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Explanations for the Low Volatility Anomaly:

An Empirical Analysis of the Norwegian Stock Market

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Abstract

In this thesis, we examine the relation between idiosyncratic volatility and stock returns. Inspired by recent studies on the *low volatility anomaly*, we document the existence of and explain this phenomenon in the Norwegian stock market. We use a rolling window model to estimate idiosyncratic volatility, and find that stocks with low idiosyncratic volatility significantly outperform stocks with high idiosyncratic volatility in terms of Fama and French (1993) alphas. Next, we evaluate various potential explanations for the anomaly. Controlling for firm characteristics by performing a double sort, we show that firm size, skewness and illiquidity effects can explain the low returns of stocks with high idiosyncratic volatility. Our results also suggest short-term return reversals as an explanation of the low volatility anomaly. Further, we show that using a more sophisticated method to estimate idiosyncratic volatility provide no evidence of a low volatility anomaly.

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1 Introduction

In one of the most interesting studies in recent financial academia, Ang et al. (2006) find that stocks with high idiosyncratic volatility have abysmally low returns. They show that stocks with low idiosyncratic volatility significantly outperform stocks with high idiosyncratic volatility. This finding of a so called *low volatility anomaly*[1] has sparked life in a debate about the relation between idiosyncratic volatility and return, as it contradicts traditional asset pricing theories suggesting a flat or positive relation. Numerous studies have been conducted trying to explain the anomaly. Possible explanations include those based on firm size, skewness, illiquidity, return reversals and the method used to estimate idiosyncratic volatility. Evidence for the low volatility anomaly has been investigated in markets around the world.

Little attention has been devoted to the low volatility anomaly in the Norwegian stock market. We use monthly stock data from Oslo Børs in the period January 1987 to December 2016 to show that the anomaly is present also in this market, and evaluate various potential explanations for the anomaly.

We follow Ang et al. (2006) and estimate idiosyncratic volatility using a simple rolling window model. Next, we sort stocks into quintile portfolios each month based on idiosyncratic volatility. We focus on the performance of the extreme portfolios. Our purpose is to investigate difference in performance between stocks with low and high volatility. To control for potential firm size effects, we calculate both equally and value-weighted excess returns. Our results provide evidence of a low volatility anomaly on Oslo Børs. Buying low and selling high volatility firms yield significantly positive Fama and French (1993) alphas. Results are most pronounced for value-weighted portfolios. We also sort stocks based on total volatility and find qualitatively identical results compared to sorting on idiosyncratic volatility. Furthermore, the vast majority of the literature on the low volatility anomaly concentrates on idiosyncratic volatility. Hence, we focus on idiosyncratic volatility when we evaluate potential explanations for the low volatility anomaly.

We find strong and monotonic patterns in firm characteristics across the volatility portfolios. More specifically; firms' skewness, bid-ask spread and Amihud (2002)'s measure

[1]The anomaly is also referred to as "The low risk anomaly", "The volatility puzzle" or "The Idiosyncratic volatility puzzle". Throughout the thesis the terms volatility and risk are used interchangeably.

of illiquidity increase monotonically going from the low to high volatility portfolio. Firms' size decrease monotonically across portfolios. A possible explanation for the low volatility anomaly is consequently that part of the low returns for the high volatility portfolio can be attributed to one or more of the above-mentioned firm characteristics. We form quintile portfolios based on these firm characteristics and find that stocks with high skewness, high bid-ask spread or high illiquidity earn significant negative Fama and French (1993) alphas.

To thoroughly test if firm characteristics might explain the low volatility anomaly, we perform a double sort. We find that firm size and the bid-ask spread are the most promising explanations for the low volatility anomaly. Skewness and Amihud (2002)'s measure of illiquidity also exhibit some explanatory power.

Next, we examine how short-term return reversals might explain the low volatility anomaly, as suggested by Fu (2009) and Huang et al. (2010). We find that stocks with high idiosyncratic volatilities have high contemporaneous returns. The positive returns tend to reverse quickly, resulting in low returns in the following month. Thus, part of the low volatility anomaly can be explained by the reversal of returns for stocks with high idiosyncratic volatility.

Most studies on the low volatility anomaly involve sorting stocks into portfolios based on volatility. As volatility is unobservable, it needs to be estimated. As a consequence, the volatility portfolios to a large extent depend on the volatility estimate used. Ang et al. (2006) use a simple rolling window model of lagged returns to estimate idiosyncratic volatility. Stock returns exhibit time-varying volatility and volatility clustering, thus this way of estimating volatility might be too simple. We argue that if the method used to estimate volatility does not matter, we would expect stocks with low volatility to outperform stocks with high volatility, regardless of the method used. To test this hypothesis, we use a GARCH(1,1) model to estimate idiosyncratic and total volatility. We use these estimates of volatility to sort stocks into quintile portfolios. Our results are intriguing. Buying low and selling high volatility firms now yield negative excess returns and insignificant Fama and French (1993) alphas. Thus, our results show no evidence of a low volatility anomaly when we estimate volatility using a more sophisticated model.

Our main contribution in this thesis is to explain why stocks with high idiosyncratic volatility earn low returns in the Norwegian stock market. To our knowledge, this thesis is the first to empirically analyze how firm characteristics, such as size, skewness and illiquidity effects, can help explain the low volatility anomaly on Oslo Børs using a double sort approach. Further, our findings of explanations related to short-term return reversals and GARCH volatility offer new insights to the Norwegian market.

The rest of this thesis is organized as follows. In Section 2, we review the relevant literature. Section 3 describes the data used. Section 4 explains the methodological approach. In Section 5, we present our results. Section 6 concludes. In Appendix A, we report results for different time periods. Appendix B includes results using an alternative data filtering.

2 Literature Review

The capital asset pricing model (CAPM)[2] assume that investors hold a broadly diversified portfolio. Thus, only systematic risk is priced and idiosyncratic risk is not. However, investors in reality might not be fully diversified. Assuming under-diversification, Merton (1987) and Malkiel and Xu (2002) suggest a positive relation between idiosyncratic volatility and returns. Recently, several papers find that stocks with high idiosyncratic volatility earn low returns. Today, the empirical evidence on the relation between idiosyncratic volatility and returns is mixed.

2.1 Low Volatility Anomaly

2.1.1 Idiosyncratic Volatility

Ang et al. (2006) examine the pricing of idiosyncratic volatility in the cross-section of stock returns. They show that stocks with low idiosyncratic volatility significantly outperform stocks with high idiosyncratic volatility. The study investigates US stocks from 1963 to 2000. Idiosyncratic volatility is measured relative to the Fama and French (1993) model. Value-weighted quintile portfolios are formed every month sorted by idiosyncratic volatility computed on daily data over the previous month. The results show that the differences in returns and FF-3 alphas between portfolio 1 (lowest idiosyncratic volatility) and portfolio 5 (highest idiosyncratic volatility) is positive and significant. To examine the robustness of their results they perform a double sort . Their findings are robust after controlling for cross-sectional effects such as size, book-to-market, leverage, liquidity, volume, turnover, bid-ask spreads, coskewness or dispersion in analyst's forecast characteristics. In a later study, Ang et al. (2009) expand their research where they apply their method to a global market. Across 23 developed markets, including Norway, they present evidence that stocks with recent past high idiosyncratic volatility earn low returns. However, detailed results for Norway are not reported.

The findings of Ang et al. (2006) have attracted much attention lately. Several studies draw different conclusions than Ang et al. (2006) on the relation between idiosyncratic volatility and stock returns.

[2]CAPM is based on the work of Sharpe (1964), Lintner (1965) and Mossin (1966).

Ang et al. (2006) use daily returns over one month to compute idiosyncratic volatility. Fu (2009) states that the lagged idiosyncratic volatility might not be a good estimate of expected idiosyncratic volatility. He uses an exponential GARCH (EGARCH) model to estimate expected idiosyncratic volatility and sort stocks into decile portfolios. His results show no evidence of a low volatility anomaly. Quite the opposite, the high volatility portfolio clearly outperforms the low volatility portfolio. Accordingly, his findings sharply contrast those of Ang et al. (2006).

Bali and Cakici (2008) highlight methodological differences in previous studies that mainly led them to give conflicting results. They find that the negative and significant return-relationship between high and low idiosyncratic volatility stocks disappears when monthly data are used instead of daily data to compute idiosyncratic volatility. Further, Ang et al. (2006)'s results are based on value-weighted portfolios. Bali and Cakici (2008) find no evidence of a low volatility anomaly when portfolios are equally weighted.

Huang et al. (2010) find that return reversals can explain both the negative relation between value-weighted portfolio returns and idiosyncratic volatility and the insignificant relation between equally weighted portfolio returns and idiosyncratic volatility. Also Fu (2009) suggests return reversals as an important explanation of the low volatility anomaly. Boyer et al. (2010) find that skewness helps explain the phenomenon that stocks with high idiosyncratic volatility earn low returns.

2.1.2 Total Volatility

Most of the recent literature on the relationship between volatility and returns focus on idiosyncratic volatility. There are also various studies investigating the relationship between total volatility and returns.

Blitz and Van Vliet (2007) examine the volatility effect on global large-cap stocks. They form decile portfolios by ranking stocks on total volatility calculated using the recent three years of weekly returns. To separate the volatility effect from other effects such as valuation, size and momentum, the authors employ both a regression based methodology and double sorting. Their results show that stocks with low historical volatility exhibit superior risk adjusted returns, both in terms of Sharpe ratios and CAPM alphas. Blitz et al. (2013) find similar results for emerging markets. Baker et al. (2011) also find that low volatility stocks outperform high volatility stocks. The low volatility strategy is characterized by a low beta, outperformance in down markets and underperformance in up markets. Their results hold after controlling for Fama French factors such as value, size and momentum.

To our knowledge, Baker and Haugen (2012) provide the only study on the total volatility puzzle that include Norway. They cover stocks in 21 developed countries and 12 emerging markets over the time period 1990 to 2011. Decile or quintile portfolios are formed ranking stocks on total volatility computed using the recent 24 months of returns. In Norway, the low volatility portfolio earns higher annual returns than the high volatility portfolio. However, they do not report any significance level of their results. Further, no robustness test are reported.

2.2 Possible Explanations for the Low Volatility Anomaly

After the findings of Ang et al. (2006) a number of articles have been published trying to explain why the low volatility anomaly exists and could persist through a long period of time. Hou and Loh (2016) bring together the most promising explanations and evaluate and quantify how much each explanation could explain of the puzzle. They find that explanations related to lottery preferences and market frictions have the highest potential of explaining the anomaly. Lottery preferences is related to behavioral finance and can be measured by skewness. Market frictions include return reversals and illiquidity effects. The paper also show that even with all the investigated explanations combined, there is still a large fraction left unexplained.

2.2.1 Lottery Preferences

Lottery preferences is a preference for stocks that behave like lotteries, where there is a high probability for a small negative return but still a slight chance for an exceptional high return. Baker et al. (2011) suggest that the reason why individual investors have the irrational preference for these lottery stocks could be linked to behaviour of representativeness and overconfidence. Representativeness could be explained by considering laymen trying to think of good investments. They can easily remember success stories like Microsoft's IPO and would thus conclude that the road to success is to make a speculative investment in new technologies. In turn, this could increase the demand for small and volatile stocks. Baker et al. (2011) argue that investors ignore the high base rate at which small, speculative investments fail. The other behavioural aspect regarding overconfidence is related to individual investors having too great confidence in their own abilities for predicting stock returns and especially for high volatile stocks. Together these aspects of behaviour finance could explain why high volatile stocks are overpriced.

Lottery preferences imply a preference for positively skewed stocks, whereby large positive returns are more likely than large negative ones. Hou and Loh (2016) show that idiosyncratic volatility is correlated with skewness. Boyer et al. (2010) find that skewness and returns are negatively correlated. They further show that skewness helps explain that stocks with high idiosyncratic volatility have low returns.

2.2.2 Return Reversals

Short-term return reversals can offer an explanation for the low volatility anomaly. Fu (2009) suggest that Ang et al. (2006)'s findings are largely driven by the return reversal of stocks with high idiosyncratic volatilities. High idiosyncratic volatilities are contemporaneous with high returns, which tend to reverse in the following month. Consequently, the returns of stocks with high idiosyncratic volatility are low in the next month. Huang et al. (2010) confirm that return reversals can explain the negative relation between value-weighted portfolio returns and idiosyncratic volatility.

2.2.3 Illiquidity Effects

Bali and Cakici (2008) suggest that small and illiquid stocks might explain the low volatility anomaly. They measure illiquidity following Amihud (2002). Also Hou and Loh (2016) find that this measure of illiquidity can explain some of the low returns of the high volatility portfolio. The bid-ask spread show even more promising results in explaining the anomaly, also shown by Han and Lesmond (2011).

2.2.4 Volatility Estimation

Studies of the relationship between risk and return are reliant on which measure of volatility is being used to represent risk. Volatility is unobservable, thus it has to be estimated. Fu (2009) argues that if idiosyncratic volatility is highly persistent, the lagged value can be used as an estimate of the expected value. However, he shows that idiosyncratic volatilities are time-varying. Thus, the one-month lagged idiosyncratic volatility, used by Ang et al. (2006), may not be an appropriate proxy for the expected idiosyncratic volatility of this month. Using a more sophisticated method to estimate idiosyncratic volatility, Fu (2009) finds no evidence of a low volatility anomaly. He suggests that there is a positive relation between idiosyncratic volatility and returns. This sharply contrast Ang et al. (2006)'s findings, emphasizing the importance of volatility estimation. Further, Bali and Cakici (2008) find that using monthly rather than daily data to compute idiosyncratic volatility yield different results. In particular, there is no evidence of a significantly positive or negative return difference between stocks with low and high idiosyncratic volatility using monthly data.

2.2.5 Limits to Arbitrage

Baker et al. (2011) suggest that institutional investors lack the initiative to utilize the arbitrage of shorting the poor performing high volatility quintile and buying the low volatility quintile. The reason for this is that the high volatility quintile consists largely of small stocks with high trading costs, especially for shorting. This could help to explain why the anomaly seem to persist over such a long period of time.

