



Index Investing and Closing Auction

*An Empirical Analysis of Closing Auction Turnover, Price Deviation
and Price Reversal on the Oslo Stock Exchange*

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Abstract

There are reasons to believe that there is increased popularity of trading in the closing auction due to the growth of index investing. We use intraday trading data from the Oslo Stock Exchange to examine and test the following hypotheses: (1) index investing drives closing auction turnover, and the turnover of stocks in the OSEBX and OBX Index is significantly higher during the closing auction relative to the remaining stocks on the Oslo Stock Exchange, and (2) prices deviate at the close and reverse overnight. Our results show that the turnover of stocks in the OSEBX and OBX are significantly higher than the remaining stocks during the closing auction. Further, prices do deviate at the close and reverse almost entirely overnight. Nevertheless, the use of the closing auction on the Oslo Stock Exchange might be more influenced by opening trends of the American stock market than index investing.

To our knowledge, this is the first paper that analyzes the implications of the Oslo Stock Exchange closing auction on underlying stocks and conducts analyses to investigate whether index investing is related to the growth of trading during the closing auction.

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1. Introduction

There is a considerable amount of literature analyzing the rise of index investing. However, only a few papers investigate the popularity of increasing closing auction trades and link the increased trading volume during the closing auction to increased trading of index funds and exchange-traded funds (ETFs). To our knowledge, no research has examined the closing auction on the Oslo Stock Exchange nor conducted the possible relationship between the closing auction and rise in index investing in Norway. Consequently, we aim to contribute to the current financial literature in both a national and global context.

By analyzing Norwegian intraday stock data combined with index fund data from the Norwegian Fund and Asset Management Association (VFF), price data from the VSTOXX volatility index, and price data of U.S. indices, we investigate the drivers behind and the relationship between index investing and the closing auction on the Oslo Stock Exchange.

Our first hypothesis states that index investing drives closing auction turnover. Additionally, we hypothesize that the turnover of stocks in the OSEBX and OBX is significantly higher during the closing auction relative to the remaining stocks on the Oslo Stock Exchange. We use panel regressions with fixed effects estimation to test this hypothesis and find that closing auction turnover is significantly higher for stocks in OSEBX and OBX than for the remaining stocks on the Oslo Stock Exchange. Moreover, the results indicate that auction turnover is higher on the last day of the month. However, OSEBX rebalancing days barely impact stocks included in the OBX Index significantly, and no significant change in auction turnover on OBX rebalancing days is discovered.

Secondly, we hypothesize that prices deviate at the close and reverse overnight. We include date fixed effects instead of stock fixed effects in the auction price deviation panel regression model and find that a higher auction turnover corresponds to a higher absolute price deviation. We find that aggregate risk drives a large portion of the price deviation and find that the price deviations are significantly higher for the smallest stocks and decrease with size, meaning that price deviations are lowest for stocks in OBX. Furthermore, 75% of the return from the end of ordinary trading to end of the closing auction is reversed by 10:00 the next morning. More than 95% of the price deviation in the closing auction is reversed overnight for stocks included in OSEBX and OBX.

To summarize, our hypotheses are supported, and the results are consistent with the area of literature that argues that the closing auction has gained importance. Nevertheless, we remain careful to conclude whether index investing directly drives closing auction turnover. We argue that as trading volume shifts from the continuous intraday sessions to the closing auction, institutional investors might be better off allowing larger tracking errors and rebalance their portfolios outside the auction.

The remainder of this thesis is organized as follows: In the remaining part of section 1, we develop hypotheses based on theoretical background on the increase in index investing and closing auctions. Thereafter, relevant research will be presented in a literature review. Section 2 provides a description of data, how the data is processed, and the construction of variables. Section 3 presents empirical methods used in the analyses and corresponding assumptions. In section 4, we present our empirical results before discussing the findings in section 5. Lastly, section 6 summarizes and concludes, and we provide suggestions for potential focus areas for further research.

