML	0,314	0,053	0,000
RMW	0,233	0,060	0,007
CMA	0,074	0,072	0,292

Regression of HighBeta portfolio

Adj R2	0,841		
	Value	Std Err	P-value
Intercept	0,004	0,002	0,118
Mkt-RF	1,305	0,048	0,000
SMB	0,092	0,064	0,303
HML	0,526	0,083	0,000
RMW	0,047	0,094	0,384
CMA	-0,040	0,112	0,397

Average of results using the QMJ factors model

	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	0,9%	0,7%	0,9%	0,9%
Std dev (m)	5,5%	4,6%	4,6%	5,9%
Max DD	-57,3%	-53,7%	-48,6%	-58,9%
Max DD length (d)	528	586	528	601
VaR (95)	-8,1%	-6,6%	-7,0%	-9,2%
CVaR (95)	-13,0%	-11,5%	-10,7%	-13,3%
VaR (99)	-14,7%	-13,7%	-11,7%	-14,8%
CVaR (99)	-19,1%	-18,3%	-18,7%	-21,0%
Sharpe R	0,142	0,120	0,151	0,127
Omage R	1,583	1,516	1,637	1,513
Upside potential R	10,09	9,28	10,20	9,98
F-T R (Rf, 0.5, 0.5)	2,453	2,549	2,891	2,150
F-T R (Rf, 0.75, 1,25)	15,83	15,16	16,65	15,13
F-T R (Rf, 1.25, 0.75)	0,166	0,161	0,172	0,158
F-T R (Rf, 2, 2)	1,164	1,032	1,127	1,188

Regression of Full portfolio

Adj R2	0,860		
	Value	Std Err	P-value
Intercept	0,002	0,002	0,173
Mkt-RF	1,096	0,047	0,000
SMB	0,077	0,064	0,326
HML Devil	0,431	0,053	0,000
UMD	0,224	0,042	0,000
QMJ	0,046	0,077	0,432

Regression of LowBeta portfolio

Adj R2	0,814		
	Value	Std Err	P-value
Intercept	0,000	0,002	0,613
Mkt-RF	0,951	0,045	0,000
SMB	0,031	0,061	0,594
HML Devil	0,387	0,050	0,000
UMD	0,260	0,040	0,000
QMJ	0,132	0,074	0,219

Regression of MidBeta portfolio

Adj R2	0,875		
	Value	Std Err	P-value
Intercept	0,001	0,001	0,363
Mkt-RF	1,022	0,037	0,000
SMB	0,049	0,050	0,367
HML Devil	0,388	0,041	0,000
UMD	0,163	0,033	0,000
QMJ	0,289	0,060	0,009

Regression of HighBeta portfolio

Adj R2	0,876		
	Value	Std Err	P-value
Intercept	0,001	0,002	0,524
Mkt-RF	1,202	0,047	0,000
SMB	0,056	0,064	0,415
HML Devil	0,550	0,053	0,000
UMD	0,150	0,042	0,038
QMJ	0,217	0,078	0,060

Average of results using the Qfact factors model

	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	1,0%	0,8%	0,8%	1,0%
Std dev (m)	5,5%	4,5%	4,4%	6,3%
Max DD	-57,1%	-51,5%	-46,9%	-58,6%
Max DD length (d)	641	573	624	641
VaR (95)	-8,1%	-6,6%	-6,9%	-9,0%
CVaR (95)	-12,5%	-11,0%	-10,1%	-13,6%
VaR (99)	-15,2%	-12,7%	-11,0%	-15,3%
CVaR (99)	-19,7%	-18,5%	-18,7%	-22,2%
Sharpe R	0,154	0,144	0,152	0,139
Omage R	1,603	1,596	1,616	1,542
Upside potential R	10,15	9,50	9,91	9,95
F-T R (Rf, 0.5, 0.5)	2,551	3,001	2,875	2,314
F-T R (Rf, 0.75, 1,25)	15,77	15,66	15,95	15,01
F-T R (Rf, 1.25, 0.75)	0,172	0,176	0,176	0,167
F-T R (Rf, 2, 2)	1,182	1,074	1,122	1,224

Regression of Full portfolio

Adj R2	0,834		
	Value	Std Err	P-value
Intercept	0,003	0,002	0,078
Mkt-RF	1,104	0,044	0,000
ME	0,183	0,051	0,015
I/A	0,367	0,080	0,007
ROE	0,080	0,067	0,269

Regression of LowBeta portfolio

Adj R2	0,802		
	Value	Std Err	P-value
Intercept	0,002	0,002	0,220
Mkt-RF	0,921	0,039	0,000
ME	0,153	0,046	0,058
I/A	0,247	0,071	0,129
ROE	0,200	0,059	0,068

Regression of MidBeta portfolio

Adj R2	0,869		
	Value	Std Err	P-value
Intercept	0,002	0,001	0,153
Mkt-RF	0,970	0,031	0,000
ME	0,045	0,037	0,279
I/A	0,368	0,057	0,000
ROE	0,170	0,048	0,003

Regression of HighBeta portfolio

Adj R2	0,814		
	Value	Std Err	P-value
Intercept	0,002	0,002	0,266
Mkt-RF	1,284	0,053	0,000
ME	-0,071	0,062	0,357
I/A	0,797	0,096	0,000
ROE	0,029	0,080	0,220

Average of results using the Novy factors model

	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	0,7%	0,5%	0,6%	0,9%
Std dev (m)	6,4%	4,6%	5,1%	6,8%
Max DD	-62,1%	-50,7%	-53,1%	-61,7%
Max DD length (d)	624	505	590	638
VaR (95)	-10,1%	-7,6%	-8,4%	-10,3%
CVaR (95)	-15,0%	-11,7%	-12,0%	-15,4%
VaR (99)	-17,9%	-14,3%	-13,1%	-19,7%
CVaR (99)	-23,1%	-18,9%	-21,4%	-24,3%
Sharpe R	0,098	0,082	0,094	0,120
Omage R	1,370	1,338	1,365	1,450
Upside potential R	8,35	7,61	8,09	8,74
F-T R (Rf, 0.5, 0.5)	1,937	2,310	2,141	2,044
F-T R (Rf, 0.75, 1,25)	12,37	12,05	12,35	13,01
F-T R (Rf, 1.25, 0.75)	0,158	0,159	0,160	0,169
F-T R (Rf, 2, 2)	1,101	0,959	1,035	1,173

Regression of Full portfolio

Adj R2	0,823		
	Value	Std Err	P-value
Intercept	0,004	0,002	0,154
Mkt-RF	1,155	0,056	0,000
HML*	0,416	0,126	0,091
UMD*	-0,026	0,059	0,362
PMU*	-0,093	0,168	0,477

Regression of LowBeta portfolio

Adj R2	0,753		
	Value	Std Err	P-value
Intercept	-0,001	0,002	0,691
Mkt-RF	0,878	0,047	0,000
HML*	0,555	0,107	0,004
UMD*	0,097	0,050	0,219
PMU*	0,309	0,143	0,098

Regression of MidBeta portfolio

Adj R2	0,862		
	Value	Std Err	P-value
Intercept	0,000	0,002	0,750
Mkt-RF	1,021	0,039	0,000
HML*	0,484	0,088	0,000
UMD*	-0,118	0,041	0,165
PMU*	0,645	0,117	0,000

Regression of HighBeta portfolio

Adj R2	0,869		
	Value	Std Err	P-value
Intercept	0,005	0,002	0,029
Mkt-RF	1,218	0,051	0,000
HML*	0,495	0,115	0,000
UMD*	-0,263	0,054	0,018
PMU*	0,136	0,153	0,299

Appendix 2: Results' tables for the standardized models

These tables display the results of the FF5, QMJ, Qfact, and Novy models while using the standardization method. In each case a 36-month rolling window is used and 50 stocks form the portfolios.