3 Data

3.1 Oslo Børs

Oslo Børs is the main regulated market for securities trading in Norway today (Oslo Børs, 2017). Important sectors on Oslo Børs are energy, shipping and seafood. Oslo Børs is a small stock exchange in a global setting, with a total market capitalization of NOK 2132 billions in December 2016. The distribution of firm size is asymmetric; a few big and many small firms (Bodie et al., 2014, p. 427). This phenomenon is observed on Oslo Børs where the five biggest firms, in terms of market capitalization, constitute 51 % of the total market in December 2016.

3.2 Filtering Stock Data

We extract monthly stock data from Børsprosjektet NHH's database *Amadeus*[3] for the period January 1987 to December 2016. Before doing any computations, we first cleanse and filter our stock data. We choose to include only ordinary shares. This excludes for instance Primary Capital Certificates and B shares. Further, we consider extreme stock prices. A very high stock price may not seem sensible, thereby we remove price observations above NOK 10,000. Low stock prices can be problematic as they can cause exaggerated returns and volatilities that affect our results. On the other side, we don't want to reduce our sample by excluding all low priced stocks. Ødegaard (2017) requires a stock to have a price above NOK 10 to be included in the sample. A stock price limit of NOK 10 will remove 25 % of the observations in our sample. We choose to exclude price observations where the stock price is below NOK 1, removing 2.1 % of the observations.

We compute a firm's market capitalization as the product of the stock price (**Last**) and the total number of shares issued (**SharesIssued**). Observations where a firm's market capitalization is below NOK 10 million are excluded, removing 0.43 % of the observations.

[3]We extract the following variables from Amadeus: **Date**, **SecurityID**, **Symbol**, **ISIN**, **SecurityName**, **SecurityType**, **IsStock**, **Last**, **AdjLast**, **OffShareTurnover**, **OffTurnover**, **SharesIssued**, **Bid**, **Offer**

For the return computation, we use the adjusted stock price (**AdjLast**) which accounts for dividends, stock splits and corporate events. We use end-of-month prices, and want to have price observations that are not too old. Thus, we require the trade to occur at most six days before the end-of-month date. We compute monthly simple returns for stock i based on the adjusted stock prices (P^i) as follows,

$$r_t^i = \frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} \tag{1}$$

Return outliers can possibly affect our results, in particular skewness calculations. Return observations below the 0.1 % quantile or above the 99.9 % quantile are for that reason removed.

The data set in our analysis is for the 30-year period January 1987 to December 2016. This enables us to investigate returns from January 1989 as we compute volatility using at least 24 months of data.

3.3 Risk-Free Rate and Fama-French Factors

The risk-free rate and Fama-French factors (SMB, HML) are downloaded from Ødegaard's database.[4] The details regarding these data are found in (Ødegaard, 2017). NIBOR is used as the estimate for the risk-free rate. The SMB and HML factors are calculated following Fama and French (1993). We calculate the market factor (MKT) every month as the value-weighted excess return across all stocks in our sample.

[4]`http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html`.

4 Method

4.1 Estimating Volatility

Four different measures of volatility are computed. We estimate volatility for the next month $t+1$ using only data available at the end of this month t. The four volatility estimates are later used to sort stocks into quintile portfolios.

4.1.1 Idiosyncratic Volatility

Following the earlier literature, we calculate idiosyncratic volatility as follows. We regress monthly excess returns on the monthly Fama and French (1993) factors:

$$r_t^i - r_{Ft} = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i \qquad (2)$$

where r_t^i is the return on stock i for month t, r_{Ft} is the risk-free rate, MKT_t is the excess return on the market portfolio, SMB_t is the return of a portfolio of small stocks in excess of the return on a portfolio of large stocks, HML_t is the return of a portfolio of stocks with a high book-to-market ratio in excess of the return on a portfolio with a low book-to-market ratio, α^i is the pricing error. We use a rolling window of the recent N months of data to do the regression. The idiosyncratic volatility of a stock is computed as the standard deviation of the regression residuals (ε_t^i). At the end of month t, we estimate idiosyncratic volatility for month $t+1$ as

$$\widehat{IVOL}_{t+1} = \sqrt{\frac{1}{N-1}\sum_{k=0}^{N-1}(\varepsilon_{t-k} - \bar{\varepsilon})^2} \qquad (3)$$

We choose to estimate idiosyncratic volatility based on the previous $N = 24$ months of data. We require a stock to have monthly return data for at least 50 % of the months in the formation period. For a formation period of 24 months we require at least 12 return observations.

In contrast to Ang et al. (2006), we use monthly data instead of daily data. Bali and Cakici (2008) investigate the relative accuracy of idiosyncratic volatility based on daily and monthly returns. They find that idiosyncratic volatility estimations based on daily data can be subject to market microstructure problems. Further, the statistical results indicate that using monthly data to measure idiosyncratic volatility provides a better characterization of expected future volatility than using daily data. Thus, we use monthly data to measure idiosyncratic volatility.

4.1.2 Total Volatility

To calculate total volatility, we use a rolling window model. Total volatility is the standard deviation of a stock's return over the most recent N months. At the end of month t, we estimate total volatility for month $t+1$ as

$$\widehat{TVOL}_{t+1} = \sqrt{\frac{1}{N-1}\sum_{k=0}^{N-1}(R_{t-k} - \bar{R})^2} \tag{4}$$

where R_t^i is the monthly excess return in month t. As for idiosyncratic volatility, we choose an estimation period of $N = 24$ months and require at least 12 return observations.

The estimation of both idiosyncratic volatility and total volatility use a rolling window model. We want to point out that using a rolling window model to estimate volatility is a simple, but not perfect method for volatility estimation. Every return observation in the estimation period of N months are weighted equally. This leads to so called ”ghost features” in the estimation of volatility. These are changes in the estimated volatility due to influential return observations leaving the window. We note that the choice of a rolling window model is motivated by previous studies, such as Ang et al. (2006). They use a rolling window model and find evidence of a low volatility anomaly. Our purpose is not to find the optimal method for volatility estimation. We want to investigate if there is a low volatility anomaly on Oslo Børs using a simple method to estimate volatility.

In the next section, we discuss a more sophisticated method of estimating volatility.

4.1.3 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

The GARCH model developed by Bollerslev (1986) has become a popular volatility model in the financial world. The benefit of a GARCH model is that it requires a small number of input parameters and allows infinite lags. The general GARCH (m,n) model is

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{n} \beta_i \sigma_{t-i}^2 \tag{5}$$

where $\alpha_0 > 0$, $\alpha_i \geq 0, i = 1, ..., m$, $\beta_i \geq 0, i = 1, ..., n$, and $\sum_{i=1}^{m} \alpha_i + \sum_{i=1}^{n} \beta_i < 1$.

The benefit of using a GARCH model is that it considers both past returns (ϵ_{t-i}^2) and past volatility (σ_{t-i}^2) when forecasting volatility. In the short run, the model will be able to forecast that high volatility is usually followed by high volatility and low volatility by low (Natenberg, 2014, p.387-388). It is also advantageous that forecasted volatility will not be constant but be reverting to the long run mean (Engle et al., 2001).

In this thesis we will use a GARCH(1,1) model,

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{6}$$

This is the simplest, but often very useful GARCH process (Bollerslev, 1986, p. 311). Our motivation for using a GARCH(1,1) model is not to find the optimal volatility forecasting model. Rather, we want to investigate if our results change when volatility is estimated using a more sophisticated methodology than a rolling window model. More specifically, we want to examine if there is evidence of a low volatility anomaly when we use the GARCH(1,1) model to estimate volatility. In our view, if low volatility stocks really outperform high volatility stocks, it should not matter how volatility is measured.

We estimate both idiosyncratic and total volatility using a GARCH(1,1) model to compare our results to those where a rolling window model is used.

We define idiosyncratic volatility estimated using a GARCH(1,1) model ($\widehat{GIVOL}_{t+1}$) as follows. We regress monthly excess returns on three Fama-French factors, as shown in Equation (2), to obtain the residual returns. We use a rolling window of 60 months to do the regression[5]. At the end of month t we estimate "GARCH idiosyncratic volatility" for month $t+1$[6] as

$$\widehat{GIVOL}_{t+1} = \sqrt{\alpha_0 + \alpha_1 \varepsilon_t^2 + \beta_1 \sigma_t^2} \tag{7}$$

where σ_t is the value of $\widehat{GIVOL}$ in month t and ε_t is the return residual from Equation (2).

The return inputs to estimate "GARCH total volatility" is simply the monthly excess returns. Thus, we estimate total volatility using a GARCH(1,1) model for month $t+1$ as

$$\widehat{GTVOL}_{t+1} = \sqrt{\alpha_0 + \alpha_1 R_t^2 + \beta_1 \sigma_t^2} \tag{8}$$

where σ_t is the value of $\widehat{GTVOL}$ in month t.

We use maximum likelihood to estimates the GARCH parameters. Using the full period of data to estimate these parameters incurs a look-ahead bias (Fu, 2009). To avoid this problem, we use an expanding window of at least 60 months to estimate the GARCH parameters. We require at least 30 monthly returns for a stock to be eligible for estimation. Our data set spans the time period January 1987 to December 2016. Thus, the first estimates of $\widehat{GIVOL}_{t+1}$ and $\widehat{GTVOL}_{t+1}$ are obtained in December 1991.

4.2 Portfolio Construction and Evaluation

We form quintile portfolios at the of end every month t by sorting stocks on the four estimates of volatility discussed in Section 4.1. Portfolio 1 (P1) contains stocks with the lowest volatility. We also refer to P1 as the "low volatility portfolio". Portfolio 5 (P5) contains stocks with the highest volatility, and we refer to this portfolio as the "high

[5]The residual returns for the first 60 months are obtained using data for that period (January 1987 - December 1991). This way, we can form portfolios at the end of December 1991 and still use out-of-sample data. For the remaining period, residual returns are obtained using a rolling window with length 60 months.

[6]We note that the general GARCH (m,n) model calculate volatility for time t at the end of time $t-1$. In our thesis, we estimate volatility for month $t+1$ using data up and until month t. Thus, we slightly rewrite the GARCH model to reflect our time perspective.

volatility portfolio". P1−P5 is a portfolio that is long P1 and short P5, also called "the low minus high volatility portfolio". We hold the portfolios for one month and calculate equally and value-weighted excess returns at the end of month $t+1$. Market capitalization at the end of month t is used to value-weight the portfolios. We rebalance the portfolios every month.

We also control for traditional risk factors using the Fama and French (1993) model. The monthly portfolio excess returns are regressed on three Fama-French factors (MKT, SMB and HML). The alpha estimates, also referred to as FF-3 alphas or alphas, and factor loadings from this regression are evaluated. We also compute the Sharpe ratio introduced by Sharpe (1966):

$$SR = \frac{\bar{r_p} - \bar{r_F}}{\sigma_p} \tag{9}$$

where $\bar{r_p} - \bar{r_F}$ is the monthly mean excess return for portfolio p and σ_p is the monthly standard deviation of excess returns.

4.3 Firm Characteristics

We evaluate firm characteristics in terms of size, skewness and illiquidity. These characteristics are chosen for two reasons. First, earlier literature and our results show that there is a clear pattern in these firm characteristics across P1 to P5. The high volatility portfolio contains, on average, small, highly positively skewed and illiquid stocks. Second, these firm characteristics are identified in the literature as potential risk factors.

Market capitalization at the end of each month is used to calculate both firm size ($Size$) and each firm's share of the total market ($MktShare$). We calculate the skewness ($Skew$) of stock returns using the previous 24 months of monthly excess returns.

Measuring liquidity is not trivial. Liquidity embodies several characteristics such as trading cost, ease of sale and necessary price concessions to effect a quick transaction (Bodie et al., 2014, p. 433). We use the bid-ask spread in percentage terms ($BidAsk$) as proxy for transaction costs. We compute the bid-ask spread as the difference between the asking and bid prices divided by the asking price at the end of each month.

To measure price impact, we follow Amihud (2002). His measure of illiquidity is widely used in empirical asset pricing. We calculate for each stock the absolute stock return divided by its NOK turnover,

$$Illiq_t = \frac{|R_t|}{Turnover_t} \tag{10}$$

where $|R_t|$ is the absolute value of excess return in month t. $Turnover_i$ is the corresponding trading volume in NOK in month t. The measure of illiquidity in Equation (10) can be interpreted as the price response per Krone of transactions, thus serving as a rough measure of price impact. For presentation purposes, we multiply $Illiq$ with 100,000,000.

To get a better understanding on the relation between firm characteristics and stock returns, we also sort stocks into quintile portfolios based on $Size$, $Skew$, $BidAsk$ and $Illiq$. We refer to the portfolio of stocks with the lowest (highest) firm characteristic, i.e. bid-ask spread, as P1^j (P5^j). P1^j−P5^j is a portfolio that is long P1^j and short P5^j. We require a stock to have at least 12 return observations over the last 24 months. Hence, the first firm characteristic portfolios are formed in December 1989.

4.4 Double Sorting

We want to investigate if the low volatility anomaly persist after controlling for firm characteristics. More specifically, we control for size, skewness, bid-ask spreads and Amihud (2002)'s measure of illiquidity by performing a double sort[7]. This method is often used in empirical asset pricing as a way of systematically neutralize other effects.

We first sort stocks into portfolios based on one of the firm characteristics. Due to the limited number of stocks on Oslo Børs, we sort stocks into three portfolios based on firm characteristics. In the next step, we form quintile portfolios sorting stocks on idiosyncratic volatility in each of the three firm characteristic portfolios. Our main focus in this thesis is the difference in returns between P1 and P5. For that reason, we still divide stocks into five portfolios sorted on idiosyncratic volatility. We report results for the low minus high volatility portfolio and the high volatility portfolio in each

[7]See for instance Friewald et al. (2014) and Ang et al. (2006) for a description on double sorting.

firm characteristic portfolio. Furthermore, we report the average P1−P5 portfolio after controlling for firm characteristics. More specifically, each month we average the P1−P5 portfolios across the three firm characteristic portfolios. We refer to this portfolio as $P1^{ds}-P5^{ds}$.

