Financial Market Anomalies

Does the Low-Volatility Anomaly still exist?

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Abstract

This thesis investigates whether the returns gathered from exploiting the low volatility anomaly still exist in the U.S. over the period January 2010 - December 2020. This thesis tries to replicate the study by Blitz & Van Vliet (2007), while altering the data and methodology slightly. A rolling window of the past 3 year volatility is used to generate decile portfolios (the first with the lowest volatility and the tenth with the highest volatility), whereafter monthly returns for these portfolio can be identified. The main result of this thesis is that the tenth decile outperforms the first decile, which means that the volatility effect (the lowest volatility portfolio should yield the highest returns) did not exist in the sample over the specified time period. In other words, the strategy to go long in the first decile portfolio and go short in the tenth decile portfolio did not yield significant returns over the time period investigated. Further, this thesis links the Fama-French 3 Factor and 5 Factor Models to the results to identify a potential relationship. These well-known pricing models have significant effects on the results and have a statistical significant relationship with the long-short portfolio in this thesis.

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1. Introduction

The stock market is gaining a lot of attention over the last few years. The fact that putting your savings at the bank is not yielding returns anymore has caused people to look for other opportunities to increase their holdings. Traditionally, the stock market yields 6-7% on average each year, which is therefore a good alternative for the savings returns from the past. The COVID-19 crisis of the past year has also increased the attention towards the stock market, due to the fact that people did not have a lot of things to spend their money on, and their savings increased. Overall, it becomes increasingly important to be aware of what happens in the stock market and what potential profitable strategies in the market can be to make sure that your money increases significantly.

Exploring several different strategies in the stock market always has large attention of researchers because of its practical nature. The Efficient Market Hypothesis (EMH) by Malkiel & Fama (1970) argues that all available information should be incorporated in the stock price at all times, which means that one strategy should not yield higher returns than others. However, several strategies (momentum, value, size) have shown to persistently yield significant returns over multiple markets in multiple time periods. Take the momentum strategy for example. The first to document this strategy were Jegadeesh & Titman (1993), who build a strategy of buying former winners and selling losers. Based on the EMH, this strategy should not yield any abnormal returns, but many papers have shown the contrary. These strategies that should not work in theory, but do work in practice, are called ‘anomalies’.

To go deeper into the specific topic of this thesis, the theory of market efficiency believes that it should not be possible to explore a strategy which yields similar returns to the market, but with systematically lower risks. In other words, low risk stocks (as measured by the volatility) should have lower returns relative to high risk stocks in the long term. However, Blitz & Van Vliet (2007) show that this is actually the other way around. The authors construct an approach in which they rank stocks by their past 3-year volatility in deciles and find that stocks in the lowest volatility decile have the highest Sharpe ratio across all the deciles over the period 1986-2006. In their paper, they call this the ‘volatility effect’, which later came to be known as the ‘low-volatility anomaly’.

The founders of the low-volatility anomaly later came up with several follow-up researches regarding their results. They find that there are similar results in developing markets (Blitz et al., 2013). More specifically, they find that the relationship between return and risk is negative in emerging markets and that this effect has become more profound over the more recent time periods. Additionally, they test for relation between the results in developed markets and emerging markets and find hardly any relationship. This shows that it is not likely that there is a common factor that can explain the anomaly.

More recently, they revisited the effect again (Blitz et al., 2019). This study gives an overview of the existing research regarding the anomaly and conclude that the effect is persistent over time and over multiple markets. They also test for drivers of the effect, but do not seem to find drivers that significantly explain the volatility effect. In addition, they conclude that there is no evidence that the effect is arbitraged away over time, which is quite surprising due to the profitable nature of the effect.

Overall, there seems to be consensus in the literature that the low volatility anomaly is profitable and outperforms the market over multiple time periods and in multiple markets. This thesis will try to replicate the study by Blitz & Van Vliet (2007) and will investigate whether the returns by exploring the low-volatility anomaly still exist in more recent time periods in the U.S. market. This results in the following research question:

‘To what extent does the low-volatility anomaly still exist in the U.S. market over the period 2010-2020?’