Results using the QMJ factors model

	Classic MOM	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	0,8%	0,8%	0,7%	0,9%	0,9%
Std dev (m)	5,3%	4,7%	4,2%	4,3%	5,6%
Max DD	-54,7%	-48,4%	-52,1%	-45,9%	-55,3%
Max DD length (d)	273	273	639	639	639
VaR (95)	-8,8%	-6,2%	-6,3%	-6,3%	-8,6%
CVaR (95)	-11,7%	-11,3%	-10,5%	-10,0%	-12,3%
VaR (99)	-12,2%	-12,7%	-12,6%	-12,1%	-12,1%
CVaR (99)	-15,7%	-16,1%	-16,1%	-16,7%	-19,3%
Sharpe R	0,141	0,167	0,169	0,207	0,157
Omage R	1,448	1,565	1,569	1,715	1,516
Upside potential R	9,75	9,72	9,43	10,45	9,95
F-T R (Rf, 0.5, 0.5)	2,152	2,715	2,794	3,212	2,241
F-T R (Rf, 0.75, 1,25)	14,57	15,62	15,78	17,50	15,33
F-T R (Rf, 1.25, 0.75)	0,151	0,168	0,166	0,181	0,157
F-T R (Rf, 2, 2)	1,133	1,103	1,027	1,126	1,159

Regression on FF3 factors

Full portfolio

Adj R2	0,838		
	Value	Std Err	P-value
Intercept	0,003	0,001	0,021
Mkt-RF	0,951	0,031	0,000
SMB	0,027	0,041	0,514
HML	0,361	0,042	0,000

LowBeta Portfolio

Adj R2	0,820		
	Value	Std Err	P-value
Intercept	0,003	0,001	0,041
Mkt-RF	0,831	0,029	0,000
SMB	0,095	0,039	0,015
HML	0,380	0,040	0,000

MidBeta Portfolio

Adj R2	0,870		
	Value	Std Err	P-value
Intercept	0,005	0,001	0,000
Mkt-RF	0,909	0,025	0,000
SMB	-0,048	0,034	0,157
HML	0,357	0,035	0,000

HighBeta Portfolio

Adj R2	0,866		
	Value	Std Err	P-value
Intercept	0,003	0,001	0,043
Mkt-RF	1,162	0,034	0,000
SMB	0,026	0,045	0,559
HML	0,506	0,046	0,000

ClassicMOM Portfolio

Adj R2	0,682		
	Value	Std Err	P-value
Intercept	0,002	0,002	0,251
Mkt-RF	0,911	0,049	0,000
SMB	0,295	0,065	0,000
HML	0,127	0,067	0,060

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Regression on QMJ factors

Full portfolio

Adj R2	0,846		
	Value	Std Err	P-value
Intercept	0,001	0,001	0,599
Mkt-RF	1,023	0,042	0,000
SMB	0,023	0,056	0,675
HML Devil	0,406	0,046	0,000
UMD	0,254	0,037	0,000
QMJ	0,189	0,068	0,006

LowBeta Portfolio

Adj R2	0,807		
	Value	Std Err	P-value
Intercept	0,001	0,001	0,562
Mkt-RF	0,886	0,043	0,000
SMB	0,049	0,056	0,385
HML Devil	0,378	0,047	0,000
UMD	0,254	0,038	0,000
QMJ	0,132	0,069	0,055

MidBeta Portfolio

Adj R2	0,883		
	Value	Std Err	P-value
Intercept	0,002	0,001	0,116
Mkt-RF	1,015	0,034	0,000
SMB	0,018	0,045	0,696
HML Devil	0,386	0,038	0,000
UMD	0,175	0,030	0,000
QMJ	0,338	0,055	0,000

HighBeta Portfolio

Adj R2	0,876		
	Value	Std Err	P-value
Intercept	0,001	0,002	0,572
Mkt-RF	1,186	0,046	0,000
SMB	0,042	0,060	0,485
HML Devil	0,533	0,050	0,000
UMD	0,182	0,040	0,000
QMJ	0,244	0,074	0,001

ClassicMOM Portfolio

Adj R2	0,892		
	Value	Std Err	P-value
Intercept	-0,001	0,001	0,293
Mkt-RF	1,142	0,041	0,000
SMB	0,194	0,054	0,000
HML Devil	0,251	0,045	0,000
UMD	0,615	0,036	0,000
QMJ	0,062	0,065	0,343

Results using the FF5 factors model

	Classic MOM	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	0,8%	0,9%	0,8%	0,8%	1,1%
Std dev (m)	5,3%	4,7%	4,0%	4,3%	6,1%
Max DD	-54,7%	-43,4%	-45,0%	-46,0%	-47,7%
Max DD length (d)	273	273	486	486	273
VaR (95)	-8,8%	-6,8%	-5,9%	-6,7%	-8,8%
CVaR (95)	-11,7%	-10,5%	-8,9%	-10,2%	-12,9%
VaR (99)	-12,2%	-11,6%	-10,2%	-11,2%	-13,1%
CVaR (99)	-15,7%	-16,3%	-14,0%	-16,4%	-19,7%
Sharpe R	0,141	0,197	0,199	0,180	0,176
Omage R	1,448	1,675	1,688	1,600	1,594
Upside potential R	9,75	10,58	10,61	9,84	10,62
F-T R (Rf, 0.5, 0.5)	2,152	2,939	2,921	2,866	2,457
F-T R (Rf, 0.75, 1,25)	14,57	16,97	16,93	16,27	16,10
F-T R (Rf, 1.25, 0.75)	0,151	0,177	0,180	0,168	0,167
F-T R (Rf, 2, 2)	1,133	1,181	1,190	1,067	1,249

Regression on FF3 factors

Full portfolio

Adj R2	0,818		
	Value	Std Err	P-value
Intercept	0,005	0,001	0,001
Mkt-RF	0,964	0,033	0,000
SMB	-0,004	0,044	0,921
HML	0,283	0,045	0,000

LowBeta Portfolio

Adj R2	0,762		
	Value	Std Err	P-value
Intercept	0,004	0,001	0,003
Mkt-RF	0,776	0,032	0,000
SMB	0,101	0,043	0,020
HML	0,170	0,044	0,000

MidBeta Portfolio

Adj R2	0,872		
	Value	Std Err	P-value
Intercept	0,003	0,001	0,003
Mkt-RF	0,889	0,025	0,000
SMB	0,022	0,033	0,503
HML	0,367	0,034	0,000

HighBeta Portfolio

Adj R2	0,858		
	Value	Std Err	P-value
Intercept	0,004	0,002	0,007
Mkt-RF	1,259	0,038	0,000
SMB	-0,004	0,050	0,940
HML	0,617	0,052	0,000

ClassicMOM Portfolio

Adj R2	0,682		
	Value	Std Err	P-value
Intercept	0,002	0,002	0,251
Mkt-RF	0,911	0,049	0,000
SMB	0,295	0,065	0,000
HML	0,127	0,067	0,060

Regression on FF5 factors

Full portfolio

Adj R2	0,820		
	Value	Std Err	P-value
Intercept	0,004	0,001	0,008
Mkt-RF	1,001	0,039	0,000
SMB	0,057	0,051	0,271
HML	0,221	0,066	0,001
RMW	0,165	0,075	0,030
CMA	0,007	0,088	0,938

