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OVERNIGHT RETURN ANOMALIES IN THE OSLO STOCK EXCHANGE: CAUSES AND POTENTIAL EXPLOITATIONS

Master Thesis

by

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MSc in Finance

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Oslo, July 1, 2023

Abstract

We investigate the overnight return anomaly in the Oslo stock exchange, confirming that overnight returns significantly outperform intraday returns. We calculate fractions of value-weighted average prices (VWAP) throughout the day and analyze the sources of overnight returns, concluding that higher prices at market open, potentially driven by changes in the overnight midpoint quote, are a significant factor of this anomaly. The presence of persistence and reversal patterns indicates that there are varied trading preferences among investors. The analysis of eleven distinct trading strategies reveals that three of the strategies earn their premia overnight, whereas the remaining eight strategies yield their premia intraday. We round off by demonstrating that lagged overnight and intraday returns, along with their exponentially weighted moving average (EWMA) values, are the most effective predictors of future returns.

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1 Introduction and Motivation

Our motivation to conduct this study comes from Cliff et al. (2008) that based their research on ETFs and found that the US equity premium over the last decade is mainly due to the returns gained throughout the night, whereas the intraday returns are close to zero or even sometimes negative. On the contrary, Lou et al. (2019) argue that this is not the case for individual stocks in the US market and concludes that most trading strategies gain their premium intraday. Therefore, we are motivated to take this study into the Norwegian stock market and analyse whether overnight returns are higher than intraday returns. Additionally, we are eager to investigate the reasons for the anomaly and explore possible ways to exploit it for profit.

The previous research that has been conducted in this field mostly based their analysis on the US market, whereas Lou et al. (2019) extended it to some global markets such as Australia, Japan, Canada, and some European countries. Nevertheless, the Norwegian stock market was never taken into account. To distinguish our study from two previous master theses with limited samples, we investigate all stocks in the Norwegian stock market (our sample consists of 569 stocks) for the substantial time period of 27 years (from 1993 to 2019). We also try to explain the anomaly by conducting several tests and exploiting it by calculating abnormal decomposed returns for various popular trading strategies and by predicting future decomposed returns utilising lagged returns and lagged firm characteristics.

Our research consists of several main steps, and every step implements a distinct methodology. First, we investigate if overnight returns are higher than intraday returns in the Norwegian stock market. We calculate value-weighted portfolio returns overnight and intraday, then compare them statistically. Second, we investigate possible explanations for this anomaly. Following Cliff et al. (2008), who found that high overnight returns are due to the high prices at open, we calculated the fraction of value-weighted average prices (VWAP) for every half-hour window in a smaller sample of 342 equities on the Oslo stock exchange for the time period from February 9, 2009, at 09:00:00 to April 21, 2023, at 16:25:00, and checked the distribution of the VWAP throughout the day. Our second approach to explore the reason behind the anomaly was to decompose overnight returns into overnight changes in the midpoint quote and the remaining market microstructure effects following Lachance (2021). This methodology allowed us to understand the phenomenon of high overnight returns deeper as it breaks them into components and explains the sources of their premia.

In the last part of our research, we focused on the possible ways to exploit the anomaly. Before digging into the calculations of returns for various trading strategies, we analysed if there is a pattern of persistence and reversal in the cross-sectional overnight and intraday returns caused by investors' heterogeneous nature. Lou et al. (2019) found that investors are heterogeneous in the sense that they have different preferences that can be distinguished by the time they choose to trade, and they conclude that different components of returns indicate the specific demand by the corresponding clientele. Therefore, assuming the order flow is persistent if one stock performs well overnight, it should perform relatively well overnight in the future. This price pressure causes the intraday returns on the stocks to be relatively low. This concept is called a pattern of persistence and reversal, or the concept of the tug of war. We followed Lou et al. (2019)'s methodology and conducted an analysis of the existence of persistence and reversal pattern in our sample.

Subsequently, we linked the preference of different clientele to the firm characteristics and investigated whether popular trading strategies earn their premia overnight or intraday, such as size, value, price momentum, industry momentum, short-term reversal, profitability, turnover, asset growth, beta, idiosyncratic volatility, and discretionary accruals. We sorted stocks on each of these firm characteristics and constructed a long-short strategy using value-weighted portfolios.

Lastly, we tested alternative methodology to earn a profit given the existence of anomaly and conducted Fama-MacBeth regressions that allowed us to predict future returns. Particularly, we tested if different combinations of the overnight and intraday portfolio returns, as well as their EWMA values and different firm characteristics, *individually* or *jointly* have a predictive power of future close-to-close, overnight, or intraday returns. This methodology helps to understand what variables have a predictive power of future returns and to understand the relationship of each variable with future returns.

Our results are fourfold. First, in the Oslo stock exchange, the overnight returns are higher than intraday returns, specifically, the overnight returns are 1.0100% (t-statistic of 6.244), and intraday returns are -1.5300% (t-statistic of -9.818). This finding is consistent with Cliff et al. (2008), and Kelly and Clark (2011).

Second, the prices during the first trading hour are on average higher than the prices during the rest of the day. This is in line with the finding of Cliff et al. (2008), namely, the high prices at the open can explain high overnight returns. As an alternative explanation, we decomposed overnight returns into overnight changes in the midpoint quote and the remaining market microstructure effects, and came to the conclusion that high overnight returns in the Norwegian stock market are due to the overnight changes in the midpoint quote. This effect might be due to different corporate events or news announcements that usually take place after the market close, but we leave it as a question for further research.

Third, we calculated 11 trading strategies and decomposed their returns. The results suggest that 3 out of 11 trading strategies, which are size, short-term reversal, and discretionary accruals, earn their abnormal returns overnight, while the remaining eight strategies, which are value, price momentum, industry momentum, profitability, turnover, asset growth, beta, and idiosyncratic volatility, earn their premia during the day. Our results are aligned with the results of Lou et al. (2019), who also concluded that most trading strategies earn their premia during the day, and explained the contradiction of results with Cliff et al. (2008)'s by the difference in nature of the sample, particularly Cliff et al. (2008) conducts their analysis on ETFs, while Lou et al. (2019) on the stocks.

Finally, we used Fama-MacBeth regressions to predict future returns. We concluded that overnight and intraday portfolio returns and their EWMA values both *jointly* and *individually* have a predictive power of future close-to-close, overnight, or intraday returns; and that eight raw value-weighted firm characteristics *jointly* have a predictive power of future close-to-close, overnight, and intraday returns, while *individually*, only momentum, beta, profitability, and accruals explain overnight and intraday returns. Lastly, our results suggested that overnight and intraday portfolio returns, as well as their EWMA values, and eight raw value-weighted firm characteristics *jointly* have a predictive power of future close-to-close, overnight, and intraday returns, while *individually* only lagged overnight and intraday returns and their EWMA values along with momentum effect have explanatory power of future returns.

Our study can be extended in several directions. Given the limitation of data, we do not take into account any type of transaction costs. Therefore, one should take them into account before implementing the results we obtained. The results from the calculations of the order imbalances contradict our findings of the first trading hour. We leave these questions open for future research.

The rest of this thesis is organized as follows: Section 2 is the literature review, where we summarize existing research in the field. Section 3 outlines 7 hypotheses that this study seeks to investigate. Section 4 provides a detailed explanation of the various data sources used in this research and data handling processes. In Section 5, we discuss the methodological framework that this study relies upon, providing an in-depth explanation of our approach and techniques. Section 6 discusses empirical findings, and Section 7 concludes the study by summarizing findings and implications.

2 Literature review

Numerous studies have extensively studied this anomaly and consistently reported higher overnight returns than their intraday counterparts. In the subsequent sections, we provide a comprehensive overview of selected studies that support this anomaly, suggest possible explanations, and propose potential strategies to exploit it.

2.1 If overnight returns are higher than intraday returns?

Cliff et al. (2008) conducted a study using TAQ (Trade and Quote) data from 1993 to 2006 to analyse the composition of the US equity premium. They decomposed the equity premium into intraday (open-to-close) and overnight (close-to-open) returns; and observed that the US equity premium during the last decade was primarily driven by overnight returns, which exhibited strong positive performance. In contrast, intraday returns were close to zero and sometimes negative. The paper reported average log daily intraday (overnight) returns based on trade prices of 1.11 basis points (4.14 basis points) for S&P 500 stocks, 3.04 basis points (5.43 basis points) for 14 ETFs, and 4.53 basis points (4.79 basis points) for S&P 500 E-mini futures.

Kelly and Clark (2011) also investigated the returns in trading and non-trading hours using ETFs and the Sharpe ratio for comparison. They looked at the overnight and intraday returns for the following ETFs: DIA (Dow 30), the IWM (Russell 2000), the MDY (S&P 400 Midcap), the QQQQ (Nasdaq 100), and the SPY (S&P 500), and reported daily returns of the range from 1.8 to 8.9 basis points intraday and 3.7 to 9.3 basis points overnight. The results from the comparison of Sharpe ratios show that the overnight Sharpe ratio is positive and consistently exceeds the intraday Sharpe ratio, which is negative. However, overnight Sharpe ratios are statistically significant for only two out of five ETFs. The most striking results were for QQQQ, where the intraday annualised risk premium was -20.4%, and the overnight annualised risk premium was 27.7% for 1999-2006.

The papers of Cliff et al. (2008) and Kelly and Clark (2011) have different methodologies. Cliff et al. (2008) use log returns, actual trade prices, and spread mid-quotes to analyse individual stocks, while Kelly and Clark (2011) use risk-adjusted excess returns and value-weighted average prices to analyse ETFs. They test if the overnight Sharpe ratio is greater than the intraday Sharpe ratio following Opdyke (2007). Despite these differences, both papers found similar results, indicating reliable findings.

Berkman et al. (2012) conducted a study using data from the 3000 largest stocks from 1996 to 2008. They used midpoint quotes at the open and close and found significant average overnight and intraday returns of 10 and -7 basis points per day, respectively. Moreover, they classified stocks into high-attention and low-attention subsamples, where high-attention stocks are the ones that have recently attracted the attention of retail investors and revealed consistent results. The subsample of high-attention stocks showed a significant average overnight (intraday) return of 13 (-13) basis points per day, while the low-attention stocks showed 3 (-3) basis points per day. These findings align with previous studies by Cliff et al. (2008) and Kelly and Clark (2011), further supporting the anomaly of overnight returns being higher than intraday counterparts.

Lachance (2021) conducted an empirical study on all ETFs, all US equity ETFs, and US individual stocks based on equal-weighted arithmetic averages from 1993 to 2017. The findings reveal that, across all ETFs included in the CRSP dataset, the overnight return mean is 5.47 basis points. In comparison, intraday returns exhibited a negative mean of -2.94 basis points, and overnight returns are statistically significantly higher than intraday returns at 0.01% level. Furthermore, the paper reported 6.29 and -2.18 basis points for overnight and intraday returns, respectively, for all US equity ETFs. Similarly, overnight returns were 4.52 basis points for US individual stocks, with intraday returns measuring at -2.61.

Overall, Lachance (2021) reinforces the existence of a phenomenon in the stock market characterised by higher overnight returns. These findings contribute to the ongoing body of literature studying the dynamics of returns in different time intervals, shedding light on the distinct performance patterns observed in overnight and intraday trading.

2.2 What might be the potential explanation for this anomaly?

Kelly and Clark (2011) discuss the influence of day traders on the market when active traders hold undiversified portfolios as one of the potential explanations for the high overnight returns. According to them, these "semiprofessional" traders fear negative stock-specific news overnight, so they liquidate their positions before the close and enter new positions at the following open.

Another possible explanation was suggested by Fenton-O'Creevy et al. (2005) in terms of behavioural finance. They conducted an experimental study revealing the presence of the "illusion of control" among institutional investors. This bias can be explained as feeling overconfident during trading hours, as traders have "control" over their portfolio, meaning they can trade. However, they feel less control during non-trading hours as the market is closed, and liquidating their positions is no longer possible. Consequently, institutional investors tend to liquidate positions near the end of the day, resulting in lower risk-adjusted intraday returns.

Lachance (2021) suggests that high overnight returns seen in ETFs are explained by market microstructure effects, particularly positive order imbalances and increases in bid-ask spread during the night. The study shows that these market microstructure effects artificially increase ETFs' overnight returns by an average of over 6% annually. The ETF market is prone to these distortions due to its rapid growth and high levels of order imbalances exceeding 10%. Therefore, she concludes that returns are predictable, and there is an opportunity to create a trading strategy out of this.

In contrast to Lachance (2021), Lou et al. (2019) stress the heterogeneity of the investors as the reason for the given anomaly. They argue that the tendency of investors to trade in one or another trading hour reveals many aspects of investors' heterogeneity. Hence, overnight and intraday components of returns can be attributed to the demand of the corresponding clientele.

Cliff et al. (2008) explain that overnight returns are partly driven by high opening prices that subsequently decline in the first trading hour and not by the volatility during the night or by the degree of earning announcements, whereas Berkman et al. (2012) support their finding and concludes that high overnight returns are due to the high opening prices relative to intraday prices, while there is no tendency for the closing prices to be lower than intraday prices. Additionally, they explain that the phenomenon occurs more frequently among stocks that have recently received attention from retail investors, is more noticeable for stocks that are hard to accurately value and costly to arbitrage, and is more pronounced during times when there is a high level of overall retail investor sentiment.

An interesting approach to explain the anomaly was taken by Heston et al. (2010) that studied the characteristics of intraday stock return by dividing the trading day into 13 half-hour trading intervals. They found that the return continuation observed at daily frequencies is more notable for the first and last hour periods up to 40 trading days, and these effects can not be attributed to factors such as firm size, systematic risk premia, or inclusion in the S&P500 index. Whereas Hong and Wang (2000) suggest that the pattern of mean and volatility of returns over trading periods are U-shaped, and these findings support the results of Heston et al. (2010) that prices at open and close are higher than other trading hours. According to them, high prices at the open might be explained by the information asymmetry that arises from the lack of trading during the market closure, but this effect smoothes away during the day once the trading starts and prices start to reflect the information.

Overall, the studies mentioned above highlight various explanations and factors contributing to the phenomenon of high overnight returns and intraday patterns in the stock markets. They provide insights into the diversified nature of high overnight returns and intraday patterns, including psychological biases, market microstructure effects, investor heterogeneity, and trading hour dynamics.

2.3 What might be a possible way to exploit this anomaly?

The discussion in the previous section mentioned Lachance (2021) found that overnight returns are higher than intraday returns, and explained it by the market microstructure effects. Hence, she concludes that returns are predictable for market microstructure returns, and there is an opportunity to create a trading strategy to exploit the anomaly. She gives an example in the case of ETFs, and suggests the strategy of buying at close and selling at open, and highlighting the importance of picking the 'right' ETFs, particularly ETFs that have predicted market microstructure returns greater than the round trip transaction costs. The results for the strategy she obtained were after-fee daily returns of 5.63 basis points (15.24% annualised). Therefore, this shows that the anomaly of high overnight returns can be exploited for profit.

Another study conducted by Kelly and Clark (2011) found that overnight risk-adjusted returns are higher than their overnight counterparts. The researchers try to exploit this difference by long-short strategy in the case of QQQQ ETF, and report that the strategy outperforms a passive buy-and-hold strategy throughout 1999-2006, even after taking into account realistic trading costs. They wrap up their study with an open question of why market participants do not take advantage of this market behaviour.

Branch and Ma (2012) shed light on a very interesting phenomenon that is inconsistent with even a weak form of market efficiency suggested by Fama (1970). They found a strong negative autocorrelation between overnight and intraday returns and suggested market-makers' behaviour and bid-ask bounce as potential explanations for the anomaly.

Lou et al. (2019) built upon it and introduced the concept of tug of war, the phenomenon of investors being heterogeneous and having preferences for trading at different day times, reflecting the specific demand and order flow persistence. Hence, on average, stocks that outperform overnight continue to perform well overnight in the future. The price pressure eventually reverses during the subsequent intraday periods when the opposing clientele dominates the market activity. This back-and-forth across two periods is referred to as the tug of war. They try to take advantage of this anomaly and test 14 different long and short strategies with the sample from the 1993-2013 time period. By decomposing the abnormal returns into overnight and intraday components, they found that 9 out of 14 strategies accrue their profit during the day and five during the night. Additionally, they reported that strategies that gain premia intraday have a statistically significant overnight premium that is opposite in sign. Therefore, Lou et al. (2019) provided insightful results and demonstrated that the tug of war exists in practice and can be monetised.

Overall, the papers above have shown clear evidence of the possible exploitations of the anomalies of high overnight returns and the concept of the tug of war at a profit. Following them, we decided to test if we could exploit them in the Norwegian stock market.

2.4 Our contributions to the existing literature

All the abovementioned papers use mostly the US market as a sample, and Lou et al. (2019) extend it to several other global markets, including Australia, Canada, Japan, and some European countries such as Germany, UK, and France. However, the Norwegian market is not considered in any of them. The only works we found are master theses written by Fjeldheim Amundsen and Bryhn (2015) and Sørensen (2020) conducted in the Norwegian stock market. Nevertheless, Fjeldheim Amundsen and Bryhn (2015) used 15 of the most liquid stocks over the period of 11 years (2003 - 2014), and Sørensen (2020) used two stocks (DNB and Yara International) and two indexes (OBX and OSEBX) over the period of 6 years (2013 - 2019). We extended the sample size to 27 years covering from 1993 - 2019 and using this sample, we decompose returns into overnight and intraday components and test if overnight returns are higher than their intraday counterparts.

In addition, we studied possible explanations for this anomaly by investigating prices throughout the day and decomposing overnight returns into overnight changes in the midpoint quote and the remaining market microstructure effects following Lachance (2021); and investigated ways to exploit the anomaly by decomposing popular trading strategies' returns into overnight and intraday components, and by forecasting future returns using past returns and firm characteristics via Fama-MacBeth regressions. These additions are not considered in the two master theses mentioned above.