This thesis will determine whether low volatility stocks outperform higher volatility stocks and to what extent this is the case. Furthermore, it will be compared to the market returns over the same period to verify if low volatility stocks outperformed the market over the 2010-2020 period. In addition, the Three Factor Model (Fama & French, 1993) as well as the Five Factor Model presented by Fama & French (2015) will be used to check for potential drivers of the gathered results.

Regarding the data, CRSP will be used to get the data for the U.S. market over the time period discussed. CRSP can be used to get the day-to-day stock prices for all U.S. stocks, which will be used to construct the volatility measure and to gather the returns of each stock. Finally, the Kenneth French database will be used to gather the data necessary for the Fama-French 3 and 5 Factor Models.

Methodology wise, the paper by Blitz & Van Vliet (2007) will serve as a benchmark. This paper will be followed for the methodology, with some slight tweaks. The main part of the methodology is to construct deciles based on past daily volatility using a rolling window of 3 years. After the deciles are constructed monthly portfolios can be formed which will show the returns for each of the deciles. The deciles will then be compared to each other, as well as to the market, to verify if there is indeed a low-volatility effect in the sample. The main part here is to construct a long-short portfolio (going long in the lowest volatility decile and going short in the highest volatility decile), to verify if the low volatility strategy yield significant results.

Additionally, a linear regression will be used to check for potential drivers of the volatility effect. In other words, there will be checked if there is a statistical significant relationship between the long-short portfolio and the Fama-French 3 and 5 Factor Models.

This thesis adds to existing literature by investigating a more recent time period in the U.S. and by twisting the existing methodology slightly. Especially the slight twist of the methodology is interesting, but also the more recent time period (also including the COVID dip) might result in different conclusions.

To be more specific regarding the methodology, this thesis will exclude penny stocks (stocks who never exceed $5 over the time period), since these stocks are generally more risky and have the potential to disrupt the results. Furthermore, the bottom 25% market cap is dropped, since it might be the case that small stocks drive the significant alpha of the anomaly.

Besides the twist in methodology, there are also different results for different studies regarding the volatility anomaly. There are ample researches who conclude that the anomaly exists, but there are also investigations which draw different conclusions (this will be more extensively covered in the theoretical framework). This thesis also contributes to the existing literature by ending this debate once and for all and to draw a conclusion regarding the existence of the volatility effect in the more recent time periods in the U.S.

In terms of results, the volatility effect appears to have disappeared in the more recent time period in this thesis. The strategy of forming a long-short portfolio (going long in the bottom decile and going short in the top decile) did not yield positive returns over the period 2010-2020 in the U.S.

Surprisingly, the long-short portfolio generates a positive alpha after including the Fama-French Three Factor and the Fama-French Five Factor Models. After controlling for these well-known asset pricing models, the alpha is 0.38% and 0.41% respectively. This result is based on the regression methodology as described. This means that the existing asset pricing models have a significant relationship with the long-short portfolio and that the pricing models can have an influence on previous results.

The remainder of this thesis will be as follows: the following section will describe the theoretical framework where previous literature will be discussed and hypothesis are formed. Thereafter the data and methodology will be described in a more extensive matter. Finally, the results will be described and this thesis will end with a conclusion together with limitations and recommendations for future research.

2. Theoretical Framework

As discussed in the introduction, the main purpose of this thesis is to find out if the volatility effect still exists in the U.S. market over more recent time periods. In other words, is it still true that low volatility stocks outperform the riskier stocks in the U.S. market? And what are potential drivers of the effect? This part of the thesis will give an overview of existing literature with regards to the volatility effect and will form hypotheses based on the previous literature in the field.