LowBeta Portfolio

Adj R2	0,763		
	Value	Std Err	P-value
Intercept	0,004	0,001	0,011
Mkt-RF	0,794	0,038	0,000
SMB	0,144	0,050	0,005
HML	0,131	0,065	0,045
RMW	0,094	0,074	0,208
CMA	-0,030	0,087	0,726

MidBeta Portfolio

Adj R2	0,881		
	Value	Std Err	P-value
Intercept	0,002	0,001	0,091
Mkt-RF	0,951	0,029	0,000
SMB	0,093	0,038	0,014
HML	0,227	0,049	0,000
RMW	0,210	0,056	0,000
CMA	0,147	0,065	0,025

HighBeta Portfolio

Adj R2	0,859		
	Value	Std Err	P-value
Intercept	0,004	0,002	0,032
Mkt-RF	1,291	0,045	0,000
SMB	0,060	0,059	0,309
HML	0,562	0,076	0,000
RMW	0,146	0,087	0,093
CMA	0,008	0,102	0,937

ClassicMOM Portfolio

Adj R2	0,686		
	Value	Std Err	P-value
Intercept	0,001	0,002	0,611
Mkt-RF	0,975	0,058	0,000
SMB	0,373	0,076	0,000
HML	-0,045	0,098	0,647
RMW	0,239	0,112	0,034
CMA	0,074	0,131	0,576

Results using the Qfact factors model

	Classic MOM	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	0,8%	0,9%	0,8%	0,8%	0,9%
Std dev (m)	5,4%	4,7%	4,2%	4,3%	5,8%
Max DD	-54,7%	-52,3%	-48,9%	-46,7%	-56,4%
Max DD length (d)	276	641	641	641	641
VaR (95)	-9,5%	-7,2%	-6,2%	-6,2%	-8,5%
CVaR (95)	-11,9%	-11,0%	-10,4%	-10,1%	-12,9%
VaR (99)	-12,8%	-12,6%	-10,8%	-11,9%	-13,5%
CVaR (99)	-18,5%	-22,5%	-18,7%	-20,8%	-21,8%
Sharpe R	0,144	0,186	0,187	0,196	0,147
Omage R	1,456	1,642	1,628	1,690	1,470
Upside potential R	9,52	9,86	9,79	9,86	9,71
F-T R (Rf, 0.5, 0.5)	2,229	2,829	2,911	2,909	2,200
F-T R (Rf, 0.75, 1,25)	14,25	16,08	16,08	16,31	14,50
F-T R (Rf, 1.25, 0.75)	0,157	0,179	0,176	0,186	0,157
F-T R (Rf, 2, 2)	1,131	1,137	1,092	1,130	1,164

Regression on FF3 factors

Full portfolio

Adj R2	0,798		
	Value	Std Err	P-value
Constante	0,004	0,002	0,013
Mkt-RF	0,926	0,035	0,000
SMB	0,072	0,047	0,129
HML	0,305	0,048	0,000

LowBeta Portfolio

Adj R2	0,801		
	Value	Std Err	P-value
Constante	0,003	0,001	0,018
Mkt-RF	0,805	0,031	0,000
SMB	0,136	0,041	0,001
HML	0,264	0,042	0,000

MidBeta Portfolio

Adj R2	0,863		
	Value	Std Err	P-value
Constante	0,004	0,001	0,001
Mkt-RF	0,875	0,026	0,000
SMB	0,024	0,035	0,490
HML	0,324	0,036	0,000

HighBeta Portfolio

Adj R2	0,851		
	Value	Std Err	P-value
Constante	0,002	0,002	0,149
Mkt-RF	1,186	0,038	0,000
SMB	-0,037	0,050	0,456
HML	0,549	0,051	0,000

ClassicMOM Portfolio

Adj R2	0,682		
	Value	Std Err	P-value
Constante	0,002	0,002	0,283
Mkt-RF	0,912	0,051	0,000
SMB	0,303	0,068	0,000
HML	0,147	0,069	0,035

Regression on Qfact factors

Full portfolio

Adj R2	0,808		
	Value	Std Err	P-value
Intercept	0,002	0,002	0,168
MKT	1,022	0,041	0,000
ME	0,127	0,047	0,008
I/A	0,333	0,073	0,000
ROE	0,268	0,062	0,000

LowBeta Portfolio

Adj R2	0,813		
	Value	Std Err	P-value
Intercept	0,002	0,001	0,245
MKT	0,893	0,035	0,000
ME	0,199	0,041	0,000
I/A	0,259	0,063	0,000
ROE	0,262	0,054	0,000

MidBeta Portfolio

Adj R2	0,859		
	Value	Std Err	P-value
Intercept	0,002	0,001	0,056
MKT	0,951	0,032	0,000
ME	0,052	0,036	0,156
I/A	0,404	0,056	0,000
ROE	0,198	0,048	0,000

HighBeta Portfolio

Adj R2	0,832		
	Value	Std Err	P-value
Intercept	0,001	0,002	0,597
MKT	1,245	0,047	0,000
ME	-0,066	0,054	0,230
I/A	0,765	0,084	0,000
ROE	0,098	0,071	0,173

ClassicMOM Portfolio

Adj R2	0,774		
	Value	Std Err	P-value
Intercept	0,000	0,002	0,799
MKT	1,124	0,051	0,000
ME	0,457	0,058	0,000
I/A	-0,083	0,090	0,361
ROE	0,637	0,077	0,000

Results using the Novy factors model

	Classic MOM	Full Portfolio	LowBeta Portfolio	MidBeta Portfolio	HighBeta Portfolio
Avg return (m)	0,7%	0,7%	0,5%	0,5%	1,0%
Std dev (m)	5,6%	5,3%	4,3%	4,8%	6,4%
Max DD	-54,7%	-52,7%	-46,2%	-53,4%	-57,3%
Max DD length (d)	276	641	488	641	641
VaR (95)	-9,9%	-8,7%	-6,6%	-8,3%	-10,2%
CVaR (95)	-12,2%	-12,9%	-11,0%	-11,7%	-14,1%
VaR (99)	-12,8%	-14,4%	-11,9%	-12,3%	-16,7%
CVaR (99)	-18,5%	-21,5%	-20,1%	-20,8%	-23,1%
Sharpe R	0,117	0,124	0,110	0,113	0,150
Omage R	1,361	1,394	1,352	1,352	1,503
Upside potential R	8,43	8,19	7,51	8,01	8,95
F-T R (Rf, 0.5, 0.5)	2,024	2,258	2,400	2,133	2,252
F-T R (Rf, 0.75, 1,25)	12,32	12,65	12,12	12,24	13,46
F-T R (Rf, 1.25, 0.75)	0,158	0,163	0,162	0,158	0,177
F-T R (Rf, 2, 2)	1,092	1,046	0,952	1,026	1,192

Regression on FF3 factors

Full portfolio

Adj R2	0,818		
	Value	Std Err	P-value
Constante	0,003	0,002	0,091
Mkt-RF	0,998	0,039	0,000
SMB	0,142	0,052	0,007
HML	0,224	0,052	0,000

LowBeta Portfolio

Adj R2	0,781		
	Value	Std Err	P-value
Constante	0,002	0,002	0,279
Mkt-RF	0,802	0,034	0,000
SMB	0,043	0,046	0,347
HML	0,327	0,046	0,000

MidBeta Portfolio

Adj R2	0,891		
	Value	Std Err	P-value
Constante	0,002	0,001	0,139
Mkt-RF	0,962	0,027	0,000
SMB	0,015	0,037	0,673
HML	0,443	0,037	0,000