4.5 Difference-in-Differences (DiD) Portfolios

To better assess the ability of firm characteristics to explain the low volatility anomaly, we construct difference-in-differences (DiD) portfolios following Boyer et al. (2010). To create DiD portfolios, we use the P1−P5 portfolio from the unconditionally sort on idiosyncratic volatility (P1−P5) and the average P1−P5 portfolios after controlling for firm characteristic j ($P1^{ds}-P5^{ds}$). We create the DiD portfolios each month by going long P1−P5 and short $P1^{ds}-P5^{ds}$. We refer to DiD portfolios as DiD^j, where $j = Size$, $Skew$, $BidAsk$, $Illiq$.

We regress monthly returns of the DiD portfolios on three Fama-French factors (MKT, SMB, HML) and report the alphas. In that way, we are able to formally test the ability of size, skewness, bid-ask spreads and Amihud (2002)'s measure of illiquidity to explain the low volatility anomaly.

5 Results

5.1 Portfolios Sorted by Volatility

In this section, we present results for portfolios sorted by two different estimates of volatility defined in Section 4.1.1 and 4.1.2: idiosyncratic volatility ($\widehat{IVOL}_{t+1}$) and total volatility ($\widehat{TVOL}_{t+1}$). Both estimates of volatility lead to similar results. The high volatility portfolio performs poorly. For value-weighted returns, P5 earns negative excess returns for both estimates of volatility. Further, there is no clear return pattern across portfolios P1 to P5. Going long P1 and short P5 yields positive, yet insignificant, excess returns. Controlling for traditional risk factors using the Fama and French (1993) model, we find positive and significant alphas for the low minus high volatility portfolio. Consistent with previous studies, we find that the high volatility portfolio, on average, contains stocks that are small, illiquid and positively skewed. Our results show that there is evidence of a low volatility anomaly on Oslo Børs when volatility is estimated using a simple rolling window model.

We report detailed results in Table 1 and 2 for equally weighted portfolios in Panel A and and value-weighted portfolios in Panel B. We find that the high volatility portfolios perform poorly, with results being most pronounced for value-weighted portfolios. Sorting on idiosyncratic volatility, P5 earns monthly excess returns of 0.29 % and −0.06 % for equally and value-weighted portfolios, respectively. Interestingly, all portfolios across P1 to P5 earn higher returns for equally weighted portfolios than for value-weighted portfolios, for both estimates of volatility. This is consistent with Huang et al. (2010) and can be explained by return reversals. We address this issue further in Section 5.4.

For both idiosyncratic volatility and total volatility, there is no clear pattern in excess returns across all portfolios from P1 to P5. Still, the low volatility portfolios exhibit higher excess returns than the high volatility portfolios. Going long P1 and short P5 sorting on idiosyncratic (total) volatility yields excess returns of 0.28 % (0.44 %) and 0.53 % (0.57 %) per month for equally and value-weighted portfolios, respectively. Although P1 outperforms P5, excess returns for the low minus high volatility portfolios are not significantly positive. This contrasts the results of Ang et al. (2006), who find that the difference in raw returns between P1 and P5 are significantly positive,

Table 1:

Portfolios Sorted by Idiosyncratic Volatility

We form quintile portfolios by sorting stocks on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$) relative to the Fama and French (1993) model. Portfolios are formed every month based on idiosyncratic volatility computed using monthly data from the previous 24 months. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. P1−P5 is a portfolio that is long P1 and short P5. *Firm characteristics* reports, within each portfolio, means of the market capitalization in NOK 1 billion ($Size$), market share in percentage terms ($MktShare$), Amihud (2002)'s measure of illiquidity ($Illiq$), bid-ask spread ($BidAsk$) in percentage terms and skewness ($Skew$). *Portfolio returns* reports monthly means and standard deviations (SD) of excess returns in percentage terms. SR is the monthly Sharpe ratio. *Fama-French Regression* reports results from regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Coefficients from the regression are also reported. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1987 to December 2016. Portfolio returns are calculated from January 1989 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: Idiosyncratic Volatility ($\widehat{IVOL}_{t+1}$)						
Mean	5.22	7.61	9.80	12.73	19.12	
Firm Characteristics						
$Size$	21.00	5.49	3.24	2.03	1.14	
$MktShare$	59.93	16.93	10.91	7.32	4.91	
$Illiq$	0.58	0.87	1.36	2.12	3.05	
$BidAsk$	1.59	1.79	2.01	2.38	2.68	
$Skew$	0.10	0.22	0.28	0.45	0.87	
Panel A: Equally Weighted Portfolios						
Portfolio Returns						
Mean	0.57	0.21	0.53	0.73	0.29	0.28
	(1.31)	(0.42)	(0.96)	(1.02)	(0.37)	(0.61)
SD	5.82	6.98	8.44	9.37	10.89	7.68
SR	0.10	0.03	0.06	0.08	0.03	0.04
Fama-French Regression						
FF-3 α	0.08	-0.51^{***}	-0.28	-0.32	-0.97^{***}	1.04^{***}
	(0.42)	(−2.65)	(−1.45)	(−0.98)	(−3.22)	(3.53)
MKT	0.91^{***}	1.08^{***}	1.24^{***}	1.39^{***}	1.63^{***}	-0.72^{***}
	(23.43)	(25.07)	(20.74)	(20.85)	(23.34)	(−9.29)
SMB	0.13^{***}	0.35^{***}	0.40^{***}	0.56^{***}	0.75^{***}	-0.62^{***}
	(3.15)	(4.83)	(4.62)	(5.83)	(6.91)	(−5.25)
HML	0.07^{*}	-0.02	-0.17^{***}	-0.02	-0.11	0.17
	(1.81)	(−0.38)	(−2.96)	(−0.33)	(−0.95)	(1.34)

(Continued)

Table 1 – *Continued*

	P1	P2	P3	P4	P5	P1−P5
Panel B: Value-Weighted Portfolios						
Portfolio Returns						
Mean	0.47	0.16	0.29	0.38	−0.06	0.53
	(1.34)	(0.33)	(0.56)	(0.52)	(−0.09)	(1.09)
SD	6.06	7.74	8.85	10.57	11.57	9.09
SR	0.08	0.02	0.03	0.04	−0.01	0.06
Fama-French Regression						
FF-3 α	0.17	−0.35	−0.27	−0.44	-1.24^{***}	1.41^{***}
	(1.59)	(−1.37)	(−1.13)	(−0.81)	(−3.44)	(3.75)
MKT	0.90^{***}	1.07^{***}	1.24^{***}	1.41^{***}	1.65^{***}	-0.74^{***}
	(34.86)	(19.67)	(17.56)	(17.12)	(16.27)	(−6.47)
SMB	-0.11^{***}	0.08	0.07	0.24^{**}	0.66^{***}	-0.77^{***}
	(−3.45)	(0.87)	(0.85)	(2.51)	(4.42)	(−4.87)
HML	0.10^{***}	−0.02	-0.12^{**}	−0.04	−0.18	0.28^{**}
	(3.31)	(−0.30)	(−2.03)	(−0.53)	(−1.52)	(1.98)

sorting on idiosyncratic volatility. However, Ang et al. (2006) use daily data to estimate idiosyncratic volatility, whereas we use monthly data. Also Bali and Cakici (2008) find weaker evidence of a low volatility anomaly when monthly data are used to estimate volatility.

As expected, the standard deviations of excess returns increase monotonically going from P1 to P5. Together with low excess returns, the high volatility portfolios exhibit low or negative Sharpe ratios.

The returns of the high volatility portfolios worsen when we control for traditional risk factors using the Fama and French (1993) model. All high volatility portfolios earn significant negative FF-3 alphas. Sorting on idiosyncratic (total) volatility, P5 yield alphas of −0.97 % (−1.07 %) and −1.24 % (−1.06 %) per month for equally weighted and value-weighted portfolios, respectively.

If we rely on differences in FF-3 alphas, we find evidence of a low volatility anomaly on Oslo Børs. Going long P1 and short P5 earns significantly positive alphas. Sorting on idiosyncratic volatility, the alpha of P1−P5 for equally weighted (value-weighted) portfolios is 1.04 % (1.41 %) per month with a robust t-statistic of 3.53 (3.75). The alpha of P1−P5 sorting on total volatility is 1.15 % and 1.26 % per month and significant

Table 2:
Portfolios Sorted by Total Volatility

We form quintile portfolios by sorting stocks on total volatility ($\widehat{TVOL}_{t+1}$). Portfolios are formed every month based on total volatility computed using monthly data from the previous 24 months. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) total volatility. P1−P5 is a portfolio that is long P1 and short P5. *Firm characteristics* reports, within each portfolio, means of the market capitalization in NOK 1 billion (*Size*), market share in percentage terms (*MktShare*), Amihud (2002)'s measure of illiquidity (*Illiq*), bid-ask spread (*BidAsk*) in percentage terms and skewness (*Skew*). *Portfolio returns* reports monthly means and standard deviations (SD) of excess returns in percentage terms. SR is the monthly Sharpe ratio. *Fama-French Regression* reports results from regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Coefficients from the regression are also reported. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1987 to December 2016. Portfolio returns are calculated from January 1989 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: Total Volatility ($\widehat{TVOL}_{t+1}$)						
Mean	7.37	10.18	12.81	16.21	23.41	
Firm Characteristics						
Size	17.44	8.35	3.64	2.18	1.29	
MktShare	51.32	23.24	12.36	7.71	5.37	
Illiq	0.64	1.02	1.33	1.88	3.06	
BidAsk	1.73	1.79	2.04	2.24	2.66	
Skew	0.13	0.20	0.28	0.43	0.87	
			Panel A: Equally Weighted Portfolios			
Portfolio Returns						
Mean	0.63	0.59	0.30	0.65	0.19	0.44
	(1.53)	(1.25)	(0.49)	(0.96)	(0.23)	(0.91)
SD	5.55	6.79	8.45	9.82	11.16	8.21
SR	0.11	0.09	0.04	0.07	0.02	0.05
Fama-French Regression						
FF-3 α	0.07	−0.06	−0.56**	−0.39	−1.07***	1.15***
	(0.39)	(−0.29)	(−2.37)	(−1.48)	(−3.19)	(3.40)
MKT	0.86***	1.03***	1.24***	1.47***	1.66***	−0.80***
	(26.82)	(26.33)	(21.76)	(20.17)	(22.50)	(−10.04)
SMB	0.24***	0.28***	0.44***	0.58***	0.73***	−0.49***
	(5.39)	(3.75)	(6.91)	(6.49)	(6.66)	(−3.40)
HML	0.07*	−0.02	−0.00	−0.21**	−0.05	0.13
	(1.81)	(−0.56)	(−0.03)	(−2.49)	(−0.46)	(0.91)

(Continued)

Table 2 – *Continued*

	P1	P2	P3	P4	P5	P1−P5
			Panel B: Value-Weighted Portfolios			
Portfolio Returns						
Mean	0.53	0.10	0.05	0.62	−0.03	0.57
	(1.52)	(0.24)	(0.10)	(0.96)	(−0.04)	(1.12)
SD	6.02	7.17	8.95	10.44	11.62	9.21
SR	0.09	0.01	0.01	0.06	−0.00	0.06
Fama-French Regression						
FF-3 α	0.21	−0.28	−0.55**	−0.18	−1.06***	1.26***
	(1.63)	(−1.38)	(−2.26)	(−0.52)	(−2.88)	(2.98)
MKT	0.89***	1.00***	1.26***	1.48***	1.62***	−0.74***
	(33.71)	(23.36)	(19.72)	(17.78)	(18.89)	(−6.99)
SMB	−0.06*	−0.05	0.11	0.26**	0.47***	−0.54***
	(−1.65)	(−0.78)	(1.48)	(2.18)	(3.61)	(−3.76)
HML	0.09***	0.05	−0.09	−0.17**	−0.16	0.25*
	(3.04)	(0.99)	(−1.33)	(−2.08)	(−1.36)	(1.82)

for equally and value-weighted portfolios, respectively.

While there are no clear patterns in excess returns going from the lower to higher volatility portfolios, we find strong and monotonic patterns in firm characteristics.

Firm size decreases considerably going from P1 to P5. The low (high) volatility portfolio contains firms with an average market capitalization of NOK 21 billion (NOK 1.14 billion) and NOK 17.44 billion (NOK 1.29 billion) sorting on idiosyncratic and total volatility, respectively. Although P5 contains 20 % of the stocks sorted on idiosyncratic (total) volatility, the market share is only 4.91 % (5.37 %). Thereby, our results indicate that P5 contains small firms.

We include two proxies for illiquidity motivated in Section 4.3. Amihud (2002)'s measure of illiquidity increases monotonically going from P1 to P5 sorting on both idiosyncratic and total volatility. Our results show that P5 contains more illiquid stocks than the lower volatility portfolios. This notion is strengthened looking at dispersion in bid-ask spreads. As expected, the bid-ask spread is increasing going from P1 to P5.

Skewness is monotonically increasing going from P1 to P5. Sorting on both estimates of volatility yields very similar results. The average skewness across firms is 0.10 for the low volatility portfolio and 0.87 for the high volatility portfolio, sorting on idiosyncratic volatility. This is consistent with Boyer et al. (2010) and Hou and Loh (2016) finding a positive relation between idiosyncratic volatility and skewness.

The coefficients from the Fama and French (1993) regression are consistent with the portfolio characteristics discussed above. Sorting on both estimates of volatility yields qualitatively identical results. Going from P1 to P5, loadings on the market factor (MKT) increase monotonically. This is not surprising, as higher volatility implies higher market beta. The factor loadings on the market factor for the low minus high volatility portfolios are negative, as expected, and significant.

Loadings on the small-firm factor (SMB) are significant and increasing monotonically with volatility for equally weighted portfolios. This is consistent with our findings that firm size is negatively related to volatility. The factor loading on size for P1−P5 is negative (-0.77) and highly significant. This is interesting, as the SMB portfolio on Oslo Børs has earned positive returns.[8] One possible interpretation is consequently that the low minus high volatility portfolio earns positive returns despite loading negative on the SMB portfolio. Further, this might lead to draw the conclusion that firm size fails to explain the low volatility anomaly. We argue that a simple interpretation of factor loadings is not sufficient in search for possible explanations of the low volatility anomaly. In Section 5.3.1, we show that firm size in fact can explain the anomaly.

