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The Beta Anomaly and the Conditional CAPM in the Norwegian Stock Market

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ABSTRACT

In this Master thesis, we investigate the relation between systematic risk and returns in the Norwegian Stock Market between 1986-2014. In an efficient market, market participants realize above average returns only by taking on above average risks. However, prior studies find that strategies that sell high-beta stocks and buy low-beta stocks have significantly negative unconditional Capital Asset Pricing Model (CAPM) alpha. In our study, we do not find this relationship to be present in Norway, and our findings are also robust to volatility sorted portfolios. Further, by utilizing the methodology of Cederburg & O'Doherty (2016), we show that the conditional CAPM does not perform better than other static empirical pricing models in Norway.

Table of Contents

1 INTRODUCTION

The Capital Asset Pricing Model (CAPM) developed independently by Sharpe (1964), Lintner (1965) and Mossin (1966), states that the cross-section of expected excess returns on any financial asset are linearly associated to its non-diversifiable risk, the beta. The model implies that in market equilibrium, the value-weighted market portfolio is mean-variance efficient, where there is a positive expected premium for beta risk, and beta is the only risk needed to explain expected return. Moreover, the CAPM is constructed to be an ex-ante, one-period model where the beta is assumed to be constant over time.

However, early studies by Friend & Blume (1970), Black, Jensen & Scholes (1972) and Fama & Macbeth (1973) shows that high-beta portfolios earn lower returns than predicted by the CAPM. Furthermore, the security market line (SML), also known as beta-return relation, is too flat relative to the predictions of the CAPM. They find positive CAPM alphas, indicating that low-beta stocks produce higher risk-adjusted returns than high-beta stocks. This is characterized as the *beta anomaly* in the academic literature, as low beta stocks generate significantly higher Sharpe ratios than stocks with higher betas. Fama & French (1992, 2006) extended this argument by showing that the SML becomes even flatter when controlling for size and book-to-market factors.

Recently, the work of Frazzini & Pedersen (2014) has drawn interest of many academics and practitioners. They developed a *betting-against-beta* (BAB) strategy that focused on the US market and 19 other international equity markets, including Norway. The MSCI Norway Index, which measures the dollar-denominated performance of large and mid-cap segments was used for the study in Norway. In their paper, they report positive excess risk-adjusted returns over the period 1989-2012, however, the results of the BAB strategy in Norway are not statistically significant. Since their findings are presented together with 18 other markets, the Norwegian result are not explicitly discussed. By applying a longer time horizon, adding more stocks to our investment universe and select different rebalancing, we investigate if the low beta anomaly is present Norway, by partly utilizing the methodology by Frazzini & Pedersen (2014).

Most empirical investigations of the beta-anomaly study the unconditional version of CAPM, where beta is assumed to be constant over time. However, large swings of portfolio beta over the sample period can lead to a bias in its unconditional alpha. Thus, the CAPM can hold period by period, even though the static model fails. Cederburg & O'Doherty (2016) finds that if one fully account for the time-varying systematic risk, the conditional CAPM alpha is insignificant and the conditional beta anomaly becomes less of a puzzle. By using lagged state variables, we investigate if conditioning helps to reduce the magnitude and significance of the CAPM alphas in Norway.

Li, Sullivan & Garcia-Feijóo (2014, 2016) presents three versions of the anomaly based on different return variability: *the low beta anomaly* (Black, Jensen & Scholes (1972), (Fama & French (2004), and Frazzini & Pedersen (2014)), *the idiosyncratic volatility anomaly* (Ang et. al (2006, 2009)) and *total return volatility anomaly* (Baker, Bradley & Wurgler (2011) and Haugen & Baker (1991, 2012)). Apart from Frazzini & Pedersen (2014), there are three other papers that have included Norwegian data in their low volatility puzzle investigations. Haugen & Baker (2012) verifies the presence of total return volatility anomaly in Norway. Ang et.al (2009) and Baker, Bradley & Taliaferro (2014) both documents the presence of idiosyncratic and the low beta anomaly, however, the results for Norway are aggregated together with rest of the countries that are studied. Therefore, due to the absence of extensive literature of the low risk anomalies in Norway, and seemingly conflicting results among researchers whether the anomalies are present, we study if the intuitively appealing and testable CAPM holds.

Several reasons motivate the study of the low beta anomaly. First, the CAPM is an equilibrium model and it is a popular framework for thinking about investments. If the market portfolio is mean-variance efficient, the CAPM result holds. However, if low-beta and high-beta stocks are consistently mispriced, there exist portfolios that have higher expected returns for a given level of risk than the value-weighted market portfolio. Second, if the conditional CAPM resolves the anomaly, it indicates that the static CAPM simply mismeasure the portfolio alpha. Thus, one does not achieve a higher risk-return tradeoff by implementing low-beta and high beta strategies compared to the market portfolio, when the market is assumed to be conditional mean-variance efficient.

In line with Frazzini & Pedersen (2014), we do not find evidence of the unconditional low-beta anomaly in Norway over the period 1986-2014. By sorting firms into quintiles based on estimated betas, which are held for 12 months before rebalancing, our high-minus-low strategy do not have a statistically significant alpha after controlling for size, book-to-market, momentum and liquidity effects. We thus conclude that the beta-anomaly is not present in Norway. Moreover, we find that the instrumental variables in the conditional CAPM produce poor conditional alphas, and that static pricing models is superior in evaluating performance of our test portfolios. Furthermore, when constructing portfolios based on past estimated volatilities, we find some significant negative alphas for high volatility portfolios but the results are not robust when tested for different sub-samples and different methodologies. This leads us to conclude that, in addition to absence of the low-beta anomaly, neither a low-volatility anomaly exists in Norway. After a number of robustness checks, we find that our initial results still hold.

The rest of the thesis is organized in the following manner; Section 2 presents the existing literature on the low-volatility anomaly, Section 3 reviews theoretical models used in the thesis, Section 4 elaborates on the empirical approach chosen to investigate the anomaly in Norway, Section 5 gives an overview of the data, Section 6 presents our empirical findings, and in Section 7 we arrive at our conclusion.

2 LITERATURE REVIEW

The cornerstone in finance theory is the relationship between risk and return. It has been studied broadly, both by academics and by practitioners. The observation that low-risk portfolios deliver higher returns is a remarkable and counterintuitive result in finance. In this section, we summarize the existing literature in this field. As there are three versions of the low-risk anomaly, we cover the total return volatility anomaly and the idiosyncratic volatility anomaly first, which is found in section 2.1 and 2.2. Section 2.3 focuses on the low-beta anomaly. Section 2.4 discusses literature of the low-beta anomaly puzzle with emphasize on the conditional CAPM. Section 2.5 reviews possible explanations of the anomaly, using both behavior finance theory and rational explanations.

2.1 The Total Return Volatility Anomaly

Several studies look at the risk-return relation that aggregates both the systematic and nonsystematic risk factors. Minimum volatility portfolios tend to hold low-beta and low residual risk stocks. Therefore, these investigations are particularly relevant in relation to the low-beta anomaly.

Haugen & Heins (1972, 1975) examined the relationship between risk and return on NYSE stocks and on the US bond market between 1926-1971. They conclude that there exists no risk premium in the US stock market. Moreover, they find that stock portfolios of lesser variance generate higher reward, suggesting an inverse relation between risk and return. The research of Haugen and Heins has been confirmed in later studies, across nearly all developed equity markets.

Recently, Scherer (2010) constructs a minimum variance portfolio using a standard multifactor regression with HAC[1] adjusted errors. His findings show that minimum variance investing implicitly picks up risk-based anomalies. Near 83% of the variation of the minimum variance portfolio excess returns can be attributed to the FF-3 model. This result favors a view that minimum variance strategies provides significant improvement over the market-cap weighted benchmark, simply because the portfolios are a more efficient way to exploit the anomalies.

[1] Applied work routinely relies on heteroscedasticity and autocorrelation consistent (HAC) standard errors when conducting inference in a time series setting.

The study by Baker & Haugen (2012) covers stocks from 1990-2011 in 21 developed countries, including Norway. The volatility is computed of the total return for each company over the previous 24 months. Stocks in each country are then ranked by their volatility and formed into deciles. The difference in total return, low risk minus high risk decile is positive across all equity markets, and even more dramatic is the positive difference in Sharpe ratios. According to the paper, this provides significant evidence of the minimum volatility anomaly in Norway, and in the 20 other developed countries. The findings of Baker and Haugen are consistent with the results of Ang et al. (2006).

Li, Sullivan & Garcia-Feijóo (2016) challenges the conclusions of Scherer (2010). Using stock returns from 1963-2011 in the US, they find that high returns on low-volatility portfolios are not solely compensation for bearing systematic risk factors. The results from their cross-sectional analyses suggest that the low-volatility anomaly is not related to some systematic risk factor and there is no value premium associated with it. Their findings indicate that the abnormal returns most likely arise from market mispricing. This stems from investors preference for high volatility stocks and thus provides a behavior explanation of the anomaly.

2.2 The Idiosyncratic Volatility Anomaly

Since the beginning of classical asset pricing theory, there has been conducted numerous research to validate if expected returns depend on idiosyncratic volatility (IVOL), that is, risk that is not correlated with the market or other systematic risk factors. According to the CAPM, idiosyncratic risk should not be priced, as it can inexpensively be diversified away.

Earlier studies find no documentation of a negative relation between very short-term IVOL and stock returns. The classic study by Fama & MacBeth (1973), who acknowledge the methodological issues raised by Miller & Scholes (1972), concludes that the coefficients and residuals of the risk-return regressions are consistent with the Efficient Market Hypothesis.

In a more recent paper, Ang et al. (2006), finds that stocks with high IVOL relative to Fama-French 3 factor model (FF-3) have significantly lower average returns. They uncover a robust result and argues that the findings cannot be explained by exposure to size, book-to-market, leverage or liquidity characteristics. Moreover, the effect perseveres both in bull and bear markets.

However, Bali & Cakici (2008) dismisses the existence of the IVOL puzzle. They argue that portfolio construction and different IVOL measures play a critical role in determining the relationship between risk and returns. From the sample period 1958-2004 on NYSE, AMEX and NASDAQ, they conclude that there exists no robust evidence for a negative relationship between IVOL and returns.

In the influential paper by Ang et al. (2009), the stock returns in 23 developed markets, including Norway are studied. The average return between the difference of the extreme quintiles portfolios sorted by short-term IVOL was -1.307% per month for all countries and -0.723% for European countries, after controlling for the FF-3 factors. They conclude that there is a strong negative relation between idiosyncratic risk and returns, however, the Norwegian market are not specifically commented.

2.3 The Low Beta Anomaly

The findings that low-beta stocks outperform high beta stocks conflict with the unconditional Capital Asset Pricing Model, and is therefore referred to as an anomaly. The predictions of the CAPM state that asset returns are proportional to its market beta, that is, the covariation between the market and the asset, which is the only risk measure.

2.1.1 Evidence Against the Unconditional CAPM

The early empirical investigations of the unconditional CAPM by Black, Jensen & Scholes (1972), Fama & MacBeth (1973), and Haugen & Heins (1975), reveals that the SML, the graphical representation of the CAPM, is much flatter than predicted by theory. Their findings show that low-beta assets have higher risk-adjusted returns than high-beta assets, thus violates the CAPM and Fama's (1970) Efficient Capital Markets theory. Two decades later, Fama & French (1992) expands the model by adding size and value factors to the market risk factor in the CAPM, in an attempt to measure market returns more precise. Investigating the period 1963-1991 in the US, they find that the market beta is unpriced, after controlling for size. This implies that firms with higher average beta, are not compensated with higher average returns. While the FF-3 explains assets returns better than the CAPM, it is considered to be an empirical factor pricing model which lacks convincing theoretical explanations of the introduced additional risk factors. The extension of the FF-3 factor model is the Carhart (1997) four factor model that includes a momentum component. Momentum is described as the tendency for a stock to continue rise (fall) if the price direction is positive (negative). However, after controlling for the FF-3 and Carhart risk factors, the superior performance between low and high beta stocks is still present in international markets (see e.g. Baker et al. (2014) and Frazzini & Pedersen (2014)). In the five-factor model, Fama & French (2015, 2016), adds profitability (RMW[2]) and investment (CMA[3]) factors to the three-factor model. The study from July 1963 to December 2014 for US stocks claims that the five-factor model is able to explain the returns of portfolios with different betas. The low-beta stocks have positive exposure to profitability and investment factors while high beta stocks have the opposite exposure. Thus, low (high) beta stocks behave like profitable (less profitable) firms that invest conservatively (aggressively), and Fama & French (2015, 2016) argues that the low-beta anomaly is resolved by the 5-factor model (FF-5). However, Blitz & Vidojevic (2016) disagrees, and claims that the rejection of the low-beta anomaly is premature. When the authors take a closer look at the time-series regression results, they do not find evidence of a positive, linear relation between market beta and return, which is assumed by the FF-5. By using Fama-MacBeth regressions, they find that all five factors, except market beta are rewarded with a significant risk premium, thus bringing further evidence of the anomaly.

2.1.2 Findings of Frazzini & Pedersen (2014)

Frazzini & Pedersen (2014) constructs market-neutral betting-against-beta (BAB) portfolios, which buys low-beta stocks and sells high-beta stocks. The paper finds that high-beta stocks have both lower FF-3 factor alphas and Sharpe ratios than low-beta stocks. When the beta increase in the portfolios, the alpha declines, which is documented for the US stock market and in 18 of 19 international markets. The flatness of the SML is not only found in stock markets, but also in

[2] RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios,
[3] CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios

Treasury, corporate bond and in futures markets, thus supporting the presence of the low-beta anomaly among different asset classes. Although they find that low-beta stocks produce higher risk-adjusted returns than high beta stocks in Norway, implying that the SML is flatter than predicted by CAPM, their results are not statistically significant.

2.4 Literature on the Conditional CAPM

Most empirical studies of the CAPM assume that betas remain constant over time and that it is commonly accepted that the static model fails to predict the cross-section of stock returns. In the search to explain this pricing error, researchers have extended the traditional CAPM to become a conditional model. The conditional CAPM measures the impact of market volatility, market risk premium and the systematic risk of an asset, that in turn affect the conditional covariance between the asset and the market.

Jagannathan & Wang (1996) finds that when expected returns are modeled to vary over time, the conditional CAPM performs rather well, and size effects[4] becomes much weaker. When investigating firm returns on NYSE, AMEX (1962-1990) and Nasdaq (1973-1990), they find that pricing errors becomes insignificant when a proxy for human capital is added to the conditional model.

Boguth et.al (2011) also demonstrate that the conditional CAPM is effective of explaining asset returns. When including realized lagged betas as instrumental variables that are available to investors ex-ante, their constructed momentum-portfolio alphas reduces by 20-40%. The authors argue that the unconditional alphas are biased when the conditional beta covaries with the market risk premium (market timing) or volatility (volatility timing), and the bias can overstate the alphas by up to 2.5 times.

2.4.1 Criticism of the Conditional CAPM

The information dependent version of the CAPM has received much attention in the recent literature. However, the model has some undesirable features and several researchers recommend that the model should be used with caution.

[4] Also called the small-cap effect, which is the tendency that firms with low market capitalization outperforms firms with high market capitalization over time.

Foremost, it is empirically challenging to model how market betas and risk premiums vary with variables that represents conditioning information, as described by Wang (2003). An econometrician has no theoretical guidance on how to deal with these specification issues, which instrumental variables[5] (IV) that are most appropriate to use, and whether the econometrician knows the full set of state variables that are available to investors.

An attempt to resolve this specification issue, where one must identify exogenous variables that are a linearly function of expected betas, the beta dynamics can rather be specified by time-series modeling. When the conditional covariance matrix follows a GARCH[6] process that does not use exogenous information set, Harvey (1989) and Ng (1991) document strong evidence of time-varying betas, and their findings indicate that the market proxy portfolio is conditional mean-variance efficient. Nevertheless, this econometric technique is also criticized, where the focus is on the time-series side of expected returns, and that the construction of the time-varying beta is too simple and lacks economic theory and explanation.

Lewellen & Nagel (2006) uses prices and returns from CRSP[7] from 1964-2001 and constructs size, B/M and momentum portfolios, to test the validity of the conditional CAPM. They provide direct evidence against the conditional model and discards the conclusions of Jagannathan and Wang (1996). In contrast, they report that the conditional CAPM does not explain asset-pricing anomalies like B/M or momentum effects, and that variation in betas and risk premiums would have to be much higher to explain large unconditional pricing errors. Moreover, they criticize the focus of cross-sectional regressions by Jagannathan and Wang (1996), and claims that time-series intercept test improves the quantitative inferences of the conditional CAPM.