HighBeta Portfolio

Adj R2	0,867		
	Value	Std Err	P-value
Constante	0,005	0,002	0,006
Mkt-RF	1,253	0,040	0,000
SMB	0,122	0,053	0,023
HML	0,350	0,054	0,000

ClassicMOM Portfolio

Adj R2	0,669		
	Value	Std Err	P-value
Constante	0,003	0,003	0,300
Mkt-RF	0,895	0,055	0,000
SMB	0,317	0,074	0,000
HML	0,153	0,075	0,042

Regression on Novy factors

Full portfolio

Adj R2	0,823		
	Value	Std Err	P-value
Intercept	0,001	0,002	0,587
Mkt-RF	1,083	0,047	0,000
HML*	0,350	0,104	0,001
UMD*	0,142	0,048	0,004
PMU*	0,286	0,139	0,041

LowBeta Portfolio

Adj R2	0,760		
	Value	Std Err	P-value
Intercept	-0,001	0,002	0,736
Mkt-RF	0,848	0,044	0,000
HML*	0,449	0,099	0,000
UMD*	0,118	0,045	0,010
PMU*	0,296	0,131	0,026

MidBeta Portfolio

Adj R2	0,857		
	Value	Std Err	P-value
Intercept	-0,001	0,002	0,427
Mkt-RF	0,997	0,038	0,000
HML*	0,546	0,086	0,000
UMD*	-0,103	0,039	0,010
PMU*	0,695	0,114	0,000

HighBeta Portfolio

Adj R2	0,882		
	Value	Std Err	P-value
Intercept	0,005	0,002	0,012
Mkt-RF	1,198	0,046	0,000
HML*	0,457	0,103	0,000
UMD*	-0,254	0,047	0,000
PMU*	0,289	0,137	0,036

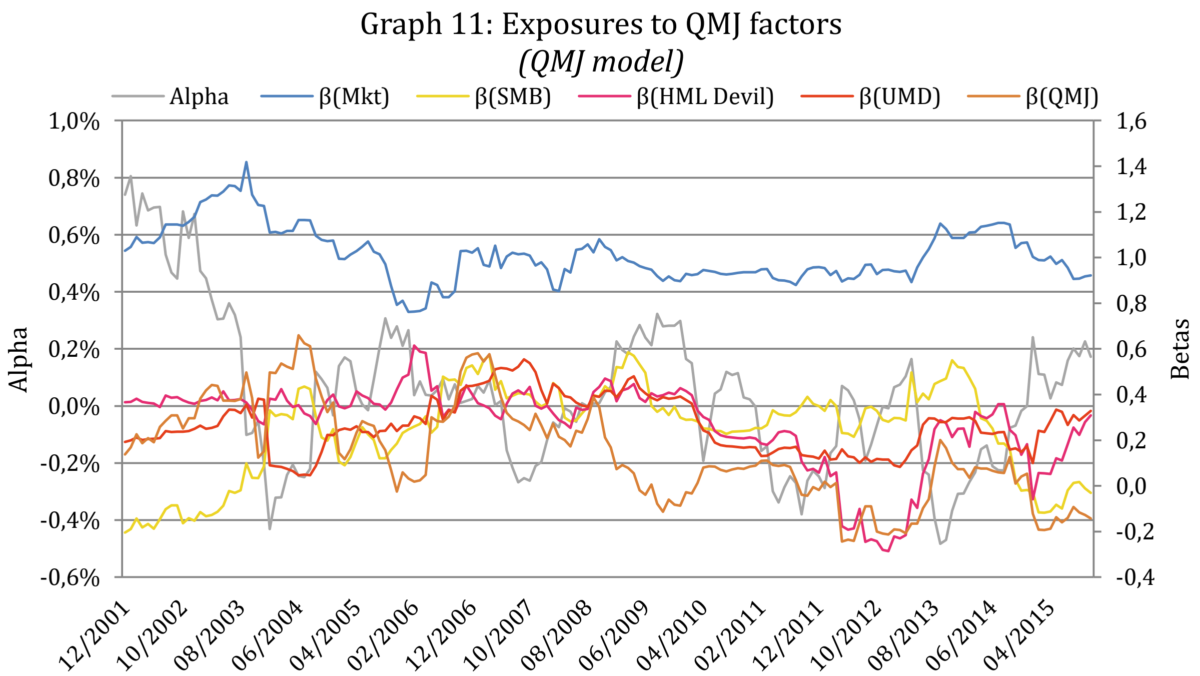
ClassicMOM Portfolio

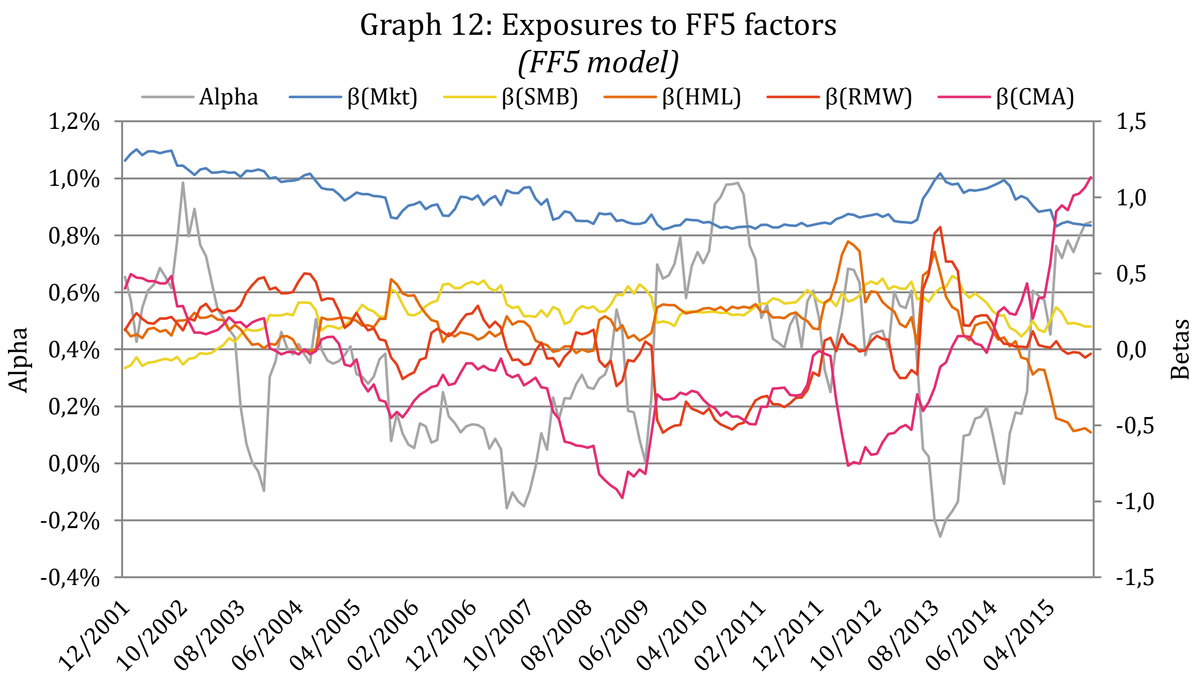
Adj R2	0,851		
	Value	Std Err	P-value
Intercept	-0,001	0,002	0,624
Mkt-RF	1,151	0,045	0,000
HML*	0,507	0,101	0,000
UMD*	0,692	0,047	0,000
PMU*	0,060	0,135	0,655