Loadings on the value-factor (HML) are mostly close to zero and insignificant. We choose to not include book-to-market (B/M) in our analysis. In our view, this does not seem like a potential explanation of the low volatility anomaly. Both Ang et al. (2006) and Bali and Cakici (2008) find little dispersion in B/M across P1 to P5. We leave investigating how B/M might explain the low volatility anomaly to future research.

Our results are not affected by time period effects. We report results from sorting stocks on $\widehat{IVOL}_{t+1}$ and $\widehat{TVOL}_{t+1}$ for the period January 1998 to December 2016 in Table 14 and 15 and find qualitatively identical results compared to the full sample period. Additionally, alter the filtering of low priced stocks does not change our results. In Table 21 we report results for portfolios sorted on $\widehat{IVOL}_{t+1}$ where the stock price limit is NOK 10.

[8]The average monthly return for the SMB portfolio is 0.78 % for the time period January 1989 to December 2016.

Our results in Table 1 and 2 show evidence of a low volatility anomaly on Oslo Børs if we rely on differences in FF-3 alphas, sorting on both idiosyncratic and total volatility. Further, we find that the high volatility portfolio contains mostly small, illiquid, positively skewed stocks with large bid-ask spreads. As a consequence, when sorting on volatility we also implicitly sort stocks to some extent on size, skewness, illiquidity and bid-ask spread. The poor performance of the high volatility portfolio can then, possibly, be explained by one of these firm characteristics. To gain deeper insights into the relation between firm characteristics and stock returns, we sort stocks on size, skewness, bid-ask spreads and illiquidity in Section 5.2. We perform a double sort to control for firm characteristics in Section 5.3.

As discussed above, we find qualitatively identical results sorting on both idiosyncratic and total volatility. Furthermore, most of the literature on the low volatility anomaly concentrates on idiosyncratic volatility. For that reason, in the subsequent analysis we focus on idiosyncratic volatility $I\widehat{VOL}_{t+1}$ as a measure of volatility in Sections 5.2-5.4.

5.2 Firm Characteristics

In this section, we present results for portfolios sorted by firm size, skewness, bid-ask spread and Amihud (2002)'s measure of illiquidity for the period January 1987 to December 2016. As we require at least 12 months of return observations over the last 24 months, the first portfolio returns are calculated in January 1989.

Before we assess the performance of portfolios sorted on firm characteristics, we look at correlations reported in Table 3. $I\widehat{VOL}_{t+1}$ is positively correlated with *Illiq*, *BidAsk* and *Skew*; and negatively correlated with *Size*. This is consistent with our findings regarding firm characteristics discussed in Section 5.1. As expected, *Illiq* and *BidAsk* are positively correlated with a correlation coefficient of 0.35. *Size* is negatively correlated to all the other firm characteristics in Table 3.

In panel A of Table 4 we present quintile portfolios sorted on firm size. There is a large difference in firm size between quintile 5 and the other quintiles. This is consistent with the notion that the distribution of firm size is asymmetric. The mean returns for both the equally and value-weighted portfolios follow a pattern where the returns decrease almost monotonically going from the smallest firms in $P1^j$ to the largest firms in $P5^j$.

Table 3:

Correlations

The table reports the time-series means of cross-sectional correlations between firm characteristics. $\widehat{IVOL}_{t+1}$ refers to idiosyncratic volatility relative to the Fama and French (1993) model calculated using the previous 24 months of returns. *Size* is a firm's market capitalization. *Illiq* refers to Amihud (2002)'s measure of illiquidity. *BidAsk* is the bid-ask spread. *Skew* refers to the skewness of a stock's excess returns, calculated using the previous 24 months of returns. The results are based on a data set from January 1987 to December 2016.

	Size	*Illiq*	*BidAsk*	*Skew*
$\widehat{IVOL}_{t+1}$	−0.21	0.10	0.16	0.38
Size		−0.05	−0.15	−0.10
Illiq			0.35	0.01
BidAsk				0.04

This result is consistent with the findings of Fama and French (1993) where smaller firms are showed to outperform bigger firms. However, our results show no significant difference in excess returns between the smallest and biggest firms.

We report results for sorting stocks on size for the time period January 1998 to December 2016 in Panel A of Table 16 and note that there is no evidence of a size effect in this period.

We report portfolios sorted by *Skew* in Panel B of Table 4. The returns for both the equally and value-weighted portfolios follow a bell shaped pattern where the highest return is for the middle skewness portfolio, $P3^j$. The FF-3 alpha for $P1^j - P5^j$ is 1.04 % per month and significant, when portfolios are value-weighted, suggesting that investors might pay a premium for stocks with high skewness. This finding is consistent with lottery preferences discussed in Section 2.2.1. Our results are very similar to Boyer et al. (2010) reporting an FF-3 alpha for $P1^j - P5^j$ of 1.00 % per month.[9] Results for sorting stocks on skewness in the time period January 1998 to December 2016, reported in Panel B of Table 16, are qualitatively identical as for the period January 1987 to December 2016.

We look at portfolios sorted on bid-ask spreads in panel A of Table 5. Returns vary across quintiles and exhibit no clear pattern. The portfolio containing stocks with the

[9]Boyer et al. (2010) use a more complex model to predict skewness. Still, our results are very similar to theirs.

Table 4:
Portfolios Sorted by Size and Skewness

We form quintile portfolios by sorting stocks on firm size ($Size$) in Panel A and on skewness ($Skew$) in Panel B. We calculate equally and value-weighted excess returns in subpanels (I) and (II), respectively. In Panel A, $P1^j$ ($P5^j$) contains stocks with the smallest (largest) firm size. In Panel B, $P1^j$ ($P5^j$) contains stocks with the lowest (highest) skewness. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1987 to December 2016. Portfolio returns are calculated from January 1989 to December 2016.

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j-\mathbf{P5}^j$
			Panel A: Size			
Sort Variable: Size						
$Size$	0.14	0.42	0.97	2.50	24.06	
$\widehat{IVOL}_{t+1}$	15.06	13.09	11.85	9.83	8.21	
			(I): Equally Weighted Portfolios			
Mean	1.68^{*}	0.81	0.58	0.46	0.49	1.19
	(1.72)	(1.18)	(0.91)	(0.85)	(1.08)	(1.62)
SD	11.36	8.80	8.42	7.49	6.98	9.25
FF-3 α	0.38	-0.21	-0.52^{**}	-0.38^{*}	0.00	0.37
	(0.66)	(-0.66)	(-2.21)	(-1.86)	(0.03)	(0.63)
			(II): Value-Weighted Portfolios			
Mean	1.39	0.81	0.58	0.49	0.39	1.00
	(1.42)	(1.18)	(0.92)	(0.90)	(1.02)	(1.32)
SD	11.40	8.75	8.46	7.51	6.24	9.59
FF-3 α	0.07	-0.25	-0.53^{**}	-0.32	0.04	0.03
	(0.13)	(-0.79)	(-2.36)	(-1.57)	(1.11)	(0.05)

(Continued)

Table 4 – *Continued*

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j\mathbf{-P5}^j$
			Panel B: Skewness			
Sort Variable: Skew						
Skew	−0.58	−0.01	0.33	0.68	1.44	
$\widehat{IVOL}_{t+1}$	8.98	9.49	10.14	11.69	14.72	
			(I): Equally Weighted Portfolios			
Mean	0.05	0.40	0.91*	0.73	0.28	−0.23
	(0.09)	(0.71)	(1.67)	(1.21)	(0.41)	(−0.56)
SD	7.92	7.98	8.22	8.52	8.99	6.34
FF-3 α	−0.70**	−0.38*	0.08	−0.11	−0.80***	0.11
	(−2.53)	(−1.74)	(0.36)	(−0.38)	(−2.82)	(0.28)
			(II): Value-Weighted Portfolios			
Mean	0.39	0.38	0.64	0.56	−0.11	0.51
	(0.81)	(0.91)	(1.35)	(1.16)	(−0.18)	(1.13)
SD	7.74	7.61	7.77	7.30	9.09	7.67
FF-3 α	−0.01	−0.02	0.22	0.06	−1.04***	1.04**
	(−0.04)	(−0.12)	(1.06)	(0.21)	(−3.08)	(2.30)

highest bid-ask spread has the lowest returns. For value-weighted portfolios, $P1^j$ clearly outperforms $P5^j$. $P1^j-P5^j$ earns a significant excess return of 0.79 % per month. The FF-3 alpha is even higher and highly significant.

Results for portfolios sorted by *Illiq* are reported in panel B of Table 5. As for sorting on bid-ask spreads, the FF-3 alpha of P1−P5 is positive (0.93 % per month) and significant for value-weighted portfolios. Hence, our results imply that the most illiquid stocks in terms of the bid-ask spread and Amihud (2002)'s measure of illiquidity are outperformed by the least illiquid stocks. Results for stocks sorted on *BidAsk* and *Illiq* are qualitatively identical for the time period 1998 to 2016, reported in Table 17, as for the full sample period. We note, however, that stocks with the highest *Illiq* no longer exhibit significant negative alphas when returns are value-weighted.

Our results presented in Table 4 and 5 suggest that stocks that are highly positively skewed, have high bid-ask spreads and are illiquid, perform poorly. More specifically, $P1^j-P5^j$ earns significant positive FF-3 alphas sorting on *Skew*, *BidAsk* and *Illiq* for value-weighted portfolios. This finding might explain the poor performance of the high

Table 5:
Portfolios Sorted by Bid-Ask Spread and Illiquidity

We form quintile portfolios by sorting stocks on the bid-ask spread ($BidAsk$) in Panel A and on Amihud (2002)'s measure of illiquidity ($Illiq$) in Panel B. We calculate equally and value-weighted excess returns in subpanels (I) and (II), respectively. In Panel A, $P1^j$ ($P5^j$) contains stocks with the lowest (highest) bid-ask spread. In Panel B, $P1^j$ ($P5^j$) contains stocks with the lowest (highest) illiquidity measure following Amihud (2002). We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1987 to December 2016. Portfolio returns are calculated from January 1989 to December 2016.

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j\mathbf{-P5}^j$
Panel A: Bid-Ask Spread						
Sort Variable: BidAsk						
$BidAsk$	0.35	0.77	1.36	2.39	6.36	
$\widehat{IVOL}_{t+1}$	9.38	10.75	11.06	11.53	12.56	
(I): Equally Weighted Portfolios						
Mean	0.47	1.10^{*}	0.49	0.45	0.36	0.12
	(0.98)	(1.91)	(0.85)	(0.71)	(0.53)	(0.30)
SD	7.56	8.19	8.18	8.10	9.31	6.86
FF-3 α	−0.04	0.22	-0.42^{**}	-0.55^{**}	-0.69^{**}	0.65^{*}
	(−0.25)	(1.12)	(−1.97)	(−2.20)	(−2.02)	(1.86)
(II): Value-Weighted Portfolios						
Mean	0.47	0.48	−0.01	0.20	−0.32	0.79^{**}
	(1.22)	(1.02)	(−0.03)	(0.34)	(−0.55)	(2.13)
SR	0.07	0.07	−0.00	0.03	−0.04	0.11
FF-3 α	0.12	0.02	-0.79^{***}	-0.57^{**}	-1.26^{***}	1.39^{***}
	(1.36)	(0.08)	(−3.80)	(−2.31)	(−3.95)	(3.82)

(Continued)

Table 5 – *Continued*

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j\mathbf{-P5}^j$
Panel B: Illiquidity						
Sort Variable: Illiq						
Illiq	0.01	0.07	0.22	0.64	6.43	
$\widehat{IVOL}_{t+1}$	8.84	10.60	11.00	11.60	12.83	
(I): Equally Weighted Portfolios						
Mean	0.35	0.39	0.78	0.51	0.33	0.02
	(0.69)	(0.74)	(1.32)	(0.81)	(0.48)	(0.05)
SD	7.48	8.16	8.47	8.61	9.29	6.95
FF-3 α	-0.29^{*}	-0.28	-0.09	-0.47	-0.74^{**}	0.46
	(-1.76)	(-1.29)	(-0.35)	(-1.62)	(-2.42)	(1.32)
(II): Value-Weighted Portfolios						
Mean	0.36	0.51	0.39	0.17	0.13	0.24
	(0.95)	(1.07)	(0.73)	(0.30)	(0.19)	(0.54)
SD	6.46	7.88	7.75	8.38	9.00	7.27
FF-3 α	0.01	-0.04	-0.23	-0.62^{**}	-0.92^{***}	0.93^{**}
	(0.07)	(-0.23)	(-1.00)	(-2.42)	(-2.65)	(2.33)

idiosyncratic volatility portfolio in Section 5.1. Stocks with high idiosyncratic volatility exhibit, on average, high positive skewness, high bid-ask spreads and high illiquidity. Further, stocks with high $\widehat{IVOL}_{t+1}$ are small in size. Panel A of Table 4 show no evidence of small firms performing poorly.

To thoroughly investigate if firm characteristics can explain the low volatility anomaly, we next perform a double sort to control for size, skewness, bid-ask spreads and illiquidity.

5.3 Double Sorting

In this section, we report results from double sorts on firm characteristics, as explained in Section 4.4. Double sorting with three firm characteristic portfolios and five idiosyncratic volatility portfolios impose 15 portfolios in total. Consequently, we need an adequate number of firms to perform the double sort. The number of stocks listed on

Oslo Børs is increasing from 1987 to 1998. We also show that the results from sorting portfolios on idiosyncratic volatility[10] in the period 1987-2016 in Table 1 are qualitatively identical for the period 1998-2016 in Table 14. The FF-3 alpha of P1−P5 for the period 1987-2016 (1998-2016) is 1.04 % (0.97 %) and 1.41 % (1.44 %) per month for equally and value-weighted portfolios, respectively. All alphas are highly significant. All firm characteristics follow the same patterns in both time periods. Weighing all evidence, we choose to perform the double sort for the time period January 1998 to December 2016. This enables us to investigate returns for the period January 2000 to December 2016.