2.1. The Founders

The main researchers/founders of the volatility effect have researched the effect in quite an extensive matter. The benchmark paper for the methodology is the paper in which Blitz & Van Vliet (2007) introduced the volatility effect. The time period of this research is the period 1985-2006 and they investigated multiple markets. The authors show that the lowest volatility decile generates the high Sharpe Ratio, mainly because of the low volatility in the denominator. The results remain strong in the regional level, and also after controlling for multiple factor (FF3 factors, among others). This result was very contradicting to the common belief that higher risk stocks yield higher returns, and the volatility anomaly was born.

After the first study, the authors gained a lot of attention and they have performed several follow-up studies thereafter. The first thing they investigated after the first study was whether the low volatility anomaly also exists in emerging markets (Blitz et al., 2013). Emerging markets are getting more attractive for investors due to the rapid growing economies, which makes this study practically relevant as well. The authors use a similar methodology as in the first paper, and they find a negative relationship between volatility and return in developing markets as well. To put differently, the low volatility anomaly also exists in developing economies and outperforms high risk stocks significantly. The researchers even conclude that the anomaly seems to grow larger over time, which is quite surprising due to the profitable nature of the strategy. Another important conclusion they draw is that the returns from the low volatility effect in emerging compared to developed countries are not related, which means that it is not likely that there is a common factor that drives the anomaly.

In a later paper, the same authors tried to find some explanations for the volatility effect, and they published an overview of potential explanations based on the CAPM assumptions (Blitz et al., 2014). The main explanations for the effect (based on CAPM assumptions) are four-fold:

1. The CAPM assumption of no constraints. Leverage constraints, regulatory constraints, and short selling constraints. These types of constraints can make sure CAPM does not longer hold and that low volatility stocks outperform riskier stocks.
2. Assumptions of investor utility. Differentiating in relative utility, agency effects, a preference for skewness, and crash aversion are also several examples of why the CAPM is not fully able to explain the anomaly.
3. One-period model: the assumption of one period might not be correct, causing the CAPM to fall short in explaining the volatility effect.
4. Complete information: attention grabbing stocks, the representativeness bias, mental accounting, and overconfidence are also several factors that could potentially explain the high returns for low risk stocks.

These are the potential factors that the authors mention that could potentially be reasons for the anomaly to exist, for deeper explanation for each of the factors I invite you to look at the paper itself. The authors do not draw a final conclusion regarding which explanation is the most likely to have an effect on the anomaly, but they give a nice overview of potential factors.

The final paper by the founders of the low volatility anomaly revisited their own results in a more recent paper (Blitz et al., 2019). In this paper they investigate multiple markets in multiple time periods and they conclude that the anomaly is still present in today's markets worldwide. As they say themselves: 'A low-risk approach has been effective for as far as the data go back, across all major stock markets, from developed to emerging, within and across industries, across various market regimes, and using different measures of risk.' Overall, the anomaly appears to be persistent over time and it seems to still exist.

2.2. Further Evidence

Besides the founders of the effect, there are plenty of other researchers that have also investigated the results and that found similar results. An example of such a study is the one by Dutt & Humphery-Jenner (2013), which try to find drivers of the low volatility anomaly. In line with previously mentioned studies, they also find that the anomaly exist in both developed and emerging markets in their study. Furthermore, they state that low volatility firms have higher operating performance, which may cause the higher stock returns. Another potential explanation they mention is limits to arbitrage, which may cause the anomaly to persist.

Additional evidence in favor of the low volatility anomaly is provided by Maguire et al. (2017) who investigate the aggregate volatility in a portfolio instead of just the performance of low volatility stocks. They specifically investigate portfolios that have been optimized to minimize aggregate volatility, and conclude that these types of portfolios outperform the market as well as the S&P Low-Volatility Index. The findings provide further support for a volatility effect.

2.3. Contradicting Results

Obviously, it is also important to see the other side of the coin. There have also been papers that contradict the results of the low volatility anomaly. One of such papers is the one by Li et al. (2014) who find that the results of the low volatility strategy over the period of 1963-2021 where not as large as widely believed. The authors conclude that the significant results disappear when penny stocks are excluded and when transaction costs are taken into account. Because of liquidity needs the authors mention that a lot of rebalancing is necessary, which causes the potential profits to disappear.

