The Low Volatility Anomaly:

Outperformance of Low Risk Stocks, and The Role of Operating Performance as a Driver

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Study Program: Master Finance

Thesis Type: Master Thesis

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Date: 01-12-2015

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1. Introduction and problem formulation

High risk, high return, that is how the equity market should work according to the modern portfolio theory. Investors should be compensated for bearing risk by earning a higher expected return. Textbooks all around the world on corporate and investment finance teach students that more risk leads to greater expected return. Widely accepted models, by practitioners and academics, such as the capital asset pricing model (CAPM), turn out to be controversial. Research of the past 25 years, show that the return for bearing more risk is negative. The evidence provided by this research argues that increasing risk leads to lower expected return. Low volatility portfolios, or portfolios consisting of low beta stocks, tend to outperform the riskier ones, also known as the low volatility anomaly. The existence of the anomaly is demonstrated within all observable equity markets and for periods up to 60 years back in time. The anomaly can be considered as an extensive appearance, so it is scientifically relevant to investigate the existence and possible drivers of it.

In this paper, the following research question will be answered; does the low volatility anomaly exist in developed and emerging markets, and what is the role of operating performance? This question will be answered in two parts. First, the existence of the anomaly in developed and emerging markets will be investigated, and then, I examine whether operating performance is a driver of the volatility effect for the total dataset. I find that low volatility portfolios outperform high volatility portfolios in developed markets, as well as in emerging markets. Further, I find a relationship between volatility and operating performance, where low volatility firms experience strong operating performance, and vice versa. In addition, I show that operating performance is related to the low volatility effect, especially, that high volatility stocks have lower operating performances, which clarifies why high volatility stocks earn lower stock returns.

Since the 1970s, CAPM's shortcomings in predicting the relationship between risk and return have been revealed by several papers. One of the first to question the traditional risk-return relationship were Black, Jensen and Scholes (1972). They show that high beta stocks experience much lower returns than predicted by the CAPM, which means that in fact the relationship between risk and return is flatter. Later on, Fama and French (1992, 1993) argued that not only systematic risk determines stock return. They adjusted the CAPM and added additional factors to the initial model, including market return, size and value. This multifactor model improves the predictions of the expected stock return. Also, Fama and French do not support the positive relationship between stock return and beta. As a result of these outcomes, many people have concerns about the empirical validation of the CAPM. In more recent studies, previous results have been confirmed, and it is shown that low risk portfolios have higher returns than high risk portfolios, irrespective whether risk is being measured by standard deviation or beta. Baker and Haugen (2012) show that the low volatility effect exists in all observable markets around the world between 1990-2011. In addition, Frazzini and Pedersen (2012) argue that the low volatility effect not merely exists for equity markets, but also within bond, future and credit markets. Based on these results, it can be concluded that the volatility anomaly is an extensive phenomenon, in terms of geographical reach, asset classes and time. Research of the last few years did not only focus on proving the existence of the anomaly, but also on causes of the anomaly. Baker, Bradley and Wurgler (2011) argue that the irrational behavior of investors lead to an excessive demand for risky stocks, which in turn decreases the stock return of these risky assets. The persistence of the anomaly is then explained by the limits on arbitrage. Because of this, institutional investors are not allowed to deviate from their benchmark, and thus are not able to profit from any mispricing caused by irrational investors. Other papers, that provide explanations for the existence of the anomaly, consider behavioral biases, agency issues, regulatory constraints and operating performance as drivers of the low volatility effect.

The drivers of the low volatility anomaly, provided by other papers, have to a different extent effect on developed markets and emerging markets. Different markets in different countries have other laws and stock exchange rules. This could affect factors such as benchmark constraints, admission of leverage/short-selling and the investing process of institutions. Therefore, it is essential to test the existence of the anomaly for different regulatory environments. Thus, in order to examine the volatility effect, I make a clear distinction between developed and emerging markets. The developed markets exist of France, Germany and the Netherlands, while the emerging markets consist of Czech Republic, Hungary, Poland and Russia. I find, for both markets, after constructing monthly value-weighted quintile portfolios based on a two-year moving volatility, that the lowest volatility quintile portfolio has a higher return than the highest volatility quintile portfolio. However, the volatility effect for emerging markets seems to be weaker, as expected. Emerging markets have a higher proportion of retail investors, who are less constrained to follow a specific benchmark. This means that these investors have more possibilities to deviate from their benchmark and invest in low risk stocks in order to benefit from their potential excess profits. In addition, most commonly followed equity index benchmarks contain the safest stocks, and foreign investors who want exposure to emerging market growth invest especially in large stocks, which are also the least volatile stocks. Therefore, investors in emerging markets might be able to arbitrage-away any low volatility effect. As a result, the demand for low volatility stocks in emerging markets is higher than it is for developed markets, which will lower the returns for low volatility stocks. Thus, based on the limits on arbitrage, the low volatility anomaly might be weaker in emerging markets.

As a possible additional driver of the anomaly, I examine the role of operating performance for the combined dataset, consisting of developed and emerging markets. The idea behind operating performance as a driver of the volatility effect is that; stable and predictable firms are more likely to be low risk firms, which makes it easier and cheaper for those firms to obtain capital. This spare capital can be used to invest in profitable projects which eventually will result in stronger operating performances for these firms. Subsequently, when the high operating returns from the investments are paid off or when the risk of the investment decreases and the payoff becomes more certain, these firms will experience an increase in stock return. Strong operating performance could increase stock return in several ways. First, assume that strong operating performance is unexpected. There should be a positive relationship between stock returns and positive earnings surprises. In an efficient market, after the occurrence of an unexpected strong operating performance, the stock return of a firm will increase as the market evaluates the price of the stock. Second, assume that strong operating performance is uncertain instead of unexpected. Investors might expect stable firms to experience strong operating performance, but it is not guaranteed. The risk of low operating returns will make the reaction of the market to its expectations more damped. As the high operating returns become more certain over time, the uncertainty of the expectations decrease, and cause the market to increase the stock price. Thus, strong operating performance experienced by low volatility firms (due to cheaper access to capital) could result in higher stock returns and explain the low volatility anomaly. I use several regressions to test the relationship between operating performance and volatility, and reversed, as well as the relationship between operating performance, volatility and stock return. I find a significant relationship between low volatility and strong operating performance and that operating performance partially explains the low volatility effect.

The rest of this paper is organized as follows. In chapter 2, literature on the risk-return relationship will be reviewed. In chapter 3, the data and methodology used to investigate the low volatility anomaly and its results will be discussed. In chapter 4, the data and methodology used to examine the role of operating performance as a driver of the anomaly and its results will be discussed. In chapter 5, the research question will be answered and concludes.

2. Literature review

The more risk a portfolio contains, the higher the expected return will be. That is how the stock market should work, investors that are willing to bear greater amounts of risk should be compensated for this in terms of higher returns. At least that is what studies on portfolio theory and investing from the past teach us, such as the CAPM. Now, however, there are some studies that reveal contradicting outcomes, showing us that the relationship between risk and return does not hold anymore. Research from the last 25 years proves that portfolios with low risk outperform high risk portfolios, with other words, increasing your risk actually decreases your return, also known as the low volatility anomaly. In this section, the early papers that challenged the risk-return relationship and papers that prove the existence of the anomaly will be reviewed, as well as drivers of the anomalous relationship.

2.1 The classical risk-return relationship and its violations

The classical way to think about risk and return is by means of the CAPM described by Sharpe (1964). This paradigm is a set of predictions concerning equilibrium expected returns on risky assets. More specifically, it predicts the expected return of a financial asset given its exposure to systematic risk. The model also takes into account the asset's beta, which is a measure of market risk, the expected return of the market and a theoretical risk-free asset. Only systematic risk is priced, because all other kinds of risk can be diversified away. The stock's covariance with the market determines the expected return. Thus, according to the model, there should be a positive relationship between systematic risk and expected return of a security. The following underlying assumptions have to be made in order to use the model: Investors hold only efficient portfolios (portfolio consisting of the highest possible return for a given level of volatility), they can buy and sell securities at competitive market prices without taxes or transaction costs, all investors have homogeneous expectations regarding the security return's parameters, and all investors can lend and borrow at the risk-free interest rate.

One of the first pieces of evidence against the traditional risk-return relationship was found by Black, Jensen and Scholes (1972). In their study they developed an alternative CAPM equation by relaxing the assumption of risk-free borrowing and lending. This adapted two-factored form model was tested using a time series test and was found to be empirically more robust than previous models. The extended model predicts that the risk and return relationship is much flatter than initially predicted by CAPM, high-beta stocks had negative alphas and low-beta stocks had positive alphas. In another study, conducted by Haugen and Heins (1975), even an inverted relationship between risk and return was found. Again, the traditional hypothesis that bearing risk is compensated by earning greater returns did not hold. The results show that long-term stock portfolios with smaller amounts of risk in monthly returns have experienced greater returns than the riskier long-term stock portfolios. In addition, Fama and Macbeth (1973), Miller and Scholes (1972), Blume and Friend (1973), and Haugen and Baker (1991) all found similar results that refute the classical risk-return relationship predicted by CAPM.

After poor empirical performance of the CAPM, Fama and French (1992, 1993) invented a new model that improved the captured cross-sectional variation in average stock returns. This new model, called the three-factor model, added two extra factors, that proxy for exposure to systematic risk, to the traditional model. Size and book-to-market ratio were the chosen factors that on past evidence seem to predict average returns, respectively denoted as SMB (Small-Minus-Big) and HML (High-Minus-Low). The risk that is probably captured by these factors is not immediately obvious, but, for example, it can be argued that firms with high book-to-market ratios are more likely to be in financial trouble and that small stocks may be more sensitive to fluctuations in the market. The tests performed by Fama and French do not support the traditional prediction that average returns and market betas are positively related over the 1963-1990 sample period. Instead, in addition to beta, they find that stock risk is multidimensional. Thus, the average returns of a security are predicted more accurately by the multifactor model consisting of market return, size and value.