5.3.1 Size

In Section 5.1 we show that the high volatility portfolio, on average, contains stocks with low size. For that reason, one explanation of the idiosyncratic volatility effect might be that small stocks exhibit low returns. We show in Section 5.2 that excess returns decrease with size for stocks on Oslo Børs in the period 1989-2016. However, the size effect is not present in the period 2000-2016. To gain deeper insight into the relation between size and the idiosyncratic volatility effect, we perform a double sort controlling for size. We first sort stocks into three portfolios based on their market capitalization. Then, within each size portfolio, we sort stocks into quintile portfolios based on idiosyncratic volatility. Thereby, we can test if there is evidence of a low volatility anomaly among small, medium and big firms. We also report the average low minus high volatility portfolio after controlling for size. Bali and Cakici (2008) and Fu (2009) suggest that small stocks are driving Ang et al. (2006)'s findings of a low volatility anomaly. Our results from double sorting on size show that firm size can help explain the low volatility anomaly.

If there is a low volatility anomaly on Oslo Børs, we would expect that P1−P5 earns positive excess returns and FF-3 alphas in all the three size portfolios. Negative returns or insignificant alphas for the low minus high volatility portfolio would suggest, rather, no evidence of a low volatility anomaly. Our results show that only for small firms there is evidence of a low volatility anomaly, whereas there is no evidence supporting this notion for big firms. For equally weighted portfolios, P1−P5 earns a significant positive

[10] We refer to sorting stocks on idiosyncratic volatility using no controls for firm characteristics as "the unconditionally sort on idiosyncratic volatility".

Table 6:
Portfolios Sorted by Idiosyncratic Volatility: Controlling for Size

We perform a double sort to control for firm size ($Size$). Each month, we first sort stocks into three portfolios based on their size. Then, within each size portfolio, we sort stocks into quintile portfolios based on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$). Panel A report, in each size portfolio, results for the low minus high volatility portfolio (P1−P5). We also report the average P1−P5 portfolio (Average) after controlling for size. Panel B report, in each size portfolio, results for the high volatility portfolio (P5). Subpanels (I) and (II) report equally and value-weighted portfolios, respectively. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports the alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	Small Size	**Medium Size**	**Large Size**	**Average**
		Panel A: P1−P5		
		(I): Equally Weighted Portfolios		
Mean	1.14	−0.16	−0.40	0.19
	(1.45)	(−0.26)	(−0.80)	(0.40)
SD	10.58	8.95	7.42	6.33
FF-3 α	1.44**	0.16	0.04	0.55
	(2.15)	(0.33)	(0.12)	(1.50)
		(II): Value-Weighted Portfolios		
Mean	0.94	−0.01	0.25	0.39
	(1.09)	(−0.02)	(0.55)	(0.88)
SD	11.86	8.67	8.15	6.59
FF-3 α	1.29	0.38	0.58	0.75**
	(1.48)	(0.75)	(1.64)	(2.06)
		Panel B: P5		
		(I): Equally Weighted Portfolios		
Mean	−0.17	0.69	0.92	
	(−0.17)	(0.72)	(1.17)	
SD	12.47	11.00	9.57	
FF-3 α	−1.17**	−0.28	0.27	
	(−2.07)	(−0.59)	(0.80)	

(Continued)

	Small Size	Medium Size	Large Size
Table 6 − *Continued*			
Panel B: P5			
(II): Value-Weighted Portfolios			
Mean	0.09	0.49	0.22
	(0.08)	(0.52)	(0.28)
SD	14.21	10.93	9.95
FF-3 α	−1.01	−0.51	−0.32
	(−1.59)	(−1.12)	(−1.07)

alpha of 1.45 % per month for small firms. The P1−P5 alpha for medium and big firms is 0.16 % and 0.04 % per month, respectively, and insignificant. Also for value-weighted portfolios, P1−P5 exhibits the highest FF-3 alpha among small firms.

The last column in Panel A of Table 6 reports the average P1−P5 portfolio across the three size portfolios. This can be interpreted as the low minus high volatility portfolio after controlling for size. The P1−P5 alphas are considerably reduced after controlling for size. Only for value-weighted returns, we still find evidence of a low volatility anomaly, where the P1−P5 alpha is 0.75 % per month and significant. On the other hand, the P1−P5 alpha is 0.57 % per month and insignificant for equally weighted portfolios. This finding confirms that firm size can explain the low volatility anomaly.

We report results for P5 in Panel B of Table 6. Our results suggest that the high volatility portfolio earn the highest returns in the big firm portfolio. For equally weighted returns, the monthly excess return of P5 increases from of −0.17 % per month for small firms to 0.92 % per month for big firms.

Our results show that firm size can help explain the low volatility anomaly. Small stocks with high idiosyncratic volatility earn low returns.

5.3.2 Skewness

In table 3 we show that there is a strong positive correlation between idiosyncratic volatility and skewness. One possible explanation for the poor performance of the high volatility portfolio is consequently that stocks with high skewness earn low returns. We provide evidence of this notion in Panel B of Table 4, in particular for value-weighted

Table 7:
Portfolios Sorted by Idiosyncratic Volatility: Controlling for Skewness

We perform a double sort to control for skewness. Each month, we first sort stocks into three portfolios based on their skewness. Then, within each skewness portfolio we sort stocks into quintile portfolios based on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$). Panel A report, in each skewness portfolio, results for the low minus high volatility portfolio (P1−P5). We also report the average P1−P5 portfolio (Average) after controlling for skewness. Panel B report, in each skewness portfolio, results for the high volatility portfolio (P5). Subpanels (I) and (II) report equally and value-weighted portfolios, respectively. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports the alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	Low Skewness	**Medium Skewness**	**High Skewness**	**Average**
		Panel A: P1−P5		
		(I): Equally Weighted Portfolios		
Mean	0.64	−0.62	0.88	0.30
	(0.78)	(−1.11)	(1.31)	(0.54)
SD	10.01	8.56	10.35	7.59
FF-3 α	1.23*	−0.03	1.62***	0.94**
	(1.95)	(−0.07)	(3.16)	(2.52)
		(II): Value-Weighted Portfolios		
Mean	0.29	−0.25	0.80	0.28
	(0.35)	(−0.29)	(1.00)	(0.47)
SD	12.48	12.72	13.21	9.62
FF-3 α	1.17	0.59	1.39	1.05**
	(1.61)	(0.86)	(1.58)	(2.26)
		Panel B: P5		
		(I): Equally Weighted Portfolios		
Mean	−0.06	0.88	−0.11	
	(0.05)	(0.89)	(−0.13)	
SD	12.36	11.38	12.03	
FF-3 α	−0.95	−0.06	−1.21***	
	(−1.51)	(−0.12)	(−2.82)	

(Continued)

Table 7 – *Continued*

	Low Skewness	Medium Skewness	High Skewness
Panel B: P5			
(II): Value-Weighted Portfolios			
Mean	0.04	0.67	−0.28
	(0.03)	(0.57)	(−0.28)
SD	14.12	15.21	14.05
FF-3 α	−0.98	−0.35	−1.22*
	(−1.35)	(−0.52)	(−1.84)

portfolios. Our results from double sorting on skewness suggest that some part of the low volatility anomaly can be explained by stocks with highly positively skewed returns.

The FF-3 alphas for P1−P5 among medium skewed stocks are clearly insignificant. For equally weighted returns the alpha is even negative (−0.03 % per month). Value-weighted returns yield a P1−P5 alpha of 0.59 % per month. Hence, there is no evidence of a low volatility anomaly among medium skewed stocks.

Our results suggest that the low volatility anomaly is driven by stocks with high skewness. For both equally and value-weighted portfolios, the FF-3 alpha of P1−P5 is highest in the high skewness portfolio. The alphas of the low minus high volatility portfolio are still positive and significant after controlling for skewness. Still, the FF-3 alphas are reduced compared to the results for the unconditionally sort on idiosyncratic volatility.

We report results for P5 across three skewness portfolios in Panel B of Table 7. The high volatility portfolios follow the same return pattern related to skewness we find in Section 5.2: P5 among medium skewed stocks earns the highest returns and FF-3 alphas.

Our findings after controlling for skewness are intriguing. There is no evidence of a low volatility anomaly in the medium skewness portfolio. However, we still find significant positive alphas for the average P1−P5 portfolio after controlling for skewness. The idiosyncratic volatility effect is most pronounced among firms with positively skewed returns. Further, our results suggest that stocks with high skewness earn low returns, consistent with lottery preferences. Stocks in the high volatility portfolio after the unconditionally sort on idiosyncratic volatility exhibit high skewness, thus some of the poor performance of P5 can be attributed to skewness.

5.3.3 Bid-Ask Spread

Idiosyncratic volatility is positively related to bid-ask spreads with a correlation coefficient of 0.16. The bid-ask spread is also monotonically increasing going from the low volatility portfolio to the high volatility portfolio. Further, we show in Section 5.2 that stocks with high bid-ask spreads earn lower returns than stocks with low bid-ask spreads, in particular when portfolios are value-weighted. Our results from double sorting show that there is no evidence of a low volatility anomaly for value-weighted portfolios after controlling for the bid-ask spread.

In Panel A of Table 8 we report the results of P1−P5 for stocks with low, medium and high bid-ask spreads. Our results suggest that there is evidence of a low volatility anomaly only in the medium bid-ask spread portfolio for equally weighted portfolios, as the FF-3 alpha of P1−P5 is 1.30 % per month and significant. Controlling for bid-ask spreads, the average low minus high volatility portfolio earns a significant FF-3 alpha of 0.79 % per month for equally weighted portfolios. Thus, although weaker, there is still evidence of a low volatility anomaly for equally weighted portfolios after controlling for bid-ask spreads.

Our results show no evidence of a low volatility anomaly after controlling for the bid-ask spread when portfolios are value-weighted. The FF-3 alpha is insignificant in all bid-ask portfolios. The average low minus high volatility portfolio yields an insignificant alpha of 0.67 % per month after controlling for bid-ask spreads.

Panel B of Table 8 show the performance of the high volatility portfolio for stocks with low, medium and high bid-ask spreads. P5 earns lowest returns in the high bid-ask portfolio with a monthly excess return of −0.60 % and −0.73 % for equally and value-weighted portfolios, respectively. The alphas are significantly negative. This is consistent with our results in Section 5.2 suggesting that high bid-ask spreads yield low returns.

Our findings suggest that the bid-ask spread can help explain the low volatility anomaly. Stocks in the high volatility portfolio have, on average, higher bid-ask spreads than stocks in the low volatility portfolio. In addition, we show that higher bid-ask spreads

Table 8:
Portfolios Sorted by Idiosyncratic Volatility: Controlling for Bid-Ask Spread

We perform a double sort to control for the bid-ask spread ($BidAsk$). Each month, we first sort stocks into three portfolios based on their bid-ask spread. Then, within each bid-ask spread portfolio, we sort stocks into quintile portfolios based on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$). Panel A report, in each bid-ask spread portfolio, results for the low minus high volatility portfolio (P1−P5). We also report the average P1−P5 portfolio (Average) after controlling for bid-ask spreads. Panel B report, in each bid-ask spread portfolio, results for the high volatility portfolio (P5). Subpanels (I) and (II) report equally and value-weighted portfolios, respectively. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports the alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	Low Bid-Ask	**Medium Bid-Ask**	**High Bid-Ask**	**Average**
		Panel A: P1−P5		
		(I): Equally Weighted Portfolios		
Mean	−0.09	0.57	0.24	0.24
	(−0.16)	(0.85)	(0.38)	(0.48)
SD	8.33	9.31	10.28	7.28
FF-3 α	0.49	1.30**	0.59	0.79**
	(1.18)	(2.44)	(0.96)	(2.34)
		(II): Value-Weighted Portfolios		
Mean	−0.48	0.41	0.28	0.07
	(−0.90)	(0.53)	(0.33)	(0.13)
SD	10.11	10.53	13.48	8.27
FF-3 α	0.08	1.21	0.74	0.67
	(0.15)	(1.53)	(0.89)	(1.48)
		Panel B: P5		
		(I): Equally Weighted Portfolios		
Mean	0.71	0.15	−0.60	
	(0.78)	(0.17)	(−0.62)	
SD	10.71	11.27	12.11	
FF-3 α	−0.07	−1.02**	−1.50***	
	(−0.18)	(−2.20)	(−2.80)	

(Continued)

Table 8 – *Continued*

	Low Bid-Ask	**Medium Bid-Ask**	**High Bid-Ask**
		Panel B: P5	
		(II): Value-Weighted Portfolios	
Mean	0.85	0.09	−0.73
	(0.92)	(0.10)	(−0.71)
SD	11.85	11.93	14.40
FF-3 α	0.09	-0.94^{*}	-1.66^{**}
	(0.19)	(−1.78)	(−2.18)

yield low returns and FF-3 alphas. Consequently, some part of the poor performance of P5 can be attributed to the bid-ask spread.

5.3.4 Illiquidity

Idiosyncratic volatility is positively correlated with Amihud (2002)'s measure of illiquidity (*Illiq*). Our results from double sorting on *Illiq* suggests that Amihud (2002)'s measure of illiquidity is the least promising explanation of the low volatility anomaly among the firm characteristics we have examined.

We report results for P1−P5 after double sorting on *Illiq* in Panel A of Table 9. The average P1−P5 alpha is positive and significant for both equally and value-weighted portfolios after controlling for *Illiq*. There are no clear pattern related to alphas across the *Illiq* portfolios. Our results suggest that the low volatility anomaly persists after controlling for Amihud (2002)'s measure of illiquidity.

We report results for P5 in three different *Illiq* portfolios in Panel B of Table 9. There are little dispersion in returns and alphas for P5 across the *Illiq* portfolios.