2.4.2 Findings of Cederburg & O'Doherty (2016)

Cederburg & O'Doherty (2016) investigates the beta-anomaly using returns data from NYSE, AMEX and Nasdaq from July 1926 to December 2012. By sorting firms into decile portfolios based on past short-window beta estimates, that are

[5] Used to resolve following problems in OLS regressions; Omitted Variable Bias, Measurement Error and Simultaneity or Reverse Causality.
[6] Generalized autoregressive conditional heteroskedasticity.
[7] Center for Research in Security Prices..

held for one year before rebalancing, the negative abnormal returns of high-beta minus low-beta decile portfolio are statistically significant only in the unconditional CAPM case.

Further, they construct the conditional CAPM using lagged macroeconomic state variables such as dividend yield[8] and default spread[9], in addition to lagged-component (LC) betas, and show that the pricing errors of high-beta and low-beta stocks becomes insignificant. In their most comprehensive conditional CAPM model, the long-short beta portfolio earns a conditional alpha of -0.18% per month (t-stat of -0.7), in contrast to the unconditional alpha of -0.59% per month (t-stat of -2.3). Cederburg & O'Doherty (2016) concludes that when time-varying market exposure is predictable, the beta-anomaly is resolved by using the innovation of instrumental variables.

2.5 Possible Explanations of The Low Risk Anomaly

2.5.1 Explanations on the Basis of Behavior Elements

Baker, Bradley & Wurgler (2011) looks at behavioral factors that affects the financial decisions of individual investors. In their paper, three biases that attracts investors towards high-volatility stocks are examined.

The view of stocks as lottery tickets: In a gamble with 50/50 percent chance of winning $110 versus losing $100, according to extensive studies by Kahneman & Tversky (1979), the possibility of losing $100 is enough to make people shy away from the gamble. This behavior is called “loss aversion”, where a dollar lost is more valuable than a dollar gained. However, in a gamble with a near-certain loss of $1 and 0.12% chance of winning $5,000, people are much more likely to participate, even if the two gambles have the same positive expected payoff of $5. This impose a behavior inconsistency. Mitton & Vorkink (2007) connects this irrationality to the behavior of investors in the stock market. Since low-priced volatile stocks have the same characteristics as in the second example, it is similar as buying lottery tickets. Blitz & van Vliet (2007) discusses the preference for

[8] In Cederburg & O'Doherty (2016), the dividend yield is the difference between the log of the sum of dividends accruing to the CRSP value-weighted market portfolio over the prior 12 months and the log of the lagged index level.

[9] In Cederburg & O'Doherty (2016), the default premium is the yield spread between Moody’s Baa- and Aaa-rated bonds. The bond yields are obtained from the Federal Reserve Bank of St. Louis website. See http://research.stlouisfed.org/fred2/.

lottery tickets related to behavioral portfolio theory mentioned in Shefrin & Statman (2000), where private investors think in terms of a two-layer portfolio. The low aspiration layer (first layer) is designed to avoid poverty, while the high aspiration layer (second layer) is designed to obtain riches. A private investor can make rational risk averse asset allocations (first layer), but he can increase the risk willingness in a specific stock or asset class (second layer). Buying few volatile stocks keeps a potential upside intact compared to a well-diversified portfolio, which limits it. This behavior increases the demand for risky stocks, causing them to be overpriced, and hence, offers investors with lower expected returns.

Representativeness: Described first by Kahneman & Tversky (1972), the representativeness heuristic is a decision-making shortcut when making judgments about the probability of uncertain events. The fact that people may overestimate their ability to accurately predict the likelihood of an event can be extended to the financial markets. Discussed in Baker, Bradley & Wurgler (2011), an investor might have the belief that the road to riches is by making speculative investments in new technologies, for example Microsoft Corporation in the 1980s. However, the fallacy of this logic is to not recognize that a large sample of speculative investments fail, and that investors might be inclined to overpay for volatile stocks.

Overconfidence: There exist extensive literature that both common individuals and market participants tend to exhibit irrationally high level of overconfidence (see e.g. Fischhoff, Slovic, & Lichtenstein (1977), Alpert & Raiffa (1982) and Barber & Odean (2001)). According to Cornell (2009), overconfidence plays an important part of demand for volatile stocks. Investors who consider themselves to have superior stock selection skills are more likely to invest heavily in volatile stocks, to capitalize on their perceived skills. Baker, Bradley & Wurgler (2011) points out that one needs to connect overconfidence with one extra assumption about the market participants. That is, either the pessimists in the stock market must act less aggressively that the optimists, or pessimists have reluctance or inability to short stocks instead of buying them. In many cases this is a reasonable assumption, and it has been investigated empirically by Diether, Malloy, & Scherbina (2002). This indicates that overconfident investors tend to overvalue risky stocks, thus leading future expected return to be lower.

2.5.2 Explanations on the Basis of Rational Elements

Leverage constraints: Black (1972) discovered that the security market line is flatter than predicted by CAPM, and notes the relevance of borrowing constraints for the beta-return relationship. Frazzini & Pedersen (2014) argues that in absence of leverage, investors that seeks higher expected returns will need to tilt their portfolios towards risky high beta assets to achieve their goals. The increasing demand for high beta assets will cause the prices to rise, and hence they will exhibit lower risk adjusted expected returns than low-beta assets.

Benchmarking: Baker, Bradley & Wurgler (2011) and Ang (2014) and blames the agency problems for the risk anomaly. Many contracts for institutional equity management specifies that the portfolio manager cannot have a large tracking error relative to the benchmark index, for instance S&P 500. Shorting small capitalized volatile stocks are costly, and volumes of shares to borrow might be limited. Therefore, institutional investors cannot take bets on the anomaly without increasing their tracking error to the benchmark.

Return skewness risk: Schneider, Wagner & Zechner (2016) investigates the relation between skewness risk (that are approximated using corporate credit risk) and average return of US firms between 1996-2014. They argue that the low-beta anomaly and the low-volatility anomaly are driven by negatively skewed return distributions due to firm`s default risk. The return skewness (firm’s downside risk) rises with beta / total volatility, and the authors suggest that the CAPM ignores the important effect of skewness risk on asset prices. Hence, they reason that the anomaly is not necessarily imposing an asset-pricing puzzle, but rather stems from misspecification of the CAPM. Because investors also care about the third and fourth moments of return distributions, they therefore demand a skewness-premium.

3 MODELS AND THEORY

We first present the unconditional Capital Asset Pricing Model in section 3.1. In section 3.2 we show conditional CAPM used by Cederburg & O'Doherty (2016).

3.1 The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM), first proposed by Sharpe (1964) and Lintner (1965), follows the mean variance optimization problem from Markowitz (1952). When investors can borrow and lend at the risk-free rate, the model predicts that the expected return of an asset above the risk-free rate is proportionate to its non-diversifiable risk. Thus, the required return of any individual asset's expected return can be formulated as:

$$E(r_i) = r_f + \beta_i(E(r_m) - r_f)\ , \tag{1}$$

where $E(r_i)$ is the expected return for the individual asset, r_f is the risk-free rate, $E(r_m)$ is the expected return on the market portfolio and $\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)}$ is the beta, measured by the covariance between the asset and the market divided by the variance of the market.

3.2 The Conditional Capital Asset Pricing Model

Following Cederburg & O'Doherty (2016), the conditional CAPM implies that:

$$a_{i,t} = E\left(R_{i,t} \middle| I_{t-1}\right) - \beta_{i,t}(E\left(R_{m,t} \middle| I_{t-1}\right) = 0, \tag{2}$$

where in equation (2) $R_{i,t}$ is the portfolio's excess return during period *t*, $R_{m,t}$ is the excess market return, $I_{t-1}$is the investor's information set at end of period *t-1*, and $\beta_{i,t} = \frac{Cov(R_{i,t}, R_{m,t} | I_{t-1})}{Var(R_{m,t} | I_{t-1})}$ is the conditional beta of the asset.

The traditional implementation of the conditional CAPM follows classical IV approach suggested by Shanken (1990), Ferson and Schadt (1996), and Ferson and Harvey (1999). Under this method, portfolio betas are modeled as a linear function of instrumental variables such as aggregate dividend yield and default spread. Boguth et al. (2011) who incorporates lags of realized portfolio betas as additional state variables improved this approach. As these lagged realized betas are known to investors ex ante, the over conditioning bias in the estimation of CAPM alphas is avoided.

4 METHODOLOGY

The objective of our thesis is to investigate the risk-return relationship of beta-sorted portfolios and to measure out-of-sample performance using both unconditional CAPM and conditional CAPM models (see section 3) in the Norwegian stock market. Furthermore, we want to study if the total return volatility anomaly is present in Norway by sorting our portfolios based on ex-ante volatility estimates.

Section 4.1 provides details of estimating formation-period betas that will be used to form beta-sorted portfolios. Section 4.2 provides details of estimating ex-ante total volatility that will be used to form volatility-sorted portfolios. In section 4.3, we outline how the ex-ante betas and volatility are used to construct our test portfolios. Section 4.4 explains how we measure the relative performance of our formed portfolios especially high-minus-low portfolio using both unconditional and conditional CAPM.

4.1 Constructing Ex-Ante Unconditional Betas

The pre-ranking betas is estimated using non-overlapping[10] regressions of stocks excess returns on market excess returns. To increase the accuracy of the covariance estimates, Frazzini & Pedersen (2014) use daily data instead of monthly, when possible. We follow the same approach. The unconditional estimated beta for stock *i* is defined as:

$$\hat{\beta}_i^U = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{3}$$

where in equation (3), $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities of the asset and the market, $\hat{\rho}$ is the estimated correlation between them and $\hat{\beta}_i^U$ is the estimated unconditional beta of stock i. The correlations are constructed using three-day log returns over a five-year horizon, $r_{i,t}^{3d} = \sum_{k=0}^{2} \ln(1 + r_{t+k}^{i})$, to alleviate the effect of nonsynchronous trading. The market volatility is collected using one-year of non-overlapping estimates, which is calculated from one-day log returns. For individual stocks, we use non-overlapping three-day log returns[11] to estimate stock volatility, such that $\hat{\sigma}_i = \frac{1}{\sqrt{3}}\hat{\sigma}_{i,3d(non-overlap)}$, to make stock volatilities and

[10] Frazzini & Pedersen (2014) use rolling regressions when estimating the pre-ranking betas.
[11] Frazzini & Pedersen (2014) use one-year rolling standard deviations for estimating stock volatility.

correlations comparable. The correlations and volatilities are estimated separately. Each year at the beginning of July, we estimate the formation-period betas[12], where we require that a stock has at least 750 return observations days over the prior 60 months. This liquidity filter of minimum 750 observations has been chosen following the methodology of both Frazzini & Pedersen (2014) and Cederburg & O'Doherty (2016). The former specifies to include a stock if there exist returns for minimum 3 years out of five years, and later specifies to include a stock if return exist for minimum 150 days out of 250 trading days in a year.

4.1.1 Alternative Beta Estimations

Our main strategy for constructing beta-sorted portfolios is to compute ex-ante betas using methodology described in Section 4.1. However, as a robustness test, we want to investigate if the performance of beta-sorted portfolios is affected by alternative beta estimations[13]. In the alternative method, we use monthly log-returns data. Following Frazzini and Pedersen (2014), we estimate correlations using a five-year window, requiring at least 36 valid monthly observations to estimate correlations, and volatilities are estimated using one-year window.

4.2 Estimating Ex-Ante Volatility

To estimate the volatility, we use the previous 12-month daily data window with same liquidity filters as explained in section 4.1, i.e. for a stock to be included in our trading strategy, it must have minimum 150 valid return observations out of 250 trading days. Haugen and Baker (2012) used 24-month window to compute the volatility. However, to keep the consistency in our portfolios concerning beta formation approach mentioned above, we have used 12-month window of daily data.

[12] Cederburg & O'Doherty (2016) uses non-overlapping unconditional CAPM regressions on daily stock returns. They include lags of excess market returns to alleviate the impact of non-synchronous trading. We have implemented the same approach on Norwegian data but the regressions produced poor beta estimates, and therefore those betas are not presented in this thesis.
[13] We also estimated correlations using overlapping three-day log returns over one-year horizon. However, the estimated ex-ante betas following equation 3 produced poorly beta estimates and will not be presented in this thesis.

4.2.2 Alternative Volatility Estimations

As a robustness test, we want to investigate if the performance of volatility-sorted portfolios is affected by alternative volatility estimations[14]. Therefore, we have used monthly data with five-year estimation window, requiring at least 36 valid return observations for a stock to be included in our investment strategy.

4.3 Constructing Beta and Volatility Sorted Quintile Portfolios

Each year at the beginning of July, we rank all stocks in ascending order based on their estimated beta or volatility using methodology shown in Section 4.1 (4.2). We then assign the stocks into quintiles, such that each portfolio represents 1/5 of our sample, where 1 (5) corresponds to the lowest (highest) betas and volatilities. Cederburg & O'Doherty (2016) constructs decile portfolios for their low-beta anomaly investigation in the US market. However, we find that constructing portfolio based on deciles is too restrictive for Norwegian data, as size of Norwegian market in terms of number of stocks listed on Oslo Stock Exchange (OSE) is considerably smaller compared to the US. Thus, we have formed quintiles instead to have adequate sample size in each portfolio every year.

The portfolios are both given equal weights and weighted by their market capitalization (value-weighted) and held from July each year to June next year as in Cederburg & O'Doherty (2016). Using this period has alternative advantage for Norwegian data as fiscal year ends in December every year and by June next year, every listed company has reported its consolidated accounts and director's report, so price and thus returns reflect all available information.

The portfolios are held for 12 months and rebalanced each year at the beginning of July. This strategy has lower transaction cost compared to strategies that require more frequent rebalancing, such as in Frazzini and Pedersen (2014). Our rebalancing scheme is therefore more comparable to a passive buy-and-hold investor[15].

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[14] We have also produced ex-ante volatility estimates using five-years of daily data, but this strategy produced poor out-of-sample performance for volatility sorted portfolios, and will therefore not be presented in this thesis.

[15] However, with infrequent rebalancing it becomes harder to maintain the desired risk exposure.

4.4 Measuring Portfolio Performance

When measuring the characteristics of the test portfolios, we use monthly return series where all portfolio returns are converted to excess returns by subtracting the corresponding risk-free rate. We then compute monthly ex-post standard deviations, ex-post betas and annualized Sharpe-ratios[16] for our quintile portfolios. The test periods differ from the value-weighted and equal-weighted[17] portfolios, where the period for the value-weighted test portfolio is from July 1986 - June 2014, and the equal-weighted test portfolio period is from July 1986 - June 2015.

4.4.1 Unconditional Performance Evaluation for the Quintile Portfolios

When assessing the unconditional performance for each quintile portfolio, we run OLS regressions of the quintile portfolios separately, using CAPM, Fama-French 3 factor, a four-factor model that includes momentum factor, and finally a five-factor model that includes a liquidity factor. The t-statistics are computed using Newey & West (1987) standard errors with lag length equal to one, to try to overcome possible autocorrelations and heteroskedasticity in the error terms. We also compute cumulative portfolio log returns, as these are additive through time.

4.4.2 Unconditional Performance Evaluation for the HL Portfolio

We define H as the highest beta (volatility) portfolio, L as the lowest beta (volatility) portfolio, and HL refers to their difference. Cederburg & O'Doherty (2016) specify the HL as a zero-cost[18] portfolio that takes long position in the high-beta (volatility) quintile and a short position in the low-beta (volatility) quintile. We specify our difference in portfolio alpha as

$$\alpha_{HL} \equiv \alpha_H - \alpha_L, \tag{4}$$

where we test if equation (4) is equal to zero as implied by the CAPM. Following Cederburg & O'Doherty (2016), we estimate the H and L alphas separately using OLS regression.

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[16] The monthly Sharpe-ratio is annualized by multiplying with $\sqrt{12}$.

[17] Our value weighted out-of-sample performance is one year shorter compared to equal weighting due to insufficient market capitalization data for 2015.

[18] Frazzini and Pedersen (2014) employs a different methodology when investigating the low-beta anomaly. They construct a self-financing beta-neutral BAB portfolio that goes long low-beta assets and short high-beta assets, $r_{t+1}^{BAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r_f)$.

To obtain standard errors from the system, we first estimate high and low OLS regressions separately, then we keep the time series of the residuals. We add up the alphas and residuals and regress $(\alpha_H + u_{H,t}) - (\alpha_L + u_{L,t})$ on a constant with HAC standard errors with lag length equal to one, to obtain valid standard errors for α_{HL}. This method[19][20] is also good at controlling for the correlation between the two portfolio residuals, since subtracting low from high perfectly captures any relevant relation between the two sets of residuals.