A follow up study by the same authors tries to find whether the previous gathered results are due to systematic risk or mispricing (Li et al., 2016). They try to find out why the low volatility anomaly exists and why the results appear to be so persistent. The authors conclude that it is not likely that systematic risk is the driver of the anomaly in their sample, the relatively high returns cannot be fully attributed to a systematic risk factor. As they conclude themselves: ‘This finding suggests that the excess returns are more likely driven by market mispricing connected with volatility as a stock characteristic.’

Another result that is interesting to mention is the paper by Burggraf & Rudolf (2021) who investigate the profitable nature of the low volatility anomaly in the cryptocurrency markets. The authors construct long-short portfolios of over a 1000 cryptocurrencies from 2013-2019 and they find no significant results for a low volatility premium in their sample. The crypto markets seems to be the only market in which the low volatility anomaly doesn't exist, in contrast to the stock market and the bond market, among others.

Overall, there are many researchers that have investigated the profitability of the low volatility anomaly, and almost every one of the researches have concluded that the anomaly exists and is profitable. Especially since transaction costs in this research will be ignored, the first hypothesis will be the following:

Hypothesis 1: The returns gathered from exploiting the low volatility anomaly still exist in the U.S. over the period 2010-2020 and the gathered results outperform the general market in the same period.

2.4. Drivers of the Anomaly

An important question that flows from the low volatility anomaly: how can it be possible that the anomaly still exists after all these years? And what drives the anomaly? Important capital pricing models are often linked to these kind of strategies to verify whether there is not a common factor that drives the gathered results. The Fama-French 3 Factor Model (Fama & French, 1993), and the 5 Factor Model (Fama & French, 2015) are often used to check for potential drivers.

There are researches who have investigated whether the 3 Factor Model can explain the low volatility anomaly. Blitz (2016) links the 3 Factor Model to the low volatility returns and concludes that the model cannot explain the gathered returns from exploiting the volatility anomaly. Furthermore, Frazzini & Pedersen (2014) link the 3 Factor Model to their famous 'betting against beta' strategy. Their paper concludes that high beta stocks are associated with low alphas in the multiple equity markets, and try to find out why this works. One of the things that the authors investigate is whether the 3 Factor Model can explain the gathered results. They also link it to the 4 Factor Model, which includes a momentum factor. Both models are not capable of explaining the anomaly.

On the contrary, there are some papers who link the 5 Factor Model to the volatility anomaly and find that this model is capable to explain the anomaly in a significant way. For instance, Novy-Marx (2014) investigates why the defensive strategies has yielded such profitable returns in the past. The author acknowledges the fact that the returns cannot be explained by the 3 Factor Model, but concludes that the profitability factor is crucial in explaining the gathered returns.

Additionally, Fama & French (2016) link their recent 5 Factor Model (adding a profitability and investment factor to their existing pricing model) to the low-volatility anomaly. The well-known authors conclude that their new model is able to explain the returns on the low volatility portfolios.

Because of the criticism on the low volatility anomaly by the previously mentioned authors, the founder of the anomaly felt necessary to react (Blitz & Vidojevic, 2017). The authors here argue that the conclusions by the mentioned papers are premature because of the lack of empirical evidence. Furthermore, the authors find that exposure to market beta is not rewarded with a positive premium, also after controlling for the Five Factor Model. Overall, they conclude (based on their own research) that the Five Factor Model does not explain the gathered returns of the volatility effect.

Overall, there appear to be different results in different researches regarding the volatility anomaly and whether it can be explained by existing pricing models. Because of the strong case that the founder makes in his reaction paper (Blitz & Vidojevic, 2017), the second hypothesis will be the following:

Hypothesis 2: Existing pricing models (the 3 Factor Model and the 5 Factor Model) do not have a significant effect on the returns that can be realized by exploiting the volatility anomaly in the U.S. over the period 2010-2020.