3 Hypotheses

Hypothesis 1: Overnight returns are equal to or lower than intraday returns. Our study is predicated on the central hypothesis that overnight returns are equal to or lower than intraday returns on the Oslo stock exchange. The hypothesis has been studied in prior research on the US stock exchanges. For instance, Kelly and Clark (2011) computed risk-adjusted returns for overnight and intraday periods and compared them following Opdyke (2007) methodology. Similarly, Lachance (2021) and Lou et al. (2019) constructed value-weighted portfolios and compared the coefficients to derive a conclusion to the same hypothesis in the different markets. They also employed t-statistics to determine the statistical significance of the results. In our analysis, we followed Lou et al. (2019) methodology by constructing a value-weighted portfolio to test our main hypothesis. To ensure the robustness of our findings, we additionally formulated an equally-weighted portfolio.

Hypothesis 2: Prices during the first trading hour, on average, are equal to or lower than the prices during the rest of the day. As we discussed above, Cliff et al. (2008) accounted for high overnight returns to the high opening prices in comparison with the prices during the rest of the day. Following this, we formulated a hypothesis that prices during the first trading hour, on average, are equal to or lower than the prices during the rest of the day. Hence, if we reject this hypothesis, we can conclude that prices at open are higher than during the rest of the day.

Hypothesis 3: High overnight returns are due to the overnight changes in the midpoint quote. Lachance (2021) decomposed the returns into two sources: overnight changes in the midpoint quote and market microstructure effects. Following her methodology, we wanted to understand which of these two sources of overnight returns are higher, meaning which of them explains the bigger proportion of overnight returns. Therefore, we formulated a hypothesis that high overnight returns are due to the overnight changes in the midpoint quote. As we test it against the second source of the overnight returns, rejecting this hypothesis would mean that the remaining market microstructure effects explain the phenomenon.

Hypothesis 4: Eleven distinct long-short strategies generate their premia overnight. Further, we want to test if we can exploit the anomaly in case of its existence and, hence, propose a hypothesis that suggests that eleven distinct long-short strategies generate their premia overnight. To formally test this hypothesis, we compared the CAPM alpha of overnight and intraday returns and evaluated their significance using associated t-statistics.

As an alternative methodology to exploit the anomaly, we suggest testing the predictive power of overnight and intraday portfolio returns, their EWMA values, and different firm characteristics and propose several hypotheses as below.

Hypothesis 5: The overnight and intraday portfolio returns, as well as their EWMA values, *individually* or *jointly* have the power to predict future close-to-close, overnight, and intraday returns. This hypothesis attempts to determine the predictive power of past returns and the direct relationship between past portfolio returns and prospective stock performance.

Hypothesis 6: Different firm characteristics *individually* or *jointly* have the power to predict future close-to-close, overnight, and intraday returns. This distinct hypothesis aims to determine whether firm characteristics can be reliable predictors of future returns.

Hypothesis 7: The overnight and intraday portfolio returns, as well as their EWMA values and different firm characteristics *individually* or *jointly* have the power to predict future returns. By testing the last hypothesis, we aim to understand better the predictive potential of firm characteristics and portfolio returns and their temporal dynamics as captured by EWMAs in predicting future stock returns.

4 Data

Our primary data sources employed include the Oslo Børs Information (OBI) database, Bloomberg, the TradingView platform via the tvdatafeed API, and asset pricing data from Professor Bernt Arne Ødegaars's data library.

4.1 General data

The sample examined in this study encompassed the period from 1993 to 2019. Data for all stocks listed on the Oslo stock exchange within this timeframe was sourced from the Oslo Børs Information (OBI) database, initially incorporating 774 stocks. The extracted variables included an OBI security identifier similar to the CRSP permno identifier, ISIN, ticker, date, close-to-close return, open price, close price, number of shares traded, and number of shares outstanding.

To ensure the robustness and reliability of the sample, specific exclusion criteria were applied. The process started by excluding any stocks that exhibited a market capitalisation of less than 300 million NOK. This allowed the analysis to focus on firms with sufficient scale and stability. In addition, stocks listed for less than three months, or 63 trading days, were eliminated to avoid the potential noise and volatility often associated with newly listed issues. The sample was further refined by excluding 17 additional stocks due to the unavailability or inadequacy of financial statement filings, as such information was crucial for the study. Following the application of these exclusion criteria, the final sample consisted of a total of 569 stocks. This refined sample formed the basis of the analysis and ensured the results were founded on reliable, robust, and high-quality financial data. A complete list of the sample stocks can be found in appendix A6.

4.2 Asset pricing data

Asset pricing data specific to the Oslo stock exchange was obtained from the data library of Professor Bernt Arne Ødegaard. This comprehensive dataset was essential for the analysis and included a range of vital financial variables. The data that was downloaded included market returns, Fama-French factors, SMB (Small Minus Big) and HML (High Minus Low), Carhart's momentum factor UMD (Up Minus Down), and the forward-looking risk-free rate.

The market returns indicate the performance of all stocks listed in the Oslo stock exchange, excluding the least liquid stocks. Fama-French factors – SMB (Small Minus Big) and HML (High Minus Low) – offer insights into the risks and returns associated with small-cap versus large-cap stocks and value versus growth stocks, respectively. Carhart's momentum factor UMD (Up Minus Down) measures a stock's momentum by evaluating the performance of stocks that had experienced recent price increases against those with recent price decreases. Lastly, a forward-looking risk-free rate represents the return an investor would have expected to earn on a risk-free investment.

Combining these variables provided a robust framework for examining overnight and intraday returns in the Oslo stock exchange.

4.3 Half-hour windows

To construct the half-hour windows for the study historical intraday stock data encompassing the entire trading day was required. The tvdatafeed open-source API was utilised to meet this requirement. Due to the limited intraday stock data from 1993, five-minute historical intraday data for 342 equities currently listed on the Oslo stock exchange were downloaded. Appendix A7 lists the securities for which we downloaded data.

The data for every five-minute interval included the date, time, open, high, low, close, and volume. The dataset encompassed the period from February 9, 2009, at 09:00:00 to April 21, 2023, at 16:25:00. This range ensured a comprehensive examination of intraday price fluctuations and trading volumes over the specified period. A resampling procedure was performed to convert the data into thirty-minute intervals based on the five-minute interval data. By transforming the data, a high level of precision was maintained while gaining a broader understanding of price fluctuations.

4.4 Market microstructure effects

Accessing detailed Trades and Quotes (TAQ) data for each tick was necessary to investigate the impact of market microstructure effects on overnight returns. This consisted of the current best bid and ask, and every trade reported to the exchange. This level of precision enabled capturing the nuances and dynamics of the market microstructure effects, thereby providing extensive insights into their contribution to the overnight returns.

Intraday tick data for 36 stocks from the OSEBX index, which consisted of 62 stocks in total, was obtained and downloaded from Bloomberg. The period for which this detailed data was obtained spanned from January 2, 2023, to May 14, 2023. Despite covering a brief time frame, this high-resolution dataset provided a foundation for the investigation into the relationship between market microstructure and overnight return.

5 Methodology

5.1 Decomposition of returns

In our analysis, the initial step was to decompose the returns into overnight and intraday components. Various studies have employed different methodologies for this decomposition.

Lachance (2021) adjusted prices at open for the distributions from the fund as her study works with the sample of ETFs. While Branch and Ma (2012) used CRSP cumulative factor to adjust prices for dividend adjustments, share splits, and other corporate events, Lou et al. (2019) calculated overnight returns taking the difference between close-to-close and intraday returns, and by doing so, they assumed all events that can move prices take place overnight. In contrast, Kelly and Clark (2011) used non-adjusted prices, and accounted them for splits in two subsamples they studied.

In this study, we used daily close-to-close returns adjusted for dividend payouts, share splits, and other corporate events that could move prices. We calculated intraday returns following the common way, as it is shown in Equation 1, and derived overnight returns from adjusted daily close-to-close returns and the intraday returns as shown in Equation 2, as Lou et al. (2019) did, and by doing so we assumed that all events that could move prices occur during the night.

$$r^s_{intraday,d} = \frac{P^s_{close,d}}{P^s_{open,d}} - 1 \tag{1}$$

$$r^s_{overnight,d} = \frac{1 + r^s_{close-to-close,d}}{1 + r^s_{intraday,d}} - 1 \tag{2}$$

Where:

- s is stock
- d is days

After calculating the daily returns, we accumulated them across days into monthly returns for each stock s using the methodology highlighted in Lou et al. (2019) as follows:

$$r^s_{i,t} = \prod_{d \in t}(1 + r^s_{i,d}) - 1 \tag{3}$$

Where:

- i is either close-to-close, intraday, or overnight
- t is month

These accumulated monthly returns are the returns that have been used to conduct our analysis.

We constructed value-weighted portfolios on the accumulated returns, where the weight for each stock is based on the market capitalisation from the previous month.

$$\omega_t^s = \frac{MarketCap_{t-1}^s}{\sum_s MarketCap_{t-1}} \tag{4}$$

$$r_{i,t}^P = \sum_s r_{i,t}^s \omega_t^s \tag{5}$$

The return of the value-weighted portfolio is given by Equation 5, and the portfolio is rebalanced every month.

5.2 Half-hour windows

As a possible explanation for the anomaly, we chose to follow the conclusions of Berkman et al. (2012) and Cliff et al. (2008), which attribute high overnight returns to high opening prices relative to intraday prices, and, thus, to examine trading price distribution throughout the day.

Following the methodology described by Lou et al. (2019), we implemented a half-hour window approach to examine the price distribution of trading activity throughout the day. We relied on volume-weighted average prices (VWAP) to ensure that market open prices were resilient to market liquidity and activity. The VWAP is a trading benchmark that provides the average price a stock has traded throughout the day, adjusted for the number of shares traded at each price level. Consideration of both price changes and the number of shares traded at each price provides a more accurate depiction of how the price of a stock has fluctuated over time.

We used our resampled half-hour data to calculate the volume-weighted average price (VWAP) for each thirty-minute period. As follows:

$$VWAP = \frac{\sum_s (P \cdot Q)}{\sum_s Q} \tag{6}$$

P is known as the Typical Price, and is calculated as following:

$$P = \frac{(High + Low + Close)}{3}$$

Where:

- High is the highest price within the 30-minute interval.
- Low is the lowest price within the 30-minute interval.
- Close is the closing price within the 30-minute interval.

- Q (Total Volume): The total volume represents the accumulated volume within each 30-minute interval.

Due to the fact that the Norwegian stock market is open from 09:00 to 16:25, we determined 15 half-hour periods, the first of which includes an open auction and the last a close auction. First, we measured the amount of trading activity associated with VWAP by decomposing NOK trading volume over each window, we summed up VWAP for every half-hour window throughout the day. Then, we calculated the fraction of the amount traded in every window with respect to the total amount for the given day. Particularly, we divided the sum of every half-hour window VWAP by the sum of VWAP for all 15 half-hour windows, which is the total VWAP of the corresponding trading day.

Then, we wanted to test hypothesis 2, which states that prices during the first trading hour (first two windows), on average, are equal to or lower than the prices during the rest of the day. To conduct this analysis, we tested the difference in means under the assumptions of population variances being equal but unknown. Detailed steps of the test can be found in Appendix A2.

5.3 Market microstructure effects

The alternative methodology we implemented to explain the anomaly of overnight returns being higher than intraday returns is measuring sources of the overnight returns, and we test hypothesis 3 which states that high overnight returns are due to the overnight changes in the midpoint quote.

Given our particular interest in the midpoint quote and market microstructure effects at market open and close, we narrowed our sample size strategically. For the market open, we examined the best bid and ask quotes preceding the first transaction that occurred after 09:00:00. As trading starts, this provides insight into the market sentiment and microstructure. Likewise, for the market close, we focused on the first transaction recorded after 16:25:00, taking into account the best bid and ask quotes preceding this trade. This depicts the market conditions and microstructure at the end of the trading day. By focusing on these specific times and the trading activity surrounding them, we can hone in on the microstructure dynamics at play during these crucial trading periods, thereby enhancing our understanding of their potential impact on overnight returns.

Following Lachance (2021), we tried to explain overnight returns by decomposing them into two sources 7. The first component focuses on the overnight change in the midpoint quote ($r_t^{O,Mid}$), while the second component captures the remaining effects of the market microstructure effects ($r_t^{O,MM}$).

$$r_t^O = r_t^{O,Mid} + r_t^{O,MM} \tag{7}$$

Where r_t^O is the overnight return.

We calculated $r_t^{O,Mid}$ as follows:

$$r_t^{O,Mid} = \frac{M_t^{Open} - M_{t-1}^{Close}}{P_{t-1}^C} \tag{8}$$

Where M is the midpoint quote that is the average of the bid and ask prices at the given time.

To quantify the remaining effects of the microstructure effects, we needed to calculate order imbalances (OI) and effective half-spread (ES). We followed Chordia and Subrahmanyam (2004) to calculate the percentage of order imbalances, which is as follows:

$$OI = \frac{\textit{Number of buys - Number of sells}}{\textit{Number of buys + Number of sells}} \tag{9}$$

The effective half-spread (ES), which is used to evaluate the cost of executing a trade, can be found by the difference between the price and midpoint quote multiplied by the dummy variable that takes the value of 1 if $P > M$, and -1 if $P < M$. The effective half-spread given in percentage is ES divided by yesterday's close price, which is the first trade we record after 16:25:00.

$$ES = D(P - M) \Rightarrow \%ES = \frac{ES}{P_{t-1}^C} \tag{10}$$

Hence, the component that captures the remaining microstructure effects can be found as follows:

$$r_t^{O,MM} = OI_t^{Open} \cdot \%ES_t^{Open} - OI_{t-1}^{Close} \cdot \%ES_{t-1}^{Close} \tag{11}$$

We also should mention that unlike Lachance (2021), our calculations are not adjusted for the distribution of the fund, as we are dealing with stocks and not ETFs.

We chose two abovementioned methodologies, particularly the half-hour windows to see if prices at open are higher than throughout the day, and the decomposition of overnight returns into market microstructure effects and overnight changes in the midpoint quote, to explain the anomaly of overnight returns being higher than their intraday counterparts. The reason for our choice of these methodologies is that they are the most fitting for the settings of our study in terms of the availability of data and the practicality of empirical implementation. These methodologies allowed us to analyse and interpret the phenomenon under investigation effectively.

5.4 Persistence and reversal pattern

As mentioned, in the final stage of our analysis, we proceeded to evaluate different approaches to exploit the anomaly of overnight returns being higher than intraday returns. Before moving to analyse the exploitability of the anomaly, we decided to do a more thorough analysis and see if the returns in the Oslo stock exchange show the pattern of persistence, meaning if stocks with high overnight returns show on average high overnight returns for the following day, and reversal, meaning if the stocks with high overnight returns generate a low intraday return for the following day. Branch and Ma (2012) found very strong negative autocorrelation between overnight and intraday returns. We followed Lou et al. (2019) and tested the stock returns for the existence of persistence and reversal as follows.

The process of forming the initial portfolio involves lagging overnight return by one month. Subsequently, our stocks were sorted into deciles according to the lagged overnight return. Following this, we proceeded to construct value-weighted portfolios for the top and bottom deciles. We then took a long position in the high decile and a short position in the low decile. This process helps us to create a long-short portfolio for both overnight and intraday returns, using sorting based on the overnight return. Similarly, two additional long-short portfolios were constructed for both overnight and intraday returns. However, in these cases, we sorted the returns based on their one-month lagged intraday returns. This methodology enables us to investigate the interplay between overnight and intraday returns within the context of long-short investment strategies.

The pattern of persistence and reversal can be explained by the heterogeneous nature of investors (Lou et al. (2019)) and can be tied to various firm characteristics. In the following, we conducted 11 popular trading strategies and checked during what time of the day (overnight or intraday) their abnormal returns are earned. This allows us to analyse if investor preference/demand is noticeable in any of those trading strategies.

5.5 Trading strategies

The last part of our thesis analyses methods we can exploit the anomaly of higher overnight returns with respect to their intraday counterparts in case of its existence. As one of the options, we conducted different trading strategies to check during what time of the day these strategies earn an abnormal return. We followed Lou et al. (2019) and identified 14 trading strategies; however, we had to exclude 3 of them (time-series momentum, equity issuance, and earnings momentum) due to the absence of data in the Oslo stock exchange for our sample. By constructing these strategies, we test our hypothesis 4 that 11 distinct long-short strategies generate their premia overnight. We list the trading strategies conducted below, describing the methodologies we followed and the data we utilised. For every strategy, we construct a long-short portfolio for overnight and for intraday returns (as outlined in Equation 5) and rebalance each portfolio on a monthly basis.

5.5.1 Size

The size strategy entails sorting each stock in our sample into deciles on a monthly basis, with the classification based on the stock's lagged one-month market capitalisation. This methodology allows for the comparison of performance across varying market capitalisation scales. We constructed two value-weighted portfolios, one for each extreme decile, based on this classification. The first portfolio contains stocks from the lowest decile, or those with the smallest market capitalisations, whereas the second portfolio contains stocks from the highest decile, or those with the largest market capitalisations.

Following Fama and French (1992), we took a long position in the portfolio with small market capitalisation stocks and a short position in the portfolio with large market capitalisation stocks in order to test our hypotheses. This long-short strategy offers a framework for analysing the performance differentials and potential strategy premiums associated with various market capitalisation levels.

5.5.2 Value

To implement the value strategy, also referred to as the book-to-market (BM) strategy, which is highlighted in Fama and French (1992), we first downloaded the annual shareholders' equity from the balance sheets for each sampled stock.

We used the shareholders' equity to calculate a book-to-market ratio for each stock. This ratio is calculated by dividing the shareholders' equity for the previous year ($y-1$) by the market capitalisation for the previous month ($t-1$). The formula can be represented as follows:

$$\textit{book-to-market}_y = \frac{\textit{Shareholders' Equity}_{y-1}}{\textit{Market Cap}_{t-1}}$$

Where:

- y is year
- t is month

After calculating the BM ratio, we sorted the stocks into deciles according to their monthly book-to-market ratios. We then constructed value-weighted portfolios for each extreme decile to examine the return disparity across value levels. We took a long position in the portfolio of stocks with high book-to-market ratios, indicating a high perceived value. At the same time, we took a short position in the portfolio of stocks with low book-to-market ratios, which indicated low perceived value.

5.5.3 *Price momentum*

In implementing the price momentum strategy, we sorted the stocks based on the cumulative close-to-close returns with the ranking period of 11 months, skipping the most recent month to avoid price pressure, bid-ask spread, and lagged reaction effects following Jegadeesh and Titman (1993). This is done following the rolling window method.