1.1 Theoretical background and hypothesis development

Index investing is a passive investment strategy that attempts to replicate the returns of an established market benchmark. Investors may implement this strategy by holding the component securities of the indices' or investing in an index fund or exchange-traded fund (ETF), which in turn replicates the performance of a specific index. Both options offer diversification benefits, but the major difference between investing in an index fund and an ETF is that ETFs are listed on an exchange in the same way as a stock. Consequently, the apparent advantage over traditional index funds is that investors can buy and sell ETFs throughout the day at the observed market price. ETFs have become very popular among investors and traders and are now dominating the U.S. fund market. As opposed to the U.S. equity market, only four ETFs are listed on the Oslo Stock Exchange. Index investing in the U.S. has in general grown extraordinarily over recent years in terms of the number of ETFs offered and as well as of total net assets under management. The total net assets of both index mutual funds and ETFs reached \$10.2 trillion by the end of 2020, where index ETFs accounted for \$5.4 trillion and index mutual funds accounted for \$4.8 trillion – which was up from \$619 billion in 2005 (ICI, 2021). A factor that has contributed to the growing investor preference for index funds in recent years is a better performance record than actively managed

investment funds. As Sushko and Turner (2018) pointed out, recent experience corresponds with empirical literature, which suggests that after fees and expenses, the average active equity funds have failed to outperform their market benchmark over longer time perspectives. A significant increase and popularity in index investing have been present during recent years in Norway as well. As seen in Figure 1, data from the Norwegian Fund and Asset Management Association (VFF) show that Norwegian index funds' capital under management has increased from approximately NOK 42 million in 2003 to NOK 22.35 billion by the end of 2019. Moreover, the number of customer relationships has in the same period increased from 249 to 140,683, and the number of index funds offered grew from 6 to 70 (VFF, 2021).

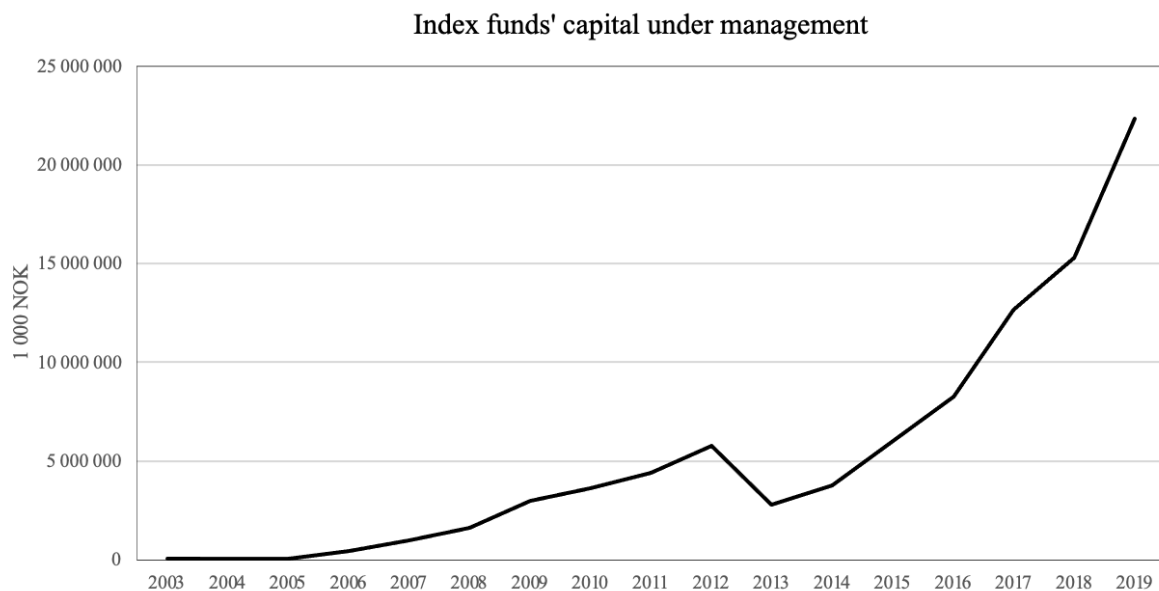


Figure 1: The evolution of index funds' capital under management expressed in 1,000 NOK from 2003 to the end of 2019, registered by VFF (VFF, 2021).