3. Data

The data in this research is similar compared to studies related to the volatility effect (such as Blitz & Van Vliet (2007)). The sample constructed consists of all the stocks in the U.S. over the period January 2010-December 2020, listed on either the NYSE, AMEX, or NASDAQ over the specified time period. The daily price data, as well as the monthly price data, is obtained from the database CRSP. This database is widely used in financial and academic research and is one of the largest databases regarding historical stock prices in the U.S.. An important aspect of the database is that it is formed to avoid survivorship bias (the bias in which defaulted firms are not taken into account, which can result in wrong conclusions), so this bias will not exist in this research.

Two main databases are used in this research: a daily stock price database and a monthly stock price database. The daily stock price database is used to calculate the daily volatility of the stock price for the past 3 years, this is needed put the stocks in a certain decile based on volatility. Further in the process, the monthly data and the daily data is merged together. The monthly data is used for the returns of the decile portfolios, while the daily data is the basis for the forming of the portfolios.

The final dataset that is used is the dataset by Kenneth French. This dataset keeps track of all the Fama-French three/five factors over the years. Furthermore, the risk-free rate over the past years is gathered from this database. The database provides each of the factors on a monthly basis, which will be used to check for potential effects that the factors might have on the low volatility returns. The specific factors for these models will be further clarified in the methodology section.

4. Methodology

4.1. Data Transformation

Besides the merging of the data, there were several other steps that were useful to make sure that the dataset is representative and free of any biases. First, there were some missing or negative values for both market cap and stock price for several securities. For the sake of completion, these observations were deleted from the dataset.

Besides the removal of the negative observations for stock price, penny stocks were also removed because of the unique characteristics of these type of securities. Penny stocks are defined in this thesis as stocks which never exceed the price of $5. These stocks are excluded because these are mostly very risky securities with large volatility and with very low liquidity, which makes it difficult to analyze. The lack of liquidity here is the main reason that these securities are not taken into account.

Finally, the bottom quartile of average market cap is deleted from the data as well. Similarly to penny stocks, these kind of small cap stocks tend to be very illiquid and risky stocks. These stocks have the potential to erupt the decile portfolios and are therefore deleted from this dataset.

Finally, the dataset consists of 6279 firms over the sample period (2010-2020). As mentioned, firms that have defaulted are also present in the data, which makes the dataset free of survivorship bias. Furthermore, the removal of both penny stocks and micro-cap stocks makes sure that there are no illiquidity issues in the sample. The descriptive statistics of the sample can be seen in Table 1.

DESCRIPTIVES	**OBS**	**MEAN**	**STD**	**MIN**	**MAX**
RETURN	426,109	1.01%	12.82%	-98.39%	956%
MKTCAP	427,850	6,189,171	24,200,000	111,680	696,000,000
PRICE	425,118	101.32	3815.67	0.0332	347,815

Table 1: descriptive statistics for all the observations for the stocks in the data. The return is the monthly return for the stocks over the sample period, mktcap stands for the average market cap for each of the companies, while price is the stock price over the sample period. Differences in observations are mainly due to missing values.

4.2. Methodology

Now that the dataset is entirely clear, this section will focus on the methodology. As mentioned before, the paper by Blitz & Van Vliet (2007) will serve as a benchmark for the methodology of this thesis. This paper will form the benchmark for this study, providing a nice foundation for exploring the low volatility anomaly. This part will explain how the portfolios are formed and how the statistical tests were performed.

The first thing that is crucial to determine is the volatility. A small difference in the volatility measure related to the previously mentioned paper is that this thesis uses daily volatility instead of weekly volatility. The daily volatility is used because this gives a more accurate image of the volatility of a stock. The daily volatility is captured by using a rolling window for the volatility over the past 3 years, which makes it a reliable measure of daily volatility. In other words, the volatility measure in this study is formed by taking the average daily volatility over the past 3 years before the particular observation.