-

Appendix 3: Evolution of risk exposures for standardized models

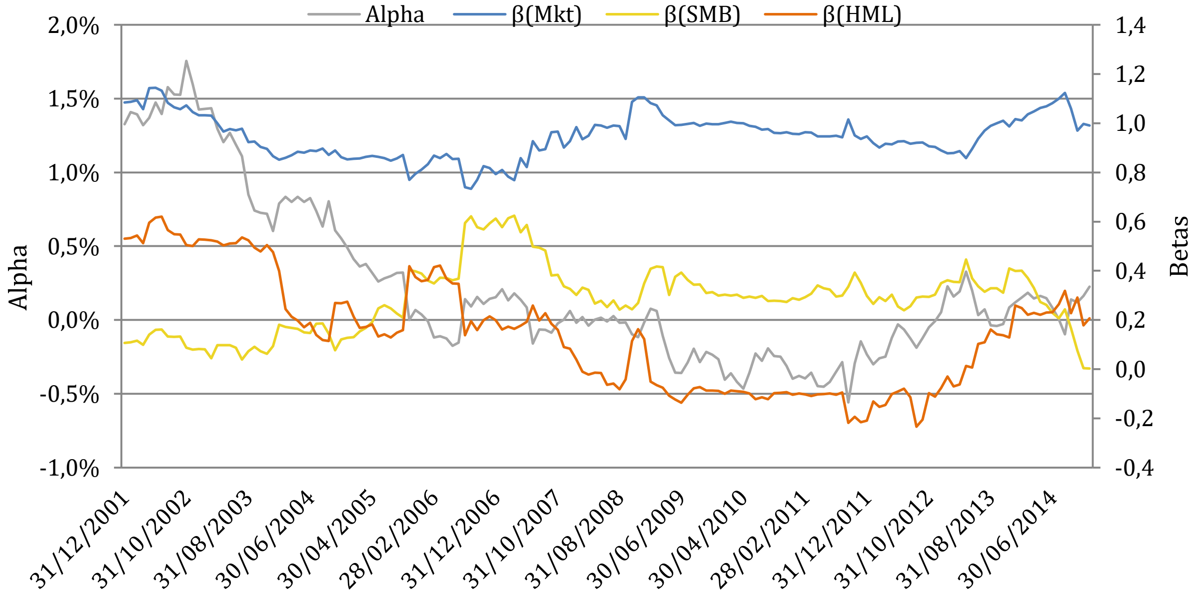
The model used in the calculation of the RMS is the model between brackets in the title, and is done using the standardized method. Alphas and betas are estimated using a 36-month rolling window and average adjusted r-square is above 80% for every model.





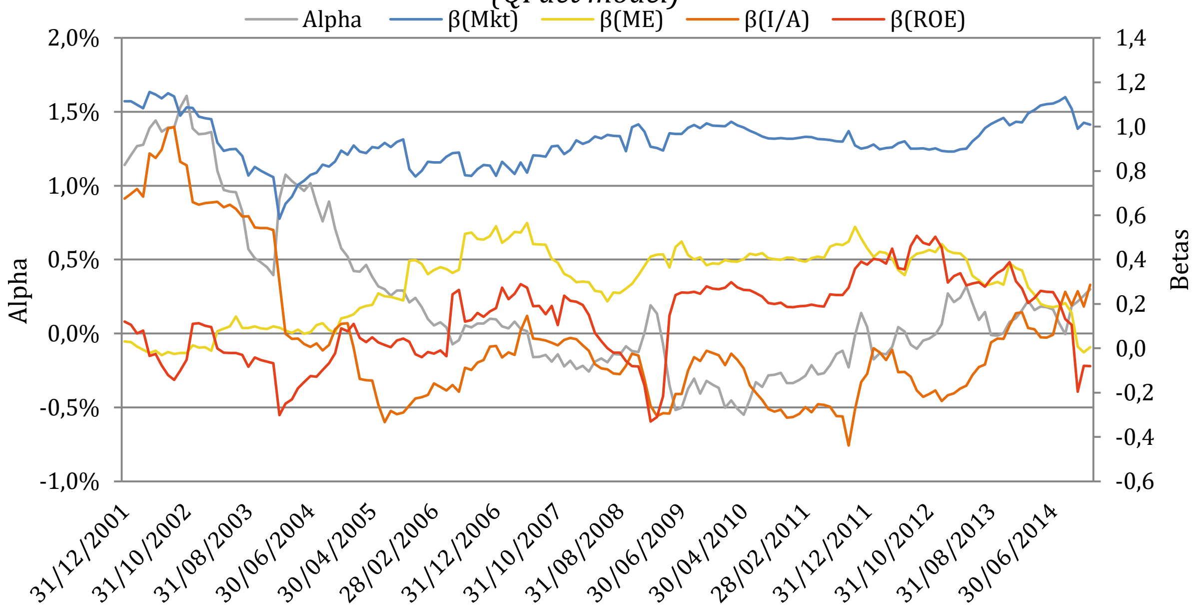
Graph 13: Exposures to FF3 factors

(QFact model)