After the development of the three-factor model, even a fourth factor was added to the model for stock return behavior. The momentum effect means that stocks that have performed well in the past (six months to a year up to the present) will tend to outperform in the future. Carhart (1997) found that past winners continued to outperform and introduced the momentum factor, denoted by WML (Winners-Minus-Losers). The momentum effect was used to evaluate the performance of mutual funds. The implementation of the momentum factor into the original three-factor model resulted in a fourth-factored model that can be used to determine the stock’s performance.

The outcomes of previous researches are inconsistent with the efficient market hypothesis, which implies that securities will be fairly priced and higher returns can only be earned by taking above-average risks. This empirical prediction has been hard to support based on historical stock return data. A risk-return relationship as it is explained by CAPM has been deteriorated in the last few decades. Some anomalies tend to disappear or weaken when time passes, while this effect seems to be persistent over time. As a result, many people have concerns about the empirical validation of the CAPM.

2.2 Evidence for the low volatility effect in more recent studies

More recent studies have continued to build on previous results and confirm the existence of an anomalous relationship between risk and return. In these more recent studies it is shown that low risk assets outperform risky assets for multiple kind of asset classes and markets worldwide. The most common way to demonstrate the existence of the anomaly is by creating portfolios based on historical return volatility quintiles/deciles and subsequently calculate the returns for these portfolios. The required outcome in order to show that the low volatility effect is present, is when the portfolio consisting of low volatile assets has a higher return than the most volatile portfolio. The papers differ from each other in the way they measure risk, which is by means of volatility or beta, the geographical region of interest, the specific asset class that is examined and the used time period.

In a paper by Ang, Hodrick, Xing and Zhang (AHXZ, 2006) it is examined whether or not aggregate volatility risk is a priced risk factor in cross-sectional expected stock returns, and if so, an estimation of the market's volatility price. They find a statistically significant negative price of aggregate volatility risk of approximately -1% per year. This finding is supported by economic theory. According to Bakshi and Kapadia (2003), the price of aggregate volatility risk should be negative. High correlation between an asset and market volatility risk provides a good hedge against market downturns, so the demand for these assets will increase among investors. As a result, the price for these assets will also increase which will lower their average returns. Thus, the increase in demand of risky assets for hedging purposes lead to an increase in price, which in turn will lead to decreasing returns for these assets.

AHXZ also examined the cross-sectional relationship between firm-specific volatility and expected stock returns. Some theories argue that investors should be compensated for holding undiversifiable risk in terms of higher expected returns. The idea behind these theories are that investors demand a premium for holding assets with high idiosyncratic risk, since this risk cannot be diversified away. For example, Merton (1987) argues that there is a positive relationship between idiosyncratic risk and expected return when investors fail to fully diversify their portfolios. But, this is not true according to AHXZ's results. They find that U.S. stocks with high idiosyncratic volatility earn very low future expected returns over the 1963-2000 period. The quintile portfolio with the lowest idiosyncratic volatility stocks outperforms the portfolio with the highest idiosyncratic volatility stocks by 1.06% per month. The low average returns of stocks with high idiosyncratic volatility is only partially explained by the high exposure of these stocks to aggregate volatility risk, which decreases their average returns, but this is not a complete explanation. The results on firm-specific risk yield a lot of ambiguities.

To check whether the negative relation between idiosyncratic volatility and future average return is not the result of a small-sample problem, AHXZ (2009) investigate if the anomalous relation exists in other markets than merely the United States. They find that stocks with high idiosyncratic volatility tend to have low average returns for the largest equity markets, namely those of the G7 countries. Alongside these markets, the negative relationship is also observed in a larger sample of 23 developed markets, which makes it more likely that there is an underlying factor behind the anomalous effect rather than a small-sample problem. In addition, the negative relationship in returns between stocks with high and low idiosyncratic volatility in international markets correlates strongly with the U.S. returns spreads between stocks with high and low idiosyncratic volatility. The large commonality in correlation also suggests that there is a broad underlying factor behind this, which is not easily diversifiable. Finally, market frictions, information dissemination, and option pricing are ruled out as explanations for the high idiosyncratic volatility and low average returns relation based on U.S. market data. Thus, AHXZ prove that the low volatility anomaly exists by providing evidence that the phenomenon holds for a longer U.S. sample and international equity markets, which is probably the result of underlying economic factors that require further investigation.

Contrary to AHXZ's findings, literature exists that shows that the realized volatility, used by AHXZ to examine its relationship with expected return, is not the correct variable to use for this purpose and thus their results are not valid to imply a negative relationship between idiosyncratic risk and expected return. Fu (2009) argues that idiosyncratic volatilities are time-varying, which means that past volatilities are inappropriate to explain expected returns. In order to examine the relationship between idiosyncratic volatilities and expected returns, one should also use expected idiosyncratic volatilities. The one-month lagged idiosyncratic volatility may not be a good estimate of expected idiosyncratic volatility. Since the expected idiosyncratic volatility is not observable and has to be estimated, Fu uses exponential generalized autoregressive conditional heteroskedasticity (EGARCH) models to do this. Then, regressions of monthly stock returns on these EGARCH estimates show that stock returns are positively related to the estimated conditional idiosyncratic volatilities, which are both economically and statistically significant. Hence, when expected idiosyncratic volatility is used, there is a positive relationship between idiosyncratic risk and expected return.

Where Fu's paper criticizes the use of realized idiosyncratic volatilities by AHXZ, Bali and Cakici (2008) also show that AHXZ's results are sensitive to the used data frequency, weighting of stocks to calculate portfolio returns, breakpoints to divide stocks into quintiles/deciles, and controlling for price, size and liquidity. Instead of using value-weighted portfolios, when equally-weighted portfolios are utilized, they find no evidence of a statistically negative relationship between firm-specific risk and expected returns. Further, quintile five with breakpoints, based on idiosyncratic volatility, used by AHXZ contains less than 2% of the market, while quintile one contains 54% of the market. This suggest that firms with high idiosyncratic risk are much smaller in size, measured by market capitalization, than firms with low idiosyncratic risk. By using alternative breakpoints, in order to balance the average market share between the quintiles, they find a very low and statistically insignificant difference between the top and bottom quintile portfolios. In addition, when they use monthly data instead of daily data to calculate firm-specific risk. They find, for all breakpoints and value-/equally-weighted portfolios, no evidence for a statistically significant relationship between idiosyncratic volatility and expected return. To test the robustness of AHXZ's results, they control for price, size and liquidity. By doing this, they remove stocks with the lowest price, lowest market capitalization and lowest liquidity. Again, they find no relationship between firm-specific risk and the cross-section of expected returns. The low volatility effect found by AHXZ is mainly driven by illiquid and small stocks.

In another paper, written by Huang, Liu, Rhee and Zhang (2007), AHXZ's results are explained by monthly stock return reversals. They find that the highest idiosyncratic volatility portfolio has the most explanatory power about the relationship between realized idiosyncratic volatilities and expected stock returns. The top quintile portfolio mostly consists of stocks with extreme performances, and these stocks experience the strongest return reversal in the next month. Since past winners have relatively a greater market capitalization than past losers in the portfolio, their return reversals decrease the value-weighted portfolio returns of the top idiosyncratic volatility portfolio during the upcoming month. As a result, the value-weighted portfolio return of the top idiosyncratic volatility quintile is lower than the bottom idiosyncratic volatility quintile. After controlling for both past returns and firm size, they find that the negative relationship between firm-specific risk and future return is no longer significant. This finding confirms that return reversal explains the negative relationship between idiosyncratic risk and expected return as found by AHXZ.

Thus, the negative relationship between idiosyncratic volatility and expected return supposed by AHXZ is controversial, regarding the outcomes of previous papers. Even, international evidence for the volatility effect provided by AHXZ (2009) is contradicted by Brockman, Schutte and Yu (2009). They use the same EGARCH model as used by Fu (2009) to estimate expected idiosyncratic volatility and provide evidence that the link between expected stock return and expected idiosyncratic volatility is also positive in international markets. These results support the theory that idiosyncratic volatility is positively related to expected stock returns. Disadvantage of the conditional idiosyncratic volatility method, which is also noticed by AHXZ (2009), is that the expected idiosyncratic volatility is unobservable and has to be estimated. Considering the conflicting outcomes of these papers, it can be concluded that the "results on idiosyncratic volatility represent a substantive puzzle" (p.262) as expressed by AHXZ (2006).

A related study, to the ones from AHXZ, by Blitz and van Vliet (2007), presents also empirical evidence for the low volatility anomaly. They find that U.S. stocks with low volatility earn significantly high risk-adjusted returns between the years 1986 and 2006. To obtain this result they constructed decile portfolios which consisted of stocks that were ranked on historical return volatility. Using this method, shows that the portfolio with the lowest historical volatility is associated with Sharpe ratio improvements, which means that this portfolio for a given level of volatility earns a higher return, and has statistically significant positive alpha, which is the excess return of the portfolio compared to the theoretical predictions of the CAPM. They also find in their sample a positive alpha for portfolios ranked on beta, but the effect is not as strong as for portfolios ranked on volatility. Besides this, they find that low risk stocks are specifically attractive compared to unattractive high risk stocks. Despite of the underperformance of low risk portfolios during up market months, it is offset by the outperformance of low risk portfolios in down months. The high risk portfolios exhibit precisely the opposite behavior, but the underperformance during down months cannot be compensated by the outperformance during up market months. The lowest decile portfolio consisting of the most risky stocks also experienced the largest maximum loss an investor in these portfolios could have been confronted with, namely a loss of -86%. Compared with the top decile portfolio consisting of the safest stocks this maximum loss was -26%.

