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Introduction

The relationship between systematic risk and expected return is commonly accepted in financial theory. The intuition behind this is that investors will only hold risky assets if they expect to obtain higher returns than when holding risk-free assets. Following this, risky assets are expected to have higher returns than low-risk assets. The Capital Asset Pricing Model (CAPM) describes this relationship, where only higher systematic risk accounts for higher returns (Sharpe, 1964; Lintner, 1965; Mossin, 1966). Fama and French (1992) found that systematic risk alone does not explain the cross section of results, and added size and value premium as explaining factors. In more recent studies Black, Jensen and Scholes (1972) found evidence of assets with low risk having too high risk adjusted returns, while stocks with high risk provided relatively low returns.

Many researchers have found the topic interesting, and major contributions have been made by Ang, Hodrick, Xing and Zhang (2006), Blitz and van Vliet (2007), Baker, Bradley and Wurgler (2011). They have all come to the conclusion that low risk assets have a high performance relative to their risk, and that they even outperform high-risk assets within several asset classes. The mentioned studies show that low systematic risk and low idiosyncratic risk outperform stocks with high systematic risk. As investors should not be rewarded for systematic risk, it is surprising that there exists a relationship between idiosyncratic risk and return. Traditional asset pricing theories predict two scenarios. Either there is no relationship between idiosyncratic volatility (IVOL) and return under the assumption that markets are complete and frictionless, and all investors are well-diversified. Alternatively there is a positive relationship under the assumption that markets are incomplete and investors face sizeable frictions and hold poorly-diversified portfolios (Merton, 1987; Hirshleifer, 1988). This implies that the literature contradicts core concepts of finance and challenges the framework of CAPM.

We find this interesting because the underlying reason for the anomaly remains unclear. Many research papers have tried to give reason for the puzzle by proposing different economic mechanism linking IVOL to stock returns. However, Hou and Loh (2016) claim that only 10% of the puzzle is explained by existing explanations.

Thus, the purpose of this thesis is to test if the low volatility anomaly is present in the Norwegian stock market.

We contribute to existing literature by expanding the evidence on the association between idiosyncratic risk and one-month ahead return in the Norwegian market. Our aim is to assess and explain the results we observe, and use the explanatory power of realized IVOL in foretelling future returns. Further we will implement these results into trading strategies. To address this issue we will apply the framework of Ang et al. (2006) and include the negative relation between IVOL and average returns into our study of Norwegian stock returns. Studying the Norwegian market will hopefully help to confirm or reject the results of previous studies, and clarify if there is a higher risk-adjusted and absolute return to low risk stocks compared to high risk stocks.

Background and Existing Literature

Black, Jensen and Scholes (1972) challenged the predictions of CAPM, and found that the security market line (SML) is flatter than originally predicted. This was supported by Haugen and Heins (1972) who examined the New York Stock Exchange between 1926 and 1971. They pointed out that the relationship between risk and return was not only flat, but sometimes inverted. They concluded that long term portfolios with lower monthly variance yielded higher average returns compared to portfolios with higher risk. Fama and French (1992) showed that systematic risk alone does not explain the cross section of results, and that the combination of size and book-to-market could absorb the effects of leverage and earnings/price in average returns. These results have become commonly known as the “idiosyncratic puzzle”.

In classic asset pricing models such as the CAPM, idiosyncratic risk can be fully diversified away, and is therefore not expected to be rewarded with higher returns. However, Levy (1978) and Merton (1987) propose a positive relationship between idiosyncratic risk and volatility when there are undiversified investors. Malkiel and Xu (2002) also found a positive relationship between IVOL and the cross-section of expected returns. They concluded that idiosyncratic risk is more important than firm size and beta in explaining the cross-section of returns. Thus, they argue that

rational investors can be compensated for taking idiosyncratic risk into account when they are not able to hold the market portfolio.

In 2006, Ang et al., examined the specific risk component by investigating the relationship between lagged IVOL and average returns. They found that stocks with high IVOL relative to the Fama and French three factor model (FF-3 model) have significantly low average returns. The cross-sectional price of risk for systematic volatility was estimated to be significantly negative. These results were proved in U.S. and international markets and the findings could not be explained by exposures to size, book-to-market, leverage, liquidity, volume, turnover, bid-ask spreads, coskewness, or dispersion in analysts' forecast. This contradicts the basic premise of the CAPM, which states that idiosyncratic risk should not be rewarded because it can be diversified away.