As discussed in Section 4.3, liquidity embodies several characteristics. Thus, it is difficult to measure with one single statistic. Part of liquidity is the cost of engaging in a transaction, particularly the bid-ask spread. Another part is price impact, which can be estimated using Amihud (2002)'s measure of illiquidity. Our findings after controlling for two proxies for illiquidity, *BidAsk* and *Illiq*, are interesting. The alpha of the low minus high volatility portfolio after controlling for *BidAsk* is 0.67 % per month and insignificant for value-weighted returns. This suggests that one dimension of liquidity, transaction cost in terms of the bid-ask spread, can help explain the low volatility

Table 9:

Portfolios Sorted by Idiosyncratic Volatility: Controlling for Illiquidity

We perform a double sort to control for illiquidity ($Illiq$). Each month, we first sort stocks into three portfolios based on Amihud (2002)'s measure of illiquidity. Then, within each illiquidity portfolio, we sort stocks into quintile portfolios based on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$). Panel A report, in each illiquidity portfolio, results for the low minus high volatility portfolio (P1−P5). We also report the average P1−P5 portfolio (Average) after controlling for illiquidity. Panel B report, in each illiquidity portfolio, results for the high volatility portfolio (P5). Subpanels (I) and (II) report equally and value-weighted portfolios, respectively. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports the alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	Low Illiquidity	**Medium Illiquidity**	**High Illiquidity**	**Average**
		Panel A: P1−P5		
		(I): Equally Weighted Portfolios		
Mean	0.81	0.42	0.19	0.47
	(1.48)	(0.71)	(0.27)	(1.06)
SD	8.26	8.73	9.99	6.75
FF-3 α	1.43***	1.00**	0.54	0.99***
	(3.10)	(2.36)	(0.86)	(3.28)
		(II): Value-Weighted Portfolios		
Mean	0.53	0.14	0.56	0.41
	(0.89)	(0.19)	(0.58)	(0.80)
SD	9.51	9.66	12.99	7.47
FF-3 α	0.89*	0.78	1.12	0.93**
	(1.70)	(1.30)	(1.18)	(2.49)
		Panel B: P5		
		(I): Equally Weighted Portfolios		
Mean	−0.23	0.09	0.30	
	(−0.27)	(0.09)	(0.32)	
SD	10.24	11.18	11.58	
FF-3 α	−1.01**	−0.88**	−0.64	
	(−2.30)	(−1.99)	(−1.12)	

(Continued)

Table 9 – *Continued*

	Low Illiquidity	Medium Illiquidity	High Illiquidity
Panel B: P5			
(II): Value-Weighted Portfolios			
Mean	−0.13	0.10	−0.12
	(−0.15)	(0.10)	(−0.10)
SD	11.17	11.40	13.62
FF-3 α	−0.68	−0.83	−1.11
	(−1.48)	(−1.57)	(−1.29)

anomaly. On the other hand, P1−P5 earns positive and significant alphas after controlling for *Illiq*. This imply that the price impact dimension of liquidity, measured following Amihud (2002), have low explanatory power. We leave further investigation of the relation between illiquidity and the low volatility anomaly using different measures of illiquidity for future research.

5.3.5 Difference-in-Differences (DiD) Portfolios

Table 10 reports FF-3 alphas of the DiD portfolios, as explained in Section 4.5. A positive and significant alpha of the DiD portfolio implies that the firm characteristic we control for can explain the low volatility anomaly. The results reported in Table 10 confirm our findings that firm size and the the bid-ask spread can explain the low volatility anomaly. Further, skewness and Amihud (2002)'s measure of illiquidity can explain some of the big difference in risk adjusted returns between the low and high volatility portfolio for value-weighted returns.

Our results are strongly supportive of the explanatory power of the bid-ask spread when returns are value-weighted. The FF-3 alpha of DiD^{BidAsk} is 0.77% and significant. Further, the difference in alphas between the low and high volatility portfolio is more than halved after controlling for the bid-ask spread. Also size has high explanatory power, as DiD^{Size} yield an FF-3 alpha of 0.70 % per month with a t-statistic of 1.65.

When portfolios are equally weighted, only size can explain the low volatility anomaly. The FF-3 alpha of DiD^{Size} is 0.42 % per month and significant with a t-statistic of 1.98. The other DiD portfolios exhibit low and insignificant alphas.

Table 10:

Fama-French Alphas of DiD Portfolios

The table reports alphas from regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. DiD^j reports alphas for the difference-in-differences portfolio, as explained in Section 4.5. P1−P5 reports alphas for the low minus high volatility portfolio after sorting stocks on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$). P1^{ds}−P5^{ds} reports alphas for the low minus high volatility portfolio after controlling for firm characteristic j by performing a double sort. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

Firm characteristic j	P1−P5	P1^{ds}−P5^{ds}	**DiD^j**
Panel A: Equally Weighted Portfolios			
Size	0.97***	0.55	0.42**
	(2.88)	(1.50)	(1.98)
Skew	0.97***	0.94**	0.03
	(2.88)	(2.52)	(0.16)
BidAsk	0.97***	0.79**	0.18
	(2.88)	(2.34)	(1.31)
Illiq	0.97***	0.99***	−0.02
	(2.88)	(3.28)	(−0.09)
Panel B: Value-Weighted Portfolios			
Size	1.44***	0.75**	0.70*
	(3.22)	(2.06)	(1.65)
Skew	1.44***	1.05**	0.40
	(3.22)	(2.26)	(0.98)
BidAsk	1.44***	0.67	0.77**
	(3.22)	(1.48)	(2.35)
Illiq	1.44***	0.93**	0.51
	(3.22)	(2.49)	(1.35)

5.4 Return Reversals

Return reversals are suggested as one of the explanations of the low volatility anomaly, as discussed in Section 2.2.2. Stocks with high idiosyncratic volatility tend to have high returns in the same month t as volatility is estimated, followed by low returns in the next month $t+1$. Our results have this far shown evidence of a low volatility anomaly, for the unconditionally sorting on idiosyncratic volatility. More specifically, P5 exhibits low or negative returns when portfolios are created at the end of month t and returns are observed the following month $t+1$. In this section, we show that return reversals can help explain the low returns of the high volatility portfolio.

Table 11 reports average monthly excess returns for portfolios sorted by idiosyncratic volatility. We refer to equally weighted (value-weighted) portfolios as EW (VW). $EW(t+1)$ and $VW(t+1)$ report returns in month $t+1$, the month following portfolio formation.[11] $EW(t)$ and $VW(t)$ report returns in the same month t as the portfolios are formed. The weights used to value-weight portfolios are based upon market capitalization for month t. For example, we create portfolios in January. $VW(t)$ reports the portfolio returns for January, while $VW(t+1)$ reports portfolio returns for February. We note that our analysis of return reversals imposes an untradable strategy. Forming a portfolio in month t, one will not earn the month t return. However, our focus is to investigate how return reversals may affect the low volatility anomaly.

The high volatility portfolios earn considerably higher returns in month t compared to month $t+1$. For equally weighted (value-weighted) portfolios, the excess return of P5 is 1.56 % (3.40 %) per month with a t-statistic of 1.93 (4.30). For value-weighted portfolios, returns increase monotonically across P1 to P5. This indicates a positive contemporaneous relation between idiosyncratic volatility and returns.

Our results show so far some evidence of a low volatility anomaly when returns are measured in month $t+1$. There is no evidence that P1 outperforms P5 for returns in month t, quite the opposite, we find that the high volatility portfolio earns the highest returns. The difference in equally weighted returns between P1 and P5 is -1.14 % per month and significant. The return difference is even more pronounced for value-weighted returns, as the P1$-$P5 return is -2.68 % per month and highly significant. This sharply contrast our findings in Section 5.1 when returns are measured in month

[11] $EW(t+1)$ and $VW(t+1)$ report the same returns as shown in Table 1.

Table 11:
Returns on Portfolios Sorted by Idiosyncratic Volatility: Evidence of Return-Reversals

The table reports average monthly excess returns for quintile portfolios sorted on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$) relative to the Fama and French (1993) model. Portfolios are formed every month based on idiosyncratic volatility computed using monthly data from the previous 24 months. P1 (P5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. P1−P5 is a portfolio that is long P1 and short P5. $EW(t)$ reports equally weighted returns in the same month t as the portfolio is formed, while $EW(t+1)$ reports returns for the following month $t+1$. $VW(t)$ denotes the value-weighted return in month t, where the weights are based upon market capitalization at the end of month t. $VW(t+1)$ reports returns for the following month $t+1$, with weights still based on month t market capitalization. Robust Newey and West (1987) t-statistics are reported in parenthesis. Results are based on a data set for the period January 1987 to December 2016. Portfolios are formed from January 1989 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
$EW(t)$	0.42	0.14	0.05	0.01	1.56*	−1.14**
	(1.11)	(0.28)	(0.10)	(0.01)	(1.93)	(−2.12)
$EW(t+1)$	0.57	0.21	0.53	0.73	0.29	0.28
	(1.31)	(0.42)	(0.96)	(1.02)	(0.37)	(0.61)
$VW(t)$	0.73**	0.98**	1.05**	1.54**	3.40***	−2.68***
	(2.09)	(2.01)	(2.02)	(2.14)	(4.30)	(−4.55)
$VW(t+1)$	0.47	0.16	0.29	0.38	−0.06	0.53
	(1.34)	(0.33)	(0.56)	(0.52)	(−0.09)	(1.09)

$t+1$, where P1−P5 earns positive returns and positive and significant FF-3 alphas.

Return reversals imply that value-weighted portfolios have lower expected returns in month $t+1$ than equally weighted portfolios, when portfolio weights are based on market capitalization in the portfolio formation month t (Huang et al., 2010). High (low) stock returns in month t will also increase (decrease) the market capitalization used to weight returns for value-weighted portfolios. Thus, if returns reverse in month $t+1$, value-weighted portfolios will place greater weight on loser stocks and smaller weight on winner stocks in month $t+1$. In contrast, equal weighted portfolios put the same weight on all stocks. Hence, the reversal effect on winner and loser stocks cancels out. The results in Table 11 supports this argument. For all quintile portfolios, the equal weighted portfolio has a higher return than the value-weighted portfolio in month $t + 1$.

Another interesting finding is that the effect of return reversals is most prominent for the high volatility portfolio. For value-weighted returns, the mean return is 3.40 % per month and highly significant when returns are measured in month t and -0.06 % and insignificant when returns are measured in month $t + 1$. This is consistent with Fu (2009). He concludes that Ang et al. (2006)'s findings are driven by a subset of small firms with high idiosyncratic volatilities. These firms have high returns in the month of high idiosyncratic volatility. These high returns reverse in the following month, resulting in the findings of negative returns.

We report results for the period January 1998 to December 2016 in Table 18 and find qualitatively identical results as for 1987-2016. This confirms our findings suggesting that return reversals help explain the low volatility anomaly.

5.5 GARCH

In this section, we report portfolio results for stocks sorted on idiosyncratic and total volatility estimated using a a GARCH(1,1) model. We sort stocks on $\widehat{GIVOL}_{t+1}$ in Table 12 and on $\widehat{GTVOL}_{t+1}$ in Table 13. Similar to the findings of Fu (2009), our results indicate that using a more sophisticated model to estimate idiosyncratic volatility yield no evidence of a low volatility anomaly. We find that the high volatility portfolio exhibit higher excess returns than the low volatility portfolio, although the difference is not statistically significant. An especially interesting finding is that the FF-3 alphas for the long-short portfolio P1−P5 are not significant. The results for sorting stocks on total volatility estimated using a GARCH(1,1) model also show that P1−P5 exhibits low and insignificant alphas. These results contradicts our findings in Tables 1 and 2, where we show evidence of a low volatility anomaly using a simple rolling window model to estimate volatility.

Sorting on $\widehat{GIVOL}_{t+1}$, the FF-3 alpha for P1−P5 is 0.37 % and 0.50 % per month and insignificant for equally weighted and value-weighted portfolios, respectively. This is consistent with Fu (2009). He finds no evidence of a low volatility anomaly using an EGARCH model to estimate idiosyncratic volatility. Our results after sorting on $\widehat{GIVOL}_{t+1}$ are also in line with CAPM and Merton (1987) suggesting a flat or positive

Table 12:
Portfolios Sorted by Idiosyncratic Volatility Estimated Using a GARCH(1,1) Model

We form quintile portfolios by sorting stocks on idiosyncratic volatility estimated using a GARCH(1,1) model ($\widehat{GIVOL}_{t+1}$) as follows. We regress excess monthly returns on three Fama-French factors (MKT, SMB, HML) and use the residuals from this regression as return inputs in the GARCH(1,1) model. GARCH parameters and residuals are obtained from an expanding window of at least 60 months and a rolling window of 60 months, respectively. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) GARCH idiosyncratic volatility. P1−P5 is a portfolio that is long P1 and short P5. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1987 to December 2016. Portfolio returns are calculated from January 1992 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: $\widehat{GIVOL}_{t+1}$						
Mean	6.24	8.36	10.76	13.62	20.45	
Panel A: Equally Weighted Portfolios						
Mean	0.77^{**}	0.77^{*}	0.68	0.68	1.15	−0.38
	(2.00)	(1.76)	(1.03)	(1.04)	(1.47)	(−0.80)
SD	5.49	6.46	8.03	9.13	10.77	8.10
FF-3 α	0.22^{*}	0.17	−0.28	-0.47^{*}	−0.14	0.37
	(1.71)	(0.81)	(−0.97)	(−1.77)	(−0.39)	(1.06)
Panel B: Value-Weighted Portfolios						
Mean	0.60^{*}	0.45	0.42	0.21	0.91	−0.31
	(1.68)	(1.05)	(0.64)	(0.32)	(1.16)	(−0.57)
SD	5.89	7.04	8.33	9.68	11.63	9.31
FF-3 α	0.26^{**}	0.05	−0.27	-0.75^{**}	−0.24	0.50
	(2.07)	(0.22)	(−0.98)	(−2.34)	(−0.55)	(1.07)

relation between idiosyncratic risk and volatility. Further, we find that using a more sophisticated model to estimate total volatility also yield low and insignificant alphas for the low minus high volatility portfolio. This corroborate our notion that the method used to estimate volatility plays an important part in the discussion of the existence of

Table 13:
Portfolios Sorted by Total Volatility Estimated Using a GARCH(1,1) Model

We form quintile portfolios by sorting stocks on total volatility estimated using a GARCH(1,1) model ($\widehat{GTVOL}_{t+1}$). GARCH parameters are obtained from an expanding window of at least 60 months. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) GARCH total volatility. P1−P5 is a portfolio that is long P1 and short P5. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1987 to December 2016. Portfolio returns are calculated from January 1992 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: $\widehat{GTVOL}_{t+1}$						
Mean	8.11	10.59	13.40	16.66	26.34	
Panel A: Equally Weighted Portfolios						
Mean	0.74	0.57	0.78	0.68	1.22	−0.47
	(1.59)	(1.32)	(1.31)	(1.07)	(1.55)	(−1.04)
SD	5.96	6.35	7.70	8.91	10.66	8.45
FF-3 α	0.12	−0.01	−0.19	−0.45*	−0.05	0.17
	(0.46)	(−0.07)	(−0.76)	(−1.83)	(−0.15)	(0.43)
Panel B: Value-Weighted Portfolios						
Mean	0.50	0.37	0.26	0.43	0.59	−0.10
	(1.11)	(0.82)	(0.46)	(0.69)	(0.80)	(−0.19)
SD	6.38	6.95	8.63	9.39	11.77	9.62
FF-3 α	0.01	−0.01	−0.39	−0.52*	−0.47	0.48
	(0.05)	(−0.05)	(−1.08)	(−1.85)	(−1.08)	(1.02)

a low volatility anomaly.