Further, Blitz and van Vliet argue that the low volatility anomaly is a self-contained effect. They compared the volatility effect with size, value and momentum strategies and control for these factors. They find that the anomalous relationship between risk and return cannot be explained by one of these factors. They also extended their analysis to a broader scale and show that their findings apply to both global and regional stock markets. Specifically, the difference between the yearly alphas of global low versus high volatility decile portfolios is 12%. They also observe that the low volatility effect is not only existing in the United States, but also in the developed equity markets of European countries and Japan.

Consistent with the results of research on developed equity markets, Blitz, Pang and van Vliet (2012) find that the empirical relation between risk and return in emerging equity markets is flat or even negative as well. They find that the first quintile portfolio, based on a past three year volatility, outperforms the fifth quintile portfolio by 4.4% per year over their 1989-2010 sample period. In line with the previous study, they observe that the volatility effect is stronger when volatility, instead of beta, is used to measure risk. Emerging markets provide some additional risk premiums in terms of political risk, liquidity risk and agency risk, which makes them more attractive for investors who want more exposure to risk. In combination with their fast growing economies, reflected by the increased weight of emerging markets in the MSCI All Countries index, makes it particularly interesting for investors and research. The analysis of the low volatility effect in emerging markets is also relevant for the empirical robustness of the effect, in order to disprove various critiques related to data mining, which is purposefully looking for statistical relationships which comply with the characteristics of the anomaly. Since the low volatility effect also holds for emerging markets it can be concluded that there exists a significant and distinct volatility effect.

Another interesting perspective of analyzing emerging markets is to see how these markets behave with respect to developed markets. By relating the volatility effect in both markets, it can be assessed whether the effects are driven by a common factor or not. The correlation between the volatility effect in emerging and developed markets is moderately positive within the U.S., Europe and Japan, which means that emerging markets' low volatility effect is independent from the low volatility effect in developed markets. This finding makes it less likely that the volatility effect can be explained by a global systematic factor.

Mainly, research of the last few years, show that the low volatility anomaly is persistent for many years, it exist for different kind of asset classes, and that the effect is comprehensive. In Baker, Bradley and Wurgler (2011) it is shown that over a period of 40 years (between 1968-2008), low volatility and low beta portfolios outperformed high risk portfolios, regardless of whether risk is measured by volatility or beta. They also find that, during a crisis, when an insurance payment is the most welcome, an investor in the most risky stocks end up paying an insurance premium only to lose even more. Remarkably, if an investor invested in the most volatile portfolio over the last 40 years he or she would have incurred even a total loss in real terms. Baker et al. (2011) “believe that the long-term outperformance of low-risk portfolios is perhaps the greatest anomaly in finance” (p.43).

The anomaly does not only occur in equity markets, but is also demonstrated for Treasury bond, corporate bond, futures and credit markets by Frazzini and Pedersen (2010). For these markets they find that securities with low risk exhibit high risk-adjusted average returns. The low volatility effect is not only widespread between financial asset classes, but is also a worldwide phenomenon. According to Dutt and Humphery-Jenner (2012), who find evidence of the volatility effect in all four of their subsamples, consisting of emerging Asia, emerging EMEA (Europe Middle, East and Africa), Latin America and developed markets excluding the U.S. and Canada. Their key finding is that the average return for the lower quintile portfolios is higher than for the higher quintile portfolios, whether they used equal-weighted or value-weighted portfolios. Moreover, Baker and Haugen (2012) argue that the low volatility effect even exists in all testable emerging and developed markets individually, which consist of 21 developed and 12 emerging markets, over the time period 1990 to 2011. They find that low-risk stocks outperform high-risk stocks for each individual country as well as all for all countries combined.

Since the anomaly extends to all stock markets around the world and exists for several securities, it can be concluded that the low volatility anomaly is a distinct effect which exists now and as far back in time as can be seen.

2.3 Drivers of the low volatility anomaly

Other research and previous papers do not only focus on whether or not the low volatility anomaly exists, but also on what the drivers of the anomalous risk-return relationship are. The volatility effect can be explained by behavioral biases of individual investors and agency related issues. Irrational behavior of investors lead to excessive demand for risky assets, this demand will push up the price for risky stocks and simultaneously lower their average returns. Benchmarking and leverage/short-selling constraints prevent arbitrageurs from offsetting the price impact of any irrational behavior, which keeps the anomaly existing. Finally, higher stock returns for low risk firms can also be explained by the firm’s high operating performance.

2.3.1 Behavioral biases

Consider the following two cases; first, one has to bet $1 in order to win $5.000 with a 0.01% chance of winning. This bet has an expected payoff of $-0.50. Second, one has the possibility to invest $100 with a 50% chance of winning $110 or losing it all. This investment has an expected payoff of $5. According to Tversky and Kahneman's (1992) cumulative prospect theory, people will choose the first bet, even while this bet has a negative expected payoff. People tend to make decisions based on the potential value of losses and gains rather than the expected payoff. By doing this, they prefer to avoid big losses over realizing gains, called loss aversion. This behavior is consistent with a positively skewed distribution, where big gains are more likely than big losses. The link between volatility and positive skewness was found by Mitton and Vorkink (2007). They argue that the return distribution of individual risky stocks, with limited liability, are positively skewed. Buying this kind of stocks is like buying a lottery ticket: small probability of making a massive return and a great probability of incurring a negative return. Combining the positive skewed distribution of volatile stocks with the cumulative prospect theory, Barberis and Huang (2008) observe that investors overweight the unlikely event of earning a huge return and underweight the likely event of incurring a loss, hence investors have a *preference for lottery-like stocks*. They find that cumulative prospect theory investors hold undiversified lottery-like portfolios for which they are willing to pay a high price, the skewed security will be overpriced. As a result, these risky securities will earn a negative average return.

Another behavioral biases is called *representativeness* and is explained by an experiment in Tversky and Kahneman (1983). In an investment context, the notion of representativeness bias holds that people tend to neglect the sample size, acting as if a small sample is sufficient to infer a certain pattern in stock returns and expect this pattern to be continued in the future. Only a small number of high risk stocks will perform very well, and some investors tend to believe that this performance will hold for all risky stocks, thus generating buying pressure that overprices high risk stocks and leads to lower returns.

Desire for highly volatile stocks is also caused by *overconfidence*. This means that people tend to overestimate the accuracy of their beliefs or predictions, and they tend to overrate their skills. In predicting future stock returns, overconfident investors systematically belief that their own forecasts are more reliable than they truly are and tend to disagree with others. The degree of disagreement is likely higher for more unpredictable events, such as the returns on risky stocks. Overconfidence can be seen as diversion of opinion, which moves together with risk and uncertainty. In addition, the given constraints with respect to short-selling for individual investors and institutions imply that prices are set by optimistic investors. As a result, overconfident investors can bid-up the stock prices for securities that reflect the greatest diversion of opinion (risky stocks) and become overpriced. Miller (1977) finds that the price of a security is higher the greater the divergence of opinion about the return of the security, causing a lower return for the high risk stock. This outcome is also supported by Diether, Malloy and Scherbina (2002), who find that stocks with greater analyst's dispersion of opinion exhibit significantly lower future returns than other equivalent stocks.

2.3.2 Agency issues

Agency issues related to delegated portfolio management also induce the excessive demand for high volatile stocks. This decentralized investment approach is carried out by a two-step investment process, in which a Chief Investment Officer (CIO) uses multiple asset managers to implement investment strategies in distinct asset classes. The CIO makes the asset allocation decision, consecutively, these funds are allocated to the managers who buy securities within their asset classes. Binsbergen, Brandt and Koijen (2007) find that this investment process leads to inefficient portfolios, because of potential conflicts of interests between the CIO and the asset managers. Managers are offered incentive contracts to diminish the difference in interests. They can earn a bonus on top of their base salary if their performance is sufficiently high. Looking at Figure 1, the more they invest in volatile portfolios, the higher the expected return on their incentive contracts, as found by Baker and Haugen (2012). As a result, managers prefer risky stocks in order to maximize the value of their contract.

Another issue of the two-step investment process arises when the asset manager tries to convince the CIO to include the stock, the asset manager has analyzed, into the portfolio. In order to impress the CIO, they are often attracted to stocks with spectacular gain potentials rather than steady stocks. But at the same time, these stocks exhibit also above average volatilities. Thus, based on the asset manager's goal to satisfy the CIO, Baker and Haugen (2012) expect that a greater amount of risky stocks will be included in the portfolio. This excess demand in risky assets, created by the inefficiencies of decentralized portfolio management, overvalues the price of risky assets and suppresses their expected returns.

Furthermore, during bull markets, managers with above average returns can earn more money when their asset classes perform well. Karceski (2002) suggests that delegated portfolio managers find it more important to outperform during bull markets than outperform during bear markets. Since high volatility stocks tend to perform better than low volatility stocks in up markets, the managers tilt their portfolios towards high volatility stocks to increase the possibility of capturing a greater part of the cash flows associated with bull markets. He argues that, the extra demand for high volatility stocks forces up their prices and lowers their equilibrium returns.