Frazzini and Pedersen (2014) explored the relationship between beta and returns by assuming that low volatility stocks are consistent with low beta stocks. They used long positions in low-beta assets and short positions in high-beta stocks while levering and de-levering them to obtain a beta of one. Their results showed that portfolios with high betas resulted in lower alphas and Sharpe ratios, compared to investments in low beta portfolios, implying that risk-adjusted returns were significantly positive. These results were consistent across U.S. equities, in international equity markets, in treasury bonds, corporate bonds and futures, showing that the anomaly is present both globally and across different assets.

Clarke, de Silva, and Thorley (2006) performed an empirical analysis of minimum variance portfolios on the 1000 largest stocks in the U.S. from 1968 to 2005. In their analysis volatility declined by 25% and beta declined by 33% compared to a capitalization weighted benchmark.

Thus, they proved that minimum variance portfolios were capable of delivering similar or higher returns than the market portfolio at a lower risk.

Blitz and van Vliet (2007) expanded the analysis of Ang et al. (2006) and controlled for value, size and momentum effects to create a more optimal portfolio construction strategy. They used a long-term volatility sample and found a clear volatility effect showing that low risk stocks yielded significantly higher returns

compared to the market portfolio. In addition they found that, on a risk adjusted basis, high-risk stocks significantly underperformed. These effects were proved in global, U.S., European and Japanese markets. In 2013, Blitz, Pang and van Vliet found persisting evidence of the low volatility anomaly in emerging markets. They observed a larger negative alpha for high volatility portfolios compared to the size of a positive alpha of a portfolio of low volatility stocks. The Sharpe ratios of this study were significantly higher for low volatility stocks compared to high volatility stocks.

Scherer (2010) shows that portfolio constructions of minimum variance investments tend to consist of stocks with low beta and low residual risk. The paper concludes that, relative to a capitalization weighted index, 83% of the variation of the minimum variance portfolio can be attributed to factors of The Fama and French three factor model and two characteristic anomaly portfolios.

Another inspection of the low volatility anomaly was done by Baker and Haugen (1991) who found evidence of the same anomaly in U.S. and international markets in the period between 1972 and 1989. The results were further verified on a sample from 1990 to 2011 (Baker & Haugen 2012). Baker and Haugen (2012) analysed the low volatility anomaly on a country level using data from the Norwegian stock market. The portfolios were sorted based on estimated total volatility from the previous 24 months. They found that portfolios with lower total volatility yielded higher realized returns and higher Sharpe ratios compared to portfolios with higher total volatility. They found evidence of the low volatility anomaly in all developed and emerging markets including Norway.

Explanations of the Low Volatility Anomaly

Black et al., (1972) developed a model contradicting CAPM's assumption on unrestricted borrowing and lending of risky assets. The model assumed restrictions on borrowing, which results in a smaller slope of the security market line (SML) than CAPM suggests, implying a smaller relationship between beta and expected return. This makes low risk assets look more attractive as the lower slope of SML indicates that more risky assets have lower Sharpe ratios, compared to forecasts of the traditional CAPM. Black et al., (1972) therefore suggested that leverage restrictions can be a plausible argument for the relatively good performance of low

risk assets, hence an explanation for the low risk anomaly. Newer research, namely Blitz and van Vliet (2007) and Frazzini and Pedersen (2014) found supporting evidence of the same explanation. Blitz and van Vliet (2007) state that leverage is a prerequisite needed to take full advantage of low risk stocks. Frazzini and Pedersen (2014) state that leverage restrictions force investors to invest directly in high-risk assets which can raise the prices and lower the realized returns.

Blitz and van Vliet (2007) also point out inefficient investment approaches as possible explanations behind the low volatility anomaly. The inefficient investment approach regards inefficiency due to decentralization, where the first asset allocation is made by a CIO or investment committee, later followed by an allocation to managers who buy securities in the different asset classes. This approach leads to inefficient portfolios, argued by Binsbergen, Jules, Brandt and Kojen (2008). The asset managers will have an incentive to buy high beta or high volatility stocks to obtain higher expected returns, if CAPM holds. This can lead to an overpricing of high risk stocks and an underpricing of low risk stocks. Asset manager's desire of outperformance and cash flow may result in inefficient portfolios.