4.4.3 Conditional Performance Evaluation for the HL Portfolio

As in Cederburg & O'Doherty (2016), we assess the conditional performance for beta-sorted portfolios using one-step instrumental variable approach (IV1), where the conditional return regression is

$$R_{i,\tau} = a_i^{IV1} + \beta_{i,\tau}^{IV1} R_{m,\tau} + u_{i,\tau}, \qquad (5)$$

where in equation (5), τ is the holding period of the test portfolio, $R_{i,\tau}$ is the yearly buy-and-hold excess return of the portfolio, $R_{m,\tau}$ is the yearly buy-and-hold excess return for market portfolio, $\beta_{i,\tau}^{IV1} = (\gamma_{i,o} + \gamma_{i,1}' Z_{i,\tau-1})$ is the conditional beta, and $Z_{i,\tau-1}$is a k x 1 vector of instruments for the investor's information set at start of $\tau - 1$. In absence of any information set, equation (5) reduces to the static CAPM as described in Section 3.1. We evaluate the conditional performance alpha, α_{HL}^{IV1}, in the same way as described in Section 4.4.2, where we test if $\alpha_{HL}^{IV1} \equiv \alpha_H^{IV1} - \alpha_L^{IV1}$ is equal to zero, as implied by equation (2).

Our test return data are available to us from July 1986. However, given that some of the empirical approaches rely on lagged estimates of conditional betas, our first portfolio formation is July 1991.

4.4.4 Constructing LC Betas

We have computed lagged component betas as in Cederburg and O'Doherty (2016), by taking averages of monthly beta estimates of low and high beta

[19] Cederburg & O'Doherty (2016) estimates the system using GMM, where they define the moment condition such that the GMM parameter estimates corresponds to ordinary-least-squares estimates.

[20] We have also run seemingly unrelated regression equations (SURE) on α_{HL}. The standard errors differ a bit due to asymptotic versus finite-sample, heteroskedasticity and autocorrelation etc. However, the difference is negligible and it does not alter our conclusion in this thesis. Therefore, these statistics are not presented for the sake of brevity.

portfolios separately. These betas estimates are from non-overlapping windows of daily data, i.e. data used to estimate our lagged component beta does not overlap with data used to estimate our formation-period betas[21]. We have formed 12 months lagged and 60 months lagged component betas. As our formation-period betas have been constructed using previous five-year correlation (see section 5.1), we need to avoid this period for constructing our LC betas. Therefore, we start evaluating performance of our beta-sorted portfolios from July 1991[22]. We have used the period July 1985 - June 1986 (July 1981 - June 1986) of daily data to form 12 (60) month LC betas.

4.4.5 Evaluating Sub samples

As the variability of the OSE changes through time, where the volatility of stocks is particularly high during recessions, we investigate if time-series variations across different sub samples affect our inference of the beta and volatility anomaly in Norway. Discussed earlier by Schneider, Wagner & Zechner (2016), an explanation of the low-beta anomaly is firms negative skewed return distribution due to credit risk, and credit risk increases during recessions. We therefore split our initial sample into two sub samples for the value-weighted (equal-weighted) portfolio, July 1986 - June 2000 and July 2000 - June 2014 (June 2015), to examine whether outlier events such as the financial crisis in 2007-2008 in the stock market affect the risk-return relation of low and high beta sorted portfolios.

Moreover, the stocks listed on the OSE in the first nine years are considerably fewer compared to the post 2000 era. In addition, the gradually presence of sophisticated institutional investors in the later years motivates the study of sub samples, to check if the risk-return relation has shifted due to increasingly use of low-volatility strategies by professional investors.

[21] According to Cederburg & O'Doherty (2016), this would avoid systematic measurement error in the lagged beta estimates.
[22] First formation period betas are constructed using data from July 1986 to June 1991.

5 DATA

We have obtained daily return data for all securities from the OBI (Oslo Børs Information) financial database from July 1980 to June 2015. These are discrete returns that are adjusted for dividends, and other corporate events, such as stock splits, etc. In order to provide a broader and clearer picture, we have done two separate analysis based on: 1) Transaction data (traded stocks), and 2) Bid/Ask Quote Returns data.

Transaction data includes the returns of those securities that are being traded after the broker has quoted price. In other words, for a security to be included in our analysis, it must have been traded following the bid/ask quote price as it represents a 'transaction'. The Bid/Ask quote returns data includes all securities for which either the bid or ask price is available and are not necessarily traded after the quote. According to the OBI financial database, these returns are computed from prices using the following algorithm: If close (trade) price is available, use that; otherwise, if both bid and ask is available, use the average; if only bid or ask is available, use that.

Details on both samples and their filtration process is included in section 5.1. In addition to daily data, details of monthly asset returns are presented in section 5.2. Risk-free rate, pricing factors and macro-economic variables that are being used in our analysis are presented in section 5.3, 5.4 and 5.5 respectively.

5.1 Sample and Filtration

Our Transaction returns sample consists of 864 (initial/pre-filtered) common stocks with annual returns between 4296 and 52586 across all securities from July 1980 to June 2015 (see exhibit A.1 in Appendix A). On the other hand, Bid/Ask quote returns sample includes 884 common stocks with annual returns between 16764 and 66168 across all securities between July 1980 and June 2015 (see exhibit B.1 in Appendix B). The higher number of annual returns in the latter sample gives an indication of noisy data being included and thus could potentially bias our results. Therefore, we have formed portfolios based on both these samples that we will discuss more in detail in section 6 while presenting empirical results.

Following Ødegaard (2017), not all stocks traded on the OSE should necessarily be included when calculating representative returns. In conducting our empirical analysis, it is important not to include assets where returns have been affected by illiquidity or any other potential noise sources that consequently bias our results. While Frazzini & Pedersen (2014) and Cederburg & O'Doherty (2016) do not specify whether they use other filters than their liquidity filters when estimating ex-ante betas and volatility, other studies exclude the smallest firms by removing those with a market capitalization in the bottom 5% to 10% (see Ang et al. (2009) and Dutt & Humphery-Jenner (2013)). Similarly, Ødegaard (2017) use a filter that excludes all stocks with a total market value below NOK 1 million, and a price below NOK 10 during a year when computing factors for empirical asset pricing investigations in the Norwegian stock market. We have therefore in addition to the liquidity filters described in Section 4, excluded any assets with market capitalization below NOK 10 million in any given year at the time of portfolio formation. However, stocks that is excluded from the sample one year may be included in subsequent years, if it fulfills the filter requirements (see exhibit A.1 and B.1 for details on number of stocks being filtered each year).

5.1.1 Winsorization of Return Outliers

When examining our initial sample of returns across listed equities, we see that the filtration rule described in section 5.1 work quite well as many stocks are removed from the sample at the date where return values could be spurious outliers. Nevertheless, we observe that few of these securities still have one or more observations of daily returns above 150% or below -100% in the July 1980-June 2015 period. Outliers can potentially bias both the in-sample estimates of the asset betas (see e.g. Martin and Simin (2003)) and Theodossiou et al. (2009), which could affect the construction of our quintiles portfolios, and the out-of-sample performance of the portfolios. Although the extreme observations are expected to be a result of illiquidity, and hence should be filtered out by the filtering rules described in Section 4, we have, as in Laeven & Tong (2012) performed annual winsorization at the 0.1st and the 99.9th percentile on our daily return sample to avoid outliers from biasing our results. The winsorization is conducted by removing all the stocks with returns below (above) the 0.1st (99.9th) percentile in any year. However, stocks that is excluded from the sample one year may be included in subsequent years, if it fulfills the percentile requirement.

From exhibit A.1 (B.1) in Appendix A (Appendix B), we see from the year-by-year 0.1st and 99.9th percentiles, that applying winsorization removes the most extreme stocks in any given year, if daily returns being below -49.3% (-57.1%) or above 71.2% (139.4%). After winsorization, we have on average 195 (205) stocks every year.

5.2 Monthly Asset Returns

We use the daily Transaction data (traded stocks return) to construct a geometric monthly return series[23]. Our main results will be presented using this constructed series. However, for robustness purposes, we have also used monthly assets returns series available on the OBI financial database.

5.3 Risk-free Rate

A time-series for a proxy of the Norwegian daily and monthly risk-free rate is attained from the website of professor Bernt Arne Ødegaard. For most of the period, overnight and monthly NIBOR[24] is used as the proxy. From July 1981 to June 1986, the overnight NIBOR is used as an approximation for the monthly risk-free rate. The interbank offered rate is mostly close to the risk-free rate, as it is short-term loans between major banks.

5.4 Pricing Factors

Similarly, to the risk-free rate, five factors for Norwegian market are obtained from Professor Bernt Arne Ødegaard website. We use the OSE Allshare-index (OSEAX) as our proxy for the market factor when evaluating the out-of-sample performance of our quintile portfolios. The index returns are adjusted using the same method as was used when the stock returns were computed. The OSEAX monthly time-series is available for the entire 1985-2015 period. However, because daily data for the OSEAX-index is not available before 1983 (this could potentially bias our beta formation strategy), and has irregularly missing observations until 1986, we use a value-weighted index formed by Professor Ødegaard to estimate the ex-ante betas of the individual assets. Professor used the previous year-end market values to construct the value-weighted index. Similarly, Fama and French (1993) factors, size (SMB), value (HML) and momentum

[23] The returns are calculated using following equation: $\prod_{i=1}^{n}(1+r_i) - 1$, where n is the number of days in the respective month and r_i is the daily stock return at day *i* that represent a trade.

[24] NIBOR - Norwegian Interbank Offered Rate is a collective term for Norwegian money market rates at different maturities.

(UMD) are obtained from his website. Professor Ødegaard follows the methodology from the Fama & French (1993) and replicates these factors using Norwegian data. The fifth factor is a liquidity factor constructed for the Norwegian stock market (see Næs, Skjeltorp & Ødegaard (2008)). The returns are computed using log differences. All monthly factors are available for the out-of-sample period July 1986-June 2015. Table 1 provides summary statistics for risk-free and pricing factors. Correlations between the monthly pricing factors for full estimation period (July 1986 - June 2015) and for sub-periods (July 1986 - June 2000 & July 2000 - June 2015) is in Exhibit A.2 in Appendix A.

Table 1 - Summary statistics, risk-free and pricing factors

This table shows descriptive statistics for variables used in our empirical analysis. The variables are daily and monthly risk-free rate and market returns, monthy returns from Fama & French (1993) mimicking Small minus BIG (SMB) market capitalization and High minus Low (HML) book-to-market ratio portfolios and Momentum factor (UMD) replicated by professor Bernt Arne Ødegaard using Norwegian data. Liquidity factor is computed as in Næs, Skjeltorp & Ødegaard (2008). Returns are reported as log returns in percent relative to their period frequency.

Varibale	Frequency	Start mth/yr	End mth/yr	Obs.	Mean	Max	Min
Risk-free rate	Daily	07.1980	06.2015	8781	0.03	0.26	0.002
Market returns	Daily	07.1980	06.2015	8781	0.11	11.37	-17.81
Risk-free rate	Monthly	07.1986	06.2015	348	0.51	2.05	0.10
Market returns	Monthly	07.1986	06.2015	348	0.83	16.08	-32.05
Excess mkt returns	Monthy	07.1986	06.2015	348	0.32	15.28	-33.81
SMB	Monthly	07.1986	06.2015	348	0.57	20.00	-18.73
HML	Monthly	07.1986	06.2015	348	0.14	13.68	-18.21
UMD	Monthly	07.1986	06.2015	348	0.32	0.23	-0,28
Liquidity	Monthly	07.1986	06.2015	348	-0.14	0.15	-0,19

5.5 Macroeconomic Variables

We have used two macroeconomic variables namely Default Spread (DS) and Oil Price (Brent) in Section 6.2 to measure out-of-sample performance of our beta-sorted portfolios using conditional beta framework as explained in section 3.2. Default spread (DS) or default premium is the yield spread between Moody's Baa- and Aaa-rated bonds. These bond yields are obtained from the Federal Reserve Bank of St. Louis website http://research.stlouisfed.org/fred2/ and are based on the US data. This can be a good proxy for Norwegian stock market, as shown by Harvey (1991).

Oil price (Brent) time-series has been obtained from DataStream. Table 2 reports summary statistics for macroeconomic variables used in our thesis. The returns are reported as monthly log differences.

Table 2 - Summary statistics, Macro economic variables

This table shows macro economic variables used in our empirical analysis in Section 6.3. Default spread (DS) or default premium is the yield spread between Moody's Baa- and Aaa-rated bonds. These bond yields are obtained from the Federal Reserve Bank of St. Louis website. Oil price (Brent) time-series has been obtained from datastream. Both variables are reported as monthly difference in log.

Varibale	Frequency	Start mth/yr	End mth/yr	Obs.	Mean	Max	Min
DS	Monthly	07.1986	06.2015	348	0.97	3.32	0.55
Oil Price	Monthly	07.1986	06.2015	348	0.56	47.14	-44.15

6 EMPIRICAL RESULTS

In this section, we present our analysis of the low-volatility anomaly in Norway. Section 6.1 reports our main findings for the low-beta anomaly using the methodology described in Section 4.1, and the dataset described in Section 5.1 and Section 5.2. In addition, we have conducted several robustness tests to check the validity of our results. In Section 6.2, we present out-of-sample performance of our beta-sorted portfolios using conditional CAPM framework explained in section 3.2 using instrumental variables. Finally, in section 6.3, we repeat the procedure as in Section 6.1, except now we construct portfolios based on total volatility to investigate if the anomaly is sensitive to different risk measures.

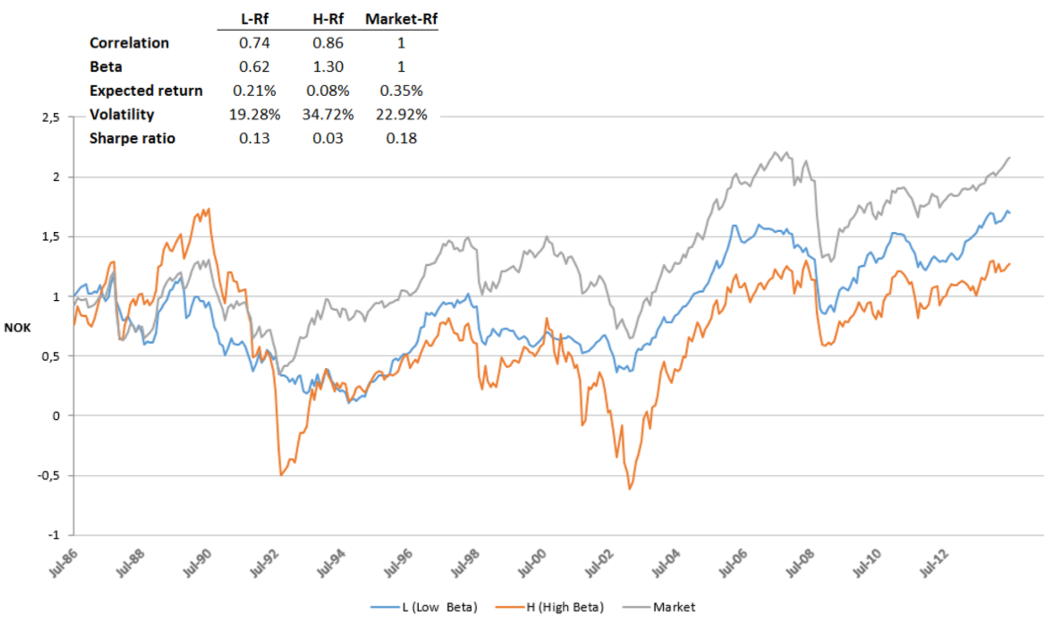
6.1 Beta-Sorted Portfolios Using Daily Returns

6.1.1 Value-Weighted Performance

Figure 1 graphically plots and compares the out-of-sample performance of the low quintile and high quintile portfolio against the market portfolio. Except for a few years in the late 1980s, the excess returns of the market portfolio produce higher total returns than both extreme quintile portfolios. Moreover, the Sharpe ratio of 0.18 for the market exceeds the Sharpe ratios for both the low quintile and high quintile portfolios, 0.13 and 0.08 for the period July 1986 – June 2014.

Figure 1 - Value of NOK 1 invested in VW beta sorted, and market portfolios in excess of risk-free rate

The figure shows the value of NOK 1 invested in beta-sorted high and low value-weighted (VW) quintile portfolios, and market portfolio. The value is based on monthly excess returns. i.e. NOK value earned above the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas. Table in the figure reports the correlation and beta of low and high quintile portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.