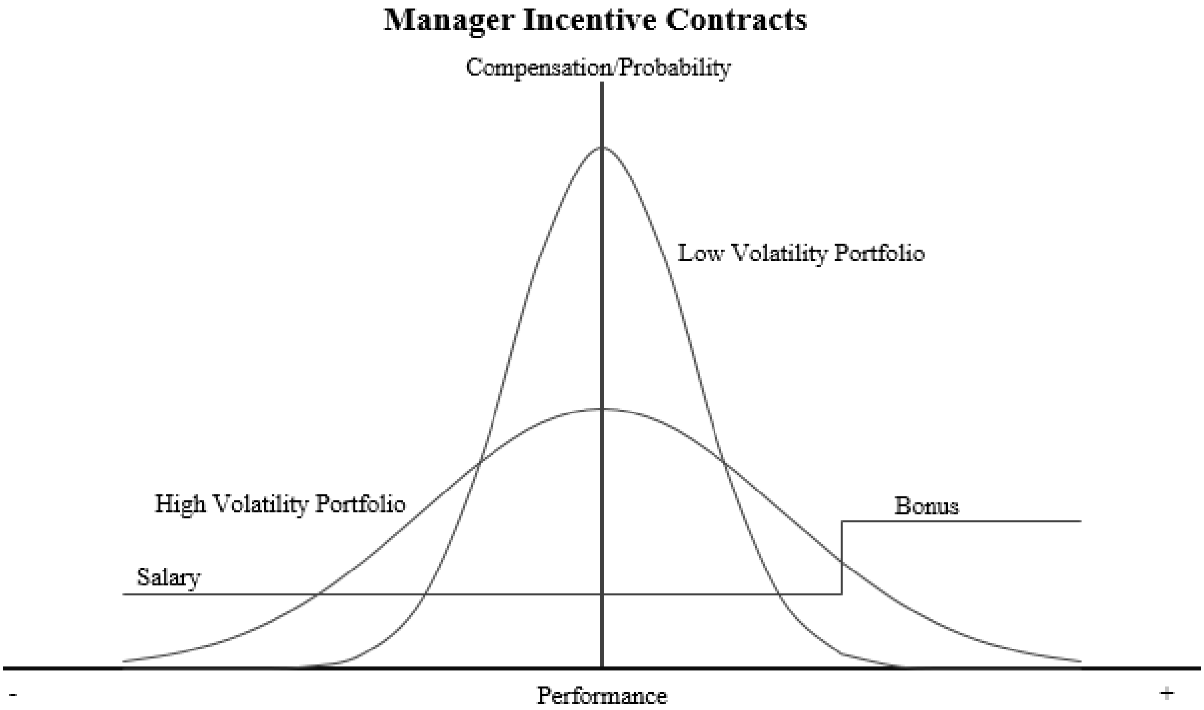

Figure 1. Manager compensation scheme based on performance *– This graph displays two probability distributions for different portfolios, namely for a safe portfolio and for a risky portfolio. Further, a base salary is paid until a specific level of performance, after which the manager receives a bonus. It shows that it is more likely for a manager to earn a bonus when investing in high volatility portfolios. As a result, managers tend to invest more in risky stocks.*

To evaluate the skills and monitor the performance of a manager, a pre-specified benchmark is used to compare the returns. The managers have an incentive to heavily invest in high-beta stocks in their attempt to outperform the benchmark and avoid a penalty for underperforming. Assuming that CAPM holds, the managers think that bearing more risk is an easy way to beat the benchmark. As a result, these high-beta stocks become overpriced, while low-beta stocks become underpriced by ignoring them, which fuels the anomaly.

To see whether the volatility anomaly is caused by agency issues, one would expect the return gap between high volatile portfolios and low volatile portfolios to have become wider over time along with the increase of institutional ownership within markets. Baker et al. (2012) show that for the U.S. stock market the volatility effect have become stronger since 1983, and simultaneously demonstrate that institutional ownership doubled since that same year. During this period, institutional investment managers became increasingly more numerous and better capitalized. In addition, Blitz et al. (2007, 2012) find also that the anomaly gained force in developed and emerging equity markets over a period in which these markets became increasingly institutionalized.

2.3.3 Regulatory constraints

According to modern portfolio theory, all investors should hold only efficient portfolios and leverage or de-leverage this portfolio to fit their preferred choice of risk. However, many financial institutions, like mutual- and pension funds, have limits on the amount of leverage that they are allowed to use. In order to expose themselves to higher levels of risk, they therefore overweight risky assets rather than using leverage. Frazzini and Pedersen (2010) argue that leverage constraints tilt financial institutions toward high-beta stocks, which indicates that high-beta stocks need lower risk-adjusted returns than low-beta stocks, which need leverage.

The same leverage constraints that cause low volatility stocks to outperform high-volatility stocks, also prevent financial institutions to benefit from the attractive absolute returns of low risk stocks. For example, assume that a portfolio with the lowest level of risk has a volatility of two-thirds with respect to the market's volatility, one would need to apply 50% leverage to obtain the same level of risk as the market. Financial institutions are not allowed to use such high levels of leverage. The same holds for correcting inflated prices of high-volatility stocks. Most financial institutions are not allowed to short the risky stocks that perform poorly. For institutional investors it is not possible to capitalize on the low-risk/high return anomaly because of these reasons. As a result, the assets remain mispriced, which means that the existence of the anomaly continues.

Another reason why investors cannot take advantage from the higher returns of low risk stocks, for instance by just overweighting low risk stocks in their portfolio, is due to benchmarking. All mutual funds are obligated to choose a well-known benchmark and disclose the fund's performance against the return of the benchmark in their prospectus. Chan, Chen and Lakonishok (2002) find that a wide range of mutual funds tend to adhere to a broad market benchmark. This implies that financial institutions who are tightly benchmarked are less able to arbitrage-away any potential excess gains that result from mispriced low volatility stocks. The findings from Cummings, Fleming and Schwienbacher (2009), a negative relationship between deviating from the benchmark and performance of the fund, strengthen the behavior of fund managers to stick with their benchmark. Thus, the leverage- and short-selling constraints in combination with benchmarking, acting as limits on arbitrage, prevent investors and financial institutions from exploiting the low volatility effect.

2.3.4 Operating performance

An alternative explanation for the low volatility anomaly comes from Dutt and Humphery-Jenner (2012). They argue that the relationship between low volatility stocks and operating performance is a driver of the anomaly. Their results show a statistically significant relationship between low volatility stocks and operating performance, where low volatility leads to stronger operating performance. The superior returns of low volatility stocks relates partially to operating performance. Further, they find that, beside higher stock returns, low volatility firms also exhibit significantly higher operation returns. They also tested if the reversed relationship would hold, and find a greater likelihood for firms with strong operating returns to be in the lowest volatility quintile, which implies a significant relationship between operating performance and low volatility. The operating performance explanation for the volatility anomaly offered by Dutt and Humphery-Jenner is not conflicting with drivers provided by other papers, instead, there can be numerous and complementary drivers.

The relationship between volatility, operating performance, and stock returns can be explained by unexpected operating returns. Stable firms would probably have strong operating performances as low bankruptcy risk leads to better and cheaper access to capital. This capital can be used for investments that helps these firms to generate higher operating returns. The unexpected earnings from these investments will be reflected in the price of the stock, when the stock is priced by an efficient market at the time the unexpected earnings arise. In this case, according to Core, Guay and Rusticus (2006), a stock increase is the most likely to occur. Hence, there is a positive relationship between earnings surprises and stock returns.

Alternatively, assume that strong operating performance is not a surprise, but rather an uncertain event to appear. Again, due to better and cheaper access to capital, the market expects that low volatility firms will realize strong operating returns, but this good operating performance is not assured. However, then it is still possible that strong operating performance increases stock returns for several reasons.

Firstly, disclosure of information over time, the uncertainty around operating forecasts and their actual realization. Even if the market predicts strong operating performance, the risk of weak operating performance is always present. The uncertainty associated with these forecasts will make the attitude of the market towards the prediction of strong performance more modest, as explained by Bird and Yeung (2012). Subsequently, Zhang (2006) argues that, when information becomes more certain over time and the firm is close to realizing the initial prediction, the firm’s stock price will move towards its fundamental value implied by those uncertain earnings. This price increase reflects the firm's risk reduction for not meeting its earnings forecasts.

Secondly, risky investment options and information, cash earned from strong operation performance permits the firm to invest in entrepreneurial and long-dated projects. These investments increase operating risk without necessarily increasing stock returns in the short-run. The uncertainty associated with such projects implies that the market will not value these earnings until they are actually realized, especially because the pricing of a long-dated asset is determined by the possibility of extreme outcomes, following Martin (2012).

Thirdly, return persistence, discussed in a paper by Alti, Kaniel and Yoeli (2012). They argue that, when the information environment is poor, like in emerging markets, investors tend to interpret subsequent performance figures as evidence of their views. This perceived confirmation can cause investors to become overconfident about their private information. This effect can cause investors to chase return trends. In terms of the anomaly, if investors perceive strong operating performance figures and observe a subsequent increase in stock price, then they will see this as a confirmation that the stock is valuable. As a result, investors tend to overpay for these stock, which will increase the price of the stock.

3. Existence of the low volatility anomaly in developed and emerging markets

In order to answer the first part of the research question it is necessary to test if the anomaly exists, which will be done for developed markets and emerging markets. The distinction between these two market types is important because both markets have certain features that are more or less sensitive for the aforementioned drivers of the low volatility effect. Most countries do not have the same stock exchange rules and regulations, which means that all markets have, for example, different degrees of constraints concerning benchmarking. Emerging markets are to a lower extent restricted by a specific benchmark than developed markets. This might encourage funds in emerging markets to invest in low volatility stocks and profit from its potential mispricing. As a result, these funds are able to arbitrage-away any mispricing induced by the volatility effect. In addition, even when funds in emerging markets have to invest around a certain benchmark, these emerging equity index benchmarks tend to contain a lower amount of stocks and also contain the most steady stocks. This gives funds more flexibility to deviate from their benchmark indices and gives them the possibility to exploit a low volatility strategy, by which the persistence of the anomaly is reduced. Thus, in advance it is not clear whether the differences in limits to arbitrage for both market types would produce a low volatility effect in emerging markets, so it is important to test for the anomaly in developed markets as well as in emerging markets.

Another reason why the low volatility effect could be weaker, or even not present at all, in emerging markets is because of foreign investors who want to invest in these markets. These investors face a great amount of information asymmetry. In order to decrease the risk resulting from this lack of information, they focus on the most transparent stocks to benefit from emerging market growth and its additional risk premiums. The stocks these investors are the most willing to invest in are typically larger stocks which are less volatile. Their focus on large stocks means an increase in demand for these stocks that, in turn, will lead to a price increase. Any potential benefit from mispriced low volatility stocks will be removed by the increase in demand for these stocks. Thus, again, the possibility of a low volatility effect in emerging markets is smaller than it is for developed markets.