Lastly, Blitz and van Vliet (2007) have a third explanation of the low volatility anomaly as an effect of behavioral bias. According to behavioral portfolio theory, private investors operate with two-layer portfolios. Shefrin and Statman (2000) define the low layer being a low aspiration layer used to avoid poverty and the high layer is used as a possibility of high returns. The allocation decision reflects investors willingness to overpay for risky assets, due to a movement from being risk-averse to being risk-neutral or risk-seeking. This two-layer separation can lead to overpricing of high risk stocks and underpricing of low risk stocks.

Baker et al. (2011) support the statements of Blitz and van Vliet (2007) by proposing that investors' irrational preference for high volatility stocks may explain the low volatility anomaly. The irrational preference for high volatility stocks comes from biases affecting individual investors, such as the preference for lotteries, the representativeness bias, and the overconfidence bias, all explained by Kahneman and Tversky (1979). First, the preference for lotteries regards how individuals usually prefer a bet involving a low probability of a large gain compared

to a bet with a high probability of a small loss even if the expected outcomes of the bets are equal. This irrationality can be linked to the stock market because investors will typically overpay for high risk stocks and underpay for low risk stocks. Second, representativeness bias is a bias that arises when making judgements about the probability of an event under uncertainty. Baker et al. (2011) relates this to the volatility anomaly by saying that laymen are likely to consider the value growth of certain IPO stocks, such as Microsoft, without considering the high failure rates of other IPOs. Following this, inexperienced investors are likely to overvalue high risk stocks, while more experienced investors will do a more thorough analysis and consider the high risk stocks less attractive. Thirdly, the overconfidence bias regards the fact that people tend to overestimate their own abilities in making decisions and forecasts. According to Cornell (2009), overconfident investors will typically invest in high volatility stocks because these give the highest reward for security selection talent. With regards to this, Baker et al. (2011) point out that overconfident investors will use their own valuation of a stock when there is disagreements on the valuation. This will especially affect high volatility stocks.

Baker et al. (2011) propose benchmarking as a limit on arbitrage to be a possible explanation of the low volatility anomaly. They explain that the low volatility anomaly may be present due to the lack of incentives to use arbitrage strategies. Investors are limited by tracking errors and leverage constraints. Thus, in the short run, investors will be hesitant to deviate from benchmarks, because this might imply lower long run returns. An obvious strategy based on the low volatility anomaly is shorting or longing stocks with desired qualities. The top volatility quintile tends to be small stocks, which are costly to trade in large quantities. Thus, stocks with high IVOL tend to be overpriced over a longer period than stocks with low IVOL.

Methodology

Our research will be based on two fundamental financial models; the CAPM and the FF-3 Model as presented by Ang et al (2006). We examine IVOL with respect to the FF-3 model rather than the CAPM, due to the wider application of the FF-3 model in empirical finance.

The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is a fundamental financial model that describes the relationship between systematic risk and expected returns for assets (Sharpe, 1964; Lintner, 1965). The model is developed from the Markowitz (1959) portfolio theory, and offers predictions on how to measure risk, and the tradeoff between risk and return. According to the CAPM, investors are compensated for risk and the time value of money by receiving higher expected returns. This relationship is displayed by the security market line where the expected rate of return is a function of systematic risk. The expected return equals the rate of a risk-free security plus a risk premium.

$$R_i = R_f + \beta_i(R_M - R_F) \quad (1)$$

R_i is the return on security i , R_f is the risk-free rate, $(R_M - R_f)$ is the market risk premium. Beta (β_i) represents systematic risk, or market sensitivity.

The assumptions underlying the CAPM are as follows: (i) Investors can invest their capital in a risk free asset. (ii) Investors only care about mean and variance, and wish to maximize their utility of end of period wealth. (iii) Investors have homogenous expectations about asset returns (iv) quantities of assets are fixed. (v) all assets are marketable and perfectly divisible (vi) all investors have access to the same information. (vii) there are perfect capital markets and no transaction costs.