The reason for focusing on close-to-close returns instead of overnight or intraday returns is to ensure a consistent comparison framework. Close-to-close returns reflect the entire trading day, including all information and events affecting the stock price during the overnight and intraday periods. This approach reduces the risk of bias or inconsistency that could be introduced by concentrating solely on overnight or intraday returns, which may be subject to market microstructure effects or time-of-day effects. By focusing on close-to-close returns, we align our methodology with standard practices in the field and ensure that our results can be meaningfully compared to those of other published studies. Consequently, this strengthens the robustness and generalisability of our findings.

To investigate this further, we created value-weighted portfolios for the highest and lowest deciles. We employed a long-short strategy in which we took a long position in the decile containing the 'winners' - stocks with the highest one-year accumulated return - and a short position in the decile containing the 'losers' - stocks with the lowest one-year accumulated return. This strategy seeks to capitalise on the momentum effect, which states that stocks that have performed well (or poorly) over the past year will continue to perform well (or poorly) in the near future.

5.5.4 *Industry momentum*

Industry momentum strategy entails sorting our sample of stocks into nine distinct industries, based on BICS (Bloomberg Industry Classification System)[1]: Communications, Industrial, Utilities, Energy, Consumer Non-cyclical, Financial, Consumer Cyclical, Basic Materials, and Technology. For each industry, we constructed a value-weighted portfolio that represents the performance of stocks within that industry as a whole.

Regarding measuring performance, we followed Moskowitz and Grinblatt (1999). First, we computed accumulated close-to-close returns over 12 months for each of these nine industry portfolios, skipping the most recent month. This approach is consistent with the rolling window method and is intended to capture evolving trends in the industry-level momentum. Second, we sorted the industries into quintiles for every month based on these 12-month accumulated returns, followed by a one-month skipping period. This stage enables the examination of return patterns across a range of industry-level momentum. Finally, we constructed value-weighted portfolios, for each of the extreme quintiles. We employed a long-short strategy in which we

[1] We divided stocks into industries following "Sectors" subsection within BICS.

took a long position in the top-performing quintile (i.e., the 'winners') and a short position in the bottom-performing quintile (i.e., the 'losers').

The industry momentum strategy seeks to capitalise on the momentum effect on the industry level, based on the premise that industries with robust (or weak) performance over the past year are likely to continue along the same trajectory in the near future.

5.5.5 Short-term reversal

Introduced by Jegadeesh (1990), the short-term reversal strategy is based on the observation that short-term return trends frequently reverse, a phenomenon attributed to the underreaction hypothesis, which states that stock prices incorporate information slowly (Barberis et al. (1998)).

We began the calculations by lagging the close-to-close returns by one month, thereby investigating the returns from the previous month. The stocks were then sorted into deciles based on these lagged returns for each month. For each extreme decile, a value-weighted portfolio was constructed. We then took a long position in the portfolio of stocks with low returns over the previous month, with the expectation that these stocks will experience a rebound or price correction. Simultaneously, we took a short position in the portfolio of stocks with high returns over the previous month, based on the assumption that these stocks will fall due to the price decline or correction.

This short-term reversal strategy seeks to capitalise on the phenomenon of underreaction observed in financial markets, where extreme price movements are frequently followed by a short-term reversal.

5.5.6 Profitability

Haugen and Baker (1996) suggest several ways to calculate profitability, such as the ratio of net earnings to book equity, also known as return on equity, operating income to total assets, operating income to total sales, etc. We decided to follow the methodology used by Lou et al. (2019), and measure profitability as the return on equity.

The Return on Equity (ROE) strategy is founded on the premise that firms with greater profitability are more likely to generate higher expected returns (Haugen and Baker (1996))[2] We retrieved the annual ROE ratio for each stock in our sample from Bloomberg, lagging this ratio by one year in accordance with the lagged returns methodology utilised elsewhere in this study. As a result, the value of ROE_y is set to ROE_{y-1}.

[2]Profitability, measured by gross profits-to-assets, derives the same conclusion as Haugen and Baker (1996) did, saying profitable firms generating significantly higher returns than unprofitable firms. Novy-Marx (2013)

Consequently, we split the stocks into deciles based on these lagged ROE ratios, a method that allows us to classify stocks based on their profitability from the previous year. For each decile, we constructed a value-weighted portfolio that represents the collective performance of the equities in that decile. In the last stage of implementing this strategy, we took a long position in the portfolio of stocks with a high ROE ratio based on the hypothesis that these high-profitability firms will generate higher returns. Concurrently, we took a short position in the portfolio of stocks with a low ROE ratio based on the premise that these less profitable firms may underperform in terms of returns.

The ROE strategy aims to leverage the relationship between a firm's profitability and its future stock performance, as suggested by existing financial theory and empirical evidence.

5.5.7 Turnover

The turnover strategy we employed is dependent on the examination of a stock's frequency of trading. We followed Lee and Swaminathan (2000) to calculate the ratio between the number of shares traded and the number of shares outstanding, commonly known as 'turnover'. We calculated the turnover ratio based on daily data.

$$Turnover = \frac{Number\ of\ shares\ traded}{Number\ of\ shares\ outstanding}$$

Following that, we aggregated these daily turnover values into monthly averages, creating a more smoothed and representative measure of each stock's trading activity over time. The monthly mean turnover values are subsequently subjected to a 12-month lag. Subsequently, we sorted our stocks into deciles on a monthly basis, utilising their respective lagged monthly mean turnover values. This categorisation allows us to understand the spectrum of trading activity across the given stock sample.

In the final step of implementing this turnover strategy, we constructed a value-weighted portfolio for each of the extreme deciles. The portfolio is assumed to generate higher returns as we take a long position in stocks with low-lagged turnover. This is based on the premise that stocks with lower trading frequency tend to yield greater returns (Lou et al. (2019)). At the same time, we took a short position in the portfolio comprised of stocks with high-lagged turnover, positing that these more frequently traded stocks may underperform in terms of returns.

Through this turnover strategy, we aim to explore the relationship between a stock's trading activity and its future return performance.

5.5.8 *Asset growth*

The asset growth strategy applied in our study focuses on the variation in a firm's total assets over time. At first, we downloaded data on the total assets of each firm in our sample from the respective annual balance sheets. Following this, each stock's asset growth is computed by determining the percentage change in total assets.

We lagged the asset growth measure by 12 months and then sorted the stocks into deciles for each month based on this lagged asset growth measure. The sorting process enables us to establish a distinct categorisation of stocks predicated on their historical asset growth. Fairfield et al. (2003), p. 353 stated, "Both components of growth in net operating assets - accruals and growth in long-term net operating assets - have equivalent negative associations with one-year-ahead return on assets". Whereas Polk and Sapienza (2008) and Titman et al. (2004) concluded that there is a negative relationship between investment and stock returns. Therefore, we constructed a value-weighted portfolio for each extreme decile to implement the asset growth strategy. We took a long position in the portfolio composed of stocks with low asset growth and a short position in the portfolio composed of stocks with high asset growth.

5.5.9 *Beta*

Following Dimson (1979), we started constructing a beta strategy by running a univariate regression of the daily close-to-close returns of each stock on the return of the value-weighted market portfolio, along with its three lags. (11) The methodology employed uses a rolling window approach for one trading year in days, shifting with one day for each window.

$$r_{CC,t} = \alpha + \beta_1 mkt_t + \beta_2 mkt_{t-1} + \beta_3 mkt_{t-2} + \beta_4 mkt_{t-3} + u_t \tag{12}$$

The beta coefficients for each stock were then summed together as follows:

$$\beta_{all} = \beta_1 + \beta_2 + \beta_3 + \beta_4$$

This methodology solves the problem of beta estimates being biased as a result of infrequent trading by inflating the risk level and, hence, adjusting the abnormal returns accordingly (Dimson (1979)).

Next, we transformed the data into monthly returns and computed the monthly averages of the beta estimates. Subsequently, we applied a 12-month lag to the average beta estimates and sorted each stock into deciles based on their respective beta estimates. Subsequent to this sorting, we constructed a value-weighted portfolio for each extreme decile. We took a long position in the portfolio that consists of low-beta stocks and a short position in the portfolio that consists of high-beta stocks.

In our analysis, we primarily employ simple return data. Financial time series frequently display non-stationarity due to the presence of a unit root, particularly in the case of prices. However, the computation of returns, including simple returns, involves the process of taking first differences that typically eliminates this unit root. Therefore, financial studies typically regard returns as stationary values, avoiding the common non-stationarity issue that arises when analysing price data directly.

The assumption of stationarity holds significant importance in ensuring the validity of our econometric analyses. This is because non-stationary data has the potential to produce results that are either misleading or spurious. While we did not conduct a formal unit root test, our usage of return data rather than price data forms the basis of our assumption of stationarity. It is important to note that this is an assumption, and while returns generally exhibit stationarity in specific contexts or over long periods, there may be additional factors that could potentially introduce non-stationarity. However, given the nature of our data and the scope of our study, we find this assumption reasonable.

5.5.10 Idiosyncratic volatility

To implement the idiosyncratic volatility (iVol) strategy, we initially conducted a regression analysis of daily close-to-close excess returns against a set of explanatory variables, including the excess market return, Fama-French factors HML (High Minus Low) and SMB (Small Minus Big), and Carhart's momentum factor UMD (Up Minus Down) following Carhart (1997) (12). This regression was performed using a rolling window approach with a window size equivalent to a trading year in days, moving forward by one day for each subsequent window. The iVol factor, which is a measure of idiosyncratic volatility, is represented by the standard deviation of the residuals obtained from each of these regressions.

The regression model can be summarised as follows:

$$r_{Excess,CC,t} = \alpha + \beta_{mkt}(r_{m,t} - r_{f,t}) + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{UMD} UMD_t + u_t \tag{13}$$

After carrying out daily regressions, we aggregated our data into a monthly format by computing the mean of the iVol factor. Subsequently, a 12-month lag was incorporated into the iVol factor.

According to Ang et al. (2006)'s argument, stocks with high idiosyncratic volatility have abnormally low returns. Hence, utilising the lagged iVol factor as a basis, we sorted our stocks into deciles on a monthly basis, thereby enabling us to establish a portfolio that is value-weighted for each of the two most extreme deciles. Subsequently, a long-short strategy was executed, wherein a long position was taken in the portfolio comprising stocks showing low idiosyncratic volatility, while a short position was taken in the portfolio comprising stocks exhibiting high idiosyncratic volatility.

5.5.11 Discretionary accruals

The initial step in creating a long-short strategy based on discretionary accruals entailed the computation of discretionary accruals for our designated sample. To conduct our analysis, we used a number of financial variables which were obtained on an annual basis. These variables included total current assets, cash and cash equivalents, total current liabilities, short-term debt, income tax payable, and depreciation and amortisation.

Subsequently, the change in the total current assets, cash and cash equivalents, current liabilities, short-term debt, and income tax payable was calculated. The accruals were computed using the following methodology highlighted in Sloan (1996):

$$Accruals = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep$$

Where:

- ΔCA is the change in current assets
- $\Delta Cash$ is the change in cash and cash and equivalents
- ΔCL is the change in current liabilities
- ΔSTD is the change in short-term debt
- ΔTP is the change in income tax payable
- Dep is depreciation and amortisation expense

The normalisation of the accruals measure was achieved by dividing it by the average total assets for the two periods being analysed. [3] This resulted in the calculation of the accruals factor.

$$Accruals\,factor = \frac{Accruals}{Average\ total\ assets}$$

Sloan (1996) concludes that there is a negative relationship between discretionary accruals and following stock returns. On a monthly basis, the stocks were sorted into deciles based on the accruals factor. A value-weighted portfolio was constructed for every extreme decile. Following this, a long-short strategy was carried out, involving taking a long position in the portfolio with

[3] The two periods are the two periods used to calculate the change in different balance sheet items. I.e. t and $t-1$

a low accruals factor while simultaneously taking a short position in the portfolio with a high accruals factor.

5.6 Fama-MacBeth regressions

To test hypotheses 5, 6, and 7, a lengthy process was employed that examined the predictive power of overnight and intraday portfolio returns, the exponentially weighted moving average (EWMA) values of these returns, and the firm-specific characteristics which we used in the trading strategies in Section 5.5.

Initially, the EWMA was calculated by skipping the most recent observation, followed by the computation of the idiosyncratic volatility using both one-period lag and one-period lead. Firm characteristics are all weighted by the one-period lagged market capitalisation to be consistent with the methodology of trading strategy calculations, then Fama-MacBeth regressions are conducted, and to see the accuracy of the prediction RMSE (root-mean-square deviation) values were calculated.

We calculated the EWMA return using the following formula and excluded the most recent observation:

$$r_{i,t}^{EWMA} = \lambda r_{i,t} + (1-\lambda) r_{i,t-1}^{EWMA} \tag{14}$$

Where λ is the decay factor, representing the degree of weighting decrease.

Furthermore, we calculated the iVol factor by extending the methodology outlined in section 5.5.10 with a one-period lead and one-period lag components. The extended specification enables us to accommodate the dynamic nature of these factors.

$$\begin{aligned} r_{\text{Excess, CC}, t} = & \alpha + \beta_{\text{mkt,t}}(r_{m,t} - r_{f,t}) + \beta_{\text{HML,t}} HML_t + \beta_{\text{SMB,t}} SMB_t + \beta_{\text{UMD,t}} UMD_t + \\ & \beta_{\text{mkt,t-1}}(r_{m,t-1} - r_{f,t-1}) + \beta_{\text{HML,t-1}} HML_{t-1} + \beta_{\text{SMB,t-1}} SMB_{t-1} + \\ & \beta_{\text{UMD,t-1}} UMD_{t-1} + \beta_{\text{mkt,t+1}}(r_{m,t+1} - r_{f,t+1}) + \beta_{\text{HML,t+1}} HML_{t+1} + \\ & \beta_{\text{SMB,t+1}} SMB_{t+1} + \beta_{\text{UMD,t+1}} UMD_{t+1} + u_t \end{aligned} \tag{15}$$

To evaluate the predictive power of different variables with respect to future close-to-close, intraday, and overnight returns, we performed a series of Fama-MacBeth regressions. Three distinct regressions were conducted for each set of variables, translating to a total of nine regression analyses. The firm characteristics under consideration in our study are momentum, book-to-market ratio, asset growth ratio, Return on Equity (ROE) ratio, discretionary accruals ratio, turnover ratio, beta, and idiosyncratic volatility (iVol). We excluded industry momentum, as the industry the firm operates in is not considered as the firm characteristic, and the same methodology was implied by Lou et al. (2019). We also excluded the short-term reversal strategy returns following their methodology.

The methodology utilised for calculating the weights assigned to each characteristic is consistent with the approach outlined in Equation 4. In the beginning, the inclusion of market capitalisation as a firm characteristic was considered because of its potential predictive effectiveness. Nevertheless, due to the incorporation of market capitalisation in the weight calculation, we faced challenges related to multicollinearity and subsequently decided to exclude this variable. The correlation matrix for the variables under consideration has been provided in appendix A5.

Despite the potential of Principal Component Analysis (PCA) as a solution for multicollinearity, it was not implemented in this study. The primary drawback of PCA lies in its lack of direct interpretability of the results, which was undesirable in our context. As a result, the decision was made to exclude market capitalisation as a firm characteristic.

Following the careful consideration of the pre-defined variable sets, we proceeded to implement the Fama-MacBeth regression methodology as originally proposed by Fama and MacBeth (1973). The efficacy of this methodology lies in its ability to effectively estimate risk premiums within asset pricing models due to its capability of handling panel data structure. We performed this analysis in two stages.

In the first stage, cross-sectional regressions were conducted for each period utilising Equation 16. Subsequently, we estimated the risk premium connected to the factor and its standard error through a time-series regression, utilising the estimates acquired from the initial stage. We also adjusted the standard errors for serial dependence with 12 lags, i.e. heteroskedasticity- and autocorrelation-consistent (HAC) standard errors.