	L-Rf	H-Rf	Market-Rf
Correlation	0.74	0.86	1
Beta	0.62	1.30	1
Expected return	0.21%	0.08%	0.35%
Volatility	19.28%	34.72%	22.92%
Sharpe ratio	0.13	0.03	0.18

Table 3 reports value-weighted quintile portfolios that are constructed from daily returns data using the CAPM beta as risk measure. The table shows that the average excess returns decreases from 0.21% per month for the lowest quintile (L) to 0.08% for the highest quintile (H). A zero-cost portfolio that takes long position in the high quintile and a short position in the low quintile (HL) earns an average negative excess return of -0.13%[25], but the result is insignificant. The study by Ang.et.al (2006) reports that average excess returns increases by going from quintile 1 to quintile 2 and 3, and then the average returns drop for the last two quintiles, which contains stocks with the highest total volatility. This pattern is very similar to our observations for Norwegian data. Ang et.al (2006) explains this pattern by although the highest quintiles represents 20% each of the stocks sorted by the corresponding risk measure, they represent a far smaller proportion of the value of the market, since high volatility stocks is likely to contain a larger portion of small, illiquid stocks. Since the OSE contains many stocks with low trading volume and low market capitalization, particularly in the first nine years[26], we believe that the excess returns for our highest quintile portfolios suffer from the same reason. Furthermore, we see that the realized betas and volatilities increases monotonically from the low quintile portfolio to the high quintile portfolio. This provides us with an indication that there exists persistence of the stocks risk characteristics, where low-beta (high-beta) stocks continues to behave like low (high) volatile stocks in the near future. However, the estimated ex-ante betas seem to be slightly underestimated (overestimated) for the lowest (highest) quintile.

Looking at the CAPM and the three, four & five factor portfolio alphas, we see an indication of an inverted SML, where the alphas are negative and becomes larger in absolute magnitude when comparing the two extreme quintiles, but they are all statistically insignificant. The HL portfolio has an unconditional CAPM alpha of -0.36% per month, and the five-factor alpha is -0.29% per month. We note that the difference in the magnitude and significance of the HL portfolio alphas is

[25] Cederburg & O'Doherty (2016) reports their zero-cost HL portfolio has an average excess return of 0.44% per month, implying that their high-beta stocks earn higher cumulative returns than the low-beta counterparts. However, they do not provide significance level for their result.
[26] Our sample contains on average of 130 stocks the first nine years, compared to an average of 218 stocks for the remaining period.

Table 3 - Beta sorted VW portfolios, July 1986 - June 2014

This table reports characteristics and regression results for value-weighted (VW) beta portfolios for the July 1986 to June 2014 period. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Beta (ex-ante) is the average estimated beta (also known as formation-period beta) while Beta (ex-post) is the realized CAPM-beta. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	Portfolio					
Characteristics	**L**	**2**	**3**	**4**	**H**	**HL**
Excess Return	0.21	0.55	0.37	0.09	0.08	-0.13
	(0.63)	(1.42)	(0.82)	(0.15)	(0.14)	(-0.29)
Beta (ex-ante)	0,41	0,66	0,85	1,07	1,51	
Beta (realized)	0.62	0.83	0.94	1.15	1.30	
Volatility	19,28	23,55	25,81	30,89	34,72	
Sharpe ratio	0.13	0.28	0,17	0.04	0.03	
Regressions						
CAPM Alpha	-0.01	0.26	0.04	-0.32	-0.37	-0.36
	(-0.03)	(1.23)	(0.19)	(-1.23)	(-1.26)	(-0.97)
Three-factor alpha	-0.11	0.22	0.03	-0.39	-0.38	-0.27
	(-0.55)	(0.97)	(0.13)	(-1.45)	(-1.22)	(-0.70)
Four-factor alpha	-0.13	0.22	0.04	-0.36	-0.35	-0.22
	(-0.61)	(0.98)	(0.18)	(-1.36)	(-1.12)	(-0.71)
Five-factor alpha	-0.13	0.22	-0.02	-0.44	-0.42	-0.29
	(-0.64)	(0.95)	(-0.08)	(-1.68)	(-1.35)	(-0.77)

negligible across the CAPM, Fama- French, momentum and liquidity factors, and we confirm that low-beta (high-beta) stocks do not significantly outperform (underperform) the predictions of the CAPM. These findings are consistent with Frazzini & Pedersen (2014), where they also find that excess returns and alphas from their BAB strategy is insignificant in Norway. In summary, our findings indicate that we do not find evidence of the low-beta anomaly in Norway.

6.1.2 Factor Returns

Exhibit A.3 reports the factor loadings of the lowest and highest value-weighted quintile portfolios. We see that the low quintile portfolio has a lower market exposure than the high quintile portfolio, which is what we should expect.

Both quintile portfolios have positive exposure to SMB, where beta for the low portfolio is significant at the 10% level. Usually, volatile stocks are positively associated with firms with low market capitalization; however, it seems that the low and high quintile portfolios both have positive exposure to small firms. Moreover, the portfolios have positive exposure to the HML factor, where the beta for low quintile is significant at the 10% level. This is in line with our expectations, as low-volatility portfolios contain many value stocks. The momentum factor has positive loading for the low quintile portfolio and negative loading for the high quintile portfolio, where the negative beta for the high quintile portfolio is significant at 5% level. This suggest a negative autocorrelation in stock returns for the high quintile portfolio, leading to a price reversal, which is not found in the low quintile portfolio.

The low quintile and high quintile portfolio have negative exposure to the liquidity factor, however, the high quintile liquidity beta is significant at the 5% level, and is considerably larger in absolute magnitude. This result is surprising, since high volatility portfolios tend to be positively related with illiquid stocks. This suggest that our high-beta portfolios do not consist of illiquid stocks on average, and that the large variation in stock returns for the high quintile portfolio originates from other sources. One support for this claim initiates from our liquidity filters when we construct our data sample, where we have removed most of the illiquid stocks from the investment universe[27].

6.1.3 Robustness Tests

There are many studies that document the presence of the low-beta anomaly across international equity markets, and our findings in Norway have hints of a negative SML. For that reason, we want to make several robustness tests to check if our initial results still hold.

6.1.3.1 Equal-Weighted Performance

Exhibit A.4 reports the same analysis discussed in Section 6.1.1 using equal weighting for the quintile stocks, and the results are similar compared to the value- weighted quintile portfolios. The average excess returns for the equal-weighted HL portfolio is a bit larger in absolute magnitude, -0.33% per month, which is caused by an increase in the performance of the low quintile portfolio,

[27] When measuring the performance of our test portfolios, we rebalance every year. If we rebalance every month, our high quintile portfolio might exhibit a positive relation towards the liquidity factor, as portfolios with more frequent rebalancing maintains the desired exposure more effectively.

however it is still insignificant. This is likely explained by that equal-weighted portfolios have higher exposure to systematic risk factors, in particular the SMB factor. Quintile 4 and quintile 5 have a negative five-factor alpha that is significant at the 5% level. When measuring the performance with respect to CAPM, and three & four factor model, none of the HL portfolio alphas are significant. Regressing the HL portfolio on the five-factor model, the alpha of -0.61% per month becomes statistically significant at the 10% level. However, due to the small decrease of the HL alphas compared to the CAPM and Fama-French model, in addition to the relative low significance level, our perception of the low-beta anomaly in Norway does not change significantly. Our findings indicate that assigning equal weights for the HL portfolio over the period July 1986 to June 2015 does not influence our conclusions drawn from initial results in Section 6.1.1.

6.1.3.2 Out-Of-Sample Test Using Monthly Returns Data from OBI

As mentioned in the Section 5.2, we construct our ex-ante betas and measure the out-of-sample performance for beta-sorted portfolios using stock returns that only represent an actual trade. However, as a robustness check, we want to test if the HL portfolio performance changes if we use Ødegaard monthly stock returns file for measuring the out-of-sample, which contains bid and ask prices, if the close (trade) price is unavailable. Exhibit A.5 reports the performance for value-weighted (equal-weighted) quintile sorted portfolios from the period July 1986 to June 2014 (June 2015). Again, the results are very similar to our results in Section 6.1.1 and Section 6.1.3.1. The average excess returns for the value-weighted and equal-weighted HL portfolio is -0.01% and -0.35% per month respectively. The alphas for the value-weighted HL portfolio is similar in magnitude across the different factor models, where the five-factor alpha is -0.22% per month and insignificant. The five-factor HL alpha for the equal-weighted portfolio is the only alpha that is significant at the 10% level, with a magnitude of -0.68% per month. As the HL alphas and risk characteristics are very comparable to our main results, we conclude that using OBI monthly stock returns file to measure out-of-sample performance of the test portfolios does not change our initial findings.

6.1.3.3 Beta-Sorted Portfolios Using Daily Returns Data from OBI

In Exhibit B.2 in Appendix B, we replicate our findings in Section 6.1.1, except now we estimate the ex-ante betas using daily Bid/Ask Quote Returns data[28], which contains bid and ask prices if the trading price are unavailable. This approach differs from Section 6.1.2.2, where we only use the monthly Bid/Ask Quote Returns data file to assess the out-of-sample performance. Note that the stocks in the low and high quintile portfolios changes from previously portfolio formations. The reason is that we get different beta estimates, and because we have a larger sample since more stocks would pass our liquidity filters.

The average excess return for the value-weighted HL portfolio is -0.03% per month from July 1986 to June 2014. The HL portfolio alphas are all insignificant and smaller in magnitude across all factor models, where the five-factor HL portfolio alpha is -0.08% per month. Looking at the equal-weighted portfolios over the period July 1986 to June 2015, the low quintile portfolio earns a monthly excess return of 0.74%, per month, which is significant at the 5% level, whereas the HL portfolio excess return is -0.51% per month and insignificant. All factor models produce negative HL alphas that are significant at the 5% level, where the five-factor HL portfolio alpha is -0.69% per month. Again, we believe that the rise of the relative mispricing between beta-sorted portfolios from value weighting to equal weighting relates to the tilt towards small stocks, which performs well especially from 2000. We see that if one is not restrictive with properly filtering of the dataset[29], the findings changes from Section 6.1.3.1. We would incorrectly conclude that equal-weighted HL portfolio produce a negative risk-adjusted return that is not explained by the CAPM, Fama-French, four-factor or the five-factor model. ‘

6.1.4 Testing Sub Samples

In this section, we test the robustness of our initial results by exploring two sub periods. As discussed in Section 4.4, the financial crisis could change the risk-return relation in the stock market. We therefore test the robustness of our findings by studying two subperiods for the value-weighted quintile portfolios, July 1986 - June 2000 and July 2000 - June 2014. In addition, the market

[28] See Section 5.1 for further details regarding Bid/Ask Quote return data

[29] Separating returns that represent an actual trade from bid and ask prices that is quoted by market-makers, is particularly important to make correct inferences

microstructure on OSE is more challenging in the first nine years. The period has fewer stocks and the illiquidity is more of an issue compared to rest of the sample period, which could cause undesirable effects such as nonsynchronous trading. This further motivates us to study different sub samples.

Table 4 reports the sub period performance for the value-weighted quintile portfolios that is presented in Section 6.1.1.

Table 4 - Beta sorted VW portfolios during sub periods 1986-2000 and 2000-2014

This table reports regression results for value-weighted (VW) beta portfolios for two sub-periods that run from July 1986 to June 2000 & July 2000 to June 2014. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Beta (ex-ante) is the average estimated beta (also known as formation-period beta) while Beta (ex-post) is the realized CAPM-beta. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	1986-2000			2000-2014		
Characteristics	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**
Excess Return	-0.22	-0.25	-0.03	0.64	0.41	-0.23
	(-0.44)	(-0.29)	(-0.05)	(1.49)	(0.56)	(-0.37)
Beta (ex-ante)	0.52	1.56		0.29	1.45	
Beta (realized)	0.65	1.31		0.59	1.28	
Volatility	20.98	35.82		17.35	34.22	
Sharpe ratio	-0.13	-0.09		0.44	0.14	
Regressions						
CAPM Alpha	-0.37	-0.55	-0.18	0.37	-0.18	-0.55
	(-1.11)	(-1.31)	(0.32)	(1.46)	(-0.43)	(-1.12)
Three-factor alpha	-0.48	-0.58	-0.10	0.25	-0.24	-0.49
	(1.41)	(-1.36)	(-0.19)	(0.99)	(-0.61)	(-1.05)
Four-factor alpha	-0.45	-0.59	-0.14	0.28	-0.11	-0.39
	(-1.34)	(-1.40)	(-0.26)	(1.10)	(-0.27)	(-0.83)
Five-factor alpha	-0.44	-0.60	-0.16	0.29	-0.34	-0.63
	(-1.34)	(-1.41)	(-0.30)	(1.15)	(-0.90)	(-1.40)

The sign of the HL portfolios excess returns, factor model alphas and significance level across both subs periods are similar to our main approach. The negative excess returns for both the low and high quintile portfolio during the 1986 - 2000 period is caused by the banking crisis in the early 1990s, in addition to an economic downturn in the Norwegian business cycle in 1998. During the 2000 -

2014 period, both extreme quintile portfolios have positive excess returns, although the Sharpe ratio of the low quintile portfolio is over three times higher than the Sharpe ratio of the high quintile portfolio. This stems partly from that the low quintile portfolio has become less risky compared to the 1986 -2000 period, in addition to that the excess return has substantially increased from -0.22% to 0.64% per month. Moreover, we observe a stronger hint of an inverted SML for the second period, where the low (high) quintile portfolio have positive (negative) alpha, however, none of them are significant. Overall, even though we observe improving performance of the low quintile portfolio during the second period, it seems that testing different sub samples for the value-weighted quintile portfolios has limited impact on our initial results.

6.1.5 Estimating Ex-Ante Betas Using Monthly Stock Returns

As can be seen from Exhibit C.1 in Appendix C, the results for the value-weighted HL portfolio across the period 1986 - 2014 are similar to our main findings in Section 6.1.1 when constructing formation-period betas using monthly returns instead of daily returns. The excess return of the HL portfolio is -0.12% per month and insignificant. The HL portfolio alphas are negative and insignificant across all factor models, where the five-factor alpha is -0.18% per month. Again, we arrive at the same conclusion in Section 6.1.1, as the findings do not imply a low-beta anomaly in Norway.

When inspecting ex-ante beta versus realized beta, the estimation error[30] is larger when using monthly data to construct the formation-period betas. In particular, the high quintile ex-ante beta and realized beta is 1.99 and 1.20, and for the low quintile portfolio, the ex-ante beta and realized beta is 0.18 and 0.49 respectively. Compared to our main strategy in Section 6.1.1, it seems that the quintile portfolios using monthly returns exhibit lower realized betas on average.

Exhibit C.1 also reports the sub period performance of the beta-sorted portfolios using monthly stock returns. The findings are similar to the sub samples from our main approach discussed in Section 6.1.3. None of the estimates are significant

[30]We see that increasing the sample frequency improves the accuracy of the covariance estimates, as described by Merton (1980).

for the period 1986 - 2000, whereas the excess return for the HL portfolio is -0.09% per month and the correspondingly five-factor alpha is 0.21% per month.

In the 2000 - 2014 period, the low quintile and high quintile stocks have positive excess returns. The excess return for the low portfolio has tripled comparing first sub period to 0.60% per month, which is significant at the 10% level. The corresponding Sharpe ratio of 0.51 is considerably larger than the Sharpe ratio of the high portfolio and the market, 0.17 and 0.29 respectively. The pattern that the low quintile portfolio exhibits a major increase in performance during the second sub sample, is very similar to what we find in 6.1.3. Furthermore, the excess return for the HL portfolio is -0.15% and insignificant. The HL alphas are mostly negative, similar in magnitude and insignificant across the factor models. We note that the HL portfolio alpha of the five-factor model is -0.67% and significant at the 10% level. Again, as in Section 6.3.1 we see a stronger tendency of an inverted SML in the period 2000 - 2014, however, our findings do not change the conclusions made in Section 6.1.1.

6.2 The Conditional CAPM

6.2.1 The Cross-Sectional Distribution of Firm Betas

The general consensus of the asset pricing literature is that the static CAPM fails to satisfactory explain the cross-section of average stock returns. The poor empirical performance might be explained by the unrealistic assumption that market beta of an asset is constant, and thus fails to account for relevant time variation in risk exposure. This could lead to a bias in the unconditional CAPM alpha. For the beta-anomaly to be explained by a mismeasurement error of the CAPM alpha, the HL portfolio must display a time-series variation that is not captured by the static model.