As discussed in Section 4.1, volatility is an unobservable variable and needs to be estimated. There are various models for volatility estimation, where none will be perfect. For that reason, the estimated volatility may vary based on which method is used. Our findings suggest that the method used to estimate volatility is a key factor for understanding the low volatility anomaly, as results drastically change. GARCH-models take into account that volatility is changing over time and tend to be reverting to a long run mean. Thereby the estimations will be less swayed by volatility clusters where volatility for short periods are unusually high or low. We leave further exploration of the relation between volatility estimation and the low volatility anomaly using more advanced volatility models for future research.

We note that estimating volatility using a GARCH(1,1) model require 60 months of data before portfolios can be formed. The first portfolios are consequently formed in December 1991. Thus, the results are not directly comparable to those where volatility is estimated using a rolling window model with a window length of 24 months, where the first portfolios are formed in December 1989. There might be subperiod effects driving our results. We show that this is not the case.

In Table 19 and 20 we form portfolios using GARCH(1,1) to estimate idiosyncratic and total volatility, respectively, for the period January 1995 to December 2016. Portfolio returns are consequently calculated from January 2000 to December 2016. Our results are qualitatively identical to portfolio returns in the period January 1992 to December 2016; all FF-3 alphas for P1−P5 are low and insignificant. Further, portfolio returns after sorting on $I\widehat{VO}L_{t+1}$ and $T\widehat{VO}L_{t+1}$ (Table 14 and 15) for January 2000 to December 2016 show that all alphas for P1−P5 are positive and significant. This strengthens our notion that there is evidence of a low volatility anomaly when a simple rolling window model is used to estimate volatility[12], while there is no evidence of an anomaly when a more sophisticated GARCH(1,1) model is used.

[12]When we not control for firm characteristics, such as firm size and bid-ask spread.

6 Conclusion

Traditional asset pricing theories suggest a flat or positive relation between idiosyncratic risk and return. Ang et al. (2006) provide intriguing findings of a low volatility anomaly; stocks with low idiosyncratic volatility outperform stocks with high idiosyncratic volatility. In this thesis, we use monthly stock data from Oslo Børs and show that the low volatility anomaly can be explained by various firm characteristics, short-term return reversals and the method used to estimate volatility.

We first estimate idiosyncratic volatility using a simple rolling window model of lagged returns. We sort stocks based on these estimates of volatility and find that the low volatility portfolio significantly outperforms the high volatility portfolio in terms of Fama and French (1993) alphas. However, there are distinct patterns in firm characteristics across the portfolios. The high volatility portfolio contains, on average, small, illiquid, positively skewed stocks with high bid-ask spreads. Controlling for firm characteristics by performing a double sort, we find that firm size and the bid-ask spread to a large extent can explain the low volatility anomaly. Further, our results indicate that the poor performance of the high volatility portfolio is most pronounced for stocks with highly positively skewed returns. Amihud (2002)'s measure of illiquidity is the least promising explanation of the anomaly.

We find that that short-term return reversals also can explain the low volatility anomaly. Our results show that stocks with high idiosyncratic volatilities have high contemporaneous returns. The positive returns tend to reverse, causing low or negative returns in the next month.

As volatility is unobservable it needs to be estimated. We show that the method used to estimate volatility greatly affects the notion on whether a low volatility anomaly exist or not. Consistent with Fu (2009), our results indicate that using a more sophisticated model to estimate idiosyncratic volatility yield no evidence of a low volatility anomaly. More specifically, Fama and French (1993) alphas are low and no longer significant for the low minus high volatility portfolio using a GARCH(1,1) model to estimate volatility.

Appendix A Subperiods

Table 14:
Portfolios Sorted by Idiosyncratic Volatility. 2000-2016.
We form quintile portfolios by sorting stocks on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$) relative to the Fama and French (1993) model. Portfolios are formed every month based on idiosyncratic volatility computed using monthly data from the previous 24 months. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. P1−P5 is a portfolio that is long P1 and short P5. *Firm characteristics* reports, within each portfolio, means of the market capitalization in NOK 1 billion ($Size$), market share in percentage terms ($MktShare$), Amihud (2002)'s measure of illiquidity ($Illiq$), bid-ask spread ($BidAsk$) in percentage terms and skewness ($Skew$). *Portfolio returns* reports monthly means and standard deviations (SD) of excess returns in percentage terms. SR is the monthly Sharpe ratio. *Fama-French Regression* reports results from regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Coefficients from the regression are also reported. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: Idiosyncratic Volatility ($\widehat{IVOL}_{t+1}$)						
Mean	5.29	8.03	10.66	14.05	21.05	
Portfolio Characteristics						
$Size$	29.98	7.25	4.04	2.43	1.33	
$MktShare$	65.64	15.85	9.35	5.87	3.29	
$Illiq$	0.47	0.85	1.37	2.20	2.80	
$BidAsk$	1.51	1.76	2.02	2.40	2.69	
$Skew$	0.11	0.25	0.34	0.51	1.01	
Panel A: Equally Weighted Portfolios						
Portfolio Returns						
Mean	0.52	0.35	0.19	0.65	0.20	0.32
	(0.99)	(0.58)	(0.28)	(0.70)	(0.23)	(0.65)
SD	5.33	6.65	7.81	9.20	10.40	7.66
SR	0.10	0.05	0.02	0.07	0.02	0.04

(Continued)

Table 14 – *Continued*

	P1	P2	P3	P4	P5	P1−P5
Panel A: Equally Weighted Portfolios						
Fama-French Regression						
FF-3 α	0.19	−0.24	−0.40	−0.18	−0.78**	0.97***
	(1.22)	(−1.14)	(−1.61)	(−0.49)	(−2.34)	(2.88)
MKT	0.89***	1.13***	1.20***	1.45***	1.59***	−0.70***
	(18.06)	(21.40)	(16.34)	(14.59)	(19.15)	(−7.30)
SMB	0.12*	0.45***	0.43***	0.69***	0.92***	−0.81***
	(1.94)	(6.17)	(4.70)	(5.70)	(6.96)	(−6.11)
HML	0.04	−0.06	−0.21***	−0.02	−0.36**	0.40***
	(1.07)	(−1.11)	(−2.70)	(−0.25)	(−2.52)	(2.70)
Panel B: Value-Weighted Portfolios						
Portfolio Returns						
Mean	0.41	0.42	0.12	0.47	−0.29	0.70
	(0.91)	(0.71)	(0.16)	(0.56)	(−0.34)	(1.33)
SD	5.47	7.50	8.93	9.92	11.26	9.30
SR	0.08	0.06	0.01	0.05	−0.03	0.08
Fama-French Regression						
FF-3 α	0.23**	0.03	−0.27	−0.16	−1.21***	1.44***
	(2.23)	(0.11)	(−0.78)	(−0.44)	(−2.80)	(3.22)
MKT	0.86***	1.10***	1.26***	1.47***	1.63***	−0.76***
	(27.56)	(14.53)	(11.34)	(17.07)	(12.54)	(−5.56)
SMB	−0.14***	0.14	0.06	0.34***	0.82***	−0.95***
	(−3.37)	(1.36)	(0.44)	(3.07)	(4.90)	(−5.15)
HML	0.14***	−0.10	−0.15	−0.04	−0.39**	0.53***
	(3.24)	(−1.31)	(−1.40)	(−0.37)	(−2.49)	(3.04)

Table 15:
Portfolios Sorted by Total Volatility. 2000-2016.

We form quintile portfolios by sorting stocks on total volatility ($\widehat{TVOL}_{t+1}$). Portfolios are formed every month based on total volatility computed using monthly data from the previous 24 months. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) total volatility. P1−P5 is a portfolio that is long P1 and short P5. *Firm characteristics* reports, within each portfolio, means of the market capitalization in NOK 1 billion ($Size$), market share in percentage terms ($MktShare$), Amihud (2002)'s measure of illiquidity (*Illiq*), bid-ask spread (*BidAsk*) in percentage terms and skewness ($Skew$). *Portfolio returns* reports monthly means and standard deviations (SD) of excess returns in percentage terms. SR is the monthly Sharpe ratio. *Fama-French Regression* reports results from regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Coefficients from the regression are also reported. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: Total volatility ($\widehat{TVOL}_{t+1}$)						
Mean	7.23	10.47	13.57	17.41	25.21	
Portfolio Characteristics						
$Size$	24.51	11.73	4.56	2.67	1.54	
$MktShare$	54.71	24.50	10.70	6.28	3.79	
Illiq	0.56	0.87	1.32	2.08	2.83	
Bid Ask	1.66	1.77	2.01	2.23	2.70	
Skewness	0.16	0.26	0.29	0.52	0.98	
Panel A: Equally Weighted Portfolios						
Portfolio Returns						
Mean	0.59	0.56	0.18	0.49	0.15	0.43
	(1.18)	(0.99)	(0.24)	(0.58)	(0.16)	(0.76)
SD	4.97	6.37	7.97	9.21	10.82	8.38
SR	0.12	0.09	0.02	0.05	0.01	0.05
Fama-French Regression						
FF-3 α	0.25	0.05	−0.48	−0.30	-0.89^{**}	1.14^{***}
	(1.49)	(0.21)	(−1.63)	(−0.98)	(−2.53)	(3.06)
MKT	0.82^{***}	1.04^{***}	1.28^{***}	1.47^{***}	1.65^{***}	-0.83^{***}
	(20.60)	(18.39)	(16.91)	(16.14)	(19.22)	(−8.61)
SMB	0.15^{***}	0.36^{***}	0.50^{***}	0.62^{***}	0.99^{***}	-0.84^{***}
	(2.89)	(4.24)	(5.61)	(5.37)	(6.34)	(−4.85)
HML	0.09^{**}	−0.07	−0.09	-0.20^{*}	-0.35^{**}	0.44^{***}
	(1.99)	(−1.22)	(−1.11)	(−1.80)	(−2.18)	(2.58)

(Continued)

Table 15 – *Continued*

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Panel B: Value-Weighted Portfolios						
Portfolio Returns						
Mean	0.40	0.09	0.00	0.55	−0.27	0.68
	(0.89)	(0.17)	(0.00)	(0.67)	(−0.31)	(1.07)
SD	5.47	6.78	8.86	10.12	11.71	9.87
SR	0.07	0.01	0.00	0.05	−0.02	0.07
Fama-French Regression						
FF-3 α	0.17	−0.14	−0.43	−0.06	−1.13***	1.30***
	(1.08)	(−0.53)	(−1.29)	(−0.18)	(−2.94)	(2.75)
MKT	0.86***	0.97***	1.29***	1.54***	1.65***	−0.79***
	(24.36)	(14.91)	(12.38)	(17.49)	(14.35)	(−5.72)
SMB	−0.04	−0.08	0.12	0.29**	0.70***	−0.75***
	(−0.86)	(−1.01)	(0.94)	(2.41)	(4.86)	(−4.28)
HML	0.14***	−0.05	−0.15	−0.12	−0.43***	0.57***
	(3.61)	(−0.75)	(−1.60)	(−1.14)	(−2.88)	(3.48)

Table 16:
Portfolios Sorted by Size and Skewness. 2000-2016.