A closing auction is a batch auction that occurs at the end of the trading day for setting the closing price for every security. On U.S. exchanges, closing prices are most commonly set through market-on-close orders, which are scheduled to be traded in the closing auction regardless of the trading price. At the NYSE, traders can enter market-on-close orders from 07:00 until 15:45 and can only modify or cancel the orders in case of an error. On the Nasdaq, market-on-close orders must be submitted by 15:50. At 16:00, both exchanges close for the day, and auctions are run for all orders. Shortly after that, closing prices for securities and indices are published. On the Oslo Stock Exchange, the continuous trading closes at 16:20,

and the final closing auction starts immediately. From 16:20, traders are allowed to place, change and delete orders until 16:25. After 16:25, all orders will be matched and closed within 30 seconds. The closing auction price is the most important stock price of the day for listed companies and institutional investors. The prices serve as reference prices for pricing derivative contracts, computing benchmarks and portfolio returns, and calculating a fund's net asset value (NAV).

Bogousslavsky and Muravyev (2020) show that the closing auction has become a great trading mechanism that has increased significantly in importance and activity during recent years. In 2010, the closing auction in the U.S. equity market accounted for 3.11% of the daily trading volume. In 2018, this number had grown to 7.48% (Bogousslavsky & Muravyev, 2020), and in 2019 the share trading volume at the end of the day had increased further to about 11% (Wu & Jegadeesh, 2020). On Euronext Paris, CAC 40 stocks traded close to 41% during the closing auction in June 2019 (Raillon, 2020). In developed countries of Europe, closing auctions represented as much as 21% of the trading day activity as of January 2020 (Novick et al., 2020). By using intraday stock data from our sample period, 26.8.2019 to 4.12.2020, we find that closing auction volume on the Oslo Stock Exchange has accounted for 23.45% of the daily trading NOK volume. In this thesis, we wish to analyze if the same shift towards trading in the closing auction is likely to be present for the Norwegian stock market and further investigate the corresponding drivers behind the closing auction.

Literature suggests that one important factor for the growth of closing auctions is the growth of index investing. Investors strive to minimize tracking errors by trading at the closing auction because closing prices often set their benchmarks. Institutional investors are benchmarked with month-end prices, something that further encourages them to trade at the close. Additionally, the development of algorithmic and high-frequency trading has also contributed to the growth of closing auction volume. Bogousslavsky & Muravyev (2020) found that closing auction turnover is 87% higher on the last day of the month. This result suggests that the increase in closing auction volume may be strongly associated with ETF ownership and is mainly driven by indexing and institutional rebalancing. Hence, closing volume behaves differently from intraday volume.

Empirical findings show that closing auction volume is growing, is mostly uninformed, and shifts prices (Bogousslavsky & Muravyev, 2020). Models developed by Admati and Pfleiderer (1988) anticipated that a congregation of trades, that are not based on firm-specific

information, at specific times during the day should reduce costs and make prices more efficient. Furthermore, theory predicts that intraday liquidity may deteriorate if traders cluster their trades around times of higher liquidity (Foster & Viswanathan, 1990). Liquidity drying up during the rest of the intraday may be a concerning trend as the opening period is crucial for pricing in overnight news. An effect where liquidity induces liquidity predicts to cause informed traders to strategically pool with these uninformed traders to minimize the price impacts of their trades (Admati & Pfleiderer, 1988), which means that market participants are attracted to the price efficiency and the liquidity that the closing auction offers.

In this thesis, we wish to analyze some of the implications increased index investing imposes on the closing auction and the corresponding effects on underlying stock dynamics and liquidity. At the close, we expect higher turnover for stocks included in indices. Thus, we propose the first hypothesis:

1. Index investing drives auction turnover, and the turnover of stocks in the OSEBX and OBX Index is significantly higher during the closing auction relative to the remaining stocks on the Oslo Stock Exchange.

If the hypothesis proves to be valid, it would also be consistent with the motivation and goal of passive institutional investors for minimizing tracking error. Additionally, there is a seemingly changing mix and concentration of market participants that drive the shift towards the closing auction.