Building on this reasoning, Figure 2 shows that the 80% interval of the cross section of firm betas exhibit strong time-variation over the sample period. We observe a relative tight dispersion between the betas in the mid-1980s towards the end of 1996, with an average beta difference between the 90th and 10th percentiles of 0.87, whereas the difference in beta spread increases to 1.10 from the late 1990s to mid-2003. The spread then contracts for a couple of years in the mid-

2000s, before it again increases drastically to end of sample period[31]. From mid-1998 to end of sample, the low-beta percentile remains remarkably stable and small in magnitude, where the median 10th percentile beta is 0.32 with a standard deviation of 7%. In contrast, the 90th percentile for the same period has a median of 1.32 and a standard deviation of 28%. Cederburg & O'Doherty (2016) states that betas of portfolios sorted on past firm beta inherent these time-series patterns. This is in line with our results in Section 6.1.1, where we find that low-beta (high-beta) sorted portfolios continues to behave as less risky (more risky) stock portfolios in the near future.

Figure 2- Cross sectional distribution of firm betas, July 1984 to June 2014

The figure displays statistics for the cross-sectional distribution of firm betas. The dashed line is the median and the solid lines show the 10th and 90th percentiles of firm betas. Firm betas are estimated at the beginning of each month using daily return returns as described in Section 4.1.

6.2.2 The Conditional CAPM Performance

Table 5 reports our main results using the conditional CAPM for the value-weighted beta-sorted portfolios over the period July 1991 – July 2014[32]. In Section 6.1, we concluded that the low-beta anomaly does not exist in Norway. However, we are motivated to perform a study using the conditional CAPM to see if the magnitude and significance of the alpha decreases.

[31] . Although Cederburg & O'Doherty (2016) reports firm betas from 1927-2012, our findings are similar when comparing the results for the same time period where they report an increase in beta-spread in later periods.

[32] As some of the empirical approaches rely on lagged estimates of conditional betas, our first portfolio formation is July 1991.

Case 1 refers to the unconditional CAPM alpha, as it is a special case of equation (2) which $Z_{i,\tau-1}$ is the null information set. When beta is constrained to be constant, the low-beta and high-beta portfolio has a realized beta for 0.60 and 1.30. The long short beta portfolio (HL) has an unconditional alpha of -0.63% per month[33] over the sample period, which is insignificant. Cases 2-7 contains alternative information sets used to estimate the conditional CAPM alphas.

Cases 2 and 3 includes the 12-month lagged-component beta, β^{LC12} and 60-month LC beta, β^{LC60}. Both LC betas are negative predictors of betas for both cases, but only the LC beta for high portfolio in case 3 is significant. The conditional alphas in case 2 and 3 does not show any sign of improvement in terms of magnitude compared to case 1, which is not surprising when only one instrumental variable is significant, and the adjusted R^2 for the four portfolios is relatively unchanged. We conclude that our LC betas provide us with little information, and is thus not a useful instrument. We do however see a tendency of a reduction in the conditional beta for the high portfolio in both cases This is also is documented by Cederburg & O'Doherty (2016), where they argue that the unconditional CAPM typically overstate beta estimates for high-beta portfolios. Case 4 includes both LC betas in the information set, but the conditional alpha estimates has not been improved.

Two macroeconomic variables are introduced, where case 5 include default spread (DS) and case 6 include oil price in the information set. Again, the HL alphas remain relatively unchanged which suggest that the two macroeconomic variables are not useful as instrumental variables for Norwegian data.

Case 7 contains the full information set to model conditional portfolio betas. Isolated, none of the instrumental variables continues to be important, where only β^{LC60} is significant at the 10% level for the low portfolio. The HL alpha is now -0.47% per month which suggest a reduction of about 25% in magnitude compared to the unconditional model in case 1. However, we should be cautious to conclude that the conditional CAPM in case 7 performs better than our unconditional asset pricing models. The reduction of alpha in case 7 is likely caused by inclusion of more variables, which do not improve our model, as only one instrumental variable is significant at the 10% level, and the R^2 for both legs

[33] Cederburg & O'Doherty (2016) reports an unconditional alpha of -0.59% per month over the period July 1930 – December 2012, which is significant at the 5% level.

has not been improved. We conclude that our conditional regression in case 7 are spurious, and we should disregard the finding.

Table 5 - Instrument variables regressions, 1991-2014

This table reports IV1 regression results for value-weighted (VW) beta portfolios for the July 1991 to June 2014 period. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas where "HL" refers to their difference. The return regression is given by $R_{i,\tau} = \alpha_i^{IV1} + (\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1})R_{m,\tau} + u_{i,\tau}$ where $Z_{i,\tau-1}$ is instrument variable. The instruments for the given portfolio include the 12-month and 60-month lagged component betas, the defualt spread (DS) and oil price (Brent). Case 1 represents unconditional CAPM as presented in section 4.1 where value of the instrument variable set to 0. Alpha is the intercept in a regression and is reported in percentage per month. The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively. R-square is adjusted R-square value for each regression.

Case		α_i^{IV1}	$R_{m,\tau} \times$					
			1	β^{LC12}	β^{LC60}	**DS**	**Oil Price**	R^2
1	L	0,13	0.60***					54.4
		(0.62)	(16)					
	H	-0,50	1.30***					70.1
		(-1.50)	(14)					
	HL	-0,63						
		(-1.60)						54.1
2	L	0,13	0.60***	-0.03				
		(0.62)	(6.03)	(-0.02)				70,1
	H	-0,45	1.79***	-0.43				
		(-1.32)	(4.04)	(-1.14)				
	HL	-0,58						
		(-1.46)						
3	L	0,10	0.71***		-0.18			54.4
		(-0.49)	(7.55)		(-1.34)			
	H	-0,53*	2.18***		-0.75***			72.0
		(-1.66)	(6.57)		(-2.72)			
	HL	-0,63						
		(-1.68)						
4	L	0,07	0,67***	0,19	-0,29			54,4
		(-0.35)	(6.42)	(0.91)	(-1.65)			
	H	-0,52	2,25***	-0,09	-0,73**			71,9
		(-1.60)	(4.75)	(-0.21)	(-2.24)			
	HL	-0,59						
		(-1.56)						
5	L	0,13	0,61***			-0,91		54,1
		(0.61)	(7.35)			(-0.11)		
	H	-0,51	1,57***			-2,60		71,1
		(-1.55)	(10)			(-1.05)		
	HL	-0,64						
		(-1.63)						
6	L	0,13	0,60***				-0,44	54,4
		(0.64)	(17)				(-1.38)	
	H	-0,49	1,29***				0,43	71,0
		(-1.47)	(14)				-0,57	
	HL	-0,62						
		(-1.60)						
7	L	0,06	0,74***	0,21	-0,32*	-3,83	-0,53	55,0
		(0.28)	(5.30)	(1.00)	(-1.89)	(-0.46)	(-1.29)	
	H	-0,41	1,19***	-0,11	0,56	-1,84	0,52	71,5
		(-1.25)	(3.93)	(-0.24)	(1.25)	(-1.59)	(0.78)	
	HL	-0,47						
		(-1.24)						

In Exhibit A.6 in Appendix A, we have included the conditional Fama-French 3 factor model for robustness purposes. However, none of the cases provide us with any additional valuable information.

6.3 Portfolios Sorted by Total Volatility

In this section, we use total volatility as the risk measure to evaluate out-of-sample performance of quintile portfolios formed using methodology given in section 4.2.

6.3.1 Value-Weighted Quintile Portfolios

Figure 3 graphically plots and compares excess cumulative returns of the market portfolio, against the value-weighted low and high quintile portfolios. For most of the period, low-volatility portfolio produces higher total excess returns with less volatility than both high-volatility portfolio and the market, which contrast our findings in Section 6.1.1. However, this result is very similar to Jagannathan & Ma (2003) and Leote de Carvalho, Xiao & Moulin (2012) who find higher returns and lower risk for minimum variance portfolios versus the market. As excess return is higher and volatility is lower, the Sharpe ratio of 0.24 for the low-volatility portfolio exceeds the Sharpe ratio of 0.18 for the market.

Figure 3 - Value of NOK 1 invested in VW volatility sorted, and market portfolios in excess of risk-free rate (July 1986 - June 2014)

The figure shows the value of NOK 1 invested in volatility-sorted high and low value-weighted (VW) quintile portfolios, and market portfolio. The value is based on monthly excess returns. i.e. NOK value earned above the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated total volatility using previous 12 month window of daily data as described in Section 4.2. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility. Table in the figure reports the correlation and beta of low and high volatility portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.

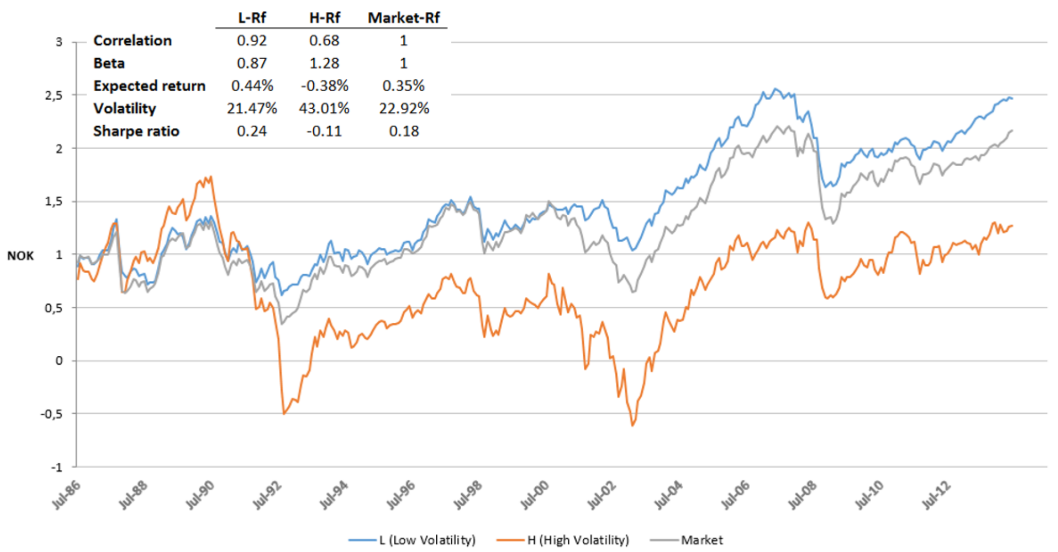


Table 6 reports characteristics and regression results for volatility sorted value-weighted quintile portfolios. The table shows that the average excess returns of low-volatility (high-volatility) portfolio is 0.41% (-0.48%) per month. This is not surprising as Baker & Haugen (2012) find high-volatility portfolio yields negative reward in their study of 21 developed countries including Norway. Their findings become more apparent with results of our CAPM regression where high-volatility portfolio has negative and significant alpha, though only at the 10% level.

However, our three, four & five factor portfolios alphas are more negative, and significant at the 1% level. The HL portfolio has a significant four factor-alpha of -1.43% per month (-17.16% annually). These findings are similar to Blitz & van Vliet (2007), who after controlling for value and momentum factors find an annual spread of -12% for their high versus low-volatility decile portfolios.[34] However, it is important to note that low-volatility portfolio has positive alphas for all factors, but then none of them is significant. This implies that it is the under-performance of high-volatility portfolios that accounts for anomaly in Norwegian market.

Table 6 - Volatility sorted VW portfolios, July 1986 - June 2014

This table reports characteristics and regression results for value-weighted (VW) volatility portfolios for the July 1986 to June 2014 period. Stocks are sorted in ascending order on the basis of their estimated total volatility using previous 12 month window of daily data as described in Section 4.2. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Volatility (ex-ante) is the average estimated volatility, beta (realized) is ex-post CAPM-beta and volatility (realized) is ex-post volatility. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	Portfolio					
Characteristics	**L**	**2**	**3**	**4**	**H**	**HL**
Excess Return	0.41	0.37	-0.20	0.13	-0.48	-0.89
	(1.14)	(0.84)	(-0.35)	(0.23)	(-0.66)	(-1.53)
Volatility (ex-ante)	6,26	8,35	10,36	12,98	19,01	
Beta (realized)	0.87	1.02	1.24	1.10	1.27	
Volatility (realized)	21,46	26,04	33,06	32,01	43,12	
Sharpe ratio	0.23	0.17	-0,07	0.05	-0.13	
Regressions						
CAPM Alpha	0.10	0.02	-0.62	-0.25	-0.92*	-1.02*
	(0.84)	(0.11)	(-1.47)	(-0.77)	(-1.83)	(-1.87)
Three-factor alpha	0.17	0.03	-0.68	-0.52	-1.29***	-1.46***
	(1.38)	(0.11)	(-0.65)	(-1.60)	(-2.78)	(-2.91)
Four-factor alpha	0.16	0.05	-0.65	-0.51	-1.27***	-1.43***
	(1.34)	(0.24)	(-1.55)	(-1.58)	(-2.69)	(-2.86)
Five-factor alpha	0.19	-0.01	-0.71	-0.58 *	-1.34***	-1.53***
	(1.59)	(-0.07)	(-0.81)	(-1.80)	(-2.85)	(-3.07)

6.3.2 Factor Returns

Exhibit A.7 reports the factor loadings of the lowest and highest value weighted quintile portfolios, which is described in previous section.

[34] In their paper, David C. Blitz and Pim van Vlie,t (2007) provided evidence in U.S., European and Japanese markets and reported annual spread of 12% for low versus high decile portfolios.

We see that the low-volatility portfolio has a lower market exposure than the high-volatility portfolio, which is in line with what we should expect. The low (high) volatility portfolio has significant negative (positive) exposure to SMB. This is consistent with our expectations as high volatility portfolios often exhibit a small cap effect, i.e. they are positively associated with firms with low market capitalization while low-volatility portfolio often has more exposure to less risky large capitalization stocks. Concerning HML factor, low (high) volatility portfolio has positive (negative) exposure, where the beta for high quintile is significant at the 5% level. This is consistent with the literature, as high-volatility portfolios on average contain more growth stocks. The low-volatility portfolio has significant positive exposure to the liquidity factor, although the magnitude is very small. This result is still surprising, since low-volatility portfolios tend to be negatively related with illiquid stocks. This can be because we may not have many illiquid stocks in our investment universe[35].

6.3.3 Robustness Tests

Although our low (high) volatility portfolio has positive (negative) excess return as shown in section 6.1.1, it is not significant. Similarly, CAPM alpha for high and high-minus-low volatility portfolios is significant but only at the 10% level. For that reason, we want to perform numerous robustness tests to check if our initial results still hold.

6.3.3.1 Testing Sub Samples

In this section, we test the robustness of our results presented in section 6.3.1 by exploring two different sub periods. As discussed in Section 4.4, the financial crisis could change the risk-return relation in the stock market. We therefore test the robustness of our findings by studying two sub periods for the value-weighted quintile portfolios, July 1986 - June 2000 and July 2000 - June 2014.

Exhibit A.8 reports that the signs of the low and high portfolios, excess returns, and factor model alphas across both subs periods are similar to our full sample. However, contrary to full period analysis, both sub-period CAPM alphas are no longer significant. Other factor alphas are still significant but both the magnitude

[35] See Section 6.1.5 for discussion of possible reasons explanation for this observation.

and significance has decreased, as for first (second) sub-period they are now only significant at the 10% (5%) level.

6.3.3.2 Equal-Weighted Performance

Exhibit A.9 reports the same analysis discussed in Section 6.3.1 using equal weighting[36] for the quintile stocks, and the results are little different compared to the value-weighted quintile portfolios. The average excess returns for the equal-weighted HL portfolio is a bit smaller in absolute magnitude, -0.45% per month, however it is still insignificant. Similarly, CAPM alpha for high portfolio is still negative, but with half the magnitude compared to value-weighted, and is no longer significant. Other factor alphas are negative and significant but regression results are not robust. Our findings therefore indicate that assigning equal weights for the HL portfolio over the period July 1986 - June 2015 does seem to differ from our conclusions drawn earlier for value-weighted portfolios.

6.3.3.3 Estimating Ex-Ante Volatility Portfolios Using Monthly Stock Returns

As can be seen from Exhibit C.2 in appendix C, the results for the value-weighted HL portfolio across the period 1986-2014 are quite dissimilar to our findings presented in Section 6.3.1. The excess return of the HL portfolio is -0.28% per month and insignificant. Most importantly, CAPM, three-factor and four-factor alphas for HL portfolios are no longer significant. Our findings therefore indicate that forming volatility portfolios using monthly data does not show over (under) performance of low (high) volatility portfolio. Thus, our results compared to Section 6.3.1 indicates that the low-volatility anomaly inference is sensitive to chosen empirical approaches. Therefore, caution should be taken before concluding that the low-volatility anomaly exists in Norway.

[36] Our value-weighted out-of-sample performance is one year shorter compared to equal weighting due to insufficient market capitalization data for 2015.