In general, it is relevant to verify the existence of a low volatility effect in multiple countries and markets. From this, it can be shown how the anomaly performs in different regulatory environments, which will be shown in this section. Further, the data and method used to obtain this result is described below.

3.1 Data

The dataset is divided between developed markets and emerging markets. Countries that belong to the developed markets in this paper are France, Germany and the Netherlands, which are based on the MSCI world index (MSCI world index, 2015) that contains 23 developed countries. The emerging markets in this paper consist of Czech Republic, Hungary, Poland and Russia, which are selected from the MSCI emerging markets index (MSCI emerging markets index, 2015) that contains 23 emerging countries. The data obtained contains daily stock price data and daily market values for all surviving firms in each country from Datastream over the period 1990-2014 for the developed markets, and 2000-2014 for the emerging markets. Since only surviving firms during the entire period are included in the investigated sample, the portfolio returns of the funds will reflect the performance of long-term survivors only. With the failed firms excluded from the dataset, the observed performance of the portfolios will be better than from the full dataset of funds, which is also known as the survivorship bias. Stocks which have a zero return, for more than 25% of the total daily observations during these periods, are removed from the dataset. There was insufficient data on the examined emerging markets before the year 2000 to test the anomaly, so that is the reason why there is a shorter testing period for the emerging markets. Further, exchange rates were collected from Datastream over the period 2000-2014, in order to convert the emerging countries' currencies to Euro. As well as, the monthly index price data for the S&P 500 over the period 1992-2014. The returns on this index are used as a benchmark, since the S&P 500 is widely considered as a good reflection of the market, in order to compute the quintile portfolio's Sharpe ratio.

3.2 Methodology

The method used to test the low volatility effect is the same for developed markets as it is for emerging markets. Except, the daily stock price and market value of firms located in emerging markets, first had to be expressed in Euro using the associated exchange rates for each currency, before any computation was made. Now, all currencies are denominated in Euro, the stock return is calculated for each stock on each day. Subsequently, starting with the first month of interest (January 1992 for the developed markets and January 2002 for the emerging markets), the volatility (standard deviation) of stock returns for each firm in each market over the previous two years is computed. A two-year moving volatility is used because this is the average number of years used in common literature. For each of both markets then the return-volatility quintiles are calculated. The stocks in each market are ranked by volatility and appointed to the associated quintile. For every quintile, a value weighted portfolio is constructed based on the firm's contribution to the total market value of that portfolio. In both markets, this procedure is repeated for the remaining months until December 2014, which implies that each portfolio is re-ranked every month according to the stock's new two-year trailing volatility value. Transaction costs are ignored when rebalancing the portfolios each month. For each day, the value weighted return for each portfolio is calculated. In the end, it can be reported from the five value weighted portfolios in each market what €1 would be worth in December 2014, assuming it was invested at the beginning of the period. In this way it can be easily observed if the lowest quintile portfolio (low risk stocks) outperforms the highest quintile portfolio (high risk stocks) in developed markets, as well as in emerging markets, during the period of interest.

Finally, Sharpe ratios for each quintile portfolio will be calculated to test whether the volatility effect is also reflected by the reward-to-volatility ratio of each portfolio. The Sharpe ratio examines the performance of the portfolio compared to a benchmark by adjusting for the portfolio's risk. In other words, it describes how well the return of the portfolio compensates the investor for the risk taken. The portfolio with the highest Sharpe ratio has the highest return for some given level of risk or, equivalently, for a given return the lowest level of risk.

In context of the low volatility anomaly, the lowest quintile portfolio should have a higher Sharpe ratio than the highest quintile portfolio. The Sharpe ratio for each quintile portfolio is calculated by its average realized annual return minus the average realized annual return of the benchmark, subsequently divided by the associated quintile portfolio's average annualized volatility.

3.3 Results

The result in Figure 2 for the developed markets shows that the portfolio consisting of low risk stocks outperforms the high risk portfolio. More precisely, the graph shows that one Euro invested at the end of December 1991 in the lowest quintile portfolio increased to €29.93, compared with €15.75 obtained by a one Euro investment in the highest quintile portfolio. If an investor, who believed in traditional theories, which tell that more risk would have led to a high return, aggressively invested in high risk stocks, he or she would have performed more than 50% less than a risk averse investor who would have invested in safe stocks.

The end value of the lowest quintile portfolio is reached in a much smoother fashion than for the higher risk portfolios, except for quintile 2, but this portfolio also has delivered the worst performance. This means that low risk portfolios are really less volatile and earn higher returns, which is in accordance with the volatility anomaly. Even during the crisis, where high volatility stocks should provide an insurance payment against economic downturns, the risky stocks fail to earn a positive return. At the time of the financial crisis during the fall in 2008, the highest quintile portfolio experienced a decent drop and produced a very low return relative to the other portfolios. However, some level of risk can be desirable as suggested by the outperformance of quintile 2 by portfolios 3, 4 and 5.

For the emerging markets, the lowest quintile portfolio also earns a higher return than the highest quintile portfolio, which can be obtained from the result in Figure 3. A one Euro investment at the end of December 2001 in the first quintile portfolio grew to €11.14, in contrast with €9.32 obtained by a one Euro investment in the fifth quintile portfolio.

The key result is that the total return for the lowest risk portfolio is higher than for the more risky portfolios. In the emerging markets, as well as in the developed markets, a certain amount of risk can be profitable, since quintile four and five are worth respectively €6.04 and €9.32 in the end, where quintile two and three are only worth respectively €3.33 and €2.89. In addition, opposite to the developed markets, quintile 1 behaves more volatile towards its end

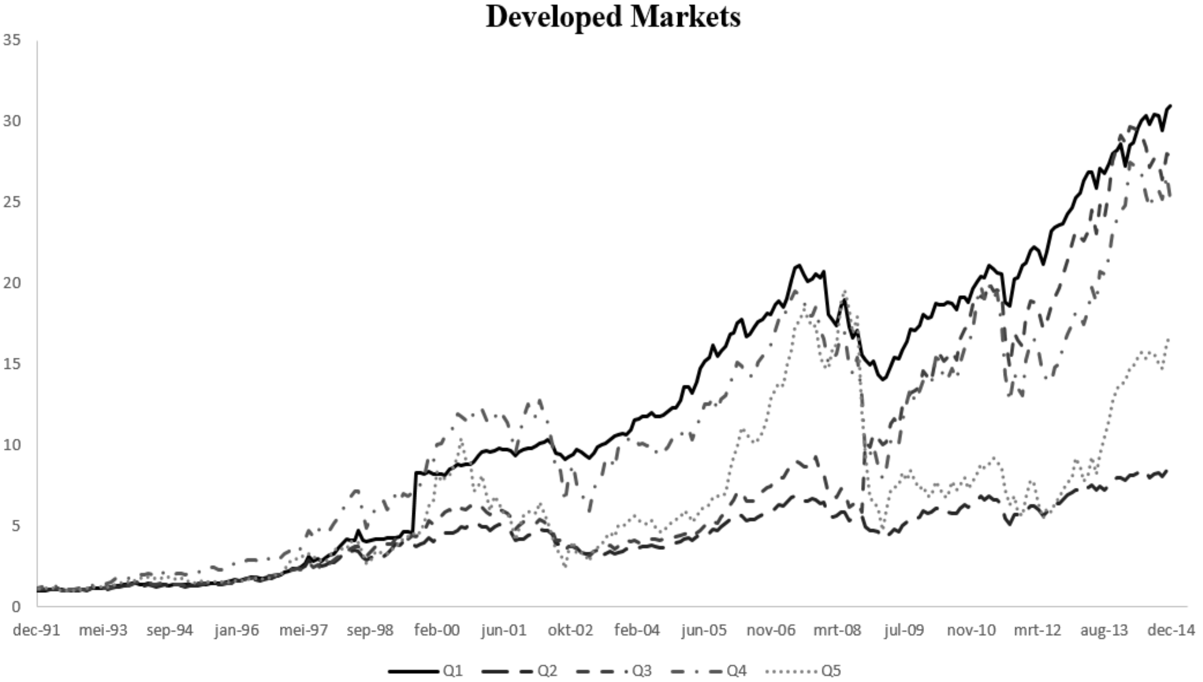

***Figure 2. Value of €1 invested in developed markets** – This graph depicts the value of €1 invested at the end of 1991. All stocks from Germany, France and the Netherlands are sorted into value-weighted quintile portfolios based on the two-year trailing return-volatility. The portfolios are rebalanced every month. The daily returns for each portfolio are computed using the market value weights of each stock relative to the total market value of its portfolio.*