As literature suggests that increased index investing seemingly shifts trading volume towards the close, high closing auction volume distorts closing prices. Our next aim for this thesis is to investigate whether the same result is valid for the Norwegian stock market. We propose the following hypothesis:

2. Stock prices deviate at the close, and the price deviation reverses overnight.

1.2 Literature review

The increase in trading volume at the close has lately started to gain attention and has been documented in the literature. Wu (2019) extended this field of research by investigating whether it was passive flows that led to the increased usage of market-on-close orders in the U.S. Considering that daily flows from index mutual funds were not available from major data vendors, Wu (2019) utilized daily ETF flows and retrieved market-on-close data from the Trade and Quote (TAQ) database. The final sample contained 6,663,021 stock-day observations over the period from July 2008 to June 2018. By estimating a panel regression of daily market-on-close volume on ETF flows, he found that the OLS results suggested an increase in market-on-close trading volume was strongly correlated with passive fund flows. The analysis focused on ETF flows, but the documented results could be generalized to index mutual funds (Wu, 2019). Next, by conducting analyses using a quasi-natural experiment based on the reconstruction of the Russell indices, the results provided support for the causal interpretation of the positive relationship between market-on-close trading volume and ETF flows. Wu and Jegadeesh (2020) further investigated if closing auction volume were related to ETF growth. Similarly, they found that trade volume in closing auctions grew simultaneously with assets invested through ETFs.

Furthermore, Bogousslavsky and Muravyev (2020) studied common stocks listed on the NYSE and Nasdaq, with prices greater than \$5 and market capitalization greater than \$100 million. Volume and auction price were obtained from the TAQ database from January 2010 to December 2018. The final sample consisted of 5,720,876 stock-day observations allocated across 1,887 NYSE-listed stocks (47.59% of all observations) and 2,946 Nasdaq-listed stocks (52.41% of all observations). By performing a difference-in-difference regression, Bogousslavsky and Muravyev (2020) supported previously mentioned results and showed that ETF and passive mutual fund ownership were strongly associated with the increase in closing auction volume. Additionally, the study confirmed that primarily institutional rebalancing and indexing contributed to increased trading during closing auctions because volume during closing auctions spiked on end-of-month and index rebalancing days. They found that while intraday turnover remained unchanged, closing auction and pre-close (15:55-16:00) turnovers were 87% and 33% higher during the last day of the month. On index rebalancing days, intraday turnover was only 7.8% higher, whereas closing auction and pre-close turnovers were 230% and 78% higher.

In addition to demonstrating that aggregate passive flows were increasing the volume of market-on-close orders, Wu (2019) showed this possessed an impact on stock price dynamics. The findings provided direct evidence that stocks with high market-on-close trading volume experienced significantly larger price movements during the end of the trading day and that the price impact distorted closing prices. Wu (2019) also investigated whether the price impact was temporary. By using Fama-MacBeth regressions, he analyzed the cross-sectional relation between market-on-close trading volume and return reversals. Cross-sectional results revealed that on the following day, stocks with high market-on-close trading volume experienced significant reversals. Moreover, these results were shown to be robust across different exchanges. Using panel regressions, Bogousslavsky and Muravyev (2020) also studied the determinants of closing price deviations. A model that studied how log overnight return depended on log auction deviation found that price deviations were primarily due to price pressure and not new information (Bogousslavsky & Muravyev, 2020). The result implied that overall, primary participants of the closing auction were mostly passive funds and other uninformed traders. They found that larger price deviations derived from higher closing auction turnover, and the same strong reversal pattern was also discovered. Results showed that the deviations reverted by half right after the closing auction. Closing price deviation was completely reversed overnight for large stocks and mostly reversed for small stocks, consistent with price pressure being mainly uninformed. Similarly, Wu and Jegadeesh (2020) studied the permanent and transitory components of the price impact by using an instrumental variables regression. They found that about 24% of the price impact reversed at the market opening the following day. The reversals continued over the next three to five days, resulting in a cumulative reversal of 83%. 17% of the reversals remained permanent, which was interpreted as that market-on-close orders additionally attracted significant participation of informed traders as well, consistent with theoretical implications of clustering of uninformed traders and informed traders.