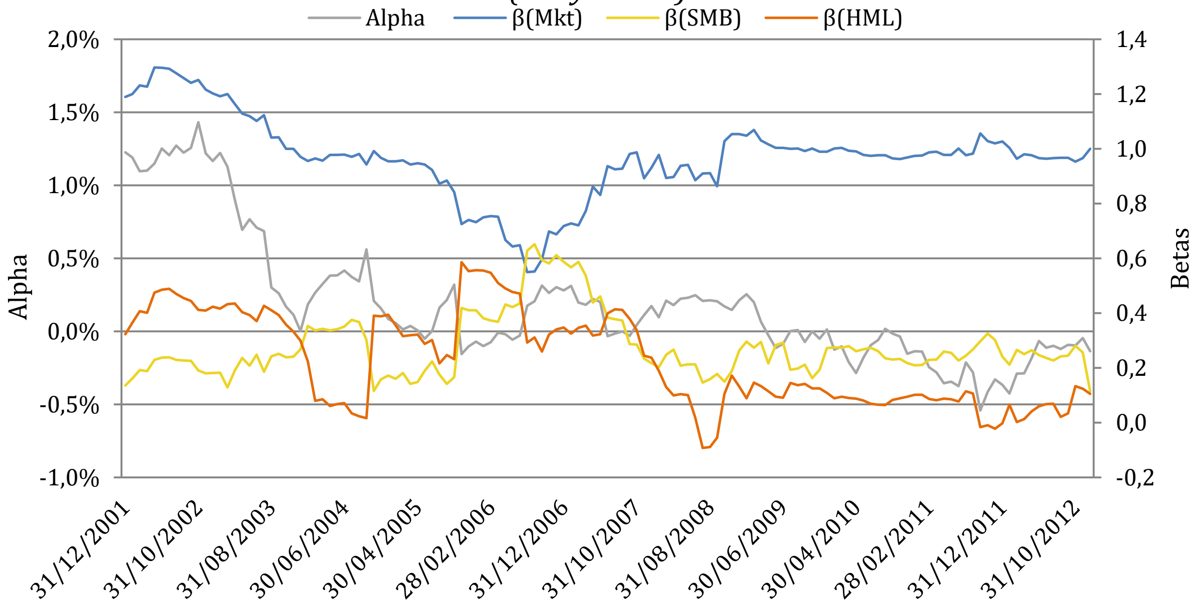


Graph 14: Exposures to QFact factors

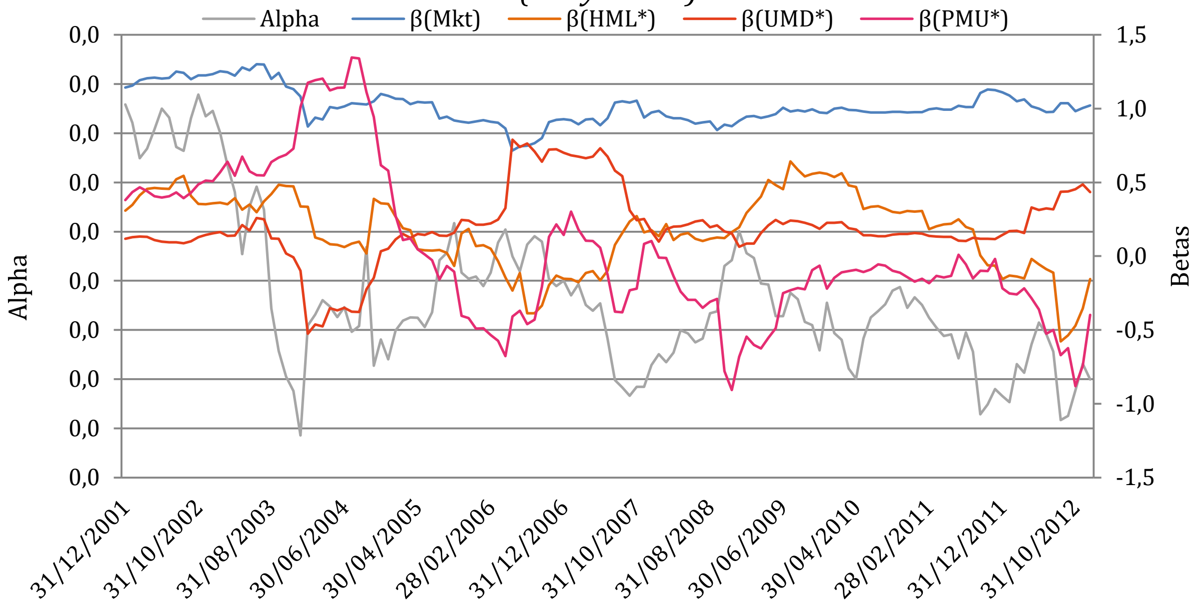
(QFact model)



Graph 15: Exposures to FF3 factors
(Novy model)

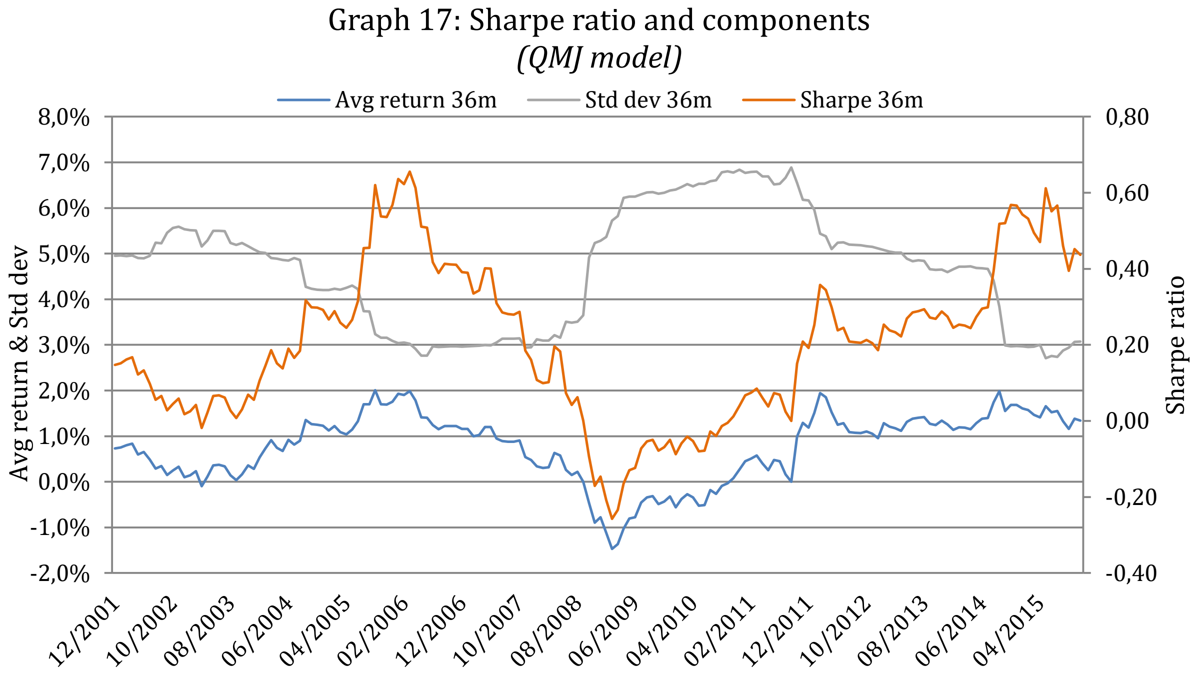


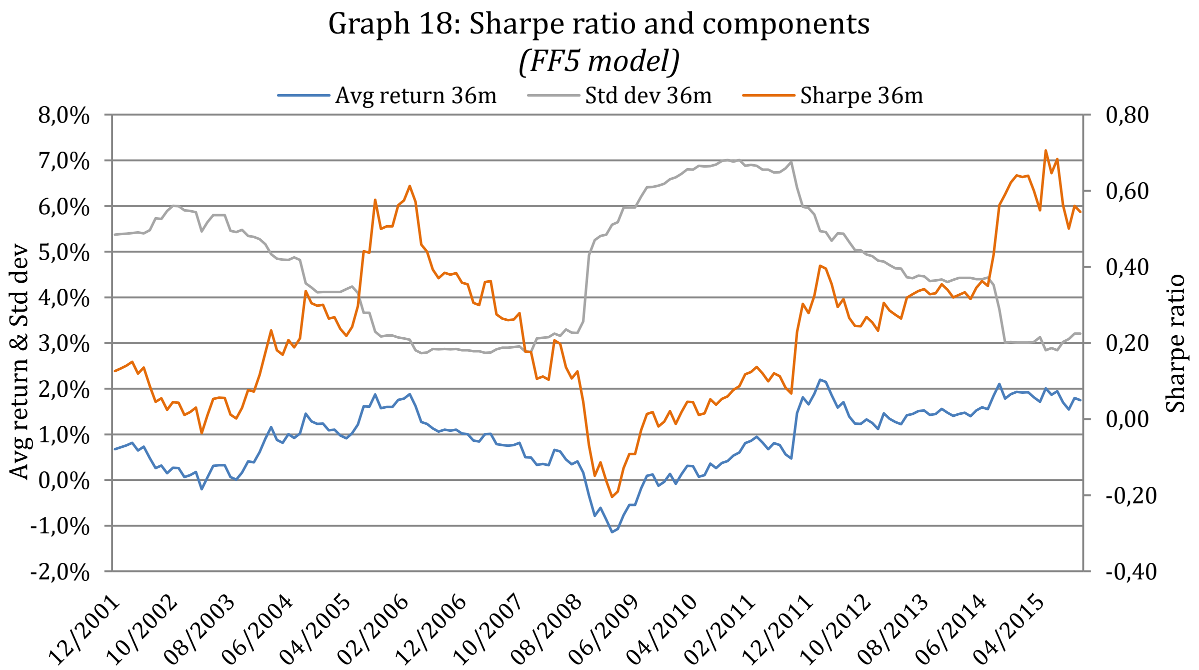
Graph 16: Exposures to Novy factors
(Novy model)