The Fama and French Three Factor Model

The Fama and French Three Factor Model (FF-3 Model) is an expansion of the CAPM which considers company size and company price-to-book ratio in addition to market risk (Fama & French, 1993). The intercept of the model measures how well the combination of common risk factors captures the cross-section of average returns.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{M,t} - R_{f,t}) + s_iSMB_t + h_iHML_t + \varepsilon_{i,t} \quad (2)$$

The FF-3 model specifies the excess return over the risk free rate ($R_{i,t} - R_{f,t}$) as a linear factor model consisting of the Fama-French adjusted alpha (α_i), and the three following factors, multiplied with their estimated factor exposures (β_i , s_i and h_i):

MKT: ($R_{M,t} - R_{f,t}$) Represents the value-weighted market excess return of the specific market portfolio over the risk free rate.

SMB: “Small minus big” represents the size premium, and accounts for the spread in between small and large sized firms, which is based on the company’s market capitalization.

HML: “High minus low” represents the value premium, and accounts for the spread in returns between value and growth stocks, in other words the spread on the book-to-market equity ratio.

SMB and HML are measures of historic excess returns of small cap companies over big cap companies and value stocks over growth stocks. Similar to the CAPM, higher systematic risk is rewarded with higher expected returns. According to the FF-3, small caps and value stocks have higher returns than large caps and growth stocks.

Estimation of Risk

We measure risk by calculating both historical monthly systematic and idiosyncratic risk, in order to find total volatility. IVOL with respect to the FF-3 model is defined as the standard deviation of the regression residuals:

$$IVOL = \sqrt{Var(\varepsilon_{i,t})} \quad (3)$$

Beta represents systematic risk with respect to CAPM, and is defined:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} \quad (4)$$

Portfolio Structure

To examine idiosyncratic risk based on the FF-3 model we will use historical data to form portfolios, following the same portfolio formation strategy as Ang et al. (2006):

We form portfolios based on an estimation period of L months, a waiting period of M months, and a holding period of N months. At month t , we compute IVOL from the regression (2) on daily historical data over an L -month period from month $t-L-M$ to month $t-M$. Our estimation period (L) consists of 4 years of historical data. To assess the effect of IVOL in stock returns, we classify the available stocks for each month into value-weighted portfolios, ranked by IVOL. After the ranking and construction of portfolios we measure the monthly returns in the portfolios in a holding period (N) of one month. The portfolios are rebalanced each month. The ranking and evaluation is repeated until the end of the sample. We then obtain time series of monthly returns for our IVOL portfolios, and we can measure average returns and the volatility of stock returns in a four year rolling window.

Performance Evaluation

We calculate the excess return of each decile portfolio, and with the resulting time series we find the portfolio performances by calculating standard deviations, Alphas and Sharpe ratios.

Alpha

We estimate alphas from the portfolio returns on the basis of FF-3 model using Newey and West (1987) standard errors. We use the alphas as a measure of interest when examining if higher IVOL reflects on higher returns. When drawing a conclusion if there is a relationship between IVOL and returns we will focus on the sign and significance of spread between the portfolios. If α is significantly different from zero, the returns from decile portfolios are not adequately explained by the size and value factor exposure. If α is not significantly different from zero, the size and value factor exposure explain all the excess returns.

Sharpe Ratio

We measure the Sharpe ratio to find the risk-adjusted performance of the portfolios. This will be used to test whether the portfolios with low-volatility stocks have a higher return than the portfolios of high-volatility stocks. The ratio is calculated as

excess return of the portfolio ($R_p - R_f$) divided by the standard deviation of the excess return:

$$\text{Sharpe ratio} = \frac{R_p - R_f}{\sigma_p} \quad (5)$$

Robustness Test

We will test if our findings are robust when changing different exposures. We will test robustness by reporting alphas for other periods, by varying the choices of L , M and N , and by changing the rebalancing frequency.

Data

We will use daily data from Norwegian equity market stocks from 1990 to 2016. We start with data from 1990, because this are the first data to be obtained in daily returns. We obtain OSEAX daily prices adjusted for dividends from Datastream. Following the FF-3 framework we will calculate size by multiplying price per share by the number of shares. Book-to-market ratio will be found using Datastream. In the Norwegian stock market the most commonly used proxy for the risk-free rate are 10-year government bonds.

We expect to encounter limitations due to the size of the Norwegian stock market. Earlier studies have used data from larger equity markets. This implies that our sample will be smaller and we expect our results to be less significant with larger standard errors and lower t-statistics compared to other studies. Earlier research excludes the firms with lowest market capitalization. Other studies have removed small cap firms to avoid small illiquid stocks with large bid-ask spreads. Ang et al (2006) eliminate 5% of the stocks of firms with the lowest market cap.

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