We ran three types of cross-sectional regressions that allowed us to test three different hypotheses. In the first regression, we took lagged overnight (ON) and intraday (ID) returns, and their EWMA values as independent variables, and the expected close-to-close, overnight, or intraday returns as dependent variables. This regression allows us to test hypothesis 5, which states that overnight and intraday portfolio returns, as well as their EWMA values, have the power to predict future returns.

$$
\begin{aligned}
r^i_{1,t+1} &= \alpha_1 + \beta_{1,ON} r_{ON,1,t} + \beta_{1,ID} r_{ID,1,t} + \beta_{1,EWMA\ ON} r_{EWMA\ ON,1,t} + \\
&\quad \beta_{1,EWMA\ ID} r_{EWMA\ ID,1,t} + u_{1,t} \\
&\quad \vdots \\
r^i_{n,t+1} &= \alpha_n + \beta_{n,ON} r_{ON,n,t} + \beta_{n,ID} r_{ID,n,t} + \beta_{n,EWMA\ ON} r_{EWMA\ ON,n,t} + \\
&\quad \beta_{n,EWMA\ ID} r_{EWMA\ ID,n,t} + u_{n,t}
\end{aligned}
\tag{16}
$$

In the second regression, we took lagged firm characteristics as independent variables, and the expected close-to-close, overnight, or intraday returns as dependent variables. This regression allows us to test hypothesis 6 that different firm characteristics have a predictive power of the future returns.

$$
\begin{aligned}
r^i_{1,t+1} =& \alpha_1 + \beta_{1,mom} mom_{1,t} + \beta_{1,bm} bm_{1,t} + \beta_{1,asset} asset_{1,t} \\
& + \beta_{1,roe} roe_{1,t} + \beta_{1,acc} acc_{1,t} + \beta_{1,turnover} turnover_{1,t} + \\
& \beta_{1,beta} beta_{1,t} + \beta_{1,ivol} ivol_{1,t} + u_{1,t} \\
& \vdots \\
r^i_{n,t+1} =& \alpha_n + \beta_{n,mom} mom_{n,t} + \beta_{n,bm} bm_{n,t} + \beta_{n,asset} asset_{n,t} \\
& + \beta_{n,roe} roe_{n,t} + \beta_{n,acc} acc_{n,t} + \beta_{n,turnover} turnover_{n,t} + \\
& \beta_{n,beta} beta_{n,t} + \beta_{n,ivol} ivol_{n,t} + u_{n,t}
\end{aligned}
\tag{17}
$$

Where:

- *mom* is price momentum
- *bm* is book-to-market ratio
- *asset* is asset-growth
- *roe* is return on equity
- *acc* is discretionary accruals

In the last regression, we took lagged overnight and intraday returns, their EWMA values, and lagged firm characteristics as independent variables, and the expected close-to-close, overnight, or intraday returns as dependent variables. This regression allows us to test hypothesis 7, which states the overnight and intraday portfolio returns, as well as their EWMA values, and different firm characteristics, have a predictive power of future returns.

$$
\begin{aligned}
r^i_{1,t+1} = {} & \alpha_1 + \beta_{1,ON} r_{ON,1,t} + \beta_{1,ID} r_{ID,1,t} + \beta_{1,EWMA\ ON} r_{EWMA\ ON,1,t} + \\
& \beta_{1,EWMA\ ID} r_{EWMA\ ID,1,t} + \beta_{1,mom} mom_{1,t} + \beta_{1,bm} bm_{1,t} + \beta_{1,asset} asset_{1,t} \\
& + \beta_{1,roe} roe_{1,t} + \beta_{1,acc} acc_{1,t} + \beta_{1,turnover} turnover_{1,t} \\
& + \beta_{1,beta} beta_{1,t} + \beta_{1,ivol} ivol_{1,t} + u_{1,t} \\
& \vdots \\
r^i_{n,t+1} = {} & \alpha_n + \beta_{n,ON} r_{ON,n,t} + \beta_{n,ID} r_{ID,n,t} + \beta_{n,EWMA\ ON} r_{EWMA\ ON,n,t} + \\
& \beta_{n,EWMA\ ID} r_{EWMA\ ID,n,t} + \beta_{n,mom} mom_{n,t} + \beta_{n,bm} bm_{n,t} + \beta_{n,asset} asset_{n,t} \\
& + \beta_{n,roe} roe_{n,t} + \beta_{n,acc} acc_{n,t} + \beta_{n,turnover} turnover_{n,t} \\
& + \beta_{n,beta} beta_{n,t} + \beta_{n,ivol} ivol_{n,t} + u_{n,t}
\end{aligned} \tag{18}
$$

To test if independent variables *jointly* have the power to predict future returns, we conducted a standard F-test as follows:

To test hypothesis 5 in case of estimating joint predictive power of variables:

1. We formulated the hypothesis as follows:

$$H_0 : \beta_{ON} = 0 \textit{ and } \beta_{ID} = 0 \textit{ and } \beta_{EWMA,ON} = 0 \textit{ and } \beta_{EWMA,ID} = 0$$

$$H_a : \beta_{ON} \neq 0 \textit{ or } \beta_{ID} \neq 0 \textit{ or } \beta_{EWMA,ON} \neq 0 \textit{ or } \beta_{EWMA,ID} \neq 0$$

2. We calculated an f-statistic robust for heteroscedasticity and autocorrelation in the error terms.

3. We calculated a critical value with 4 and 26403 degrees of freedom, and a significance level of 5%.

4. We reject the null hypothesis if the f-statistic is higher than the critical value.

To test hypothesis 6 in case of estimating joint predictive power of variables:

1. We formulated the hypothesis as follows:

$$
\begin{aligned}
H_0 : & \beta_{mom} = 0 \textit{ and } \beta_{bm} = 0 \textit{ and } \beta_{asset} = 0 \textit{ and } \beta_{roe} = 0 \textit{ and } \beta_{acc} = 0 \\
& \textit{and } \beta_{turnover} = 0 \textit{ and } \beta_{beta} = 0 \textit{ and } \beta_{ivol} = 0
\end{aligned}
$$

$$
\begin{aligned}
H_a : & \beta_{mom} \neq 0 \textit{ or } \beta_{bm} \neq 0 \textit{ or } \beta_{asset} \neq 0 \textit{ or } \beta_{roe} \neq 0 \textit{ or } \beta_{acc} \\
& \neq 0 \textit{ or } \beta_{turnover} \neq 0 \textit{ or } \beta_{beta} \neq 0 \textit{ or } \beta_{ivol} \neq 0
\end{aligned}
$$

2. We calculated an f-statistic robust for heteroscedasticity and autocorrelation in the error terms.

3. We calculated a critical value with 8 and 26403 degrees of freedom, and a significance level of 5%.

To test hypothesis 7 in case of estimating joint predictive power of variables:

1. We formulated the hypothesis as follows:

$$\begin{aligned}H_0 :&\beta_{ON} = 0 \; and \; \beta_{ID} = 0 \; and \; \beta_{EWMA\ ON} = 0 \; and \; \beta_{EWMA\ ID} = 0\\ &\beta_{mom} = 0 \; and \; \beta_{bm} = 0 \; and \; \beta_{asset} = 0 \; and \; \beta_{roe} = 0 \; and \; \beta_{acc} = 0\\ &and \; \beta_{turnover} = 0 \; and \; \beta_{beta} = 0 \; and \; \beta_{ivol} = 0\end{aligned}$$

$$\begin{aligned}H_a :&\beta_{ON} \neq 0 \; or \; \beta_{ID} \neq 0 \; or \; \beta_{EWMA,ON} \neq 0 \; or \; \beta_{EWMA,ID} \neq 0\\ &\beta_{mom} \neq 0 \; or \; \beta_{bm} \neq 0 \; or \; \beta_{asset} \neq 0 \; or \; \beta_{roe} \neq 0 \; or \; \beta_{acc}\\ &\neq 0 \; or \; \beta_{turnover} \neq 0 \; or \; \beta_{beta} \neq 0 \; or \; \beta_{ivol} \neq 0\end{aligned}$$

2. We calculated an f-statistic robust for heteroscedasticity and autocorrelation in the error terms.

3. We calculated a critical value with 12 and 26403 degrees of freedom, and a significance level of 5%.

Lastly, we calculated the root mean square error (RMSE). RMSE is a frequently used metric for quantifying the differences between the values predicted by a model or an estimator and the values that have been observed. This measure is widely regarded as a reliable indicator of precision.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Y_i - \widehat{Y_i}]^2} \tag{19}$$

6 Empirical results

6.1 Overnight versus intraday returns on the Oslo stock exchange

To test hypothesis 1, which states that overnight returns on the Oslo stock exchange are either equal to or lower than intraday returns, we analysed the value-weighted portfolio comprising 569 stocks on the exchange. The results in table 1 show the returns in excess of the risk-free rate and the systematic risk (CAPM alpha). Notably, the overnight returns of 1.42% and 1.01% are statistically significant at a 1% significance level, while their intraday counterparts of -0.55% and -1.53% are also statistically significant at 5%. Consequently, our findings suggest that overnight returns in the Norwegian stock market are higher than intraday returns, leading us to reject our initial hypothesis. We further provide results for the equally-weighted portfolio in appendix A1 as a robustness test, where we include raw returns, excess returns, CAPM-derived abnormal returns, and returns adjusted for the Fama-French three-factor model, both for the value-weighted and equally-weighted portfolios.

Table 1: Value-weighted portfolio overnight/intraday returns

The table reports the results for the value-weighted portfolio of 569 stocks from the Oslo stock exchange for the time period from 1993 to 2019. The portfolio is rebalanced every month. Overnight and intraday returns are reported in excess of the risk-free rate, and returns that are adjusted for the CAPM. T-statistics are reported in parentheses.

	Excess	CAPM
Overnight	1.4200%	1.0100%
	(8.021)	(6.244)
Intraday	-0.5496%	-1.5300%
	(-2.179)	(-9.818)
Close to close	0.8704%	-0.5300%
	(3.054)	(-11.021)

6.2 Possible explanations for the overnight anomaly

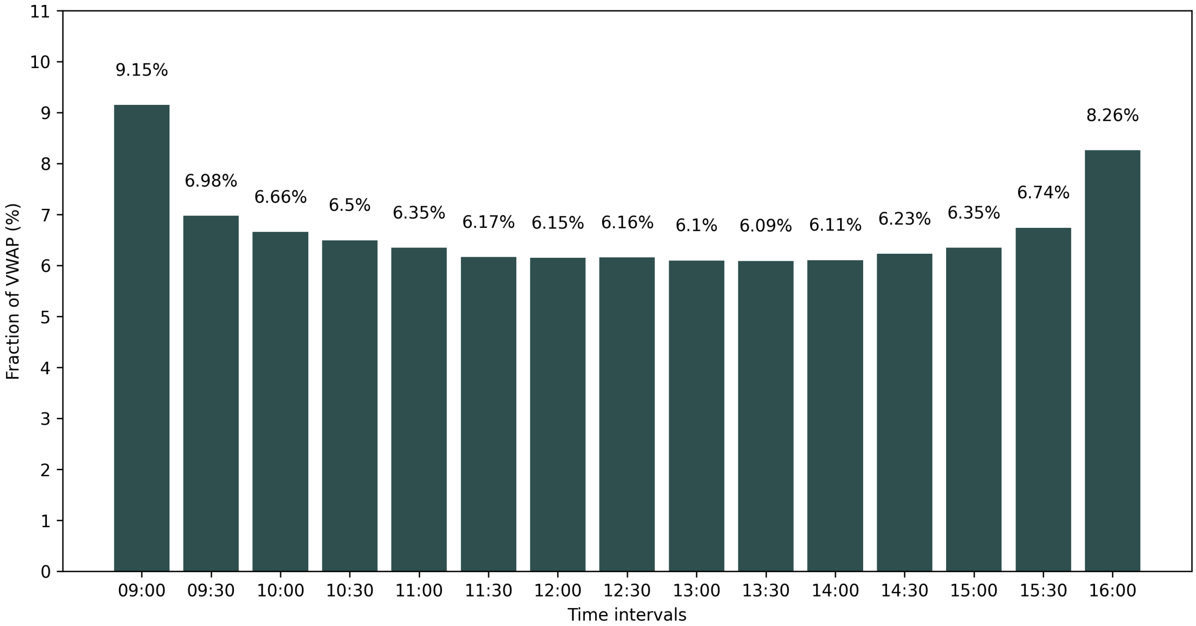
6.2.1 Half-hour windows

As one of the ways to explain the anomaly, we have calculated the fraction of VWAP for each half-hour window for the given time period in the Oslo stock exchange. Cliff et al. (2008) accounted for high overnight returns to the high prices at open. Hence, we wanted to test hypothesis 2, which states that prices during the first trading hour (first two windows), on average, are equal to or lower than the prices during the rest of the day.

First, from Fig1. we can see that VWAP at open, which includes an open auction, accounts for 9.15% of the total VWAP for the day. At close, including the auction at the close, they go up to

Figure 1: Half-hour windows

This figure shows the fraction of VWAP throughout the trading day in 30-minute intervals, for the period from February 9, 2009, 09:00:00 to April 21, 2023, 16:25:00. Initially, we sum up the VWAP in each half-hour window. We then compute the fraction of the VWAP that is attributed to every 30-minute interval with respect to the total daily VWAP (the sum over these 15 windows). In other words, the sum of these bars is equal to 1. The first and last half-hour windows include the open and the close auctions, respectively.



8.26%, which is still lower than at the first window.

To test the hypothesis, we conducted a difference in means test under the assumption of population variance being equal but unknown, and we obtained the t-statistic of 3.012, which is higher than the critical value even at a 1% significance level (2.326). Hence, we reject the null hypothesis and conclude that prices during the first trading hour, on average, are higher than the prices during the rest of the day. Therefore, we can conclude that prices at open are higher than prices during the rest of the day, which would yield high overnight returns, and this result is aligned with the findings of Cliff et al. (2008).

6.2.2 Market microstructure effects

Inspired by Lachance (2021), our study proposes an alternative explanation for the observed anomaly. We employ a methodology to decompose overnight returns into two distinct components: one that captures changes in overnight midpoint quotes, while the other accounts for the remaining market microstructure effects. This methodology allows us to test hypothesis 3 which states that high overnight returns are due to the overnight changes in the midpoint quote.

We reported the results in Table 2 above. The results show that the overnight return component that captures the remaining market microstructure effects is 0.0022% but insignificant, and its standard deviation is 2.4356%. In contrast, the overnight return component that captures

Table 2: Decomposition of overnight returns

The overnight returns (R^O) are decomposed into a component representing the change in the midpoint quote ($R^{O,Mid}$) and a component representing market microstructure effects ($R^{O,MM}$). The component representing market microstructure effects ($R^{O,MM}$) is then decomposed into order imbalances and effective half-spread components. We used TAQ data for 36 stocks from the OSEBX index for the time period of January 2, 2023, to May 14, 2023.

	Overnight Returns			OI		ES	
	R^O	$R^{O,Mid}$	$R^{O,MM}$	Open	Close	Open	Close
Mean	0.0557%	0.0457%	0.0022%	-3.2009%	1.6452%	0.5244%	0.1775%
	(1.329)	(5.884)	(0.049)				
Std	2.2735%	0.4213%	2.4356%			0.4815%	0.3042%
5th	-3.4940%	-3.4752%	-0.2965%			0.0305%	0.0219%
95th	3.6754%	3.6366%	0.3080%			1.6548%	0.5223%

changes in the midpoint quote is reported to be 0.0457%, which is higher in value, highly significant, and less risky, with a standard deviation equal to 0.4213%. Therefore, we fail to reject the hypothesis that states that high overnight returns are due to the overnight changes in the midpoint quote. In other words, the overnight changes in the midpoint quotes can indeed explain higher overnight returns in the Norwegian stock market. We assume this might be due to different corporate events or news announcements that usually occur after the market closes, but this is a question for further investigation.

We also reported the sources of the market microstructure effects: order imbalances and effective half-spread. The effective half-spread value at open is 0.5244%, while at close, it is equal to 0.1775%. The spread is wider at open and has a higher volatility of 0.4815% compared to 0.3042% at the close. The results of the order imbalances show a different pattern: at open, we obtained a negative number of -3.2009% and a positive number at the close of 1.6452%. This result contributes to the overnight return component that captures the market microstructure effects being lower than the component capturing the overnight change in the midpoint quote. The market microstructure effects for all the individual stocks in our sample can be found in appendix A3.

Moreover, it suggests that the number of selling orders at the open is higher than the number of buying orders, meaning there is a selling pressure at the market open than at the close. This would result in lower prices at the open, which contradicts the findings we obtained in the analysis of half-hour windows that suggest that prices at open are high. Therefore, we suggest studying order imbalances in a bigger sample in further studies.

Table 3: Overnight/intraday return persistence/reversal

The table presents findings on overnight and intraday return patterns in terms of persistence and reversal. Panel A categorizes stocks into deciles based on their lagged one-month overnight returns, while Panel B categorizes stocks based on their lagged one-month intraday returns. We then implement a long-short strategy by taking a long position in the value-weighted winner decile and a short position in the value-weighted loser decile. We report monthly portfolio returns adjusted for CAPM and a three-factor model. The t-statistics are shown in parentheses and based on standard errors corrected for serial dependence with 12 lags. The sample period is from 1993 to 2019.

Panel A: Portfolio sorted by one-month overnight returns

	Overnight		Intraday	
Decile	CAPM	3-Factor	CAPM	3-Factor
1	-1.8171%	-2.0254%	2.9267%	2.8778%
	(-5.327)	(-6.189)	(6.862)	(6.078)
10	4.6395%	4.4850%	-4.6446%	-4.7102%
	(6.466)	(6.135)	(-7.841)	(-7.946)
LS	6.1438%	6.1981%	-7.8841%	-7.9003%
	(8.615)	(8.549)	(-11.488)	(-10.885)

Panel B: Portfolio sorted by one-month intraday returns

	Overnight		Intraday	
Decile	CAPM	3-Factor	CAPM	3-Factor
1	5.7683%	5.5172%	-5.6752%	-5.8330%
	(6.096)	(5.946)	(-8.859)	(-9.239)
10	-1.2067%	-1.6124%	2.4653%	2.4150%
	(-4.413)	(-6.003)	(4.955)	(5.287)
LS	-7.2858%	-7.4397%	7.8297%	7.9379%
	(-8.511)	(-8.570)	(9.502)	(9.898)

6.3 Persistence and reversal pattern

One of Lou et al. (2019) main arguments is that investors exhibit varying preferences regarding their trading activity. While some prefer intensive trading during market open, others prefer to trade during market close. The authors propose that if there is persistent firm-specific order flow associated with this clientele, one would expect to observe persistence in both overnight and intraday returns and a reversal effect across different periods. To analyse the presence of intraday and overnight clientele, we decomposed past returns into their overnight and intraday components and looked for the persistence and reversal patterns within our sample.

To conduct our analysis, we sorted all stocks into deciles based on their lagged one-month overnight returns (Panel A) and based on their lagged one-month intraday returns (Panel B). In each case, we took a long position in the value-weighted winner decile and a short position in the value-weighted loser decile. We reported returns adjusted for the CAPM and for the Fama-French three-factor model.

From Table 3, it can be found that the results we obtained show very strong persistence and reversal patterns. The long-short portfolio of stocks sorted based on lagged one-month overnight returns earns an average overnight return adjusted for CAPM of 6.1438% with an associated t-statistic of 8.615. The results do not change even after adjusting for the risks associated with the size and value of the firms as three-factor alpha is equal to 6.1981% per month with an associated t-statistic of 8.549. These results are indicators of strong persistence in the firm-specific order flow. Our findings also showed a strong reversal pattern as a hedge portfolio of the stocks sorted based on lagged one-month overnight returns earns an average intraday monthly return adjusted for CAPM of -7.8841% (t-statistic of -11.488) and alpha of three-factor model of -7.9003% (t-statistic of -10.885).

The results are persistent independently of the components of the close-to-close returns. In Panel B, we reported the returns of the long-short portfolio of stocks that are sorted based on the lagged one-month intraday returns. We found negative and statistically significant overnight returns that are adjusted for CAPM and three-factor model of -7.2858% and -7.4397% with associated t-statistic of -8.511 and -8.570, respectively. These findings are followed by positive and statistically significant intraday returns adjusted for CAPM and the three-factor model of 7.8297% and 7.9379% with associated t-statistic of 9.502 and 9.898, respectively. Therefore, as we found strong results for persistence and reversal patterns of returns in the Norwegian stock market, we can conclude that investors in Norway have distinct preferences that are shown by firm-specific demands in different periods of the day.