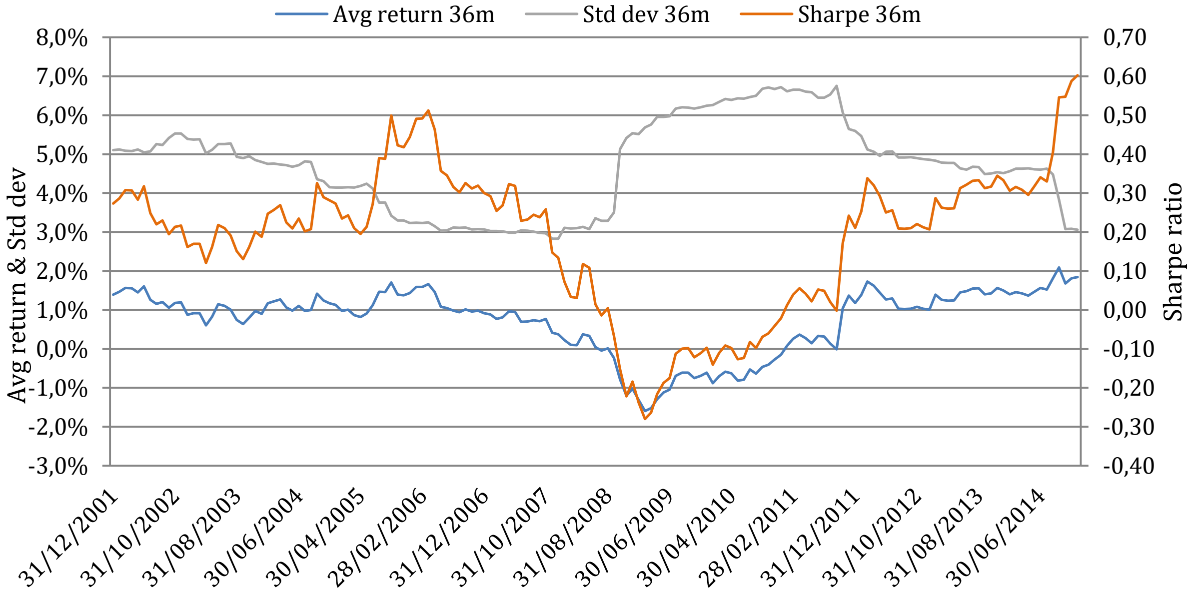
Appendix 4: Evolution of performance for standardized models

The model used in the calculation of the RMS is the model between brackets in the title, and is done using the standardized method. Average return, standard deviation, and Sharpe ratios are monthly.

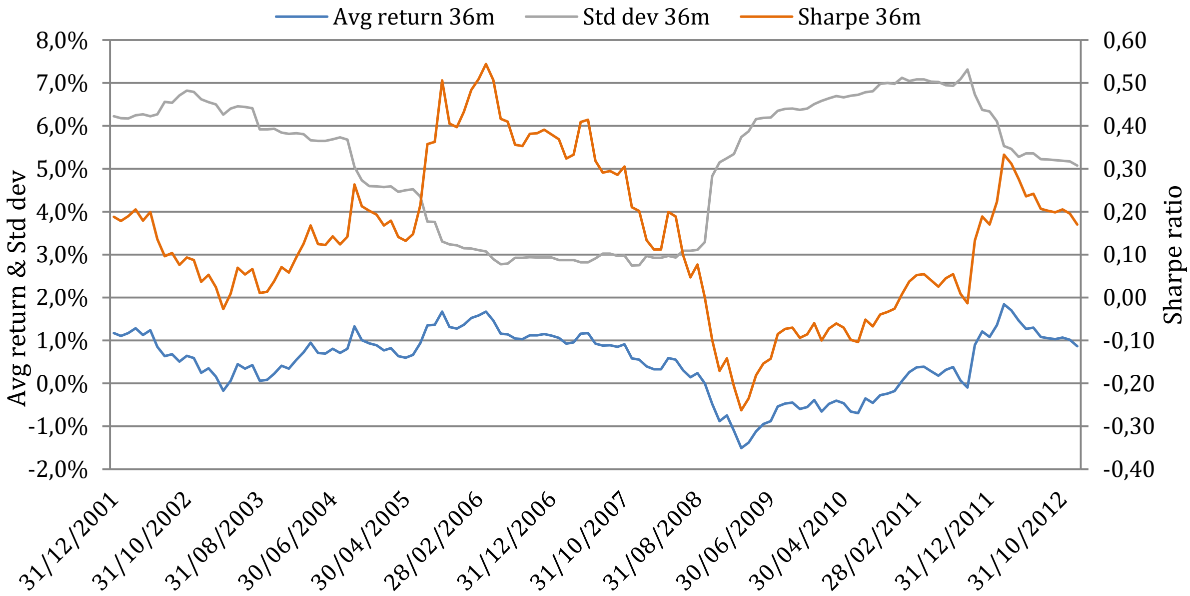




Graph 19: Sharpe ratio and components
(QFact model)



Graph 20: Sharpe ratio and components
(Novy model)