After the volatility measure was constructed, the daily stock price file was merged with the monthly stock price file, since the monthly returns (in excess of the risk-free rate) will be used to identify differences between the deciles. Monthly data is used to construct equally weighted portfolios based on the volatility measure described. In short, the stocks are ranked in deciles based on daily volatility and thereafter the monthly returns for each of this deciles will be computed. The monthly file gives a more detailed overview of the dataset, since the daily dataset contains a lot of unnecessary observations. The only thing that is taken from the daily dataset is the volatility measure, which is the basis for the portfolios. Since the monthly data gives a more structured overview, this is used for the remaining analysis.

After the deciles are computed, the main thing to do is to identify the differences between the first and tenth decile (first decile being the lowest volatility decile and tenth decile being the highest volatility decile). This will be done by constructing a long-short portfolio, going long in the first decile and going short in the tenth decile will show whether there is a significant outperformance of the first decile and whether using the volatility anomaly was still profitable in the U.S. over the 2010-2020 period. The first decile is used as a benchmark since this should be the best performing decile, following the study by Blitz & Van Vliet (2007).

This approach is mostly in line with the paper mentioned above with some subtle tweaks, which ensures that the methodology is viable. As mentioned in the theoretical framework, the expectation of this study is that the first decile (lowest volatility stocks) will significantly outperform the tenth decile (highest volatility stocks). In other words, the long-short portfolio should yield positive, significant returns.

The next step in this research is that two well-known pricing models will be used to check for robustness of the results. This research will use both the Fama-French Three and Five Factor Models to check for potential drivers of the results and for potential relationships between the long-short portfolio and the pricing models. A standard regression methodology will be used to investigate this. The regression equation for the Fama-French Three Factor Model will thus be as follows:

$$R_i - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \varepsilon_i \qquad (1)$$

The dependent variable (left part of the equation) is here the return of the low volatility strategy (long-short portfolio) reduced by the risk free rate (R_f). The alpha in the equation will show what the returns of the volatility effect will be after controlling for the FF3 factors. Further, the R_m – R_f part of the equation stands for the general market return minus the risk-free rate (the market premium). SMB stands for Small Minus Big, which try to capture the difference in stock returns between small and big firms. HML stands for High Minus Low, which captures the difference in stock returns between high book-to-market value and low book-to-market value. These factors (as well as the factors from the next regression) are gathered from the Kenneth French database.

Next to the Fama-French Three Factor Model, the more recent Fama-French Five Factor Model will also be used to check if these factors can explain the returns from the low volatility anomaly. This regression equation will be as follows:

$$R_i - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon_i \qquad (2)$$

As can be seen from formula (1), the Five Factor Model uses the three factors previously described, but also adds two additional factors. The RMW factor is a profitability factor (Robust Minus Weak) and CMA is a factor capturing investment intensity (Conservative Minus Aggressive). These two factors are added to the Fama-French Three Factor Model to check if the additional factors might be able to explain the low volatility returns.

5. Results

To form a conclusion on the first hypothesis it is important to identify the returns of the decile portfolios. Table 2 shows the results of the excess returns (returns minus the risk free rate) sorted on the past 3-year volatility. This table also shows, besides the excess returns, the standard deviation of the portfolios and the accompanied Sharpe ratios (which can be used to compare the performance of the portfolios).

LOW VOL	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Excess Return	0.45%	0.91%	0.94%	1.01%	0.99%	0.97%	1.20%	1.20%	1.51%	1.58%	-1.13%
Standard Deviation	1.95%	3.74%	3.83%	4.39%	4.95%	5.15%	5.50%	6.33%	7.74%	8.41%	7.34%
Sharpe Ratio	0.23	0.24	0.25	0.23	0.20	0.19	0.22	0.19	0.20	0.19	-0.15

Table 2: The Excess Return and the Standard Deviation of each of the decile portfolios over the sample period 2010-2020. D1 stands for the portfolio with the lowest volatility (measured by daily volatility over the past three years), and the portfolios are sorted on volatility. The Sharpe Ratio is defined by the Excess Return divided by the Standard Deviation.