6.4 Trading strategies

The previous results suggested the existence of persistence and reversal patterns among investors in the Oslo stock exchange. We further investigated the importance of different investor clientele in the given market on popular trading strategies: size, value, price momentum, industry momentum, short-term reversal, profitability, turnover, asset growth, beta, idiosyncratic volatility, and discretionary accruals.

Table 4: Overnight/intraday return decomposition

This table reports returns to the Oslo stock exchange and various cross-sectional strategies during the day versus at night. In the left column of the first row, we report the overnight/intraday returns of the value-weighted OSE. For the rest of the table, we report returns of long-short portfolios where we take a long position in one extreme value-weighted decile(quintile) and a short position in the other value-weighted decile(quintile) based on a particular firm/industry-specific characteristic.

In the right column of row 1, at the end of each month, all stocks are sorted into deciles based on the prior month's market capitalisation. In row 2, stocks are sorted into decile portfolios based on lagged book-to-market ratio and lagged 12-month cumulative returns (skipping the most recent month), respectively. In row 3, all industries are sorted into quintiles based on lagged 12-month cumulative industry returns, and stocks are sorted into deciles based on lagged one-month returns, respectively. In row 4, stocks are sorted into deciles based on lagged return on equity and lagged 12-month share turnover, respectively. In row 5, stocks are sorted based on lagged asset growth and lagged 12-month market betas (using daily returns with three lags and summing coefficients), respectively. In row 6, stocks are sorted into deciles based on lagged 12-month daily idiosyncratic volatilities (with respect to the Carhart four-factor model) and lagged discretionary accruals, respectively.

The cross-sectional strategies are structured to have positive average returns based on findings in previous research. Hence, we take a long position in small-cap stocks, value stocks, past one-year winners, past one-month industry winners, low past one-month losers, stocks with high profitability, stocks with low turnover, low asset growth stocks, low beta stocks, low idiosyncratic volatility stocks, and low accruals stocks. We report CAPM-adjusted returns with associated t-statistics in parentheses. The sample period is from 1993 to 2019. Extended results can be found in appendix A4.

	Overnight	Intraday		Overnight	Intraday
OSE	1.0100%	-1.5300%	SIZE	2.0500%	5.3600%
	(6.244)	(-9.818)		(3.943)	(15.290)
BM	0.2200%	-0.6000%	MOM	-1.3600%	4.7600%
	(0.612)	(-1.177)		(-2.864)	(8.167)
INDMOM	-0.9300%	0.1400%	STR	1.4200%	-3.8700%
	(-3.135)	(0.344)		(3.054)	(-7.938)
ROE	-2.6600%	3.2700%	TURNOVER	-2.3500%	3.0100%
	(-6.756)	(6.674)		(-6.540)	(7.421)
AG	-0.9800%	0.7200%	BETA	-2.4100%	4.5300%
	(-2.828)	(1.527)		(-6.717)	(10.271)
IVOL	-2.1200%	0.2400%	ACCRUALS	-0.0500%	-1.1200%
	(-5.103)	(0.404)		(-0.149)	(-2.368)

6.4.1 *Size and value*

In line with the methodology introduced by Fama and French (1992), we analysed investment strategies structured to capture the average returns associated with the size and value factors.

In our analysis, we initially examined a strategy that involved taking a long position in the small-stock decile and a short position in the big-stock decile. According to the findings presented in Table 4, we observed that this size-based strategy generated its premium primarily during intraday trading. Specifically, the overnight CAPM alpha was measured at 2.05% and is statistically significant (t-statistic of 3.943), while the intraday CAPM alpha is positive and significant at 5.36% (t-statistic of 15.290).

Subsequently, we analysed the intraday and overnight returns of a hedged value-weighted portfolio constructed based on the book-to-market ratio. This strategy entailed taking a long position in value stocks and a short position in growth stocks. The results indicated that the portfolio achieved its premium predominantly during the overnight period. Specifically, the overnight CAPM alpha is 0.22% (t-statistic of 0.612), while the intraday CAPM alpha is -0.60% (t-statistic of -1.177), and none of them is statistically significant.

6.4.2 *Price momentum and industry momentum*

In line with the approach proposed by Jegadeesh and Titman (1993), we implemented a classic momentum strategy by measuring the momentum effect over an 11-month ranking period, skipping the most recent month, and holding positions for another one month. This involved taking a long position in past one-year winners and a short position in past one-year losers. Our findings indicate that the value-weighted long-short portfolio, sorted based on the momentum effect, generated its premium predominantly during intraday trading. To be more specific, the overnight CAPM alpha was measured at -1.36%, while the intraday CAPM alpha stood at 4.76%, and both results are statistically significant with associated t-statistics of -2.864 and 8.167, respectively.

Following the methodology introduced by Moskowitz and Grinblatt (1999) to evaluate industry momentum, we employed a 12-month ranking period for nine distinct industries based on Bloomberg Industry Classification System (BICS) codes. Similarly, we observed that the value-weighted long-short portfolio, sorted based on the industry momentum effect, achieved its premium primarily during intraday trading. More precisely, the overnight CAPM alpha being statistically significant (t-statistic of -3.135) amounted to -0.93%, while the intraday CAPM alpha is positive and insignificant at 0.14% (t-statistic of 0.344).

6.4.3 Short-term reversal and profitability

According to the findings by Jegadeesh (1990), there is evidence of profitability in selling short-term winners and buying short-term losers. In line with this, we constructed a value-weighted long-short portfolio based on lagged one-month returns and determined that it primarily achieved its premium during the overnight period. Specifically, the overnight CAPM alpha was measured at 1.42%, and it is statistically significant (t-statistic of 3.054), while the intraday CAPM alpha is also statistically significant(t-statistic of -7.938) and stood at -3.87%.

Haugen and Baker (1996) further demonstrated that firms with higher profitability tend to generate higher expected returns. By employing return on equity as a measure of profitability, we constructed a value-weighted portfolio that sorted stocks based on lagged return on equity ratios. Subsequently, a long position was taken in the decile of stocks with high profitability, while a short position was taken in the decile with low profitability. Hence, we found that the strategy sorted based on the lagged profitability indicators generated its abnormal return primarily during the day. Specifically, the overnight CAPM alpha being negative and significant is equal to -2.66% (t-statistic of -6.756), and intraday CAPM alpha is 3.27%, which is positive and also statistically significant (t-statistic of 6.674).

6.4.4 Turnover and asset growth

Following Lee and Swaminathan (2000), we computed the turnover ratio and sorted stocks into deciles based on the lagged values of this ratio. Subsequently, we constructed a value-weighted portfolio by taking a long position in a decile with a low lagged turnover ratio and a short position in a decile with a high lagged turnover ratio. The results suggest that a value-weighted hedge portfolio sorted based on the lagged turnover ratio earned its premium primarily intraday. To be more precise, the overnight CAPM alpha is negative and significant at -2.35% (t-statistic of -6.540), and the intraday CAPM alpha is positive and also significant at 3.01% (t-statistic of 7.421).

To implement the asset growth strategy, we calculated the percentage change in total assets and sorted stocks into deciles based on the lagged asset growth. Drawing from the conclusions of Titman et al. (2004), which revealed a negative relationship between investment and stock returns, we took a long position in the decile with low asset growth and a short position in the opposite decile, constructing a value-weighted portfolio. The results we obtained suggests that the asset growth strategy achieved its abnormal return mostly during daytime trading. Specifically, the overnight CAPM alpha is negative and significant at -0.98% (t-statistic of -2.828), and the intraday CAPM alpha is positive but insignificant at 0.72% (t-statistic of 1.527).

6.4.5 *Beta and idiosyncratic volatility*

In line with the approach introduced by Dimson (1979), we calculated the beta values for each stock, considering three lags, and sorted the stocks based on the lagged sum of these values. We then constructed a value-weighted portfolio by taking a long position in the decile comprising stocks with low beta and a short position in the decile with high beta. The results suggest that the beta strategy earned its premium primarily intraday. Specifically, the overnight return exhibited a negative and statistically significant value of -2.41% (t-statistic of -6.717), while the intraday return displayed a positive and statistically significant value of 4.53% (t-statistic of 10.271).

To implement the idiosyncratic volatility strategy, we computed the volatility of residuals for each stock by regressing the stock's excess returns on the Fama-French 4-factor model. Subsequently, we sorted stocks into deciles based on the lagged volatility values and constructed a value-weighted portfolio, taking a long position in the decile with low volatility and a short position in the decile with high volatility. The results suggest that the idiosyncratic volatility strategy primarily generated its premium during daytime trading. Specifically, the overnight CAPM alpha is negative and significant at -2.12% (t-statistic of -5.103), while the intraday CAPM alpha is positive and significant at 0.24% (t-statistic of 0.404).

6.4.6 *Discretionary accruals*

Following the methodology outlined by Sloan (1996), we computed the accruals factor to conduct a strategy based on discretionary accruals. Stocks were then sorted into deciles according to their calculated accruals factors, and a value-weighted portfolio was constructed by taking a long position in stocks with low accruals and a short position in stocks with high accruals. Our findings suggest that the discretionary accruals strategy primarily earned its premium during the overnight period. Specifically, the overnight CAPM alpha was determined to be -0.05% (t-statistic of -0.149), while the intraday CAPM alpha amounted to -1.12% (t-statistic of -2.368).

Overall, after looking at the results of each strategy, we reject hypothesis 4 of our thesis, which states that 11 distinct long-short strategies generate their premia overnight. Specifically, only three (value, short-term reversal, and discretionary accruals) strategies earn their premia overnight in the Oslo stock exchange, while the remaining eight (size, price momentum, industry momentum, profitability, turnover, asset growth, beta, and idiosyncratic volatility) earn their premia primarily intraday. Our results align with the results of Lou et al. (2019) in the sense that most of the strategies generate their abnormal returns during the day, but only the short-term reversal strategy generates its premium at the same period of the day as they reported. Our findings contradict the results of other papers, such as Lachance (2021) and Kelly and Clark (2011), which suggested that the anomaly of high overnight returns might be exploited in the trading strategies. This contradiction might come from the difference in samples under investigation. While Lachance (2021) and Kelly and Clark (2011) work on ETFs in the USA market, our sample considers equities from the Norwegian stock market.

6.5 Fama-MacBeth regressions

As an alternative way to exploit the anomaly of overnight returns being higher than its intraday components and of the tug of war, we implemented Fama-MacBeth regressions and investigated how well the lagged overnight/intraday returns and different firm characteristics predict future returns. Fama-MacBeth regressions, compared to the cross-sectional analysis, allow us to measure the partial effects of many variables simultaneously.

6.5.1 Predictive power of portfolio returns

Table 5: Fama-MacBeth regressions — hypothesis 5

The table reports results for three regressions. In regression (1) close-to-close returns are taken as a dependent variable, and one-month lagged overnight returns, one-month lagged intraday returns, one-month lagged EWMA of overnight returns, and one-month lagged EWMA of intraday returns are considered as independent variables. In regressions (2) and (3) dependent variables are overnight and intraday returns, respectively. 569 stocks from Oslo stock exchange are considered as a sample, with a period from 1993 to 2019. T-statistics are reported in parentheses.

	Close-to-close (1)	Overnight (2)	Intraday (3)
ON	0.0780	0.1006	-0.0651
	3.614)	(5.332)	(-1.297)
ID	0.0957	-0.0661	0.1509
	(5.129)	(-3.508)	(7.451)
EWMA_ON	0.2810	0.3847	-0.0944
	(3.854)	(6.661)	(-2.040)
EWMA_ID	0.2395	-0.0870	0.3969
	(3.940)	(-1.487)	(8.863)
No, observations	26415	26415	26415
RMSE	0.18256	0.17678	0.17337
Critical value	2.3723	2.3723	2.3723
F-statistic	15.9606	103.8562	89.4678

We initially developed hypothesis 5, which suggested that both overnight and intraday portfolio returns, in addition to their Exponentially Weighted Moving Average (EWMA) values, have the power to predict future returns. However, we expanded the hypothesis in two ways. First, we categorized the returns into three types: close-to-close, overnight, and intraday returns. Second, we explored whether the independent variables, *individually* or *jointly*, could predict future returns. As a result, we expanded hypothesis 5 into six different tests. The revised hypothesis is as follows: Overnight and intraday portfolio returns, along with their EWMA values, can *individually* or *jointly* predict future close-to-close returns, future overnight returns, or future intraday returns.

To test hypothesis 5, we used Fama-MacBeth regression, first, taking close-to-close return (1) as the dependent variable and one-month lagged overnight and intraday returns, as well as one-month lagged EWMA values of both overnight and intraday returns as independent variables. We then repeated the process taking overnight (2) and intraday (3) returns as the dependent variables independently.

We first started to test the hypothesis that states the overnight and intraday portfolio returns, along with their EWMA values, can *individually* predict future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

The results of regression (1), which estimates expected close-to-close returns, suggest that all four independent variables particularly lagged overnight/intraday returns and lagged EWMA of overnight/intraday returns, *individually* have positive and statistically significant predictive power. The same explanatory variables in regression (2), which predict future overnight returns, gave results consistent with persistence and reversal. Notably, lagged overnight returns and lagged EWMA of the overnight returns *individually* have positive and statistically significant predictive power, whereas lagged intraday returns and lagged EWMA of the intraday returns *individually* have negative predictive power, and only the lagged EWMA of the intraday returns coefficient is statistically insignificant. Regression (3), which predicts future intraday returns, reported results that are also consistent with the existence of the tug of war. Specifically, lagged overnight returns and lagged EWMA of the overnight returns *individually* have negative predictive power, but only the latter is statistically significant, while lagged intraday returns and lagged EWMA of the intraday returns *individually* have positive and statistically significant predictive power.

Overall, we fail to reject our hypotheses that say that the overnight and intraday portfolio returns, as well as their EWMA values, *individually* have the power to predict future close-to-close returns, future overnight returns, or future intraday returns.

Further, we test the hypothesis that states the overnight and intraday portfolio returns, along with their EWMA values, can *jointly* predict future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

In order to evaluate the credibility of our hypotheses, we used the standard F-test, adjusting the F-statistic to consider heteroscedasticity and autocorrelation in the error terms. The results we obtained showed that we had to reject the null hypothesis, which states that all explanatory variables are *jointly* equal to zero in all three regressions. As a result, we failed to reject the hypothesis suggesting that overnight and intraday portfolio returns, along with their EWMA values, can *jointly* predict future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

6.5.2 Predictive power of firm characteristics

Table 6: Fama-MacBeth regressions— hypothesis 6

The table reports results for three regressions. In regression (1) close-to-close returns for the following month are taken as a dependent variable, and eight raw value-weighted firm characteristics, which are momentum, value, idiosyncratic volatility, beta, turnover, return on equity, asset growth, and discretionary accruals, are taken as independent variables. In regressions (2) and (3) dependent variables are overnight and intraday returns for the following month, respectively. 569 stocks from Oslo stock exchange are considered as a sample, with a time period from 1993 to 2019. T-statistics are reported in parentheses.

	Close-to-close (1)	Overnight (2)	Intraday (3)
mom	2.4207	-0.0380	2.3520
	(5.431)	(-0.075)	(4.633)
bm	0.5091	0.0299	0.5201
	(2.248)	(0.113)	(1.724)
ivol	56.5130	118.7500	-27.7020
	(1.832)	(3.370)	(-0.937)
beta	-1.4603	-1.0732	-0.6139
	(-3.591)	(-2.275)	(-1.894)
turnover	-111.6200	-40.7980	-94.6610
	(-1.194)	(-0.409)	(-2.468)
roe	-0.0056	-0.0489	0.0344
	(-0.447)	(-2.238)	(3.144)
asset growth	5.4207	6.9735	-1.0920
	(1.124)	(1.203)	(-1.426)
accruals	0.5593	3.6515	-2.7936
	(0.374)	(2.477)	(-2.194)
No, observations	26415	26415	26415
RMSE	0.25844	0.29912	0.18858
Critical value	1.9388	1.9388	1.9388
F-statistic	6.8828	14.0677	9.9969

We initially formulated hypothesis 6, which proposed that different firm characteristics have a predictive power of future returns. Nevertheless, we enhanced the hypothesis in two ways. We first divided the returns into three categories: close-to-close, overnight, and intraday returns.

We further investigated whether the independent variables, *individually* or *jointly*, could predict future returns. Therefore, we broadened hypothesis 6 into six distinct tests. The updated hypothesis is as follows: Different firm characteristics, *individually* or *jointly*, have a predictive power of the future close-to-close returns, future overnight returns, or future intraday returns.

In order to test the hypothesis, we applied Fama-MacBeth regression. Initially, we took close-to-close returns (1) as the dependent variable and eight raw value-weighted firm characteristics, that are momentum, value, idiosyncratic volatility, beta, turnover, return on equity, asset growth, and discretionary accruals, as independent variables. We then repeated the process by taking overnight (2) and intraday (3) returns as the explanatory variables independently.

We first started to test the hypothesis that states different firm characteristics *individually* have a predictive power of the future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

The results for regression (1), which estimates expected close-to-close returns, suggest that among all listed firm characteristics, only momentum, value, and beta have individual predictive power as these are the only variables that are statistically significant. Particularly, momentum has a positive coefficient of 2.4207 along with a book-to-market ratio that is 0.5091, whereas beta has a negative coefficient of -1.4603 and it is consistent with the argument that high beta stocks generate low returns found in the previous research. [4]

Regression (2) results suggest that idiosyncratic volatility, beta, return on equity, and discretionary accruals *individually* have a predictive power of future overnight returns. Idiosyncratic volatility has a positive and very large coefficient of 118.7500, along with discretionary accruals that are also positive predictors of future overnight returns (coefficient of 3.6515). Whereas beta and return on equity are negative predictors with coefficients of -1.0732 and -0.0489, respectively. However, all the results we reported, except for the beta, contradict the findings from the previous papers that discussed the relationship between the particular firm characteristic and the stock returns. Particularly, Ang et al. (2006) argued that stocks with high idiosyncratic volatility have abnormally low returns, Haugen and Baker (1996) concluded that firms with greater profitability are more likely to generate higher expected returns and Sloan (1996) acknowledged the negative relationship between the discretionary accruals and following stock returns.