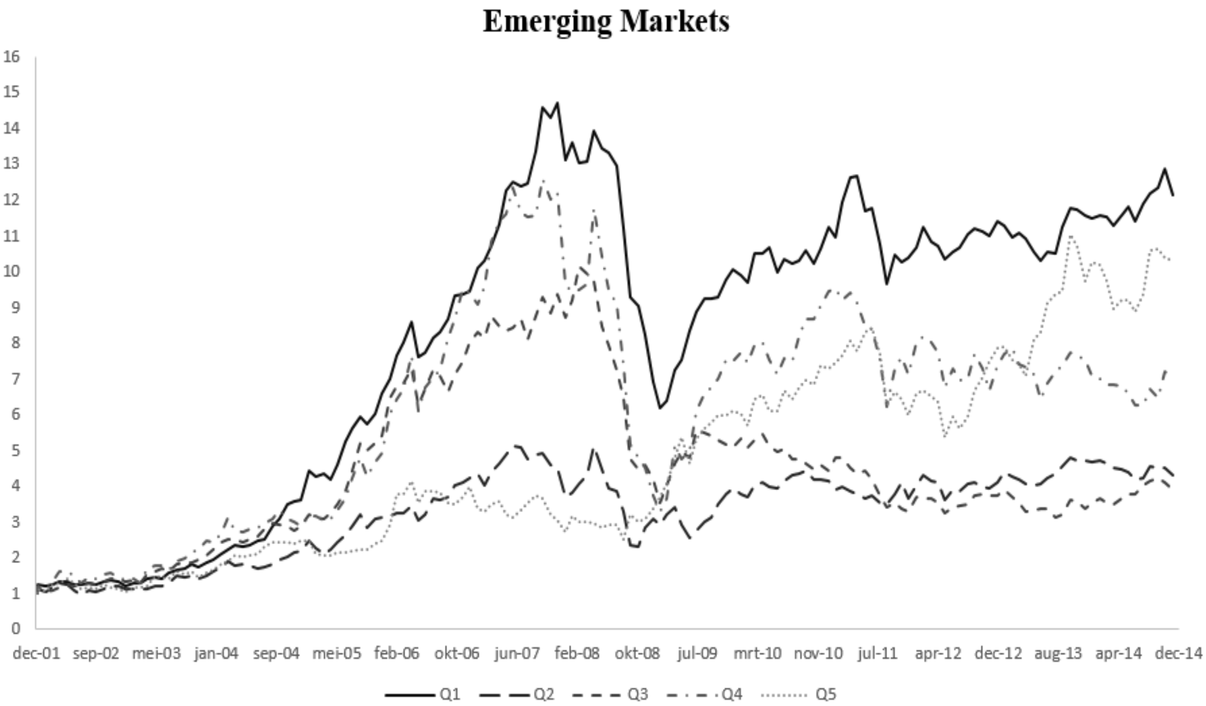

***Figure 3. Value of €1 invested in emerging markets** – This graph depicts the value of €1 invested at the end of 2001. All stocks from Czech Republic, Hungary, Poland and Russia are sorted into value-weighted quintile portfolios based on the two-year trailing return-volatility. The portfolios are rebalanced every month. The daily returns for each portfolio are computed using the market value weights of each stock relative to the total market value of its portfolio.*

value and even experienced a huge decline in value during the crisis. While the most risky portfolio simultaneously earns a positive return. From this, it can be confirmed that the volatility anomaly is weaker for emerging markets than it is for developed markets, which was expected considering the greater possibilities to arbitrage in emerging markets. Nevertheless, even in emerging markets, the lowest risk portfolio outperforms the riskier portfolios during the investigated period.

In addition, the Sharpe ratios for each quintile portfolio in both markets are reported in Table 1. From this it can be observed that the lowest volatility quintile portfolio has the highest Sharpe ratio in developed markets, as well as in emerging markets. This means that the portfolio with the lowest level of risk has the best trade-off between reward and risk. For a given level of risk, the bottom quintile portfolio has the highest return. Based on the value of these Sharpe ratios and realized returns for each portfolio, it is shown that the volatility effect exists in both market types.

Table 1. Sharpe ratios *– This chart consists of the Sharpe ratios for each quintile portfolio in both market types. The Sharpe ratios are calculated by subtracting the quintile's average realized annual returns and the benchmark's average realized annual returns, scaled by the quintile's average annualized volatility, where the S&P 500 index is used as the benchmark. For the developed markets the Sharpe ratios are obtained over the years 1992-2014 and for the emerging markets over the years 2002-2014.*

Quintile	Developed	Emerging
1 (Lowest volatility)	3.54	4.90
2	0.61	1.63
3	2.04	2.00
4	2.01	2.83
5 (Highest volatility)	1.75	2.71

Overall, the lowest volatility quintile portfolio outperforms the highest volatility quintile portfolio, in terms of realized return and reward-to-volatility ratio, during the examined period of time. Considering these results it can be concluded that the low volatility anomaly exists in developed markets as well as in emerging markets. This result makes it interesting to examine if there is an additional driver besides the limits to arbitrage, as it was expected for this driver to have less influence on the investing strategies of investors outside developed markets, since the low volatility effect is also present in emerging markets. Next, I will investigate if this additional driver could be operating performance. Now, the issue is, whether the higher stock returns earned by low risk stocks can be related to stronger operating performance. Any additional driver would not be in conflict with other drivers, instead, there can be different complementary and consistent drivers of the anomaly.

4. Operating performance as a driver of the anomaly

From the previous chapter it can be observed that low volatility stocks have higher stock returns, in both markets. Since the effect also applies for emerging markets, which are to a lower extent influenced by limits to arbitrage, it is interesting to investigate if there is another driver of the anomaly. In this chapter, the role of operating performance as an additional possible explanation for the low volatility effect is going to be examined in order to answer the second part of the research question. In doing this, it is necessary to check if there is a relationship between operating performance, volatility and stock return, which will be done for both market types combined.

There are several reasons why operating performance could cause the outperformance of low volatility stocks, as shown by Dutt and Humphery-Jenner (2012). Stable firms that experience less volatility in their stock price are more likely to have better and cheaper ways that enhance the firm's access to capital. As a result, these firms have more capital that they could spend on potentially profitable investing opportunities. Subsequently, the positive earnings from these investments, or the strong operating performance, will increase the stock price of these firms. This could happen in two different ways; first, if the positive operating return is unexpected to arise, the market will not revalue the stock price until the unexpected earning occurs. In this case, the re-valuation will most likely result in an increase in stock price. Second, consider the case where positive earnings from operations are uncertain to be earned. The risk associated with this uncertainty prevents the market from immediately increasing the stock price that belongs to the future earnings potential from their operations. The stock price of these firms will increase when the operating performance uncertainty decreases and as information on the investments' payoffs becomes more certain. Another reason could be return-persistence, which means that investors in poor information environments perceive strong operation performance figures as confirmation of their predictions. This irrational behavior causes an excessive demand for this stock and leads investors to bid-up the stock price. From all this, it can be assumed that there is a relationship between operating performance, volatility and stock return. Overall, I expect that the relationship between low volatility stocks and strong operating performance explains why low volatility stocks earn higher stock returns, hence, I expect operating performance to be a cause of the low volatility anomaly.

In order to examine whether or not operating performance is a possible driver of the volatility effect I am going to run several regressions. The models that I used to test the relationships are described in this section. Further, the data that I used and the interpretation of the results are also discussed below.

4.1 Data

The regression dataset used in this chapter is the same dataset as the one I used in the previous chapter, besides a few adjustments. In this dataset, developed markets and emerging markets are merged into one sample. This means that there is no separate distinction between market types, so the whole sample consists of 4691 yearly observations, where the previous dataset contained daily data. I use yearly data because the operating data is at a yearly frequency. In addition, since the role of operating performance is of interest I had to add some variables that would capture this along with some control variables. These performance measurements stated in the annual reports for every stock were downloaded from Compustat Global over the period 1992-2014. The definition of all variables used in the yearly models that try to explain the relationship between operating performance, volatility and return are listed in Table 2 and the summary statistics for these variables are described in Table 3.

Table 2. Variable definitions *– This exhibit describes all regression variables and their definition.*

Variable	Definition
I(Volatility Quintile *M*)	A factor variable that indicates to which volatility quintile the stock belongs to. The variable equals one if the firm's volatility is in quintile *M* for the year, where the lowest volatility stocks (safe stocks) are in quintile 1 and the highest volatility stocks (risky stocks) are in quintile 5
I(Operating Quintile *M*)	A factor variable that indicates to which operating quintile the stock belongs to. The variable equals one if the firm's operating performance is in quintile *M* for the year, where the stocks with the lowest operating performance are in quintile 1 and the stocks with the highest operating performance are in quintile 5
Stock Return	The firm’s yearly stock return
EBIT/Assets	The firm's earnings before interest and taxes divided by the firm's book assets
Current Assets/Current Liabilities	The firm's current assets divided by its current liabilities
Debt/Assets	The firm's outstanding long-term debt obligations scaled by the firm's book assets
Intangibles/Assets	The firm's intangible assets scaled by the firm's book assets
CAPEX/Sales	The firm's capital expenditures scaled by the firm's net sales

The volatility quintiles that were used for the regressions are computed exactly the same way as I did in the previous chapter to show the existence of the anomaly. To repeat, for every month, the two-years trailing volatility of stock return for each stock is computed. Then, the monthly return volatility quintiles are calculate based on prior volatility values. Subsequently, the stocks are classified into the associated quintile for each month. For the yearly regression analysis, the date of the firm’s annual report determines which volatility quintile should be allocated to the stock. For the operating quintiles, it holds that the quintiles are computed based on the yearly operating performance figures for each firm. The stocks are now ranked by operating performance and appointed to the associated quintile. Only the bottom operating quintile and top operating quintile are of interest. The operating performance of a firm is measured by the firm's earnings before interest and taxes (EBIT). This cash flow reflects the actual economic profit earned by the assets. Since the degree of economic profit depends substantially on the firm's total assets, I divide the EBIT cash flow by the firm's book assets so that this performance measurement can be compared across firms and time. The ratio of current assets to current liabilities, the debt to assets ratio, the intangibles to assets ratio and the capital expenditures scaled by net sales are control variables that might have an effect on operating performance and are commonly used by other papers.

Table 3. Summary statistics *– This chart shows the summary statistics for all variables in the regression sample.*

Variable	Mean	Median	Min	Max	Std.dev.
Stock Return	0,148	0,059	-0,962	27,757	0,762
EBIT/Assets	0,060	0,060	-4,495	0,550	0,122
Current Assets/Current Liabilities	1,888	1,405	0,029	237,128	5,111
Debt/Assets	0,116	0,092	0,000	0,681	0,111
Intangibles/Assets	0,113	0,046	0,000	0,793	0,145
CAPEX/Sales	0,072	0,041	0,000	20,161	0,344

4.2 Methodology

As mentioned before, in order to test whether there is a relationship or not between operating performance, volatility and stock return I am going to run several regressions. In this section, the models and regression types used to explain the low volatility anomaly will be discussed.