When looking at the table, the first thing that catches the eye is that the returns of the decile portfolios have an upward trend. Generally speaking, the higher the volatility, the larger the returns for the portfolios in this sample. When comparing the excess returns of decile 1 versus decile 10, one can see that the highest volatility portfolio outperforms the lowest volatility portfolio by 1.13% per month, which is quite substantial. Is it noteworthy to see that this is entirely in line with the general theory that higher risk leads to higher returns, and that there is not an anomaly in this sample.

The volatility is constructed to increase over the deciles, which makes it interesting to look whether the higher returns actually leads to a higher Sharpe ratio as well. The Sharpe ratio can be seen as a measure to compare different portfolios (using excess return and volatility). Therefore, it is more interesting to look at the Sharpe ratios rather than the dry returns of the portfolios.

As the table shows, the Sharpe ratio stays more or less the same over the different portfolios. The Sharpe ratio ranges between 0.19 and 0.25, where decile 3 has the highest Sharpe ratio of all the deciles and decile 6, 9, and 10 have the lowest Sharpe ratio. Following the low-volatility anomaly, the expectation of the study was that the returns, as well as the Sharpe ratio would be the highest for the first decile portfolio. As one can see, this is not the case over this sample period.

To further go into this and to formally show whether there are significant differences between the two decile portfolios, a standard t-test is performed to identify these differences. The t-test shows statistically (with a p-value of 0.000), that there are significant differences between the first decile portfolio and the tenth decile portfolio, and that the tenth decile portfolio yield statistically significantly higher returns. This shows in a more formal matter that there is no volatility effect present in this dataset.

In other words, the first hypothesis: *the returns gathered from exploiting the low volatility anomaly still exist in the U.S. over the period 2010-2020 and the gathered results outperform the general market in the same period* is rejected based on the statistical evidence.

Thereafter it is important to identify what the low volatility effect is after controlling for several other factors. As described, the Fama-French 3 Factor Model and the Fama-French 5 Factor Model are regressed on the long-short portfolio to see what the results are after controlling for these well-known asset pricing models. Since the hypothesis investigates whether there is a relationship between the volatility anomaly and the Fama-French Factors, this thesis will focus on researching the long-short portfolios, and not really on the other decile portfolios because the other portfolios are not quite relevant for investigating the volatility anomaly.

Surprisingly, there appears to be a positive alpha for the long-short when controlling for both pricing models. Regressing the long-short portfolio on the factors results in a positive, significant alpha with a monthly return of 0.38%. This means that the returns of the long-short portfolio are positive after controlling for the Fama-French Three Factor Model.

Further, when looking at the Fama-French Five Factor Model, the alpha is slightly higher with an average monthly return of 0.41%. Similar to the Three Factor Model, all the separate factors have a significant effect on the return of the long-short portfolio.

The alpha is also statistically significant, which leads to the same conclusion as with the Three Factor Model, which is that there are positive returns after controlling for this asset pricing model. The R-Squared of the model with the Fama-French Three Factor Model is the same as with the Five Factor Model at 9.8%.

Overall, the Fama-French adjusted alphas are positive, while the general alpha is negative over the sample. The market beta is significant and negative over both models, which makes sense if the low volatility stocks yield higher returns than the high volatility stocks after controlling for each of the Fama-French factors. In summary, after controlling for the Fama-French pricing models, the excess returns of the long-short portfolio are significant and positive, which is contradicting to the results based on the Sharpe ratios of the portfolios. In conclusion, there appears to be a significant relationship between the returns of the long-short portfolio and both asset pricing models tested.

In short, the second hypothesis: *existing pricing models (the 3 Factor Model and the 5 Factor Model) do not have a significant effect on the returns that can be realized by exploiting the volatility anomaly in the U.S. over the period 2010-2020* is rejected. The expectation of this study was that the pricing models could not explain the returns of the long-short portfolio, but the previous part shows that it actually has a large effect on the returns that could be achieved by exploiting the volatility anomaly. Actually, after controlling for the 3 Factor Model and the 5 Factor Model, the sign of the returns from the long-short portfolio changes from negative to positive. This shows that the pricing models have a significant impact on the returns achieved by engaging in a low volatility strategy, and therefore the second hypothesis is rejected.