Regression (3) results suggest that momentum, turnover, return on equity, and discretionary accruals *individually* have a predictive power of future intraday returns. Momentum effect has a positive coefficient of 2.3520 along with the return on equity, which obtained a coefficient of 0.0344, whereas turnover reported a negative and very large result of -94.6610 along with the discretionary accruals that obtained a negative result of -2.7936. All the results align with the

[4]"The Cross-Section of Expected Stock Returns" by Fama and French (1992)

previous paper's findings that discussed the relationship between the firm characteristics and the stock returns.

Overall, we fail to reject the hypotheses that state that different firm characteristics *individually* have a predictive power of future close-to-close returns, future overnight returns, or future intraday returns.

Further, we test the hypotheses that state the different firm characteristics *jointly* have a predictive power of the future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

We utilized the standard F-test to test our hypotheses, adjusting the F-statistic for heteroscedasticity and autocorrelation in the error terms. The results of our analysis led us to reject the null hypothesis, which stated that all explanatory variables are *jointly* equal to zero in all three regressions. Consequently, we failed to reject the hypothesis suggesting that the different firm characteristics *jointly* have a predictive power of the future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

6.5.3 Combined predictive power of portfolio returns and firm characteristics

The last hypothesis formulated suggested that overnight and intraday portfolio returns, as well as their EWMA values and different firm characteristics, have a predictive power of future returns. As implemented previously, we expanded it in two dimensions as well: first, in terms of returns, second, in terms of individual or joint predictive power. Thus, the ultimate version of hypothesis 7 is as follows: Overnight and intraday portfolio returns, as well as their EWMA values and different firm characteristics, *individually* or *jointly* have a predictive power of the future close-to-close returns, future overnight returns, or future intraday returns.

To test this hypothesis, we applied the Fama-MacBeth regression. We took close-to-close return (1), as the dependent variable and one-month lagged overnight and intraday returns, as well as one-month lagged EWMA values of both overnight and intraday returns and eight raw value-weighted firm characteristics listed in the previous section as independent variables. We then repeated the process taking overnight (2) and intraday (3) returns as the dependent variables independently.

We first started to test the hypothesis that states overnight and intraday portfolio returns, as well as their EWMA values and different firm characteristics, *individually* have a predictive power of the future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

The results of regression (1), which estimates expected close-to-close returns, suggest that

Table 7: Fama-MacBeth regressions — hypothesis 7

The table reports results for three regressions. In regression (1) close-to-close returns for the following month are taken as a dependent variable, and overnight returns, intraday returns, EWMA of overnight returns, and EWMA of intraday returns along with eight raw value-weighted firm characteristics, that are momentum, value, idiosyncratic volatility, beta, turnover, return on equity, asset growth, and discretionary accruals, are considered as independent variables. In regressions (2) and (3) dependent variables are overnight and intraday returns for the following month, respectively. 569 stocks from Oslo stock exchange are considered as a sample, with a time period from 1993 to 2019. T-statistics are reported in parentheses.

	Close-to-close (1)	Overnight (2)	Intraday (3)
ON	0.0590	0.1051	-0.0933
	(2.872)	(5.738)	(-1.773)
ID	0.0800	-0.0720	0.1397
	(5.116)	(-4.082)	(6.621)
EWMA_ON	0.2645	0.3811	-0.0674
	(4.112)	(6.027)	(-1.641)
EWMA_ID	0.3327	-0.0661	0.4258
	(5.538)	(-1.159)	(9.608)
mom	1.3450	0.5238	0.7481
	(3.003)	(1.215)	(2.550)
bm	0.2879	0.1804	0.0788
	(1.147)	(1.371)	(0.300)
ivol	19.2280	36.6030	-11.8440
	(0.899)	(1.941)	(-0.621)
beta	-0.7299	-0.6961	0.0652
	(-1.952)	(-1.752)	(0.293)
turnover	-7.2259	-9.2531	-7.3100
	(-0.251)	(-0.233)	(-0.149)
roe	0.0084	-0.0149	0.0199
	(1.415)	(-1.336)	(1.376)
asset growth	0.7704	3.5429	-3.1588
	(0.962)	(1.096)	(-1.235)
accruals	-1.6231	1.1505	-3.2040
	(-1.785)	(1.550)	(-2.983)
No, observations	26415	26415	26415
RMSE	0.18609	0.21192	0.20095
Critical value	1.7525	1.7525	1.7525
F-statistic	15.3656	61.6417	90.9107

lagged overnight returns and intraday returns, along with their lagged EWMA values and momentum effect *individually*, have predictive power. The results are consistent with our results for hypothesis 5, where all lagged returns had positive and significant coefficients. The momentum effect has positive and significant predictive power with a coefficient of 1.3450 and a t-statistic of 3.003. Our results are aligned with the findings of Jegadeesh and Titman (1993) that concluded that past returns have some explanatory power for future returns, and it is explained by the systematic risk or by the delayed stock price reactions to the common factors.

The results we obtained for regression (2) show that lagged overnight and lagged intraday returns, along with the lagged EWMA of the overnight returns *individually*, have a predictive power of future overnight returns. As lagged overnight returns reported a positive and significant coefficient of 0.1051 (t-statistic of 5.738), while lagged intraday returns reported a negative and significant coefficient of -0.0720 (t-statistic of -4.082), we can notice the pattern of persistence and reversal in the cross-sectional overnight and intraday returns. A positive and significant coefficient of 0.3811 (t-statistic of 6.027) for EWMA of overnight returns is the additional support to our finding of the tug of war in the given sample.

Regression (3) results suggest that lagged intraday and lagged EWMA of the intraday returns, along with the momentum and discretionary accruals *individually*, have a predictive power of future intraday returns. Even though lagged overnight returns and lagged EWMA of the overnight returns have insignificant coefficients, they are still negative. Said differently, we still have evidence for the pattern of persistence and reversal in the cross-sectional overnight and intraday returns. Moreover, we have positive and significant coefficients of 0.7481 (t-statistic of 2.550) and -3.2040 (t-statistic of -2.983) for momentum and discretionary accruals, respectively. These results are aligned with the findings of previous research [5] that stated that winners will be performing well in the upcoming time period and discretionary accruals have a negative relationship with the stock returns for the following periods (Sloan (1996)).

Overall, we fail to reject the hypotheses that state that overnight and intraday portfolio returns, as well as their EWMA values, and different firm characteristics *individually* have a predictive power of the future close-to-close returns (1), future overnight returns (2), or future intraday returns (3).

Further, we test the hypotheses that state that overnight and intraday portfolio returns, as well as their EWMA values, and different firm characteristics *jointly* have a predictive power of the future close-to-close returns (1), future overnight returns (2), and future intraday returns (3).

To test it, we followed the methodology used previously in terms of standard F-test with modification for the heteroscedasticity and autocorrelation in the error terms. As critical values

[5]"The Cross-Section of Expected Stock Returns" by Fama and French (1992)

obtained for 26403 and 12 degrees of freedom, is less than the F-statistic we obtained for regression (1) which is 15.3656, for regression (2) which is 61.6417 and for regression (3) which is 90.9107, we reject the hypothesis of junk test that states that all explanatory variables *jointly* are equal to zero. Therefore, we fail to reject the hypotheses that state that overnight and intraday portfolio returns, as well as their EWMA values, and different firm characteristics *jointly* have a predictive power of the future close-to-close returns (1), future overnight returns (2), or future intraday returns (3). Meaning, even though *individually* most of the independent variables do not have predictive power in all three regressions, *jointly* they all have predictive power in all three regressions.

6.5.4 Goodness of fit

Finally, we wanted to check how well these regressions performed in estimating expected returns and calculated root mean squared errors. We then checked vertically, comparing how well three regressions differentiated in terms of the set of dependent variables performed in predicting future close-to-close returns. The first regression took one month lagged overnight and intraday returns and one-month lagged EWMA values of both overnight and intraday returns as explanatory variables. The second one considered eight raw value-weighted firm characteristics as the independent variables. The last regression put one-month lagged overnight and intraday returns, as well as one-month lagged EWMA values of both overnight and intraday returns and eight raw value-weighted firm characteristics as explanatory variables. We then compared these regressions to estimate expected overnight returns and intraday returns independently.

Comparing the RMSE across different regressions, we found that lagged overnight and intraday returns and their lagged EWMA values performed the best in predicting future close-to-close, intraday, and overnight returns. These results were expected, according to Jegadeesh and Titman (1993). The regression that took one-month lagged overnight and intraday returns, as well as one-month lagged EWMA values of both overnight and intraday returns, and eight raw value-weighted firm characteristics as explanatory variables performed better than the regression that put only eight value-weighted firm characteristics as independent variables in predicting future close-to-close and overnight returns, but worse in predicting future intraday returns.

7 Conclusion

This research has confirmed the existence of the overnight return anomaly in the Oslo stock exchange, in which positive overnight returns are observed with a CAPM alpha of 1.01% (t-statistic of 6.244), in contrast to negative intraday returns with a CAPM alpha of -1.53% (t-statistic of -9.818). This finding is consistent with the research conducted by Cliff et al. (2008), which indicates that the primary source of the total equity premium in the US stock market is generated overnight. Similarly, our study demonstrates that the entire premium on the Oslo stock exchange is achieved overnight. To ensure the robustness of these findings, we conducted a check using equally weighted portfolios, which yielded similar results, further confirming that overnight returns are consistently higher than intraday returns.

To explain this anomaly we found higher prices at market open compared to market close. Dividing the trading day into 15 half-hour windows revealed that the fraction of volume-weighted average price (VWAP) was highest (9.15%) at market open and lowest (8.26%) at market close. This finding is aligned with the results of Cliff et al. (2008) and suggests that the higher overnight returns are largely due to higher prices at open.

Upon conducting a more thorough investigation into the origin of the anomaly, we proceeded to analyse the impact of market microstructure effects and the fluctuations in midpoint quotes during overnight trading, as suggested by Lachance (2021) work. We observed that higher overnight returns were primarily driven by overnight midpoint quotes, which had a significant mean value of 0.0457% (t-statistic of 5.884). This result might be due to various corporate events or news announcements that mostly take place after the market close, but we would recommend investigating it in further research. We also found that market microstructure effects had a minimal impact of 0.0022% and lacked statistical significance. Our findings revealed a noteworthy inconsistency concerning order imbalances at the open and close of the market, which contradicted the observations we made regarding the VWAP. In the analysis of half-hour windows, we found that order imbalances at open are negative compared to close, meaning that the theoretical price at open should be lower than the price at close, due to higher selling pressure. We also recommend further research on this topic.

Lou et al. (2019) have suggested that the persistence and reversal pattern of stock returns can be attributed to the distinct trading preferences of investors. We aimed to examine this phenomenon and found noticeable persistence and reversal patterns in the Norwegian stock market, indicating the presence of visible trading preferences among investors during different periods of the day.

We also assessed 11 different trading strategies to exploit the identified overnight return anomaly. Out of these, three strategies - value, short-term reversal, and discretionary accruals strategy - yielded their premia overnight, while the remaining strategies generated their abnormal returns intraday. The results of this study are generally consistent with the findings of Lou et al. (2019), but differ from those of Lachance (2021) and Kelly and Clark (2011), who suggested taking advantage of the overnight anomaly in trading strategies.

Finally, we employed three Fama-MacBeth regressions to test the predictive power of various variables for future returns. Certain variables showed significant predictive ability when analysed independently. However, their joint impact was found to be more substantial, emphasising the joint significance of these variables in predicting future returns. The predictive accuracy of these regression sets through Root Mean Squared Errors (RMSE). This assessment revealed that lagged overnight and intraday returns, along with their lagged EWMA values, were the most effective predictors for future close-to-close, overnight, and intraday returns, aligning with Jegadeesh and Titman (1993). The regression that combined all explanatory variables outperformed the one that only included firm characteristics for predicting future close-to-close and overnight returns. However, it was less effective in predicting future intraday returns.

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A Appendix

A1 Overnight versus intraday returns — Robustness test

Table A1: Value-weighted and equal-weighted portfolio

The table below reports close-to-close, overnight, and intraday raw returns, returns in excess of the risk-free rate, CAPM alpha, and FF3 alpha for EW and VW portfolios of the stocks in the Norwegian stock market for the period of (1993-2019). We exclude (these stocks).

Value-Weighted Portfolio				
	Raw	Excess	CAPM	3-Factor
Overnight	1.7300%	1.4200%	1.0100%	0.9000%
	(9.817)	(8.021)	(6.244)	(5.400)
Intraday	-0.2431%	-0.5496%	-1.5300%	-1.3800%
	(-0.968)	(-2.179)	(-9.818)	(-8.664)
Close to close	1.2200%	0.9200%	-0.5300%	-0.4900%
	(4.097)	(3.054)	(-11.021)	(-10.136)
Equal-Weighted Portfolio				
	Raw	Excess	CAPM	3-Factor
Overnight	2.2200%	1.9100%	1.6300%	1.5700%
	(12.235)	(10.412)	(10.381)	(9.776)
Intraday	1.0243%	0.7161%	0.2800%	0.4600%
	(5.271)	(3.670)	(2.246)	(3.752)
Close to close	2.5300%	2.2200%	1.4400%	1.5500%
	(8.669)	(7.575)	(12.884)	(13.780)

A2 Half-hour windows

Hypothesis test:

We formulate the hypothesis as:

$$H_0 : \mu_{open} \leq \mu_{rest}$$

$$H_a : \mu_{open} > \mu_{rest}$$

T-stat: 3.0124 and p-value: 0.0050

Reject the null hypothesis, hence the average price in the first hour (first two windows) of the market open is greater than the average price during the rest of the day.

A3 Market microstructure effects

Table A2 shows the mean, and Table A3 shows the standard deviation. The tables can be found on the next two pages.

Table A2: Market microstructure effects — Mean

	Returns			OI		Effective half spread	
	r^{O}	$r^{O,Mid}$	$r^{O,MM}$	Open	Close	Open	Close
ABG	-0.1051 %	-0.0771 %	0.0080 %	-17.6311 %	-5.4833 %	0.6820 %	0.2707 %
ADE	0.4556 %	0.4818 %	-0.0034 %	1.0301 %	-1.8316 %	0.6118 %	0.1098 %
AFG	0.1679 %	0.1552 %	-0.0047 %	-11.3356 %	22.6521 %	0.5402 %	0.2174 %
AFK	-0.1411 %	-0.1285 %	0.0339 %	-16.6955 %	-1.4148 %	1.0161 %	0.5077 %
AKER	-0.1237 %	-0.1379 %	-0.0052 %	3.6057 %	8.4555 %	0.2684 %	0.0816 %
AKSO	0.0132 %	-0.0247 %	-0.0006 %	3.5669 %	5.6925 %	0.3057 %	0.0769 %
ATEA	0.3088 %	0.3039 %	0.0012 %	-10.1067 %	0.9985 %	0.4731 %	0.1758 %
AZT	-0.7418 %	-0.7210 %	0.0035 %	-2.3840 %	7.7823 %	1.2380 %	0.3692 %
B2H	-0.0716 %	-0.1041 %	0.0002 %	-12.5826 %	-28.7524 %	0.7596 %	0.2628 %
BAKKA	0.3402 %	0.3006 %	-0.0004 %	5.8071 %	7.0039 %	0.3424 %	0.0808 %
BONHR	0.0940 %	0.0638 %	-0.0042 %	4.4197 %	27.4741 %	0.9876 %	0.3446 %
BOUV	0.1535 %	0.1465 %	-0.0050 %	-14.0587 %	-1.0249 %	0.7566 %	0.2322 %
BRG	0.3281 %	0.3222 %	0.0083 %	-3.5988 %	-1.2754 %	0.5083 %	0.1468 %
BWLPG	0.1992 %	0.1377 %	-0.0005 %	-16.4447 %	-10.0836 %	0.3389 %	0.1082 %
CADLR	0.1409 %	0.1333 %	0.0024 %	4.3204 %	-4.2465 %	0.6821 %	0.1183 %
CLOUD	-0.1283 %	-0.1292 %	0.0121 %	-1.5037 %	25.1837 %	1.1287 %	0.2840 %
CRAYN	-0.1238 %	-0.1439 %	-0.0001 %	10.5842 %	1.9192 %	0.3180 %	0.0937 %
DNO	0.0389 %	0.0102 %	0.0039 %	-9.4763 %	1.3314 %	0.3068 %	0.0754 %
ELK	-0.0785 %	-0.0819 %	0.0045 %	0.6075 %	0.0955 %	0.2400 %	0.0689 %
ELMRA	-0.0382 %	-0.0574 %	0.0077 %	-5.9052 %	-7.9009 %	0.5508 %	0.8249 %
ENTRA	-0.0739 %	-0.0662 %	0.0006 %	-4.7609 %	2.3579 %	0.9328 %	0.0970 %
EPR	0.1082 %	0.1168 %	0.0031 %	-7.5124 %	-9.2183 %	0.2247 %	0.0763 %
FLNG	0.0200 %	-0.0146 %	-0.0024 %	-3.1999 %	38.2595 %	0.5499 %	0.0735 %
GJF	-0.0747 %	-0.0847 %	0.0000 %	-8.3856 %	9.9528 %	0.0932 %	0.0524 %
HAFNI	0.1431 %	0.0950 %	-0.0034 %	2.2552 %	6.2970 %	0.2706 %	0.0984 %
HEX	-0.0316 %	-0.0100 %	0.0050 %	-0.1252 %	4.9380 %	0.7185 %	0.1529 %
KID	0.3901 %	0.3399 %	0.0173 %	-0.8070 %	13.0756 %	1.0175 %	0.3225 %
KIT	0.6416 %	0.6453 %	0.0040 %	15.3468 %	1.0660 %	0.3291 %	0.1520 %
KOA	-0.0513 %	-0.0360 %	-0.0043 %	-2.9817 %	-3.7464 %	0.2889 %	0.0935 %
KOG	0.0548 %	0.0468 %	0.0015 %	3.1913 %	-27.4318 %	0.0933 %	0.0503 %
LSG	0.0366 %	0.0689 %	-0.0016 %	-9.7776 %	-9.5761 %	0.2672 %	0.0751 %
MPCC	0.0208 %	-0.0005 %	-0.0007 %	-7.4201 %	1.8008 %	0.1617 %	0.0471 %
TGS	0.4200 %	0.3978 %	-0.0009 %	-2.1722 %	4.8113 %	0.2859 %	0.0730 %
ULTI	0.1228 %	0.1421 %	0.0108 %	-6.8692 %	-13.8919 %	0.8763 %	0.3492 %
VEI	0.0681 %	0.0577 %	0.0001 %	-5.3866 %	-7.4946 %	0.3441 %	0.1307 %
WAWI	-0.4766 %	-0.5009 %	-0.0106 %	11.1525 %	1.4514 %	0.3683 %	0.0972 %