7 CONCLUSION

The cornerstone in finance theory is the relationship between risk and return. Developed from modern portfolio theory, the standard Capital Asset Pricing Model states that the expected return of any asset is linearly related to its systematic risk, measured by the market beta. In early empirical studies, however, Friend & Blume (1970) and Black, Jensen & Scholes (1972) find that stocks with higher betas experience lower returns and their low-risk counterparts exhibit higher returns than predicted by CAPM, indicating a flat, or even negative SML. These findings have been confirmed by numerous researchers over the past 40 years, and it has been known as the *low-beta anomaly*. Several investigations offer an explanation for this relation where Cederburg & O'Doherty (2016), among others, suggest that prior studies fail to account for biases in unconditional performance measures.

Our analysis study the relation between systematic risk and return, and whether the low-beta anomaly is present in Norway over the period July 1986- June 2014. By partly utilizing the methodology by Frazzini & Pedersen (2014), we find that the vast internationally evidence of the anomaly is not present in the Norwegian stock market. Looking at the value-weighted portfolios, we see a tendency that the lowest quintile portfolio performs better than the highest quintile portfolio, both on a beta-adjusted risk level and in cumulative returns. These findings become more dominant from 2000 - 2014, where low-beta stocks perform noticeably better compared to the first sub period. Karceski (2002) finds that the beta-anomaly in the US becomes more persistent in the 1980s, which is likely due to the increase of institutional investors. As explained by the author, professional fund managers may prefer high-beta stocks because the performance in rising markets exceeds the poor performance in falling markets. As the presence of foreign institutional investors in Norway happened at a later stage, we believe that the preference of high-beta stock among fund managers is likely to cause an increase in the performance of low-beta stocks on OSE. Nevertheless, neither the whole period nor the sub periods produce any statistically significant results in our study.

When assigning equal-weights to the HL portfolio, it seems to provoke a beta-anomaly in the sub period July 2000 – June 2014. This mainly stems from the poor underperformance of the high quintile, as assigning equal weights gives a tilt toward small-capitalized stocks that in addition, is quite volatile. This leads to an underperformance of the high quintile relative to the low quintile. We conclude that weighting schemes seems to be quite important when drawing inferences on the anomaly. As the results are only significant for the second period and only for equal-weighted portfolio, we do not consider the findings robust, and we conclude that the beta-anomaly in Norway is absent.

As far as we are aware, our investigation of the conditional CAPM using instrumental variables are the first of its kind in Norway. Using lagged component betas, default spread and oil price as instruments does not seem to perform better than the static asset pricing models. We have thus not achieved to reduce the alpha of our high-minus-low beta sorted portfolio adequately.

For the total volatility sorted portfolios, we find some similarities between our results and Baker & Haugen (2012) study of 21 developed countries including Norway. The similarities encompass negative excess return, lower Sharpe ratio and negative CAPM alpha of high volatility portfolio. However, excess returns are not statistically significant and alpha is barely significant at the 10% level. Moreover, our findings are not robust for equal-weighted portfolios. Therefore, contrary Baker & Haugen (2012), we conclude that total volatility anomaly is not present in Norway.

When assessing the conditional performance, we utilize the conditional CAPM on the beta-sorted portfolios estimated from the static model. Regarding future research, addressing different aspects of dynamic portfolio construction is of interest. The use of conditional betas to form testing portfolios can combine useful properties of information-dependent models, which can be superior in out-of-sample performance.

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APPENDIX

Appendix A – Supplementary Results

Exhibit A.1 - Winsorization descriptives

This table reports our winsorization descriptives for those stocks that were traded following the bid/ask quote, where the annual period starts from July 1 and ends June 30 next year. Our initial sample contains 864 securities. The initial number of stocks column reports the number of securities in each time period. The number of returns column reports the total number of returns across all securities in each time period. The maximum (minimum) return columns reports the highest (lowest) return observation across all securities in each time period. The 99.9 (0.1) percentile returns columns reports the cut off point of extreme high (low) return observations in each time period. The number of stocks with extreme returns column reports the number of stocks having returns either higher (lower) than 99.9 (0.1) percentile in each time period. Column next to it reports number of stocks with market capitalization less than NOK 10 million in each time period. Number of filtered stocks (last) column reports the number of stocks included in our estimations each year after adapting extreme return and market capitalization filtering rules.

Start mth/yr	End mth/yr	# Initial/Pre-filtered stocks	# returns	Maximum return	Minimum return	99.9 percentile returns	0.1 percentile returns	# stocks with extreme returns	# stocks with market cap < 10 million	# Filtered stocks
07.1980	06.1981	85	4296	33.3 %	-25.0 %	27.0 %	-11.1 %	18	4	63
07.1981	06.1982	97	5886	21.2 %	-32.8 %	17.3 %	-14.4 %	8	6	83
07.1982	06.1983	120	10535	57.9 %	-33.3 %	25.0 %	-21.4 %	6	11	103
07.1983	06.1984	136	17866	54.5 %	-50.0 %	22.5 %	-15.9 %	3	10	123
07.1984	06.1985	163	21064	54.5 %	-28.9 %	21.2 %	-16.0 %	1	9	153
07.1985	06.1986	175	25557	50.0 %	-47.8 %	20.0 %	-18.2 %	2	8	165
07.1986	06.1987	171	22932	53.5 %	-51.0 %	20.0 %	-18.8 %	2	3	166
07.1987	06.1988	169	21905	900.0 %	-72.2 %	30.5 %	-29.1 %	1	4	164
07.1988	06.1989	158	21267	185.7 %	-60.0 %	33.3 %	-28.6 %	2	1	155
07.1989	06.1990	183	24092	50.0 %	-39.8 %	22.1 %	-20.0 %	1	0	182
07.1990	06.1991	169	23464	100.0 %	-58.3 %	24.0 %	-21.5 %	4	0	165
07.1991	06.1992	173	21833	212.5 %	-70.4 %	40.0 %	-35.0 %	4	0	169
07.1992	06.1993	168	21143	312.5 %	-79.2 %	71.2 %	-49.3 %	3	5	160
07.1993	06.1994	180	28485	90.0 %	-70.0 %	29.4 %	-19.2 %	11	1	168
07.1994	06.1995	189	27448	80.0 %	-76.5 %	22.4 %	-15.4 %	6	0	183
07.1995	06.1996	195	32245	200.0 %	-44.4 %	25.9 %	-18.0 %	7	1	187
07.1996	06.1997	218	36999	50.0 %	-62.9 %	18.8 %	-14.0 %	8	0	210
07.1997	06.1998	262	43055	133.3 %	-50.0 %	21.2 %	-17.0 %	9	0	253
07.1998	06.1999	263	40636	589.5 %	-99.9 %	41.8 %	-28.6 %	10	0	253
07.1999	06.2000	259	40575	200.0 %	-91.8 %	38.0 %	-24.1 %	12	0	247
07.2000	06.2001	255	39556	115.4 %	-76.8 %	33.7 %	-25.6 %	14	0	241
07.2001	06.2002	234	34889	200.0 %	-71.4 %	46.0 %	-30.4 %	13	0	221
07.2002	06.2003	217	31229	146.7 %	-89.7 %	58.3 %	-44.0 %	13	0	204
07.2003	06.2004	208	35553	130.8 %	-79.6 %	36.6 %	-25.2 %	13	2	193
07.2004	06.2005	219	39430	84.2 %	-41.5 %	25.9 %	-14.8 %	11	0	208
07.2005	06.2006	247	46612	115.4 %	-36.5 %	24.6 %	-14.3 %	11	0	236
07.2006	06.2007	276	48642	50.9 %	-39.3 %	18.4 %	-11.9 %	10	0	266
07.2007	06.2008	289	52586	282.1 %	-80.9 %	25.7 %	-17.6 %	10	0	279
07.2008	06.2009	280	47465	570.9 %	-76.2 %	51.9 %	-36.1 %	11	1	268
07.2009	06.2010	258	47101	150.0 %	-97.1 %	41.3 %	-26.7 %	11	2	245
07.2010	06.2011	256	49023	1938.5 %	-81.4 %	36.5 %	-25.0 %	13	2	241
07.2011	06.2012	251	47473	273.7 %	-64.7 %	50.0 %	-33.3 %	13	0	238
07.2012	06.2013	237	44924	169.2 %	-87.9 %	44.1 %	-28.9 %	13	3	221
07.2013	06.2014	237	45727	300.0 %	-78.9 %	32.0 %	-23.0 %	13	2	222
07.2014	06.2015	224	46160	361.9 %	-76.3 %	36.7 %	-21.9 %	12	0	212

Exhibit A.2 - Correlation Matrix Pricing Factors

Correlations of monthly pricing factors, July 1986 June 2015

This table reports correlations between the explanatory variables described in Section 5.4, namely market (Market), small-minus-big (SMB) or size, high-minus-low (HML) or value, up-minus-down (UMD) or momentum, and liquidity (LIQ) for the Jul-86 to Jun-15 period.

	Market	SMB	HML	UMD	LIQ
Market	1				
SMB	-0.46	1			
HML	0.05	-0.14	1		
UMD	-0.09	0.09	-0.11	1	
LIQ	-0.64	0.60	0.07	-0.06	1

Correlations of monthly pricing factors, July 1986 June 2000

This table reports correlations between the explanatory variables described in Section 5.4, namely market (Market), small-minus-big (SMB) or size, high-minus-low (HML) or value, up-minus-down (UMD) or momentum, and liquidity (LIQ) for the Jul-86 to Jun-00 period.

	Market	SMB	HML	UMD	LIQ
Market	1				
SMB	-0.40	1			
HML	0.20	-0.31	1		
UMD	-0.08	0.08	-0.21	1	
LIQ	-0.53	0.64	-0.05	-0.20	1

Correlations of monthly pricing factors, July 2000 June 2015

This table reports correlations between the explanatory variables described in Section 5.4, namely market (Market), small-minus-big (SMB) or size, high-minus-low (HML) or value, up-minus-down (UMD) or momentum, and liquidity (LIQ) for the Jul-00 to Jun-15 period.

	Market	SMB	HML	UMD	LIQ
Market	1				
SMB	-0.54	1			
HML	-0.15	0.11	1		
UMD	-0.10	0.12	0.01	1	
LIQ	-0.76	0.54	0.22	0.12	1

Exhibit A.3 - Pricing Factor Loadings Beta-Sorted VW

This table reports factor loadings for the low beta and high beta portfolios for July 1986 to June 2014 period. Portfolios are regressed on a five-factor model. The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

Portfolio	**1 (Low)**	**5 (High)**
Alpha	-0.13	-0.42
	(-0.64)	(-1.35)
Market	0.66***	1.21***
	(13.05)	(14.31)
SMB	0.14*	0.13
	(1.91)	(1.24)
HML	0.09*	0.06
	(1.75)	(0.67)
UMD	0.06	-0.16**
	(1.46)	(-1.98)
LIQ	-0.02	-0.25**
	(-0.64)	(-2.31)

Exhibit A.4 - Beta sorted EW portfolios, July 1986 - June 2015

This table reports characteristics and regression results for equal-weighted (EW) beta portfolios for the July 1986 to June 2015 period. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Beta (ex-ante) is the average estimated beta (also known as formation-period beta) while Beta (ex-post) is the realized CAPM-beta. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	Portfolio					
Characteristics	**L**	**2**	**3**	**4**	**H**	**HL**
Excess Return	0,36	0.50	0,37	0,18	0,03	-0,33
	(1.08)	(1.28)	(0.80)	(0.35)	(0.04)	(-0.73)
Beta (ex-ante)	0.40	0.66	0.85	1.08	1.51	
Beta (realized)	0.65	0.81	0.98	1.06	1.31	
Volatility	20,24	23,33	27,55	28,55	37,03	
Sharpe ratio	0.22	0.26	0,16	0.07	0.01	
Regressions						
CAPM Alpha	0.15	0.24	0.00	-0.17	-0.40	-0.55
	(0.73)	(1.06)	(0.23)	(-0.67)	(-1.17)	(-1.49)
Three-factor alpha	-0.06	-0.03	-0.20	-0.43*	-0.63*	-0.57
	(-0.33)	(-0.13)	(-0.89)	(-1.78)	(-1.88)	(-1.51)
Four-factor alpha	-0.07	-0.00	-0.15	-0.40	-0.58	-0.51
	(-0.36)	(-0.04)	(-0.69)	(-1.63)	(-1.70)	(-1.39)
Five-factor alpha	-0.06	-0.00	-0.20	-0.48**	-0.67**	-0.61*
	(-0.29)	(-0.02)	(-0.92)	(-1.99)	(-2.01)	(-1.68)

Figure A.1 - Value of NOK 1 invested in EW beta sorted, and market portfolios in excess of risk-free rate (July 1986 - June 2015)

The figure shows the value of NOK 1 invested in beta-sorted high and low equal-weighted (EW) quintile portfolios, and market portfolio. The value is based on monthly excess returns. i.e. NOK value earned above the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas. Table in the figure reports the correlation and beta of low and high beta portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.

	L-Rf	H-Rf	Market-Rf
Correlation	0,72	0,80	1
Beta	0,65	1,32	1
Expected return	0,36 %	0,03 %	0,32 %
Volatility	20,24 %	37,03 %	22,60 %
Sharpe ratio	0,22	0,01	0,17

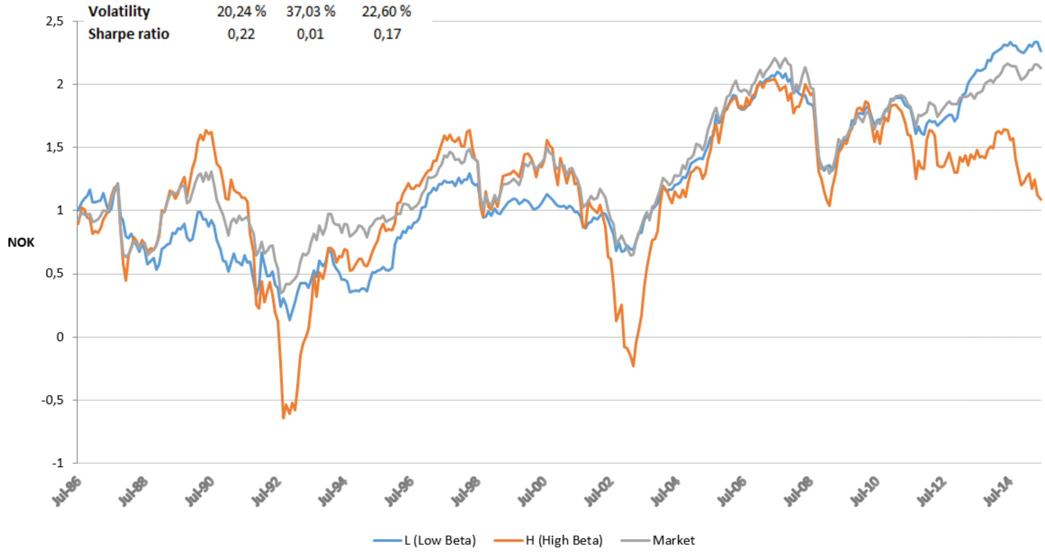


Exhibit A.5 - Robustness test, monthly asset returns from OBI

This table reports characteristics and regression results for value-weighted (equal-weighted) beta portfolios for the July 1986 to June 2014 (July 1986 to June 2015) period using monthly returns of stocks published by prof. Bernt Arne Ødegaard. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Beta (ex-ante) is the average estimated beta (also known as formation-period beta) while Beta (ex-post) is the realized CAPM-beta. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	VW (1986-2014)			EW (1986-2015)		
Characteristics	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**
Excess Return	0,2	0,19	-0,01	0,51	0,16	-0.35
	(0.59)	(0.31)	(-0.02)	(1.41)	(0.26)	(-0.73)
Beta (ex-ante)	0.41	1.51		0.40	1.50	
Beta (realized)	0.63	1.33		0.68	1.36	
Volatility	19,29	35,79		22,98	37	
Sharpe ratio	0.12	0.06		0.26	0.05	
Regressions						
CAPM Alpha	-0.02	-0.27	-0.25	0.28	-0.27	-0.55
	(-0.10)	(-0.87)	(-0.64)	(1.22)	(-0.85)	(-1.47)
Three-factor alpha	-0.11	-0.33	-0.22	0.07	-0.53*	-0.60
	(-0.57)	(-1.04)	(-0.55)	(0.32)	(-1.67)	(-1.58)
Four-factor alpha	-0.12	-0.29	-0.17	0.09	-0.47	-0.56
	(-0.61)	(-0.93)	(-0.44)	(0.41)	(-1.49)	(-1.51)
Five-factor alpha	-0.12	-0.34	-0.22	0.13	-0.55*	-0.68*
	(-0.60)	(-1.06)	(-0.57)	(0.55)	(-1.76)	(-1.80)

hibit A.6 - Fama-French model regressions, 1991-2014

is table reports IV1 regression results for value-weighted beta (VW) beta portfolios for the July 1991 to June 2014 period using Fama-French (1993) three-factor model. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas where "HL" refers to their difference. The return regression is given by $_{\tau} = \alpha_i^{IV1} + (\gamma_{i,0} + \gamma_{i,1}' Z_{i,\tau-1}^{\gamma}) R_{m,\tau} + (\theta_{i,0} + \theta_{i,1}' Z_{i,\tau-1}^{\theta}) R_{smb,\tau} + (\omega_{i,0} + \omega_{i,1}' Z_{i,\tau-1}^{\omega}) R_{hml,\tau} + u_{i,\tau}$ where Zi,τ-1 is instrument variable. The instruments for the given portfolio include the 12-month and 60-month lagged mponent betas, the defualt spread (DS) and oil price (Brent). Case 1 represents unconditional CAPM as presented in section 3.1 where value of the instrument variable set to 0. Alpha is the intercept in a regression and is eported in percentage per month. The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively. R-square is adjusted R-square value for each regression.