The results of this study are not entirely in line with the study by Blitz & Van Vliet (2007), since the authors find in their paper that the lowest volatility stocks outperform the higher volatility stocks (based on absolute return), which is not the case in the sample period of this thesis. Furthermore, Blitz & Vidojevic (2017) showed that the Fama-French pricing models did not have a significant relationship to the volatility effect, which is also rejected in this paper.

6. Conclusion

This thesis investigates whether the returns from exploring the low volatility anomaly still exist in the U.S. over the period 2010-2020, and use the paper by Blitz & Van Vliet (2007) as a benchmark for the methodology, with some slight alterations. This part will conclude the hypothesis and give an answer to the following research question:

'To what extent does the low-volatility anomaly still exist in the U.S. market over the period 2010-2020?'

Two separate hypotheses were formed to answer this research question, with the first one forming a long-short portfolio and the second one by comparing the short-long portfolio to the Fama-French asset pricing models.

Firstly, the data is split into deciles based on past three year daily volatility. Thereafter this daily data measure is merged with a monthly data file to check for the average return for each month for every decile. The long-short portfolio is then formed by going long in the first decile (the decile with the lowest volatility stocks), and going short in the tenth decile (the decile with the highest volatility stocks). The average monthly return by engaging in this strategy is -1.13%, which means that the highest volatility stocks have a larger return relative to the lowest volatility stocks.

In addition, the long-short portfolio is compared to the Fama-French Three Factor Model, as well as the Fama-French 5 Factor Model to verify if there is a relationship between the volatility effect and the pricing models. A regression methodology is used to check for the potential relationship between the Fama-French factors and the long-short returns. Surprisingly, the alpha is significant and positive after controlling for these factors. The alpha amounts to 0.38% with the Three Factor Model and 0.41% with the Five Factor Model. This means that the long-short portfolio and the asset pricing models from Fama and French have a significant relationship, and that the pricing models have the potential to explain previous results.

Overall, the strategy by forming a long-short portfolio based on the three year past daily volatility and going long in the lowest volatility decile, while going short in the highest volatility decile, appears to have lost profitability over the more recent time periods. The Sharpe Ratio of both strategies is similar, while the absolute returns of the highest volatility portfolios is more than one percent higher. Furthermore, there appears to be a significant relationship between asset pricing models and the volatility effect. In conclusion, hypothesis 1 as well as hypothesis 2 are rejected over the time period investigated.

This thesis contributes to existing literature by altering data and methodology slightly. The first important alteration is the more recent time period, which could be the reason for the less profitable results. It could potentially be the case that the anomaly has been arbitraged away over the more recent time periods, since the anomaly is widely documented. Furthermore, penny stocks, as well as micro-cap stocks are excluded from this study. The results from this study could suggest that penny stocks and micro-cap stocks are the main drivers for the volatility effect in previous papers.

Another important sidenote of this study is the absence of transaction costs. The strategy requires monthly rebalancing of stocks, which can make the transaction costs substantial. It is possible that transactions costs erode the excess returns of the portfolio due to this frequent rebalancing. However, there is no extra value to add transaction costs to this research, since the long-short portfolio already yields negative returns, even without transaction costs. In strategies that do appear to be profitable, it might be more relevant to look into transaction costs.

A potential limitation of this research is that only the U.S. market is investigated. The main researchers investigating the volatility effect are almost all in the U.S., which could lead to large attention by U.S. investors, this could potentially result in lower returns for exploring the low volatility anomaly, because the effect might be arbitraged away.

These limitations are simultaneously suggestions for future research, it might be useful to look into different markets in the more recent time periods, to verify whether the effect exists in potentially less efficient markets (emerging markets for example). Further, if there appear to be significant results in other time periods or in other markets it might be very useful to include transaction costs in the research, since this is quite important for investors in practice.

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