Table A3: Market microstructure effects — Standard deviation

	Returns			Effective half spread	
	r^{O}	$r^{O,Mid}$	$r^{O,MM}$	Open	Close
ABG	1.6122 %	1.6309 %	0.3097 %	0.5181 %	0.1844 %
ADE	2.3561 %	2.3657 %	0.1185 %	0.7331 %	0.1108 %
AFG	1.3980 %	1.3873 %	0.1783 %	0.6288 %	0.1528 %
AFK	2.0684 %	1.9386 %	0.6217 %	0.8803 %	0.5041 %
AKER	1.7412 %	1.7475 %	0.0849 %	0.2501 %	0.0638 %
AKSO	2.6003 %	2.6125 %	0.0817 %	0.2845 %	0.0915 %
ATEA	1.8246 %	1.7939 %	0.2078 %	0.4380 %	0.1411 %
AZT	3.6997 %	3.6544 %	0.2951 %	1.1596 %	0.2908 %
B2H	1.2237 %	1.3123 %	0.2651 %	0.8587 %	0.1615 %
BAKKA	2.0947 %	2.1199 %	0.1076 %	0.3050 %	0.0764 %
BONHR	2.5032 %	2.4236 %	0.3180 %	1.0469 %	0.2330 %
BOUV	1.3912 %	1.4340 %	0.2196 %	0.7289 %	0.1411 %
BRG	1.8866 %	1.8503 %	0.1943 %	0.4604 %	0.1317 %
BWLPG	2.6637 %	2.7074 %	0.1303 %	0.2889 %	0.0942 %
CADLR	2.1979 %	2.1813 %	0.1775 %	0.6180 %	0.1307 %
CLOUD	2.4730 %	2.4579 %	0.2676 %	0.8472 %	0.2007 %
CRAYN	3.1835 %	3.1613 %	0.1121 %	0.2703 %	0.1049 %
DNO	2.8185 %	2.8109 %	0.0615 %	0.3611 %	0.0508 %
ELK	2.4006 %	2.3817 %	0.1018 %	0.2461 %	0.0644 %
ELMRA	2.8250 %	8.8650 %	9.1775 %	0.5543 %	6.4566 %
ENTRA	2.0318 %	2.0232 %	0.0956 %	0.8397 %	0.0909 %
EPR	1.4401 %	1.4035 %	0.0973 %	0.1588 %	0.0624 %
FLNG	2.2320 %	2.2561 %	0.0895 %	0.4677 %	0.0722 %
GJF	1.4400 %	1.4348 %	0.0778 %	0.0638 %	0.0481 %
HAFNI	2.5475 %	2.5776 %	0.1096 %	0.4548 %	0.0591 %
HEX	2.5693 %	2.5867 %	0.1789 %	0.7024 %	0.1653 %
KID	2.5452 %	2.5089 %	0.3539 %	0.7092 %	0.2392 %
KIT	2.6263 %	2.5868 %	0.1764 %	0.3079 %	0.1162 %
KOA	3.1253 %	3.1113 %	0.1209 %	0.2465 %	0.0654 %
KOG	1.4472 %	1.4442 %	0.0701 %	0.0760 %	0.0496 %
LSG	2.0223 %	2.0299 %	0.0790 %	0.2389 %	0.0507 %
MPCC	2.5773 %	2.5716 %	0.0562 %	0.1193 %	0.0412 %
TGS	2.6460 %	2.6309 %	0.0951 %	0.2497 %	0.0725 %
ULTI	2.5149 %	2.5655 %	0.3002 %	0.6313 %	0.2495 %
VEI	1.6942 %	1.6845 %	0.1339 %	0.2945 %	0.0863 %
WAWI	3.4234 %	3.4286 %	0.1004 %	0.2943 %	0.0971 %

A4 Trading Strategies

The tables below contain the raw return, return in excess of the risk-free rate, CAPM alpha and FF3 alpha for each strategy and each extreme decile. The excess return for each decile is calculated as following: $r_{Excess} = r_{raw} - rf$. However, the excess return for each long-short strategy is calculated as following: $r_{LS,Excess} = (r_{decile(quintile)\ x} - r_{decile(quintile)\ y}) - rf$.

Table A4: Size

We long decile 1 (VW portfolio with small market capitalisation stocks), and short decile 10 (VW portfolio with large market capitalisation stocks).

	Overnight			Intraday		
Decile	Raw	Excess	CAPM	Raw	Excess	CAPM
1	3.97 %	3.67 %	3.24 %	4.7418 %	4.4352 %	3.99 %
	(7.978)	(7.356)	(6.364)	(16.740)	(15.541)	(14.220)
10	1.58 %	1.27 %	0.87 %	-0.3557 %	-0.6623 %	-1.68 %
	(8.333)	(6.686)	(4.907)	(-1.283)	(-2.377)	(-8.791)
LS	2.40 %	2.09 %	2.05 %	5.0975 %	4.7909 %	5.36 %
	(4.777)	(4.164)	(3.943)	(14.318)	(13.425)	(15.290)

Table A5: Value

We short decile 1 (VW portfolio of small BM-ratio stocks), and long decile 10 (VW portfolio of high BM-ratio stocks).

	Overnight			Intraday		
Decile	Raw	Excess	CAPM	Raw	Excess	CAPM
1	2.20 %	1.90 %	1.45 %	-0.32 %	-0.63 %	-1.55 %
	(8.130)	(6.995)	(5.494)	(-0.769)	(-1.484)	(-3.929)
10	2.81 %	2.50 %	1.99 %	-0.57 %	-0.88 %	-1.84 %
	(9.042)	(7.976)	(6.491)	(-1.452)	(-2.236)	(-5.234)
LS	0.60 %	0.30 %	0.22 %	-0.25 %	-0.55 %	-0.60 %
	(1.766)	(0.868)	(0.612)	(-0.499)	(-1.117)	(-1.177)

Table A6: Price Momentum

We short decile 1 (VW portfolio of loser stocks), and long decile 10 (VW portfolio of winner stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	4.23 %	3.93 %	3.46 %	3.24 %	-3.45 %	-3.75 %	-4.93 %	-5.24 %
	(10.393)	(9.641)	(8.496)	(7.725)	(-7.201)	(-7.818)	(-11.943)	(-12.362)
10	3.36 %	3.06 %	2.40 %	2.12 %	1.29 %	0.99 %	0.13 %	0.22 %
	(9.632)	(8.757)	(7.327)	(6.326)	(3.103)	(2.382)	(0.353)	(0.572)
LS	-0.87 %	-1.16 %	-1.36 %	-1.43 %	4.74 %	4.44 %	4.76 %	5.16 %
	(-1.872)	(-2.513)	(-2.864)	(-2.890)	(8.343)	(7.810)	(8.167)	(8.703)

Table A7: Industry Momentum

We short decile 1 (VW portfolio of loser industries), and long decile 10 (VW portfolio of winner industries).

	Overnight				Intraday			
Quintile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	2.18 %	1.88 %	1.38 %	1.18 %	-0.77 %	-1.06 %	-1.88 %	-1.94 %
	(7.438)	(6.411)	(4.957)	(4.168)	(-2.171)	(-3.008)	(-6.108)	(-6.076)
5	1.48 %	1.18 %	0.76 %	0.66 %	-0.29 %	-0.59 %	-1.44 %	-1.23 %
	(6.416)	(5.108)	(3.505)	(2.957)	(-0.864)	(-1.738)	(-5.085)	(-4.244)
LS	-0.70 %	-1.00 %	-0.93 %	-0.82 %	0.48 %	0.18 %	0.14 %	0.40 %
	(-2.442)	(-3.471)	(-3.135)	(-2.690)	(1.236)	(0.465)	(0.344)	(0.983)

Table A8: Short-term Reversal

We long decile 1 (VW portfolio of low past-month return stocks), and short decile 10 (VW portfolio of high past-month return stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	4.45 %	4.15 %	3.80 %	3.55 %	-2.83 %	-3.13 %	-4.39 %	-4.47 %
	(10.913)	(10.165)	(9.106)	(8.265)	(-6.251)	(-6.913)	(-11.322)	(-11.073)
10	3.11 %	2.80 %	2.06 %	1.55 %	0.12 %	-0.18 %	-0.83 %	-0.72 %
	(8.889)	(8.004)	(6.300)	(4.762)	(0.370)	(-0.549)	(-2.598)	(-2.171)
LS	1.35 %	1.04 %	1.42 %	1.69 %	-2.95 %	-3.26 %	-3.87 %	-4.06 %
	(2.960)	(2.288)	(3.054)	(3.509)	(-6.070)	(-6.691)	(-7.938)	(-8.005)

Table A9: Profitability

We short decile 1 (VW portfolio of low ROE-ratio stocks), and long decile 10 (VW portfolio of high ROE-ratio stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	4.66 %	4.36 %	3.79 %	3.27 %	-3.25 %	-3.56 %	-5.00 %	-5.38 %
	(11.315)	(10.571)	(9.232)	(7.869)	(-6.479)	(-7.071)	(-11.780)	(-12.344)
10	2.24 %	1.93 %	1.45 %	1.29 %	-0.28 %	-0.59 %	-1.42 %	-1.24 %
	(9.426)	(8.107)	(6.438)	(5.594)	(-0.891)	(-1.860)	(-5.108)	(-4.305)
LS	-2.42 %	-2.73 %	-2.66 %	-2.29 %	2.97 %	2.67 %	3.27 %	3.83 %
	(-6.410)	(-7.211)	(-6.756)	(-5.669)	(6.089)	(5.463)	(6.674)	(7.666)

Table A10: Turnover

We short decile 1 (VW portfolio of low turnover stocks), and long decile 10 (VW portfolio of high turnover stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	0.64 %	0.34 %	-0.01 %	-0.03 %	1.08 %	0.78 %	0.46 %	0.51 %
	(2.717)	(1.435)	(-0.051)	(-0.115)	(4.848)	(3.517)	(2.125)	(2.288)
10	2.96 %	2.66 %	2.03 %	1.66 %	-1.52 %	-1.82 %	-2.86 %	-2.83 %
	(9.615)	(8.643)	(7.177)	(5.906)	(-3.907)	(-4.660)	(-8.831)	(-8.399)
LS	-2.32 %	-2.62 %	-2.35 %	-1.99 %	2.60 %	2.30 %	3.01 %	3.03 %
	(-6.619)	(-7.424)	(-6.540)	(-5.454)	(6.112)	(5.423)	(7.421)	(7.196)

Table A11: Asset Growth

We short decile 1 (VW portfolio of low asset-growth-ratio stocks), and long decile 10 (VW portfolio of high asset-growth-ratio stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	2.76 %	2.47 %	2.01 %	1.81 %	-0.96 %	-1.25 %	-2.24 %	-2.17 %
	(10.381)	(9.261)	(7.900)	(6.942)	(-2.127)	(-2.763)	(-5.513)	(-5.154)
10	3.33 %	3.04 %	2.69 %	2.49 %	-1.72 %	-2.01 %	-3.26 %	-3.21 %
	(9.125)	(8.333)	(7.309)	(6.589)	(-3.753)	(-4.366)	(-8.567)	(-8.100)
LS	-0.57 %	-0.86 %	-0.98 %	-0.98 %	0.77 %	0.48 %	0.72 %	0.74 %
	(-1.702)	(-2.558)	(-2.828)	(-2.719)	(1.666)	(1.038)	(1.527)	(1.511)

Table A12: Beta

We long decile 1 (VW portfolio of low beta stocks), and short decile 10 (VW portfolio of high stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	0.91 %	0.62 %	0.46 %	0.36 %	1.65 %	1.36 %	0.65 %	0.77 %
	(3.457)	(2.348)	(1.713)	(1.288)	(4.745)	(3.899)	(2.035)	(2.306)
10	3.43 %	3.14 %	2.58 %	2.30 %	-2.49 %	-2.78 %	-4.17 %	-4.06 %
	(11.111)	(10.147)	(8.815)	(7.710)	(-5.558)	(-6.185)	(-12.480)	(-11.719)
LS	-2.52 %	-2.81 %	-2.41 %	-2.24 %	4.14 %	3.85 %	4.53 %	4.53 %
	(-7.025)	(-7.836)	(-6.717)	(-6.028)	(9.135)	(8.506)	(10.271)	(9.881)

Table A13: iVol

We long decile 1 (VW portfolio of low iVol stocks), and short decile 10 (VW portfolio of high iVol stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	1.38 %	1.08 %	0.78 %	0.66 %	-0.28 %	-0.58 %	-1.51 %	-1.21 %
	(6.596)	(5.114)	(3.797)	(3.094)	(-0.886)	(-1.832)	(-6.383)	(-5.160)
10	3.40 %	3.10 %	2.60 %	2.08 %	-0.87 %	-1.17 %	-2.06 %	-2.07 %
	(8.523)	(7.785)	(6.616)	(5.344)	(-1.565)	(-2.092)	(-3.832)	(-3.721)
LS	-2.02 %	-2.32 %	-2.12 %	-1.73 %	0.59 %	0.29 %	0.24 %	0.56 %
	(-4.999)	(-5.714)	(-5.103)	(-4.106)	(1.009)	(0.502)	(0.404)	(0.896)

Table A14: Diccretionary Accruals

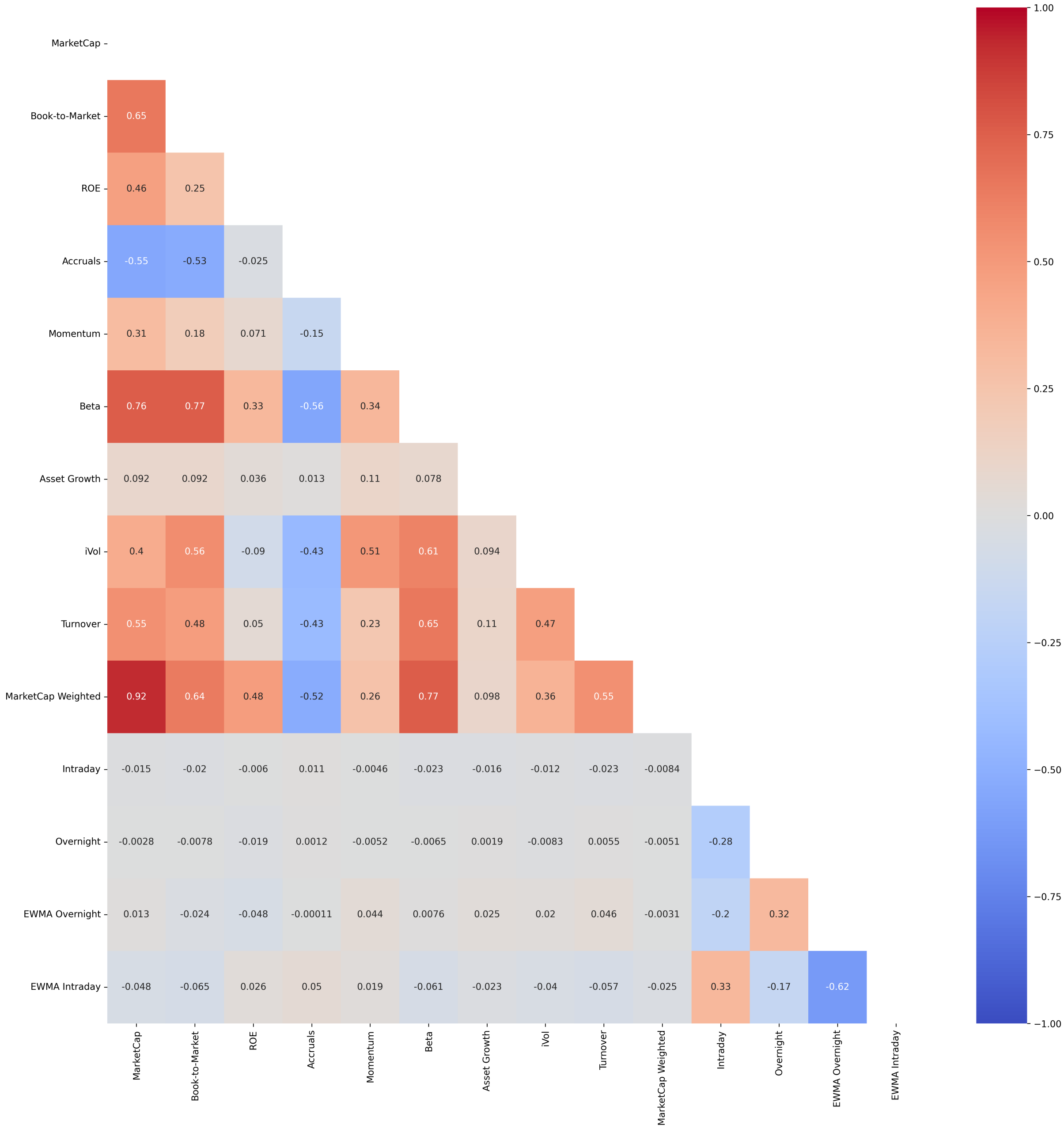
We long decile 1 (VW portfolio of low accruals factor stocks), and short decile 10 (VW portfolio of high accruals factor stocks).

	Overnight				Intraday			
Decile	Raw	Excess	CAPM	3-Factor	Raw	Excess	CAPM	3-Factor
1	2.32 %	2.02 %	1.55 %	1.38 %	-0.37 %	-0.67 %	-1.61 %	-1.61 %
	(8.118)	(7.079)	(5.734)	(4.958)	(-0.848)	(-1.530)	(-4.176)	(-4.017)
10	2.08 %	1.79 %	1.29 %	0.98 %	0.22 %	-0.07 %	-0.80 %	-0.84 %
	(7.509)	(6.419)	(4.977)	(3.774)	(0.636)	(-0.212)	(-2.514)	(-2.555)
LS	0.24 %	-0.06 %	-0.05 %	0.09 %	-0.59 %	-0.89 %	-1.12 %	-1.07 %
	(0.787)	(-0.207)	(-0.149)	(0.274)	(-1.288)	(-1.934)	(-2.368)	(-2.190)

A5 Correlation Matrix

Figure A1: Correlation Matrix

Correlation matrix of the characteristics and the returns used in the Fama-MacBeth Regressions



A6 List of sample stocks

Table A15: The sample of stocks used in our analysis.