4.2.1 Does volatility influence operating performance and vice versa?

The first regression will analyze the effect of a firm's past volatility quintile on its mean operating performance, where I expect the average operating performance to be higher for low volatility firms than it is for highly volatile firms. In other words, the riskier a firm was (the higher the firm's volatility quintile was), the lower the average operating performance will be. This is analyzed by an ordinary least squares regression of the following form:

$$Operating\ Performance_{i,t} = \beta I(Volatility\ Quintile)_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}$$

This regression is executed without a constant term in order to obtain immediately the average results for each volatility quintile, which means that the volatility quintile's coefficients are not relative to some base group anymore. The regression outcomes for this model can be found in Table 4.

Now, the second regression will test this relationship the other way around, namely, it predicts the firm's volatility quintile with respect to its past operating performance. As operating performance increases, I expect the firm's likelihood of having a low volatility quintile (Quintile 1 or 2) is more likely than having a high volatility quintile (Quintile 4 or 5). More specifically, the higher the past operating performance of a firm, the greater the firm's probability to have a low volatility quintile. This is tested by a multinomial logit regression of the following form:

$$I(Volatility\ Quintile)_{i,t} = \alpha + \beta Operating\ Performance_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}$$

A multinomial logit regression is used here because the dependent variable is a factor variable consisting of five possible outcomes, namely the volatility quintiles. The dependent variable equals one if the firm's volatility is in a given quintile for the year, otherwise it equals zero. This model predicts the firm's likelihood of having its volatility within a certain quintile based on its past operating performance and control variables. In other words, in a multinomial logit regression, a change in the independent variable makes the outcome in the dependent variable more or less likely. By executing this regression, I chose quintile 3 as the base outcome, because this quintile separates the low volatility stocks from the risky stocks. The coefficients of the base outcome are assumed to be equal to zero and the likelihood of the other quintiles are compared to the base outcome. The results for this regression can be found in Table 5.

4.2.2 Does operating performance and volatility influence stock return?

Before testing the effect of volatility, while controlling for operating performance, on stock return, I test the effect of past volatility and operating performance on stock return separately. For examining the effect of operating performance, I also need to create operating performance quintiles for each year. For the effect of volatility on stock return I expect the average stock return to be higher for the bottom volatility quintile, while for the operating performance effect on stock return I expect the average stock return to be higher for the top operating performance quintile. Thus, the lower the past volatility quintile, and the higher the past operating performance quintile, the higher the average stock return will be. This is examined by quantile regressions of the following form:

$$Stock\ Return_{i,t} = \alpha + \beta I(Bottom\ Volatility\ Quintile)_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}$$

$$Stock\ Return_{i,t} = \alpha + \gamma I(Top\ Volatility\ Quintile)_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}$$

$$Stock\ Return_{i,t} = \alpha + \theta I(Bottom\ Operating\ Quintile)_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}$$

$$Stock\ Return_{i,t} = \alpha + \varphi I(Top\ Operating\ Quintile)_{i,t-1} + Controls_{i,t-1} + \varepsilon_{i,t}$$

Quantile regressions are used in order to obtain regression estimates that are more robust against outliers in the dependent variable. The distribution of the yearly stock return (dependent variable) cannot be considered as smooth and contains some outliers, as can be implied by Table 3. Therefore, I use the 0.25^{th} quantile of the dependent variable in these regressions, because this fraction of the stock return data contains the most stable observations.

Now, it needs to be checked to what extent operating performance relates to the firm's volatility quintile and its stock return. I expect that low volatility firms experience on average higher stock returns when their operating performance is strong, while I expect that high volatility firms experience lower stock returns when their operating performance is weak. So, the outperformance of low volatility stocks is due to strong past operating performance, and vice versa; the underperformance of high volatility stocks is due to past weak operating performance. This is tested by quantile regressions of stock return on volatility quintile, while at the same time controlling for operating performance. This suggests models of the following form:

$$\begin{aligned} Stock\ Return_{i,t} &= \alpha + \delta I(Bottom\ Volatility\ Quintile)_{i,t-1} + \phi I(Top\ Operating\ Quintile)_{i,t-1} \\ &\quad + Controls_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

$$\begin{aligned} Stock\ Return_{i,t} &= \alpha + \varpi I(Top\ Volatility\ Quintile)_{i,t-1} + \mathrm{X}I(Bottom\ Operating\ Quintile)_{i,t-1} \\ &\quad + Controls_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

The most important goal now is to test if β and δ, and also γ and ϖ, are statistically different from each other. A statistically significant difference would imply that operating performance plays a significant role in explaining the relationship between stock return and volatility. This will be examined by using t-tests. By doing this, I analyze the magnitude to which the volatility effect relates to operating performance. The quantile regression results can be found in Table 6 and the t-test conclusions can be found in Table 7.

4.3 Results

Overall, the results show that low volatility stocks have strong operating performance, which leads to higher stock returns. In this section, the regression outcomes and their interpretations are discussed into further detail.

4.3.1 The relationship between operating performance and volatility

The OLS regression results are in Table 4. Operating performance times 100 is the dependent variable and the firm's 1-year-lag volatility quintile is the independent variable, as well as the control variables. It can be observed that low risk stocks have on average stronger operating performance than risky stocks. The lower the volatility quintile, the stronger the average operating performance is, excluding volatility quintile 2. Key result is that the coefficients of indicator variables for quintile 1 and 2 (safe stocks) are higher and statistically

Table 4 – Regressions investigating the determinants of operating performance. *This table contains the regression of operating performance in year t on the firm's volatility quintile in year t-1. All independent variables are lags. The models used are OLS regressions. The values between brackets are p-values.*

Dependent Variable	EBIT/Assets x 100				
Model	Ordinary Least Squares Regression				
	(1)	(2)	(3)	(4)	(5)
I(Volatility Quintile 1)	3.650***				
	(0.000)				
I(Volatility Quintile 2)		4.140***			
		(0.000)			
I(Volatility Quintile 3)			3.142***		
			(0.000)		
I(Volatility Quintile 4)				2.331***	
				(0.000)	
I(Volatility Quintile 5)					-2.026***
					(0.000)
Current Assets/Current Liabilities	0.517***	0.490***	0.500***	0.512***	0.581***
	(0.000)	(0.000)	(0.000)	(0.000)	
Debt/Assets	9.938***	8.644***	9.090***	9.663***	12.283***
	(0.000)	(0.000)	(0.000)	(0.000)	
Intangibles/Assets	12.427***	11.744***	12.574***	13.199***	13.708***
	(0.000)	(0.000)	(0.000)	(0.000)	
CAPEX/Sales	-1.277**	-1.229**	-1.189**	-1.248**	-1.121**
	(0.020)	(0.024)	(0.029)	(0.023)	(0.041)
Observations	4534	4534	4534	4534	4534
R-squared	13.90%	14.73%	13.98%	13.42%	13.11%

* Significance at 10%
** Significance at 5%
*** Significance at 1%

significant than the indicator variables' coefficients for quintile 4 and 5 (risky stocks), where I(Volatility Quintile 5) is even statistically significant negative. This indicates that low volatility firms encounter strong operating performance, and high volatility firms encounter weak operating performance. Now consider that low volatility stocks experience superior stock returns, a possible explanation could be that these firms just have better fundamentals.

Next, I execute the reversed regression to see whether operating performance has an effect on return volatility. The multinomial logit regression results are in Table 5. Here, the dependent variable is the firm's volatility quintile, and the past performance and control variables are the independent variables. This model predicts the probability that the volatility of a firm is in a given quintile based on past operating performance and controls. It can be observed that the volatilities of firms with strong past operating performance are significantly more likely to be in the lowest volatility quintiles (Quintile 1 and 2), and are significantly less likely to have volatilities in the highest volatility quintiles (Quintile 4 and 5) compared to the base outcome (Quintile 3). Hence, this implies that firms experiencing strong operating performance are more likely to be low volatility firms.

Table 5 – Regressions predicting the likelihood of volatility quintiles. *This table contains the regression of the firm's volatility quintile in year t on the firm's operating performance in year t-1. All independent variables are 1-year-behind. The models used are multinomial logit regressions, where Quintile 3 is chosen as the base outcome. The values between brackets are p-values.*

Dependent Variable	I(Q1)	I(Q2)	I(Q3)	I(Q4)	I(Q5)
Model	Logit Regression				
	(1)	(2)	(3) [Base Outcome]	(4)	(5)
EBIT/Assets	3.006***	2.669***	0	-2.522***	-7.36***
	(0.000)	(0.000)		(0.000)	(0.000)
Current Assets/Current Liabilities	-0.039	0.019	0	0.052	0.031
	(0.401)	(0.592)		(0.105)	(0.350)
Debt/Assets	0.176	0.480	0	0.761*	-0.264
	(0.704)	(0.249)		(0.065)	(0.598)
Intangibles/Assets	0.664**	0.506*	0	-0.542*	-2.092***
	(0.045)	(0.095)		(0.092)	(0.000)
CAPEX/Sales	0.387	0.238	0	0.317	0.258
	(0.231)	(0.489)		(0.322)	(0.438)
Constant	-0.682***	-0.394***	0	-0.081	-0.181*
	(0.000)	(0.000)		(0.415)	(0.093)
Observations	4677	4677	4677	4677	4677
Pseudo R-squared	2.71%	2.71%	2.71%	2.71%	2.71%

* Significance at 10%
** Significance at 5%
*** Significance at 1%

4.3.2 Operating performance as a driver of the volatility effect

The purpose of the following set of regressions is to test the influence of volatility and operating performance on stock returns, but especially what the role of operating performance is between the firm's volatility and its stock return. The plan is to investigate if the existence of the volatility effect can be partially explained by the firm's operating performance. The dependent variable in these models are the yearly stock returns for each firm, and past operating performance quintile and past volatility quintile are the independent variables, just as the control variables. The quantile regression results for these models can be found in Table 6. From this, it can be observed that at the 0.25th quantile, the coefficient of the indicator variable for the bottom volatility quintile is significantly positive, in contrast with a significantly negative coefficient for the top volatility quintile. This implies that low volatility