		$R_{m,\tau} \times$					$R_{smb,\tau} \times$					$R_{hml,\tau} \times$					
se	α_i^{IV1}	1	β^{LC12}	β^{LC60}	DS	Oil Price	1	β^{LC12}	β^{LC60}	DS	Oil Price	1	β^{LC12}	β^{LC60}	DS	Oil Price	R^2
L	0,04	0.63***					0.09					0,06					54,7
	(0.21)	(14)					(1.14)					(1.07)					
H	-0,49	1.29***					-0.09					0,01					70,4
	(-1.51)	(13)					(-0.10)					(0.13)					
HL	-0,53																
	(-1.35)																
L	0,11	0,74***	-0,16				0,49***	-0,61***				-0,03	0,10				56,1
	(0.54)	(7.65)	(-1.01)				(3.63)	(-3.06)				(-0.29)	(0.69)				
H	-0,45	1,79***	-0,43				0,9*	-0,83*				-1,78***	1,61***				73,1
	(-1.43)	(5.42)	(-1.54)				(1.69)	(-1.81)				(-4.17)	(4.30)				
HL	-0,56																
	(-1.49)																
L	-0,03	0,93***		-0,45***			0,57***		-0,66**			-0,17		0,32*			56,5
	(-0.15)	(8.59)		(-2.94)			(3.19)		(-2.57)			(-1.36)		(1.88)			
H	-0,57*	1,98***		-0,60**			-0,77		0,69			0,43		-0,41			72,1
	(-1.78)	(6.91)		(-2.47)			(-1.61)		(1.64)			(1.29)		(-1.40)			
HL	-0,54																
	(-1.43)																
L	0,01	0,90***	0,09	-0,46***			0,64***	-0,57	-0,22			-0,16	-0,04	0,33*			57,0
	(0.06)	(6.53)	(0.45)	(-2.56)			(2.59)	(-1.48)	(-0.62)			(-1.16)	(-0.20)	(1.68)			
H	-0,59	2,13***	-0,16	-0,71**			0,37	-1,24**	0,89**			-1,5***	1,65***	-0,33			75,1
	(-1.77)	(4.12)	(-0.03)	(-2.00)			(0.52)	(-2.08)	(2.09)			(-3.09)	(3.41)	(-0.92)			
HL	-0,60																
	(-1.67)																
L	0,09	0,47***			17,32		-0,13			23,77		-0,05			6,09		55,2
	(0.42)	(4.05)			(1.49)		(-0.83)			(0.39)		(-0.03)			(0.50)		
H	-0,45	1,51***			-22,36		-0,12			8,32		0,21			-23,97		70,9
	(-1.31)	(7.00)			(-1.12)		(-0.70)			(0.60)		(1.04)			(-1.42)		
HL	-0,54																
	(-1.40)																
L	0,04	0,63***				-0,61	0,11				-0,85	0,05				0,16	54,8
	(0.22)	(13)				(-1.58)	(1.24)				(-1.34)	(0.85)				(0.34)	
H	-0,50	1,29***				0,35	-0,13				0,18	0,04				-0,78	70,3
	(-1.39)	(12)				(0.40)	(-0.14)				(0.20)	(0.36)				(-1.03)	
HL	-0,54																
	(-1.38)																
L	0,02	0,82***	0,11	-0,45**	7,47	-0,71*	0,49	-0,53	-0,16	9,19	-0,69	-0,42*	-0,02	0,41**	19,20	0,11	57,3
	(0.12)	(4.20)	(0.58)	(-2.44)	(0.59)	(-1.83)	(1.50)	(-1.40)	(-0.42)	(0.81)	(-1.36)	(-1.88)	(-0.09)	(1.98)	(1.38)	(0.25)	
H	-0,56	2,32***	-0,03	-0,71**	-18,48	0,55	0,41	-1,22**	0,82*	0,55	-0,03	-1,26**	1,60***	-0,32	-20,00	-0,49	75,2
	(-1.70)	(3.57)	(-0.06)	(-2.06)	(-1.20)	(0.68)	(0.51)	(-2.04)	(1.87)	(0.04)	(-0.02)	(-2.45)	(3.24)	(-0.93)	(-1.22)	(-0.62)	
HL	-0,58																
	(-1.60)																

Exhibit A.7 - Pricing Factor Loadings Volatility-Sorted VW

This table reports factor loadings for the low volatility and high volatility portfolios for July 1986 to June 2014 period. Portfolios are regressed on a five-factor model. The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

Portfolio	1 (Low)	5 (High)
Alpha	0.19	-1.34 ***
	(1.59)	(-2.85)
Market	0.87***	1.38***
	(28.35)	(10.90)
SMB	-0.15***	0.73***
	(-3.94)	(5.13)
HML	0.03	-0.36**
	(1.09)	(-2.47)
UMD	0.03	-0.12
	(1.50)	(-1.09)
LIQ	0.10**	-0.24
	(2.35)	(-1.54)

Exhibit A.8 - Volatility sorted VW portfolios during sub periods 1986-2000 and 2000-2014

This table reports regression results for value-weighted (VW) volatility portfolios for two sub-periods that run from July 1986 to June 2000 & July 2000 to June 2014. Stocks are sorted in ascending order on the basis of their estimated total volatility using previous 12 month window of daily data as described in Section 4.2. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Volatility (ex-ante) is the average estimated volatility, beta (realized) is ex-post CAPM-beta and volatility (realized) is ex-post volatility. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	1986-2000			2000-2014		
Characteristics	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**
Excess Return	0.24	-0.69	-0.93	0.58	-0.27	-0.85
	(0.44)	(-0.71)	(-1.16)	(1.25)	(-0.25)	(-1.01)
Volatility (ex-ante)	6.28	17.92		6.23	20.09	
Beta (realized)	0.93	1.10		0.81	1.46	
Volatility (realized)	23.50	40.28		19.27	45.90	
Sharpe ratio	0.12	-0.21		0.36	-0.07	
Regressions						
CAPM Alpha	0.03	-0.94	-0.97	0.20	-0.95	-1.15
	(0.17)	(-1.28)	(-1.22)	(1.15)	(-1.44)	(-1.61)
Three-factor alpha	0.18	-1.31*	-1.49**	0.20	-1.37**	-1.57**
	(1.07)	(-1.95)	(-2.07)	(1.14)	(-2.19)	(-2.34)
Four-factor alpha	0.18	-1.30*	-1.48**	0.17	-1.21*	-1.38**
	(1.05)	(-1.95)	(-2.06)	(0.96)	(-1.81)	(-2.08)
Five-factor alpha	0.19	-1.27*	-1.46**	0.24	-1.39**	-1.63**
	(1.16)	(-1.92)	(-2.04)	(1.41)	(-2.11)	(-2.53)

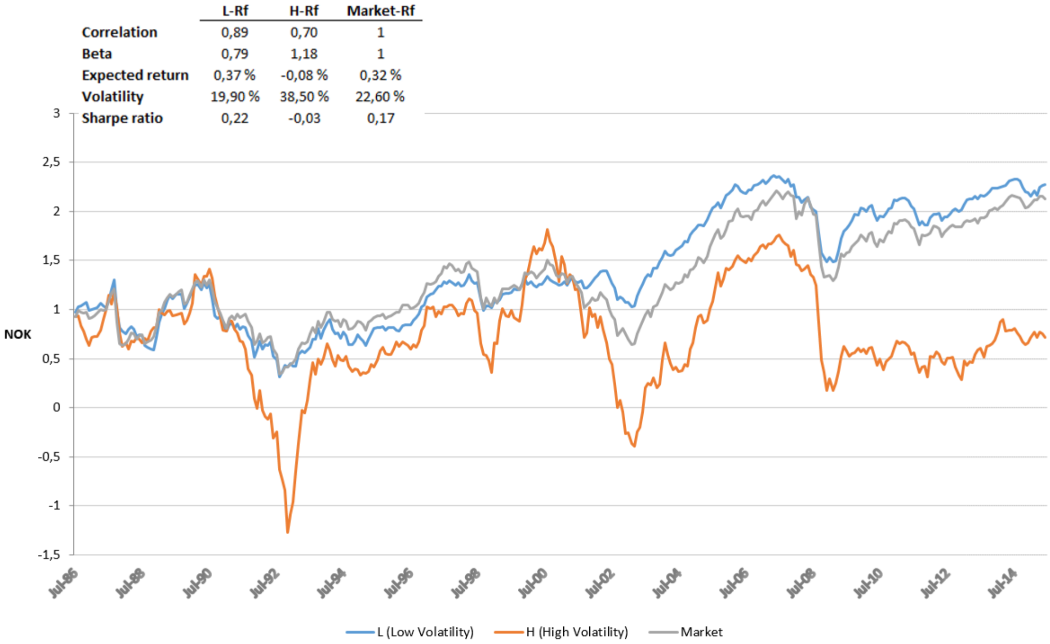
Exhibit A.9 - Volatility sorted EW portfolios, July 1986 - June 2015

This table reports characteristics and regression results for equal-weighted (EW) volatility portfolios for the July 1986 to June 2015 period. Stocks are sorted in ascending order on the basis of their estimated total volatility using previous 12 month window of daily data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Volatility (ex-ante) is the average estimated volatility, beta (realized) is ex-post CAPM-beta and volatility (realized) is ex-post volatility. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	Portfolio					
Characteristics	**L**	**2**	**3**	**4**	**H**	**HL**
Excess Return	0.37	0.27	-0.01	0.15	-0.08	-0.45
	(1.08)	(0.66)	(-0.02)	(0.27)	(-0.12)	(-0.89)
Volatility (ex-ante)	6.26	8.34	10.36	12.99	19.01	
Beta (realized)	0.79	0.93	1.06	1.09	1.18	
Volatility (realized)	19.90	23.64	27.33	30.48	38.50	
Sharpe ratio	0.22	0.14	-0.00	0.06	-0.03	
Regressions						
CAPM Alpha	0.11	-0.03	-0.35	-0.21	-0.46	-0.57
	(0.79)	(-0.19)	(-1.62)	(-0.74)	(-1.07)	(-1.24)
Three-factor alpha	0.06	-0.19	-0.62***	-0.58**	-1.11***	-1.17***
	(0.41)	(-1.17)	(-3.05)	(-2.26)	(-2.94)	(-2.87)
Four-factor alpha	0.07	-0.16	-0.58***	-0.53**	-1.05***	-1.12***
	(0.50)	(-0.97)	(-2.89)	(-2.11)	(-2.73)	(-2.77)
Five-factor alpha	0.06	-0.20	-0.63***	-0.57**	-1.04***	-1.10***
	(0.44)	(-1.31)	(-3.18)	(-2.28)	(-2.66)	(-2.72)

Figure A.2 - Value of NOK 1 invested in EW volatility sorted, and market portfolios in excess of risk-free rate (July 1986 - June 2015)

The figure shows the value of NOK 1 invested in volatility-sorted high and low equal-weighted (EW) quintile portfolios, and market portfolio. The value is based on monthly excess returns. i.e. NOK value earned above the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated total volatility using previous 12 month window of daily data as described in Section 4.1. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility. Table in the figure reports the correlation and beta of low and high volatility portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.



	L-Rf	H-Rf	Market-Rf
Correlation	0,89	0,70	1
Beta	0,79	1,18	1
Expected return	0,37 %	-0,08 %	0,32 %
Volatility	19,90 %	38,50 %	22,60 %
Sharpe ratio	0,22	-0,03	0,17

Appendix B – Results based on Bid/Ask Quote Returns Data

Exhibit B.1 - Winsorization Descriptives, Bid/Ask Quote Returns Data

This table reports our winsorization descriptives, where the annual period starts from July 1 and ends June 30 next year. Our initial sample contains 883 securities. The initial number of stocks column reports the number of securities in each time period. The number of intial returns column reports the total number of returns across all securities in each time period. The maximum (minimum) return columns reports the highest (lowest) return observation across all securities in each time period. The 99.9 (0.1) percentile returns columns reports the cut off point of extreme high (low) return observations in each time period. The number of winsorized returns column reports the number of stocks replaced due to having extreme high or low returns. Column next to it reports number of stocks with market capitalization less than NOK 10 million in each time period. Number of filtered stocks (last) column reports the number of stocks included in our estimations each year after adapting filtering rules.

Start mth/yr	End mth/yr	# Initial/Pre-filtered stocks	# initial returns	Maximum return	Minimum return	99.9 percentile returns	0.1 percentile returns	# returns after winsor-ization	# stocks with market cap < 10 million	# Filtered stocks
07.1980	06.1981	99	16764	85 %	-50 %	28,6 %	-19,1 %	16729	20	79
07.1981	06.1982	111	22935	89 %	-75 %	25,0 %	-20,0 %	22879	14	97
07.1982	06.1983	123	27337	67 %	-57 %	27,9 %	-25,0 %	27280	13	110
07.1983	06.1984	137	31384	55 %	-57 %	26,7 %	-21,2 %	31319	13	124
07.1984	06.1985	165	35899	67 %	-48 %	25,1 %	-20,0 %	35817	9	156
07.1985	06.1986	177	40938	90 %	-49 %	27,8 %	-21,4 %	40855	8	169
07.1986	06.1987	177	39260	71 %	-81 %	28,6 %	-23,1 %	39178	5	172
07.1987	06.1988	175	36844	900 %	-95 %	41,0 %	-33,9 %	36770	4	171
07.1988	06.1989	163	33766	700 %	-87 %	60,0 %	-40,2 %	33693	8	155
07.1989	06.1990	187	36891	350 %	-84 %	36,4 %	-28,6 %	36815	2	185
07.1990	06.1991	174	36989	313 %	-66 %	47,1 %	-33,3 %	36904	0	174
07.1991	06.1992	177	36403	1900 %	-91 %	66,7 %	-42,6 %	36325	0	177
07.1992	06.1993	173	35058	2900 %	-88 %	139,4 %	-57,1 %	34984	2	171
07.1993	06.1994	183	38356	1000 %	-94 %	54,9 %	-37,3 %	38278	2	181
07.1994	06.1995	195	40712	267 %	-76 %	38,3 %	-27,4 %	40630	1	194
07.1995	06.1996	197	42088	650 %	-75 %	35,6 %	-27,4 %	42002	0	197
07.1996	06.1997	220	46172	100 %	-63 %	26,7 %	-20,8 %	46074	0	220
07.1997	06.1998	264	55244	161 %	-67 %	26,8 %	-21,8 %	55132	0	264
07.1998	06.1999	264	59915	590 %	-100 %	56,6 %	-36,5 %	59795	0	264
07.1999	06.2000	261	57051	78025 %	-92 %	45,7 %	-28,6 %	56935	1	260
07.2000	06.2001	258	55342	750 %	-77 %	50,0 %	-32,8 %	55223	0	258
07.2001	06.2002	235	53650	303 %	-71 %	60,0 %	-38,3 %	53539	0	235
07.2002	06.2003	218	51408	1325 %	-95 %	105,0 %	-52,7 %	51304	0	218
07.2003	06.2004	209	46119	11567 %	-96 %	50,0 %	-33,0 %	46024	2	207
07.2004	06.2005	219	48265	101 %	-41 %	29,2 %	-21,3 %	48167	0	219
07.2005	06.2006	247	54723	700 %	-88 %	25,7 %	-16,3 %	54613	0	247
07.2006	06.2007	276	58368	51 %	-39 %	19,5 %	-13,9 %	58249	0	276
07.2007	06.2008	291	66168	2867 %	-81 %	26,8 %	-19,0 %	66034	0	291
07.2008	06.2009	281	64569	10150 %	-99 %	82,8 %	-49,2 %	64439	1	280
07.2009	06.2010	258	59080	9950 %	-99 %	49,9 %	-31,0 %	58960	2	256
07.2010	06.2011	256	59515	1938 %	-81 %	36,9 %	-25,0 %	59373	2	254
07.2011	06.2012	251	58754	274 %	-65 %	50,0 %	-33,3 %	58614	0	251
07.2012	06.2013	237	54624	169 %	-88 %	41,3 %	-28,2 %	54514	3	234
07.2013	06.2014	237	53724	300 %	-79 %	34,3 %	-25,0 %	53614	2	235
07.2014	06.2015	224	53723	362 %	-76 %	41,7 %	-25,9 %	53615	0	224