Bloomberg Ticker	**Bloomberg Ticker**	**Bloomberg Ticker**
AAV NO Equity	ORO NO Equity	NAVA NO Equity
ACS NO Equity	WEN NO Equity	HRG NO Equity
ADE NO Equity	PRX NO Equity	REC NO Equity
ADEB NO Equity	SMEB NO Equity	BWO NO Equity
AFK NO Equity	RIG NO Equity	WEIFA NO Equity
AKE NO Equity	PFI NO Equity	OILRIG NO Equity
AKEB NO Equity	AMA NO Equity	NGT NO Equity
AKEF NO Equity	SUP NO Equity	IOX NO Equity
ARD NO Equity	OCR NO Equity	AGR NO Equity
AWS NO Equity	HEX NO Equity	AKFP NO Equity
AWSB NO Equity	TAT NO Equity	TROLL NO Equity
BEA NO Equity	IMSK NO Equity	TPO NO Equity
BEB NO Equity	STM NO Equity	AUSS NO Equity
BEL NO Equity	COV NO Equity	MAFA NO Equity
BET NO Equity	KBK NO Equity	NAUR NO Equity
NRC NO Equity	PRS NO Equity	COD NO Equity
BNB NO Equity	CHS NO Equity	NPRO NO Equity
BON NO Equity	PDR NO Equity	AKVA NO Equity
BOR NO Equity	NWS NO Equity	3498680Q NO Equity
BRA NO Equity	ROX NO Equity	ECHEM NO Equity
BSH NO Equity	SUBC NO Equity	ELE NO Equity
BBA NO Equity	ROX NO Equity	FAKTOR NO Equity

Continued on next page

Table A15 – continued from previous page

Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
CKR NO Equity	EDB NO Equity	DESSC NO Equity
WIN NO Equity	FRO NO Equity	REPANT NO Equity
COL NO Equity	TEC NO Equity	OTS NO Equity
ATG NO Equity	NLD NO Equity	COP NO Equity
DNB NO Equity	RCL NO Equity	SIMTRO NO Equity
SASB NO Equity	TOR NO Equity	TSU NO Equity
DNO NO Equity	BMA NO Equity	ALGETA NO Equity
DYN NO Equity	AFG NO Equity	OHL NO Equity
NOCC NO Equity	IPL NO Equity	WAVE NO Equity
SPOG NO Equity	MBN NO Equity	EMGS NO Equity
EKJ NO Equity	ULS NO Equity	NEXUS NO Equity
ELK NO Equity	DDASA NO Equity	FRID NO Equity
ELKF NO Equity	SOFF NO Equity	REM NO Equity
FAR NO Equity	SWR NO Equity	PROTCT NO Equity
ASC NO Equity	NYA NO Equity	CECON NO Equity
FOS NO Equity	NYAB NO Equity	PMENA NO Equity
FOT NO Equity	TGS NO Equity	FOP NO Equity
GOD NO Equity	VME NO Equity	JAEREN NO Equity
GRO NO Equity	EMS NO Equity	SCAN NO Equity
GYL NO Equity	IGNIS NO Equity	BOUVET NO Equity
WAT NO Equity	AIK NO Equity	WEMI NO Equity
HAG NO Equity	AXA NO Equity	SALM NO Equity
HAV NO Equity	DAT NO Equity	ARROW NO Equity

Continued on next page

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Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
HES NO Equity	DOF NO Equity	HUNT NO Equity
HNA NO Equity	NCO NO Equity	GSF NO Equity
HNB NO Equity	NIS NO Equity	ROM NO Equity
TIDE NO Equity	KIT NO Equity	SCANG NO Equity
IMS NO Equity	AKBM NO Equity	TRI NO Equity
FIN NO Equity	NEC NO Equity	AKRBP NO Equity
KVE NO Equity	FRO NO Equity	EMAS NO Equity
AKVR NO Equity	LUX NO Equity	LOND NO Equity
KVIB NO Equity	IFN NO Equity	DOCK NO Equity
KVIF NO Equity	HYDB NO Equity	NOM NO Equity
LHO NO Equity	PRO NO Equity	PRON NO Equity
LOI NO Equity	RIS NO Equity	SEAJ NO Equity
MAG NO Equity	HSU NO Equity	ADRL NO Equity
ATEA NO Equity	AHM NO Equity	NOF NO Equity
TEN NO Equity	SOR NO Equity	FBU NO Equity
MOE NO Equity	AURG NO Equity	NOR NO Equity
MORG NO Equity	SCSA NO Equity	LHC NO Equity
DUA NO Equity	SFM NO Equity	PPROD NO Equity
DUAB NO Equity	OTR NO Equity	THIN NO Equity
NAL NO Equity	ELT NO Equity	INFRA NO Equity
NTS NO Equity	CNR NO Equity	PHLY NO Equity
UNS NO Equity	NOL NO Equity	ENDUR NO Equity
NBK NO Equity	SOI NO Equity	CSOL NO Equity

Continued on next page

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Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
KOG NO Equity	MELG NO Equity	BWGAS NO Equity
NHY NO Equity	FRO NO Equity	NPEL NO Equity
NOE NO Equity	IFB NO Equity	PROD NO Equity
NOK NO Equity	ITE NO Equity	PCIB NO Equity
REACH NO Equity	ASD NO Equity	SPU NO Equity
NSI NO Equity	ENI NO Equity	GIPS NO Equity
NSGB NO Equity	EVRY NO Equity	HAVA NO Equity
NSG NO Equity	PCL NO Equity	POL NO Equity
LSW NO Equity	INM NO Equity	GOLE NO Equity
BOH NO Equity	CRU NO Equity	PLCS NO Equity
OLT NO Equity	HELG NO Equity	FLNG NO Equity
ORK NO Equity	STP NO Equity	NORTH NO Equity
ORKB NO Equity	INVEST NO Equity	IDEX NO Equity
ORKF NO Equity	EXPERT NO Equity	CRUR NO Equity
PGS NO Equity	SOLON NO Equity	PEN NO Equity
PRF NO Equity	PHO NO Equity	BAKKA NO Equity
PRO NO Equity	SCO NO Equity	STRANS NO Equity
RAU NO Equity	CMX NO Equity	SSC NO Equity
RIC NO Equity	IFC NO Equity	BRIDGE NO Equity
RIE NO Equity	TCO NO Equity	AVM NO Equity
RIEB NO Equity	ZENT NO Equity	DMABB NO Equity
ROO NO Equity	HND NO Equity	MORPOL NO Equity
SAG NO Equity	FJO NO Equity	WALWIL NO Equity

Continued on next page

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Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
SAGB NO Equity	CSG NO Equity	SAGA NO Equity
SAGF NO Equity	DOF NO Equity	STORM NO Equity
SCHA NO Equity	NOF NO Equity	SFR NO Equity
SEN NO Equity	KOM NO Equity	ARCHER NO Equity
SFJ NO Equity	TEL NO Equity	FLOAT NO Equity
SKI NO Equity	SNS NO Equity	GJF NO Equity
ARK NO Equity	SINO NO Equity	PROS NO Equity
SMD NO Equity	UNI NO Equity	SDSD NO Equity
SME NO Equity	FDR NO Equity	NRS NO Equity
SMT NO Equity	SSI NO Equity	SEVDR NO Equity
SNOG NO Equity	SIN NO Equity	DISC NO Equity
SOLV NO Equity	PEL NO Equity	AWDR NO Equity
SPA NO Equity	SCRIBNOK NO Equity	HLNG NO Equity
SPT NO Equity	STRONG NO Equity	KVAER NO Equity
STA NO Equity	FAST NO Equity	AOD NO Equity
STK NO Equity	DOM NO Equity	ALNG NO Equity
ODF NO Equity	SASNOK NO Equity	HBC NO Equity
ODFB NO Equity	GOL NO Equity	SRBANK NO Equity
NAV NO Equity	HIDDN NO Equity	NAURR NO Equity
SLA NO Equity	PAR NO Equity	SBO NO Equity
AVE NO Equity	QFR NO Equity	CRUDE NO Equity
TAA NO Equity	CARA NO Equity	VPOS NO Equity
TAD NO Equity	LSG NO Equity	BRG NO Equity

Continued on next page

Table A15 – continued from previous page

Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
TOD NO Equity	TECH NO Equity	ASETEK NO Equity
TOM NO Equity	GNO NO Equity	EAM NO Equity
STBP NO Equity	SUB NO Equity	MCG NO Equity
STB NO Equity	TFDS NO Equity	OCY NO Equity
UTO NO Equity	TST NO Equity	ODL NO Equity
NCL NO Equity	NAS NO Equity	WBULK NO Equity
VBY NO Equity	NEXT NO Equity	RECSOL NO Equity
VEI NO Equity	OTELLO NO Equity	BWLPG NO Equity
VIT NO Equity	YAR NO Equity	NAPA NO Equity
VITF NO Equity	CATCH NO Equity	LINK NO Equity
VVL NO Equity	AKA NO Equity	TIL NO Equity
WBS NO Equity	GNR NO Equity	INSR NO Equity
WIR NO Equity	MAMUT NO Equity	VOW NO Equity
WWI NO Equity	FIND NO Equity	AVANCE NO Equity
WWIB NO Equity	MEDI NO Equity	PNOR NO Equity
GRE NO Equity	STXEUR NO Equity	MSEIS NO Equity
MING NO Equity	AXX NO Equity	ZAL NO Equity
NONG NO Equity	CNS NO Equity	NEXT NO Equity
ROGG NO Equity	JSHIP NO Equity	CXENSE NO Equity
AXI NO Equity	PRI NO Equity	HYARD NO Equity
SBVG NO Equity	NORMAN NO Equity	AQUA NO Equity
SST NO Equity	NEL NO Equity	AURLPG NO Equity
HIT NO Equity	AKER NO Equity	AKSO NO Equity

Continued on next page

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Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
LSL NO Equity	OIL NO Equity	SSO NO Equity
KLI NO Equity	MGN NO Equity	XXL NO Equity
EEG NO Equity	GOGL NO Equity	ENTRA NO Equity
KEN NO Equity	BJORGE NO Equity	RAKP NO Equity
STN NO Equity	GIG NO Equity	RENO NO Equity
AVA NO Equity	JACK NO Equity	TEAM NO Equity
JIN NO Equity	RISH NO Equity	NANO NO Equity
RGT NO Equity	WILS NO Equity	GOGL NO Equity
FOK NO Equity	APL NO Equity	MULTI NO Equity
EQNR NO Equity	IMAREX NO Equity	SCHB NO Equity
NOV NO Equity	POLI NO Equity	VISTIN NO Equity
SVEG NO Equity	OSLO NO Equity	EPR NO Equity
NER NO Equity	AWO NO Equity	PPGPREF NO Equity
KOA NO Equity	VIZ NO Equity	SBANK NO Equity
APR NO Equity	HFISK NO Equity	KID NO Equity
EKO NO Equity	HAVI NO Equity	GOGLR NO Equity
NKR NO Equity	NEMI NO Equity	PARB NO Equity
ORC NO Equity	QEC NO Equity	TRE NO Equity
FOU NO Equity	KOA NO Equity	B2H NO Equity
CRP NO Equity	EIOF NO Equity	TRVX NO Equity
MSG NO Equity	EDRILL NO Equity	ARCUS NO Equity
FSL NO Equity	SIT NO Equity	CARBN NO Equity
NOW NO Equity	WEN NO Equity	BGBIO NO Equity

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Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
NAT NO Equity	AMSC NO Equity	FJORD NO Equity
SMG NO Equity	SIOFF NO Equity	SAFE NO Equity
SEL NO Equity	SDRL NO Equity	MPCC NO Equity
SADG NO Equity	CONSA NO Equity	SPOL NO Equity
AGR NO Equity	DESS NO Equity	EVRY NO Equity
ALV NO Equity	BLU NO Equity	BDRILL NO Equity
VIS NO Equity	POWEL NO Equity	INFRNT NO Equity
TOTG NO Equity	BIOTEC NO Equity	WSTEP NO Equity
SCI NO Equity	CEQ NO Equity	NODL NO Equity
MSL NO Equity	GAS NO Equity	SSG NO Equity
MOWI NO Equity	GGG NO Equity	CRAYON NO Equity
SNIB NO Equity	SOAG NO Equity	KOMP NO Equity
CAG NO Equity	NORGAN NO Equity	SALMON NO Equity
SUO NO Equity	FAIR NO Equity	FKRAFT NO Equity
NOR NO Equity	BHOC NO Equity	ELK NO Equity
SNI NO Equity	ODIM NO Equity	SHLF NO Equity
MDX NO Equity	DOFSUB NO Equity	OET NO Equity
MHO NO Equity	NORD NO Equity	SBLK NO Equity
1045871D NO Equity	CONF NO Equity	SDRL NO Equity
ALX NO Equity	DEEP NO Equity	PLT NO Equity
NOD NO Equity	FUNCOM NO Equity	SBTE NO Equity
PRV NO Equity	RXT NO Equity	ADEA NO Equity
NTC NO Equity	PBG NO Equity	ADE NO Equity

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Bloomberg Ticker	Bloomberg Ticker	Bloomberg Ticker
MAD NO Equity	TREF NO Equity	ICE NO Equity
RING NO Equity	AKD NO Equity	KCC NO Equity
NYC NO Equity	SCORE NO Equity	ULTIMO NO Equity
NYCB NO Equity	SONG NO Equity	OKEA NO Equity
RNA NO Equity	SBX NO Equity	NORBIT NO Equity
SPC NO Equity	BWG NO Equity	2020 NO Equity
HYD NO Equity	DOLP NO Equity	

A7 Half-Hour Window sample

Table A16: The sample of stocks used in our analysis.

Euronext Symbol	Euronext Symbol	Euronext Symbol
2020	PEN	PARB
5PG	GIGA	PSKY
AASB	GJF	PCIB
ABG	GEOS	PSE
ABL	GOGL	PNOR
ADE	GOD	PEXIP
ADS	GCC	PGS
AEGA	GEM	PHLY
AFG	GSF	PHO
AGLX	GRONG	PPG

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Euronext Symbol	Euronext Symbol	Euronext Symbol
AIRX	GYL	POL
AKAST	HAFNI	PLT
AKER	HMONY	PLTT
AKBM	HAV	PRS
AKRBP	HKY	PROT
ACC	HAVI	PROXI
AKH	HEX	PRYME
AKSO	HPUR	PYRUM
AKOBO	HSHP	QFR
AKVA	HBC	QFUEL
ALT	HRGI	QUEST
AMSC	HUDL	QEC
ANDF	HDLY	RANA
ABTEC	HUNT	REACH
ARCH	HYPRO	RECSI
ABS	HYN	RCR
AFISH	HYON	RIVER
AZT	HAUTO	ROMER
AFK	HSPG	ROM
ARGEO	IFISH	ROMSB
ARR	ISLAX	SDSD
ASTK	IDEX	SAGA
ASTRO	INDCT	SALM

Continued on next page

Table A16 – continued from previous page

Euronext Symbol	Euronext Symbol	Euronext Symbol
ATEA	INIFY	SALME
ASA	ININ	SACAM
AURA	INSTA	SADG
AURG	IWS	SASNO
AUSS	IOX	SATS
AUTO	ITERA	SCANA
AGAS	JIN	SCATC
AWDR	JAREN	SCHA
ALNG	KAHOT	SCHB
ACR	KID	SBX
AYFIE	KIT	SEAPT
B2H	KCC	SDRL
BAKKA	KMCP	SEAW7
BALT	KOMPL	SSG
BARRA	KOMP	SBO
BELCO	KOA	SHLF
BMK	KOG	SDNS
BCS	KRAB	SIOFF
BGBIO	KYOTO	SIKRI
BEWI	LEA	SKAND
BIEN	LSG	SKUE
BFISH	LIFE	SMCRT
BSP	LINK	SMOP

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Table A16 – continued from previous page

Euronext Symbol	Euronext Symbol	Euronext Symbol
BONHR	LUMI	SOFTX
BOR	LYTIX	SOGN
BORR	MVW	SOFF
BRG	MGN	SB68
BOUV	MEDI	MING
BWE	MELG	SRBNK
BWEK	MWTR	SOON
BWIDL	MNTR	MORG
BWLPG	MOWI	SOR
BWO	MPCC	SVEG
BMA	MPCES	SPOG
CADLR	MULTI	SNOR
CAMBI	MAS	SPOL
CAN	NAPA	HELG
CARA	NAVA	NONG
CARBN	NKR	RING
CIRCA	NEL	SOAG
CSS	NEXT	STSU
CLOUD	NISB	STATT
CAPSL	NORAM	SNI
CONTX	NORBT	STB
CLCO	NCOD	STRO
CRAYN	NORDH	SUBC

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Euronext Symbol	Euronext Symbol	Euronext Symbol
CSAM	NOAP	SUNSB
CYVIZ	NOHAL	TRVX
DVD	NOM	TECH
DSRT	NANOV	TECO
DLTX	NOD	TEKNA
DNB	NTG	TEL
DNO	NUMND	TGS
DOF	NORSE	KING
DDRIL	NHY	TIETO
EAM	NSOL	TOM
ECIT	NTI	TOTG
EWIND	NSKOG	TRE
EIOF	NTEL	TYSB
EMGS	NORTH	ULTI
ELIMP	NODL	VEI
ELK	NOL	VISTN
ELABS	NAS	VOLUE
ELMRA	NBX	VVL
ELO	NOR	VOW
ENDUR	NRC	VGM
ENERG	NYKD	VAR
ENSU	OBSRV	WAWI
ENTRA	OCEAN	WPU

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Euronext Symbol	Euronext Symbol	Euronext Symbol
ENVIP	OSUN	WSTEP
EQNR	OTS	WEST
EQVA	ODL	WWI
EPR	ODF	WWIB
EFUEL	ODFB	WILS
EXTX	OTL	XPLRA
FLNG	OKEA	XXL
FRO	OET	YAR
FROY	OLT	ZAL
GIG	ORK	ZAP
RISH	OTEC	ZENA
GENT	OTOVO	ZWIPE