Appendix 5: Samples of the VBA code

The code posted here is linked to the excel files used to carry this research and is not meant to work flawlessly without the proper setup. Please note a couple different version have been used, notably modifications are done for the standardized version as opposed to the non-standardized one. The excel files containing the entire code can be downloaded at: #www.laurent-prunier.eu/mastersthesis

```
'The date must be order with the "oldest" date at the bottom of the range, if you want to change this behaviour you must swap the FOR loop components
Public Function MaxDD(dateRange As Range, valueRange As Range) As Double()
    Dim max, min, temp As Variant
    Dim maxDate, minDate As Variant
    Dim i As Integer
    Dim PV() As Variant
    Dim PVDate() As Variant
    Dim results(0 To 1) As Double

    PV = valueRange.Value
    PVDate = dateRange.Value
    results(0) = 0
    results(1) = 0

    max = 0
    min = 0
    maxDate = 0
    minDate = 0

    For i = UBound(PV) - 1 To 1 Step -1
        If PV(i, 1) > max Then
            max = PV(i, 1)
            min = PV(i, 1)
            maxDate = PVDate(i, 1)
            minDate = PVDate(i, 1)
        End If
        If PV(i, 1) < min Then
            min = PV(i, 1)
            minDate = PVDate(i, 1)
        End If
        temp = (min - max) / max
        If temp < results(0) Then
            results(0) = temp
            results(1) = minDate - maxDate
        End If
    Next i
    MaxDD = results()
End Function
```

```
'This function gives the Historical VaR on the first cell and the CVaR on the second cell
Public Function VARandCVAR(returnsRange As Range, confLevel As Double) As Variant()
Dim dataArray(), cvarTemp As Double
Dim numVaR, i As Integer
Dim c As Object
Dim tempArray() As Variant
ReDim tempArray(1)
ReDim dataArray(1 To returnsRange.Count)
For i = 1 To returnsRange.Count
    dataArray(i) = returnsRange.Cells(i).Value
Next i
dataArray = BubbleSrt(dataArray, True)
numVaR = WorksheetFunction.RoundUp((1 - confLevel) * returnsRange.Count, 0)
tempArray(0) = dataArray(numVaR)
For i = 1 To numVaR - 1 'Dans ce cas l'ajout du -1 est justifié car on ne veut prendre en compte que les pertes supérieures à la VaR
    cvarTemp = cvarTemp + dataArray(i)
Next i
tempArray(1) = cvarTemp / (numVaR - 1)
VARandCVAR = tempArray()

End Function
```

```
Public Function BubbleSrt(ArrayIn, Ascending As Boolean)
Dim SrtTemp As Variant
Dim i As Long
Dim j As Long

If Ascending = True Then
    For i = LBound(ArrayIn) To UBound(ArrayIn)
        For j = i + 1 To UBound(ArrayIn)
            If ArrayIn(i) > ArrayIn(j) Then
                SrtTemp = ArrayIn(j)
                ArrayIn(j) = ArrayIn(i)
                ArrayIn(i) = SrtTemp
            End If
        Next j
    Next i
Else
    For i = LBound(ArrayIn) To UBound(ArrayIn)
        For j = i + 1 To UBound(ArrayIn)
            If ArrayIn(i) < ArrayIn(j) Then
                SrtTemp = ArrayIn(j)
                ArrayIn(j) = ArrayIn(i)
                ArrayIn(i) = SrtTemp
            End If
        Next j
    Next i
End If

BubbleSrt = ArrayIn
End Function
```

```
Public Function FTR(returnsRange As Range, threshold As Double, highAversion As Double, lowAversion As Double) As Double
Dim arrHPM(), arrLPM(), dataArray(), HPM, LPM As Double
Dim i As Integer

ReDim dataArray(1 To returnsRange.Count)
ReDim arrHPM(1 To UBound(dataArray))
ReDim arrLPM(1 To UBound(dataArray))

For i = 1 To returnsRange.Count
    dataArray(i) = returnsRange.Cells(i).Value
Next i

'HPM part
For i = 1 To UBound(dataArray)
    If dataArray(i) > threshold Then
        arrHPM(i) = (dataArray(i) - threshold) ^ highAversion
    Else
        arrHPM(i) = 0
    End If
    Debug.Print arrHPM(i)
Next i
HPM = WorksheetFunction.Sum(arrHPM) ^ (1 / highAversion)

'LPM part
For i = 1 To UBound(dataArray)
    If dataArray(i) < threshold Then
        arrLPM(i) = (threshold - dataArray(i)) ^ lowAversion
    Else
        arrLPM(i) = 0
    End If
Next i
LPM = WorksheetFunction.Sum(arrLPM) ^ (1 / lowAversion)

FTR = HPM / LPM
End Function
```

```
'La fonction renvoit en premier paramètre la somme des erreurs des X derniers facteurs. X étant le nombre de de lignes dans la régression / 3 (arondi à l'inférieur)
'Attention le calcul des pValue est erroné
Function Regression(factor As Integer, stockRange As Range, factorRange As Range, Optional sheetName As String) As Double()
    Dim factorReturn(), stockReturn(), alphaBeta(), prederror(), diffMean(), s2Matrix(), pValue(), errorArray(), results() As Double
    Dim meanReturn, prediction, sumError, sumDiffMean, adjR2, s2, stdDevError As Double
    Dim i, j, nbRecord, sumMomentumFactor As Integer
    On Error GoTo ErrHandler
    stockReturn = stockRange.Value
    factorReturn = factorRange.Value
    nbRecord = UBound(stockReturn) - LBound(stockReturn) 'Attention nbRecord renvera le nombre de record reel-1 car les array sont en base 0
    sumMomentumFactor = WorksheetFunction.RoundDown(nbRecord / 3, 0)
    meanReturn = WorksheetFunction.Average(stockReturn)
```

```
alphaBeta=WorksheetFunction.MMult(WorksheetFunction.MInverse(WorksheetFunction.MMult(WorksheetFunction.Transpose(factor
Return), factorReturn)), WorksheetFunction.MMult(WorksheetFunction.Transpose(factorReturn), stockReturn))
  ReDim prederror(nbRecord)
  ReDim diffMean(nbRecord)
  For i = 0 To nbRecord
    prediction = alphaBeta(1, 1)
    For j = 1 To factor
      prediction = prediction + factorReturn(i + 1, j + 1) * alphaBeta(j + 1, 1)
    Next j
    prederror(i) = stockReturn(i + 1, 1) - prediction
    diffMean(i) = stockReturn(i + 1, 1) - meanReturn
  Next i
  sumError = WorksheetFunction.SumSq(prederror)
  sumDiffMean = WorksheetFunction.SumSq(diffMean)
  s2 = sumError / (nbRecord)
  s2Matrix() = (WorksheetFunction.MInverse(WorksheetFunction.MMult(WorksheetFunction.Transpose(factorReturn),
factorReturn)))
  ReDim pValue(UBound(s2Matrix))
  For i = 1 To UBound(s2Matrix, 1)
    For j = 1 To UBound(s2Matrix, 2)
      s2Matrix(i, j) = s2 * s2Matrix(i, j)
    Next j
    pValue(i) = WorksheetFunction.TDist(Abs(alphaBeta(i, 1) / Sqr(s2Matrix(i, i))), (nbRecord - 1), 2)
  Next i
  adjR2 = 1 - (1 - (1 - (sumError / sumDiffMean))) * (nbRecord / (nbRecord - factor))
  ReDim results(2 + UBound(alphaBeta) + UBound(pValue))
  ReDim errorArray(sumMomentumFactor)
  For i = 1 To sumMomentumFactor
    errorArray(i - 1) = prederror(i)
    results(0) = results(0) + prederror(i)
  Next i
  stdDevError = WorksheetFunction.StDev_S(errorArray)
  results(0) = results(0) / stdDevError
  results(1) = adjR2
  For i = 2 To factor + 2
    results(i) = alphaBeta(i - 1, 1)
  Next i
  For j = i To factor + i
    results(j) = pValue(j - i + 1)
  Next j
 Regression = results()
  If sheetName = "" Then
    Sheets("Results").Activate
  Else
    Sheets(sheetName).Activate
  End If
  Exit Function
ErrHandler:
End Function
```

EXECUTIVE SUMMARY

Contrary to conventional momentum, the literature treating the subject of residual momentum is very narrow. The aim of this thesis is to contribute to the literature, first by using pricing models that have been recently proposed and were not available at the time when previous researchers published their work. Secondly, by adopting the point of view of an investor who has limited access to the market and its instruments. Mainly, this investor would be unable to short sell stocks. This second choice is of particular interest for portfolio managers who sometimes have limited choices regarding the instruments they are allowed to use. Taking all the aforementioned information into account, the research question is stated as: *does a residual momentum strategy is profitable, what are the risks associated with it and how does it perform compare to a classic price momentum strategy?*

To answer this question, the analysis is conducted in two steps. The first one presents a macro view of the strategies, focusing on identifying the sensitivities of the model according to its various parameters. Namely: the pricing model and the rolling window length used in the calculation of the residual momentum score and the number of stocks composing the portfolios. The second step offers a micro view of four particular strategies, each using a different pricing model for the RMS calculation, in order to try to identify their characteristics. For instance, this part analyzes the effect of standardizing the residuals, the performance and the exposure to common risk factors over time. It also compares the strategies' performance during a period of recession, and identifies the type of investor for whom the strategies are most suited.

Following the analysis, it appears that residual momentum outperforms its conventional counterpart in every aspect detailed in this research. It generates higher returns with lower volatility and lower extreme-risk in term of maximum drawdown and value-at-risk. Moreover, it has a fairly constant market beta as opposed to the classic strategy that is known to exhibit a volatile exposure to market. Above all, it seems that there is no reason for an investor who is currently using a conventional momentum strategy not to switch, at least partially, to a residual momentum strategy.

Keywords: momentum, residual returns, risk factors, asset pricing, stock-specific returns.