Exhibit B.2 - Beta sorted VW and EW portfolios, Bid/Ask quote data

This table reports characteristics and regression results for value-weighted (equal-weighted) beta portfolios for the July 1986 to June 2014 (July 1986 to June 2015) period using bid/ask quote data published by prof. Bernt Arne Ødegaard. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Beta (ex-ante) is the average estimated beta (also known as formation-period beta) while Beta (ex-post) is the realized CAPM-beta. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	VW (1986-2014)			EW (1986-2015)		
Characteristics	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**
Excess Return	0.08	0.05	-0.03	0.74**	0,23	-0,51
	(0.23)	(0.08)	(-0.08)	(2.24)	(0.41)	(-1.30)
Beta (ex-ante)	0.16	1.33		0.15	1.32	
Beta (realized)	0.56	1.24		0.53	1.18	
Volatility	20.20	31,38		19,35	31,69	
Sharpe ratio	0.05	0.02		0.46	0.09	
Regressions						
CAPM Alpha	-0.11	-0.38*	-0.27	0.57**	-0.16	-0.73**
	(-0.43)	(-1.73)	(-0.80)	(2.39)	(-0.58)	(-2.36)
Three-factor alpha	-0.39	-0.38	0.01	0.25	-0.33	-0.58*
	(-1.54)	(-1.64)	(0.02)	(1.20)	(-1.22)	(-1.92)
Four-factor alpha	-0.37	-0.37	0.00	0.29	-0.28	-0.57*
	(-1.46)	(-1.60)	(0.02)	(1.36)	(-1.04)	(-1.89)
Five-factor alpha	-0.34	-0.42*	-0.08	0.37*	-0.32	-0.69**
	(-1.34)	(-1.83)	(-0.27)	(1.77)	(-1.20)	(-2.36)

Figure B.1 - Value of NOK 1 invested in EW beta sorted, and market portfolios in excess of risk-free rate, Bid/Ask quote data

The figure shows the value of NOK 1 invested in beta-sorted high and low equal-weighted (EW) quintile portfolios, and market portfolio (1986-2015). The value is based on monthly excess returns. i.e. NOK value earned above the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas. Table in the figure reports the correlation and beta of low and high beta portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.

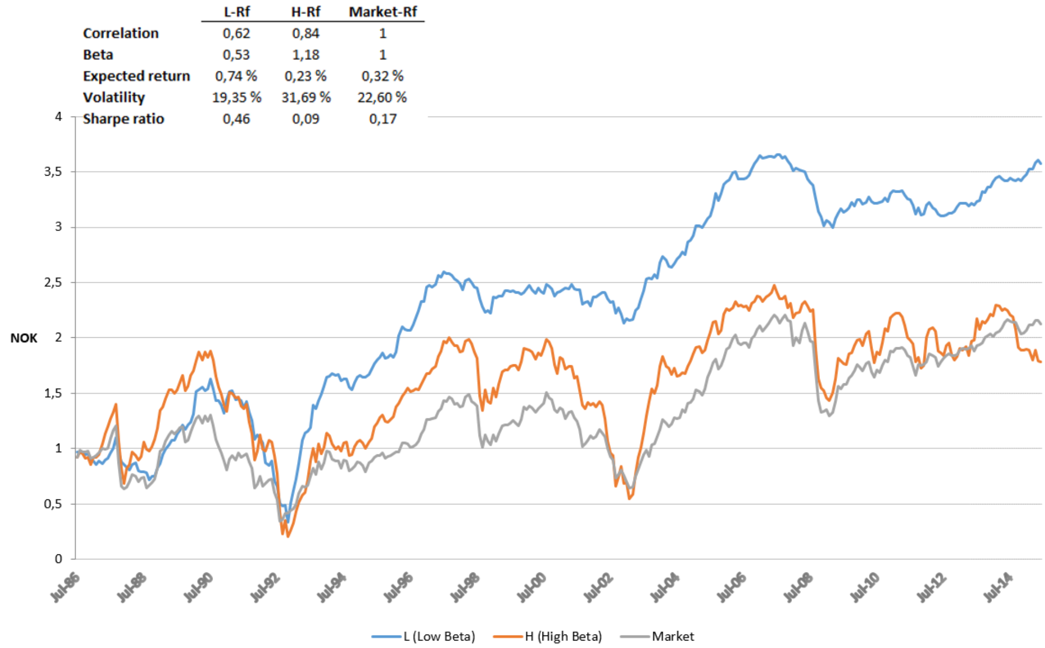
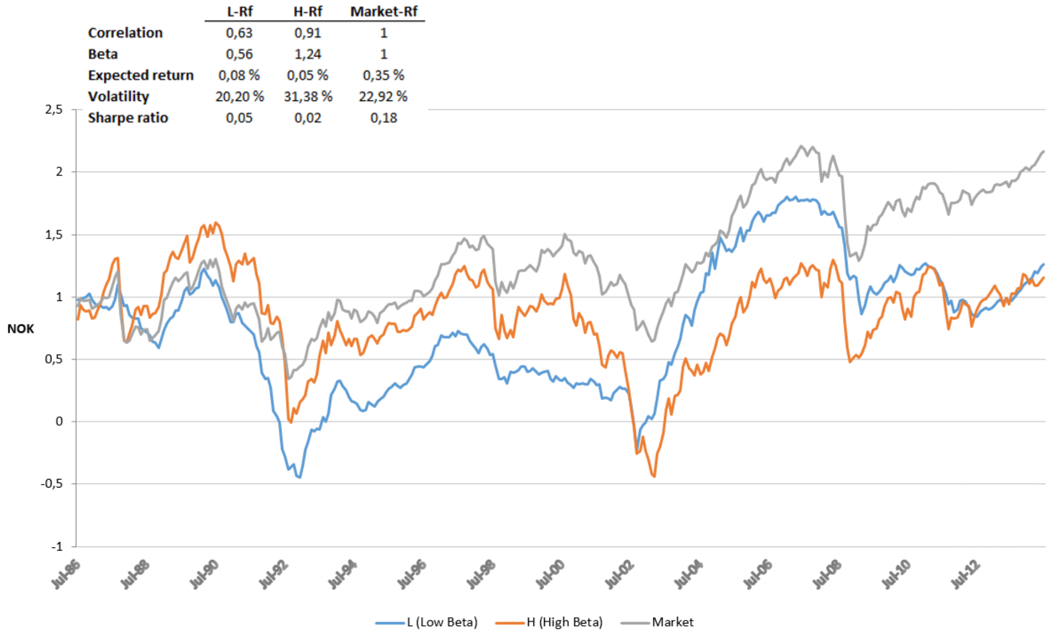


Figure B.2 - Value of NOK 1 invested in VW beta sorted, and market portfolios in excess of risk-free rate, Bid/Ask quote data

The figure shows the value of NOK 1 invested in beta-sorted high and low value-weighted (VW) quintile portfolios, and market portfolio (1986-2014). The value is based on monthly excess returns. i.e. NOK value earned above the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) betas. Table in the figure reports the correlation and beta of low and high beta portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.



Appendix C – Results based on Monthly data

Exhibit C.1 - Beta sorted VW portfolios for whole and sub-periods, Monthly data

This table reports characteristics and regression results for value-weighted beta portfolios for the July 1986 to June 2014 and sub-periods (1986-2000 & 2000-2014) using monthly data. Stocks are sorted in ascending order on the basis of their estimated beta using 5-year window of monthly correlation and 1-year window of volatility data as described in Section 4.1.1. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Beta (ex-ante) is the average estimated beta (also known as formation-period beta) while Beta (ex-post) is the realized CAPM-beta. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	VW			1986-2000			2000-2014		
Characteristics	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**
Excess Return	0,39	0,27	-0.12	0.18	0.09	-0.09	0.60*	0.45	-0.15
	(1.16)	(0.52)	(-0.28)	(0.31)	(0.12)	(-0.14)	(1.76)	(0.59)	(-0.26)
Beta (ex-ante)	0.18	1.99		0.22	1.73		0.15	2.68	
Beta (realized)	0.19	1.20		0.53	1.14		0.45	1.27	
Volatility (realized)	19.99	31.10		24.52	29.63		14.11	32.58	
Sharpe ratio	0.23	0.10		0.09	0.04		0.51	0.17	
Regressions									
CAPM Alpha	0.22	-0.15	-0.37	0.06	-0.17	-0.23	0.39*	-0.14	-0.53
	(0.85)	(-0.66)	(-1.04)	(0.13)	(-0.66)	(-0.40)	(1.78)	(-0.38)	(-1.30)
Three-factor alpha	-0.00	-0.14	-0.14	-0.31	-0.12	0.19	0.29	-0.24	-0.53
	(-0.04)	(-0.63)	(-0.38)	(-0.81)	(-0.49)	(0.37)	(1.32)	(-0.67)	(-1.32)
Four-factor alpha	-0.13	-0.01	0.12	-0.29	-0.11	0.18	0.30	-0.18	-0.48
	(-0.08)	(-0.62)	(0.35)	(-0.74)	(-0.45)	(0.35)	(1.37)	(-0.53)	(-1.24)
Five-factor alpha	-0.03	-0.21	-0.18	-0.31	-0.10	0.21	0.29	-0.38	-0.67*
	(-0.17)	(-0.95)	(-0.52)	(-0.94)	(-0.43)	(0.40)	(1.27)	(-1.19)	(-1.76)

Figure C.1 - Value of NOK 1 invested in VW beta sorted, and market portfolios in excess of risk-free rate, Monthly data

The figure shows the value of NOK 1 invested in beta-sorted high and low value-weighted (VW) quintile portfolios, and market portfolio (1986-2015). The value is based on monthly excess returns. i.e. NOK value earned above the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated beta using previous 60 month daily correlation and 12 month daily volatility data as described in Section 4.1. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.2. Portfolio L (H) is the portfolio with the lowest (highest) betas. Table in the figure reports the correlation and beta of low and high beta portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.

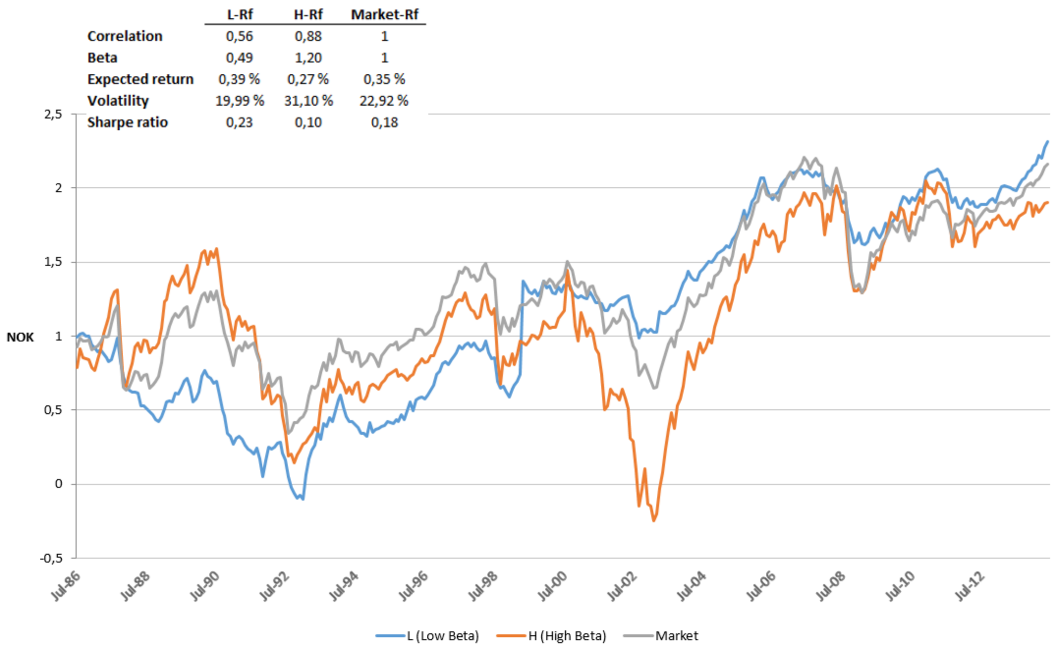


Exhibit C.2 - Volatility sorted VW portfolios for whole and sub-periods, Monthly returns

This table reports characteristics and regression results for value-weighted volatility portfolios for the July 1986 to June 2014 and sub-periods (1986-2000 & 2000-2014) using monthly returns data. Stocks are sorted in ascending order on the basis of their estimated volatility using previous 12 month window of daily data as described in Section 4.2. The sorted stocks are assigned to one of the five quintile portfolios and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility where "HL" refers to their difference. Returns of portfolios are reported in monthly percent in excess of risk-free rate. Volatility (ex-ante) is the average estimated volatility, beta (realized) is ex-post CAPM-beta and volatility (realized) is ex-post volatility. Volatilites and Sharpe ratios are annualized. Alpha is the intercept in a regression and is reported in percentage per month. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, momentum factor (UMD) replicated by prof. Bernt Arne Ødegaard using Norwegian data and liquidity factor computed as in Næs, Skjeltorp & Ødegaard (2008). The numbers in parentheses are Newey-West (1987) corrected t-statistics with a lag length equal to 1, and 10%, 5% & 1% significance is indicated with *, ** & *** respectively.

	VW			1986-2000			2000-2014		
Characteristics	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**	**1 (Low)**	**5 (High)**	**HL**
Excess Return	0.15	-0.13	-0.28	-0.18	-0.20	-0.02	0.48	-0.06	-0.54
	(0.38)	(-0.20)	(-0.57)	(-0.34)	(-0.24)	(-0.03)	(0.83)	(-0.06)	(-0.72)
Volatility (ex-ante)	6.81	23.48		7.42	21.17		6.15	25.96	
Beta (realized)	0.88	1.30		0.81	1.14		0.97	1.49	
Volatility (realized)	22.08	38.09		22.55	34.12		24.72	41.79	
Sharpe ratio	0.08	-0.04		-0.10	-0.07		0.23	-0.02	
Regressions									
CAPM Alpha	0.15	-0.58	-0.43	0.36	-0.46	-0.10	0.03	-0.75	-0.78
	(0.77)	(-1.50)	(-0.95)	(1.28)	(-0.91)	(-0.16)	(0.12)	(-1.35)	(-1.20)
Three-factor alpha	0.08	-0.80**	-0.72	0.30	-0.65	-0.35	0.01	-1.12*	-1.13*
	(0.40)	(-2.02)	(-1.64)	(1.04)	(-1.24)	(-0.58)	(0.34)	(-1.97)	(-1.93)
Four-factor alpha	0.07	-0.76*	-0.69	0.31	-0.68	-0.36	0.11	-0.92*	-1.03*
	(0.34)	(-1.95)	(-1.57)	(0.14)	(-1.31)	(-0.59)	(0.41)	(-1.67)	(-1.71)
Five-factor alpha	0.03	-0.86**	-0.83*	0.32	-0.69	-0.37	0.25	-1.16**	-1.41**
	(0.17)	(-2.25)	(-1.93)	(1.14)	(-1.32)	(-0.62)	(1.00)	(-2.20)	(-2.43)

Figure C.2 - Value of NOK 1 invested in VW volatility sorted, and market portfolios in excess of risk-free rate, Monthly data

The figure shows the value of NOK 1 invested in volatility-sorted high and low value-weighted (VW) quintile portfolios, and market portfolio (1986-2014). The value is based on monthly excess returns. i.e. NOK value earned avove the risk-free rate. Stocks are sorted in ascending order on the basis of their estimated total volatility using previous 12 month window of daily data as described in Section 4.2. The sorted stocks are assigned to high and low quintile portfolios, and the portfolios are rebalanced at the beginning of each July using methodology outlined in Section 4.3. Portfolio L (H) is the portfolio with the lowest (highest) volatility. Table in the figure reports the correlation and beta of low and high volatility portfolios with regards to market portfolio. It also reports expected return, volatility and Sharpe ratio of portfolios.

	L-Rf	H-Rf	Market-Rf
Correlation	0,86	0,78	1
Beta	0,88	1,30	1
Expected return	0,15 %	-0,13 %	0,35 %
Volatility	22,08 %	38,09 %	22,92 %
Sharpe ratio	0,08	-0,04	0,18