We form quintile portfolios by sorting stocks on firm size ($Size$) in Panel A and on skewness ($Skew$) in Panel B. We calculate equally and value-weighted excess returns in subpanels (I) and (II), respectively. In Panel A, $P1^j$ ($P5^j$) contains stocks with the smallest (largest) firm size. In Panel B, $P1^j$ ($P5^j$) contains stocks with the lowest (highest) skewness. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j-\mathbf{P5}^j$
			Panel A: Size			
Sort Variable: Size						
Size	0.15	0.47	1.18	3.23	34.29	
$\widehat{IVOL}_{t+1}$	15.91	14.31	12.82	10.28	8.46	
			(I): Equally Weighted Portfolios			
Mean	0.42	0.50	0.51	0.49	0.28	0.14
	(0.46)	(0.57)	(0.64)	(0.73)	(0.49)	(0.30)
SD	9.48	8.87	8.01	7.08	6.58	6.88
FF-3 α	−0.45	−0.33	−0.25	−0.20	−0.08	−0.36
	(−0.99)	(−0.86)	(−0.87)	(−1.00)	(−0.64)	(−0.91)
			(II): Value-Weighted Portfolios			
Mean	0.14	0.47	0.49	0.55	0.27	−0.13
	(0.14)	(0.53)	(0.61)	(0.82)	(0.56)	(−0.23)
SD	9.66	8.86	8.13	7.03	5.84	7.69
FF-3 α	−0.76	−0.38	−0.30	−0.10	0.03	−0.79
	(−1.53)	(−0.98)	(−1.08)	(−0.51)	(1.18)	(−1.51)

(Continued)

Table 16 – *Continued*

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j$–$\mathbf{P5}^j$
Panel B: Skewness						
Sort Variable: Skew						
Mean	−0.57	0.01	0.38	0.77	1.58	
$\widehat{IVOL}_{t+1}$	9.49	10.02	10.81	12.85	16.30	
(I): Equally Weighted Portfolios						
Mean	0.05	0.31	0.62	0.70	0.25	−0.20
	(0.06)	(0.46)	(0.85)	(0.95)	(0.33)	(−0.53)
SD	7.73	7.44	7.72	8.03	8.49	5.43
FF-3 α	−0.54*	−0.33	−0.03	−0.03	−0.49*	−0.05
	(−1.70)	(−1.42)	(−0.09)	(−0.09)	(−1.82)	(−0.13)
(II): Value-Weighted Portfolios						
Mean	0.58	0.34	0.28	0.45	−0.17	0.76
	(0.90)	(0.60)	(0.46)	(0.89)	(−0.23)	(1.48)
SD	7.87	7.43	7.35	6.21	8.71	7.78
FF-3 α	0.29	0.06	−0.01	0.11	−0.74*	1.03**
	(1.00)	(0.27)	(−0.03)	(0.42)	(−1.86)	(1.96)

Table 17:

Portfolios Sorted by Bid-Ask Spread and Illiquidity. 2000-2016

We form quintile portfolios by sorting stocks on the bid-ask spread (*BidAsk*) in Panel A and on Amihud (2002)'s measure of illiquidity (*Illiq*) in Panel B. We calculate equally and value-weighted excess returns in subpanels (I) and (II), respectively. In Panel A, $P1^j$ ($P5^j$) contains stocks with the lowest (highest) bid-ask spread. In Panel B, $P1^j$ ($P5^j$) contains stocks with the lowest (highest) illiquidity measure following Amihud (2002). We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1998 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j\mathbf{-P5}^j$
			Panel A: Bid-Ask Spread			
Sort Variable: BidAsk						
Mean	0.27	0.65	1.24	2.36	6.63	
$\widehat{IVOL}_{t+1}$	10.06	11.63	11.91	12.45	13.65	
			(I): Equally Weighted Portfolios			
Mean	0.44	0.89	0.40	0.24	0.11	0.32
	(0.67)	(1.28)	(0.57)	(0.31)	(0.14)	(0.89)
SD	7.43	7.63	7.66	7.76	8.53	5.48
FF-3 α	−0.02	0.27	−0.34	−0.51	−0.69*	0.66*
	(−0.10)	(1.11)	(−1.49)	(−1.58)	(−1.85)	(1.88)
			(II): Value-Weighted Portfolios			
Mean	0.35	0.20	−0.06	0.02	−0.62	0.97**
	(0.71)	(0.35)	(−0.09)	(0.02)	(−0.87)	(2.59)
SD	6.23	6.80	7.35	6.86	8.15	6.34
FF-3 α	0.10	−0.05	−0.71***	−0.57**	−1.30***	1.40***
	(0.99)	(−0.22)	(−2.68)	(−1.99)	(−3.70)	(3.66)

(Continued)

Table 17 − *Continued*

	$\mathbf{P1}^j$	$\mathbf{P2}^j$	$\mathbf{P3}^j$	$\mathbf{P4}^j$	$\mathbf{P5}^j$	$\mathbf{P1}^j$−$\mathbf{P5}^j$
			Panel B: Illiquidity			
Sort Variable: Illiq						
Mean	0.00	0.04	0.16	0.61	6.48	
$\widehat{IVOL}_{t+1}$	9.25	11.59	11.94	12.65	13.97	
			(I): Equally Weighted Portfolios			
Mean	0.26	0.24	0.62	0.60	0.28	−0.02
	(0.41)	(0.35)	(0.80)	(0.71)	(0.36)	(−0.04)
SD	7.12	7.91	7.84	8.24	8.72	6.39
FF-3 α	−0.13	−0.39*	−0.08	−0.16	−0.55*	0.42
	(−0.70)	(−1.81)	(−0.29)	(−0.45)	(−1.65)	(1.20)
			(II): Value-Weighted Portfolios			
Mean	0.31	0.33	0.05	0.32	0.17	0.15
	(0.65)	(0.56)	(0.07)	(0.47)	(0.24)	(0.33)
SD	5.97	7.42	7.03	7.77	8.48	7.24
FF-3 α	0.09	−0.23	−0.47**	−0.28	−0.61	0.70*
	(1.09)	(−1.23)	(−2.01)	(−0.95)	(−1.60)	(1.68)

Table 18:

Returns on Portfolios Sorted by Idiosyncratic Volatility: Evidence of Return-Reversals. 2000-2016

The table reports average monthly excess returns for quintile portfolios sorted on idiosyncratic volatility ($\widehat{TVOL}_{t+1}$) relative to the Fama and French (1993) model. Portfolios are formed every month based on idiosyncratic volatility computed using monthly data from the previous 24 months. P1 (P5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. P1−P5 is a portfolio that is long P1 and short P5. $EW(t)$ reports equally weighted returns in the same month t as the portfolio is formed, while $EW(t+1)$ reports returns for the following month $t+1$. $VW(t)$ denotes the value-weighted return in month t, where the weights are based upon market capitalization at the end of month t. $VW(t+1)$ reports returns for the following month $t+1$, with weights still based on month t market capitalization. Robust Newey and West (1987) t-statistics are reported in parenthesis. Results are based on a data set for the period January 1998 to December 2016. Portfolios are formed from January 2000 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
$EW(t)$	0.36	0.05	−0.12	−0.03	1.74*	−1.37**
	(0.74)	(0.09)	(−0.17)	(−0.04)	(1.78)	(−2.12)
$EW(t+1)$	0.52	0.35	0.19	0.65	0.20	0.32
	(0.99)	(0.58)	(0.28)	(0.70)	(0.23)	(0.65)
$VW(t)$	0.74*	0.93	1.35**	1.58*	3.65***	−2.91***
	(1.71)	(1.54)	(2.13)	(1.87)	(3.64)	(−4.14)
$VW(t+1)$	0.41	0.42	0.12	0.47	−0.29	0.70
	(0.91)	(0.71)	(0.16)	(0.56)	(−0.34)	(1.33)

Table 19:

Portfolios Sorted by Idiosyncratic Volatility Estimated Using a GARCH(1,1) Model. 2000-2016

We form quintile portfolios by sorting stocks on idiosyncratic volatility estimated using a GARCH(1,1) model ($\widehat{GIVOL}_{t+1}$) as follows. We regress excess monthly returns on three Fama-French factors (MKT, SMB, HML) and use the residuals from this regression as return inputs in the GARCH(1,1) model. GARCH parameters and residuals are obtained from an expanding window of at least 60 months and a rolling window of 60 months, respectively. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) GARCH idiosyncratic volatility. P1−P5 is a portfolio that is long P1 and short P5. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1995 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: $\widehat{GIVOL}_{t+1}$						
Mean	6.35	8.66	11.42	14.67	21.54	
Panel A: Equally Weighted Portfolios						
Mean	0.59	0.74	0.12	0.45	0.85	−0.26
	(1.23)	(1.37)	(0.16)	(0.55)	(0.96)	(−0.50)
SD	5.16	6.00	7.59	8.85	10.28	7.77
FF-3 α	0.25^{*}	0.31	−0.41	−0.33	−0.08	0.33
	(1.70)	(1.29)	(−1.39)	(−1.05)	(−0.20)	(0.91)
Panel B: Value-Weighted Portfolios						
Mean	0.44	0.51	−0.23	−0.20	0.74	−0.30
	(0.95)	(0.94)	(−0.30)	(−0.26)	(0.81)	(−0.58)
SD	5.61	6.80	8.56	9.96	10.85	8.72
FF-3 α	0.24^{**}	0.28	-0.63^{**}	-0.86^{**}	−0.15	0.39
	(2.05)	(1.05)	(−1.99)	(−2.04)	(−0.33)	(0.79)

Table 20:

Portfolios Sorted by Total Volatility Estimated Using a GARCH(1,1) Model. 2000-2016

We form quintile portfolios by sorting stocks on total volatility estimated using a GARCH(1,1) model ($\widehat{GTVOL}_{t+1}$). GARCH parameters are obtained from an expanding window of at least 60 months. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) GARCH total volatility. P1−P5 is a portfolio that is long P1 and short P5. We report monthly means and standard deviations (SD) of excess returns in percentage terms. FF-3 α reports alpha estimates of regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1995 to December 2016. Portfolio returns are calculated from January 2000 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: $\widehat{GTVOL}_{t+1}$						
Mean	8.07	10.83	13.91	17.39	26.82	
Panel A: Equally Weighted Portfolios						
Mean	0.72	0.37	0.57	0.25	0.80	−0.08
	(1.46)	(0.66)	(0.82)	(0.31)	(0.88)	(−0.15)
SD	5.08	5.99	7.65	8.36	10.51	8.12
FF-3 α	0.38**	−0.06	−0.01	−0.48	−0.12	0.50
	(2.04)	(−0.25)	(−0.03)	(−1.64)	(−0.28)	(1.27)
Panel B: Value-Weighted Portfolios						
Mean	0.43	0.33	−0.03	−0.03	0.34	0.09
	(0.96)	(0.55)	(−0.04)	(−0.04)	(0.38)	(0.15)
SD	5.47	6.98	9.27	9.20	11.94	9.93
FF-3 α	0.24	0.07	−0.50	−0.64**	−0.53	0.77
	(1.58)	(0.28)	(−1.04)	(−2.07)	(−1.01)	(1.39)

Appendix B Alternative Filtering

Table 21:
Portfolios Sorted by Idiosyncratic Volatility. Removing Observations with Stock Price Under NOK 10

We form quintile portfolios by sorting stocks on idiosyncratic volatility ($\widehat{IVOL}_{t+1}$) relative to the Fama and French (1993) model. We remove observations where the stock price is less than NOK 10. Portfolios are formed every month based on idiosyncratic volatility computed using monthly data from the previous 24 months. We calculate excess returns for equally and value-weighted portfolios in Panel A and B, respectively. P1 (P5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. P1−P5 is a portfolio that is long P1 and short P5. *Firm characteristics* reports, within each portfolio, means of the market capitalization in NOK 1 billion ($Size$), market share in percentage terms ($MktShare$), Amihud (2002)'s measure of illiquidity ($Illiq$), bid-ask spread ($BidAsk$) in percentage terms and skewness ($Skew$). *Portfolio returns* reports monthly means and standard deviations (SD) of excess returns in percentage terms. SR is the monthly Sharpe ratio. *Fama-French Regression* reports results from regressing monthly excess returns on three Fama-French factors (MKT, SMB, HML). The alpha estimates are in monthly percentage terms. Coefficients from the regression are also reported. Robust Newey and West (1987) t-statistics are reported in parenthesis. The superscripts indicate statistical significance at the 10 percent level (*), 5 percent level (**) and 1 percent level (***). Results are based on a data set for the period January 1987 to December 2016. Portfolio returns are calculated from January 1989 to December 2016.

	P1	**P2**	**P3**	**P4**	**P5**	**P1−P5**
Sort Variable: Idiosyncratic Volatility ($\widehat{IVOL}_{t+1}$)						
Mean	5.00	7.02	8.96	11.45	17.62	
Portfolio Characteristics						
$Size$	25.12	7.81	4.83	3.26	1.59	
$MktShare$	50.22	19.41	13.65	9.95	6.77	
$Illiq$	0.59	0.58	0.93	0.92	2.54	
$BidAsk$	1.50	1.60	1.71	1.75	2.34	
$Skew$	0.11	0.20	0.21	0.35	0.79	
Panel A: Equally Weighted Portfolios						
Portfolio Returns						
Mean	0.52	0.25	0.68	0.88	0.01	0.51
	(1.21)	(0.53)	(1.20)	(1.25)	(0.01)	(1.14)
SD	5.95	6.92	8.66	10.08	11.10	8.36
SR	0.09	0.04	0.08	0.09	0.00	0.06

(Continued)

Table 21 – *Continued*

	P1	P2	P3	P4	P5	P1−P5
Panel A: Equally Weighted Portfolios						
Fama-French Regression						
FF-3 α	0.05	-0.44^{**}	-0.10	0.05	-1.21^{***}	1.26^{***}
	(0.28)	(-2.07)	(-0.35)	(0.14)	(-4.10)	(4.05)
MKT	0.88^{***}	1.06^{***}	1.22^{***}	1.27^{***}	1.60^{***}	-0.72^{***}
	(23.37)	(25.04)	(20.11)	(15.67)	(20.88)	(-8.63)
SMB	0.06	0.25^{***}	0.33^{***}	0.31^{***}	0.62^{***}	-0.56^{***}
	(1.03)	(4.52)	(3.70)	(2.71)	(5.76)	(-5.28)
HML	0.07	0.03	-0.10	-0.10	-0.17	0.24^{*}
	(1.64)	(0.60)	(-1.45)	(-0.81)	(-1.45)	(1.69)
Panel B: Value-Weighted Portfolios						
Portfolio Returns						
Mean	0.38	0.15	0.42	0.58	-0.37	0.75
	(1.05)	(0.33)	(0.81)	(0.84)	(-0.51)	(1.49)
SD	6.09	7.33	8.77	10.53	11.94	9.58
SR	0.06	0.02	0.05	0.05	-0.03	0.08
Fama-French Regression						
FF-3 α	0.10	-0.32	-0.14	-0.06	-1.45^{***}	1.55^{***}
	(0.71)	(-1.37)	(-0.54)	(-0.16)	(-4.12)	(3.90)
MKT	0.85^{***}	1.03^{***}	1.22^{***}	1.28^{***}	1.68^{***}	-0.82^{***}
	(25.79)	(23.99)	(19.87)	(14.43)	(17.82)	(-7.32)
SMB	-0.16^{***}	-0.002	0.03	0.06	0.41^{***}	-0.57^{***}
	(-2.91)	(-0.04)	(0.34)	(0.63)	(3.05)	(-4.32)
HML	0.09^{**}	-0.04	-0.10	-0.03	-0.19^{*}	0.27^{**}
	(2.42)	(-0.95)	(-1.46)	(-0.24)	(-1.66)	(1.97)

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