Table 6 – Regressions investigating the drivers of yearly stock returns. *This table contains the regression of the firm's stock return in year t on its operating performance quintile and volatility quintile in year t-1. All independent variables are 1-year-behind. The models used are quantile regressions, based upon a 25% quantile of stock returns. The values between brackets are p-values.*

Dependent Variable	Stock Return (Yearly)					
Model	Quantile Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Volatility Quintile 1)	0.077***		0.074***			
	(0.000)		(0.000)			
I(Operating Quintile 5)		0.065***	0.062***			
		(0.001)	(0.001)			
I(Volatility Quintile 5)				-0.184***		-0.143***
				(0.000)		(0.000)
I(Operating Quintile 1)					-0.134***	-0.121***
					(0.000)	(0.000)
Current Assets/Current Liabilities	0.001	0.001	0.001	0.002	0.002	0.003
	(0.599)	(0.577)	(0.534)	(0.399)	(0.391)	(0.162)
Debt/Assets	-0.065	-0.027	-0.010	-0.109	-0.096	-0.077
	(0.379)	(0.707)	(0.880)	(0.112)	(0.147)	(0.190)
Intangibles/Assets	0.095*	0.083	0.064	0.060	0.030	0.018
	(0.091)	(0.128)	(0.224)	(0.254)	(0.551)	(0.698)
CAPEX/Sales	-0.022	-0.022	-0.021	-0.024	-0.018	-0.019
	(0.337)	(0.324)	(0.321)	(0.259)	(0.383)	(0.302)
Constant	-0.167***	-0.172***	-0.185***	-0.126***	-0.116***	-0.109***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4676	4676	4676	4676	4676	4676
Pseudo R-squared	0.48%	0.40%	0.70%	1.13%	1.08%	1.74%

* Significance at 10%

** Significance at 5%

*** Significance at 1%

firms earn superior stock returns over high risk firms. Then, looking at operating performance, it can be noticed that at the .25th quantile, the coefficient of the indicator variable for the top operating quintile is significantly positive, in contrast with a significantly negative coefficient for the bottom operating quintile. This means that, strong operating firms outperform firms with low operating performances.

But, the main point of interest is the change in the bottom volatility quintile's coefficients and the top volatility quintile's coefficients after controlling for operating performance. The results show that, after controlling for operating performance, the economic significance of the bottom volatility quintile indicator and the top volatility quintile indicator reduces. This indicates that operating performance might relates to the volatility effect. In order to examine whether the difference in coefficients is statistically significant, a t-test is used. Any significant difference would provide statistical evidence for the role operating performance plays in the volatility anomaly. Table 7 contains the test procedures and results.

Table 7 – Testing the difference between volatility quintile coefficients. *This table contains the t-test procedure and test statistics whether the regression coefficients of Table 6 are significantly different. The values between brackets are p-values.*

Hypothesis Test	Test statistic	Conclusion
$H_0: \beta = \delta = 0.074 \; vs. H_1: \beta \neq \delta \neq 0.074$	0.177 (0.860)	Do not reject H_0
$H_0: \gamma = \varpi = -0.143 \; vs. H_1: \gamma \neq \varpi \neq -0.143$	-1.859* (0.064)	Reject H_0

* Significance at 10%
** Significance at 5%
*** Significance at 1%

The test results show that the difference between the bottom volatility quintiles is not statistically different, which means that the outperformance by low volatility stocks caused by strong operating performance lacks statistical evidence. However, the test results also show that the difference between the top volatility quintiles is statistically different. This implies that the negative effect risky firms have on their stock returns is explained by the firm's weak operating performance. The relationship between stock return and volatility is partly influenced by operating performance. Although the statistical test only provides evidence that weak operating performance causes high volatility firms to earn lower stock returns, it can be concluded that operating performance plays a significant role in the low volatility anomaly.

5. Conclusion

This paper examined the existence of the low volatility anomaly, whether low volatility stocks earn higher stock returns than high volatility stocks, and the role of operating performance. Earlier papers have shown that the low volatility effect exists for different periods of time, across several financial assets, as well as, in all testable equity markets around the world. These papers also provided possible explanations for the anomalous risk-return relationship. Some of these explanations are to a different extent applicable to developed markets and emerging markets, such as benchmarking. Investors in emerging markets are to a lower extent constrained to follow a specific index. However, even when investors are tied to a benchmark index, the indices in emerging markets contain a lot more low volatility stocks than in developed markets. That is why, in proving the existence of the low volatility effect, I made a clear distinction between developed and emerging markets.

The findings show that, for both market types, the low volatility portfolio outperforms the high volatility portfolio. More specifically, for the developed markets, a one Euro investment in the low volatility portfolio is worth €29.93 at the end of 2014, compared with €15.75 for the high volatility portfolio. This means an outperformance of €14.18 by the lowest quintile portfolio. For the emerging markets, a one Euro investment in the low volatility portfolio is worth €11.14 at the end of 2014, compared with €9.32 for the high volatility portfolio. This shows that, if an investor invested in the lowest quintile portfolio, instead of the highest quintile portfolio, the investor would have gained €1.82. Looking at the Sharpe ratios of each portfolio, it is found that, for both market types, the low volatility portfolio has the highest Sharpe ratio. This means that the low volatility portfolio also provides the best risk-return trade-off.

As an answer on the first part of the research question, it can be concluded from these findings that, low risk stocks really do have higher stock returns than high risk stocks in both market types. The result shows how the anomaly behaves in different regulatory environments, namely, the volatility effect is weaker for emerging markets than it is for developed markets. The lowest quintile portfolio reaches its end value, in emerging markets, in a less smooth way than the highest quintile portfolio, and the magnitude of outperformance by the low risk portfolio in emerging markets is lower than in developed markets.

Since the low volatility anomaly also exists in emerging markets, I investigated if operating performance could be an additional driver besides the given explanations of the effect in other papers, which mainly apply to developed markets. To test whether high stock returns earned by low risk firms is reflected by low risk firms experiencing strong operating performance, the total dataset was used, so no distinction anymore between developed and emerging markets. Low risk firms are expected to have strong operating performance since low risk enhances the firm’s access to additional fund. This additional fund can be used by stable firms to invest in entrepreneurial projects which can lead to unexpected earnings in the future. Subsequently, these unexpected earnings, will be expressed by an increase in stock price. Alternatively, the investment in risky projects increases the uncertainty of future earnings. The stock price will increase after more information is being disclosed, and the uncertainty of earnings decrease.

The results show, indeed, that firms with low volatility values experience strong future operating performance, and high volatility firms experience weak future operating performance. Further, it is also more likely for a firm to be in the lowest volatility quintiles as a function of strong past operating performance. Thus, there is a significant relationship between operating performance and volatility, and reversed, which states that low volatility firms have stronger operating returns and that strong operating firms are more likely to be low risk ones. But, the key result is, how operating performance relates to the relationship between volatility and stock return. It shows that the economic significance of the bottom and top volatility quintiles decreases after controlling for operating performance. I find statistical evidence for weak operating performance to have a significantly negative influence on the stock return of high volatility firms.

As an answer on the second part of the research question, it can be concluded from these findings that, operating performance partially explains the risk-return relationship of firms. The high returns of low volatility stocks, but especially, the low returns of high volatility stocks are related to operating performance. This implies that operating performance plays a significant role in the low volatility anomaly, and can be seen as a complementary explanation next to drivers provided by other papers.

Based on these results, it can be recommended to institutional investment funds to remove their benchmark constraint in order to monitor the manager’s performance. This constraint prevents the manager from exploiting the benefit of low volatility stocks, because deviating only increases the manager’s tracking error. Without the constraint, and by introducing a benchmark free Sharpe ratio, managers are able deviate and profit from the superior returns low volatility stocks have to offer. As an alternative for removing the benchmark constraint, I would recommend to investment funds and policy makers to allow the use of (more) leverage. Bounded to a benchmark, investors can capitalize on the low volatility effect by using leverage within their investing process. In this way, the manager can keep the tracking error constant, because leverage increases the exposure to risk, while simultaneously outperform the benchmark due to the high returns of low risk stocks. The results have also implications for the individual investor’s portfolio management. They should consider to build their own portfolio consisting of the lowest volatility stocks, and for example, rebalance their portfolio quarterly by selling the stocks which no longer belong to the lowest volatility stocks and replace them by stocks which do. By doing this, an individual investor is also able to exploit the low volatility effect.

By obtaining these results, there are some points to consider, such as the use of a two-year trailing volatility. It would be interesting to check whether the existence of the anomaly is robust to other lengths of trailing volatility. Further, in this process, I ignored the transaction costs associated with the monthly rebalancing of the quintile portfolios. In order to extract the profits of any volatility effect, an investor has to rebalance frequently. Trading costs increase with frequent rebalancing and decrease the potential excess returns. Additionally, volatile stocks are most likely to be small stocks that are characterized by low liquidity. This low liquidity also increases the stock's transaction costs, which in turn will decrease the return of risky stocks. High transaction costs and low liquidity are the main criticisms of the low volatility anomaly. Although, I removed some low liquidity stocks from the dataset, these points can act as possible limitations of the results I found. In addition, the inferences made from my dataset could be subject to error due to survivorship bias, because firms that failed during the sample period were excluded from the dataset. Further, to see the actual influence of low volatility on the safe stocks' outperformance, it would also be interesting to perform a regression of each quintile's return on market return, size, value and momentum factors. By doing this, the magnitude of the volatility factor that actually relates to the stock return can be observed.

Most literature on the volatility effect proves the existence of the anomaly for equity markets worldwide. Only a few papers investigate other securities. Therefore, in future research it would be interesting to examine the anomaly for a wider range of financial assets, such as government bonds, corporate bonds, derivatives and credit markets. A lot of papers also provide several possible explanations for the anomaly. So, another interesting area for future research would be to generate a model for better distinguishing between various drivers, provided by other papers, for explaining the ongoing presence of the low volatility anomaly in different market types.

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