Theory predicts that liquidity may deteriorate at the open and dry up during the trading day as volume migrates towards the close (Foster & Viswanathan, 1990), something that becomes a possible externality due to the rise of index investing. To test whether intraday liquidity deteriorated as volume migrated to the close, Bogousslavsky and Muravyev (2020) focused on another crucial intraday period – the open. They estimated a panel regression and found that liquidity indeed deteriorated at the open over the sample period. The results additionally

showed that in the first 15 minutes of trading, turnover declined by approximately 21% over the sample period for S&P 500 stocks.

Bogousslavsky and Muravyev (2020) concluded that the continuing shift towards index investing might lead to further increased growth of trading during the closing auction, and Wu (2019) concluded that his findings impose important implications for investor welfare. He proposed that if the increase of market-on-close orders induces closing prices to distort and stock prices to deviate from the fundamental values, some index funds may benefit from accepting larger tracking errors by trading at other times than during the closing auction.

2. Data

In this section, we present our data used to examine our hypotheses, data processing and assumptions we make. We start by describing our collection of intraday stock data, issued shares, and the price history of major U.S. indices. Further, we explain the data processing and possible weaknesses in the data.

2.1 Data collection

Intraday stock data was collected from the Oslo Stock Exchange and consists of every trade made on the Oslo Stock Exchange for 174 listed companies over a span of 15 months, from 26.08.2019 to 04.12.2020. The stock data contains timestamps, trade volume, and price. All companies in the OBX and OSEBX Index are included. As shown in Table 8 in Appendix A.1, 31.61% of the stocks in our sample do not have a complete dataset for the whole time period due to a change in ticker or delisting (e.g., mergers). These companies were still included in our analysis as they did not exhibit any apparent unusual behavior and the changes did not affect our analysis. A complete list of all included companies is shown in Table 9 in Appendix A.2. The dataset contains a total of 46,085,457 unique observations.

To compute stock turnover, we needed information about the number of shares available for each company during our sample period. We used NHH's Børsprosjektet and sorted for TradeDate and include Symbol and Shares Issued. Before we could merge this data with our intraday stock data, we needed to manually adjust for companies that had changed tickers or were delisted during the sample period. Børsprosjektet would only present the new ticker for the whole period, so we used news reports from the Oslo Stock Exchange to find the number of shares issued for these companies and manually include it in our dataset.

As the OBX and OSEBX Index constituents are reevaluated twice a year, we added an indicator for the constituents at all times during our sample period. We used the Oslo Stock Exchange NewsWeb site to find historical composition reports and created indicators for stocks in the OBX and OSEBX Index continuously throughout our sample period.

To remedy the fact that the Norwegian stock market to a certain degree is affected by the U.S. stock market, we collected price data of three major U.S. indices; Dow Jones Industrial Average, Nasdaq Composite, and Standard & Poor's 500 (S&P 500) from Yahoo Finance (Yahoo Finance, 2021). The U.S. stock market opens at 15:30 CET (except for four weeks a year which it opens at 14:30 CET due to difference in change to/from summertime). This allows Norwegian investors to react to the opening rise or fall of the U.S. market before the close of the Oslo Stock Exchange. We computed the overnight return and daily return of the three indices to be included in our analysis.

We chose to include the Euro Stoxx 50 Volatility Index (VSTOXX) as a measure of aggregate risk as it indicates the aggregate risk in the European equity market. The index measures implied volatility of near-term EuroStoxx 50 options that are traded on the Eurex exchange. VSTOXX can be considered the European equivalent of the Chicago Board Options Exchange's CBOE Volatility Index (VIX). We retrieved historical price data from Investing.com (Investing.com, 2021) corresponding with our sample period and manually created time series.

2.2 Data processing

We defined the closing auction as all trades made after 16:20 each trading day. Although the closing auction is highly used for trading, some stocks had zero auction trades on occasional days in our sample. These observations would lead to a log turnover of negative infinity and computational problems. Out of the total of 52,491 stock trading days (nr. of stocks multiplied with nr. of trading days for each stock), 13,345 had zero trades during the closing auction. We encountered this problem in several intervals. As this constituted a large part of our dataset, we adjusted by adding 1 trade for all stocks in all intervals. By doing so, we prevented exclusion of a substantial part of our dataset, and the increase of 1 trade had a negligible impact on the final empirical results. To ensure that these observations were not driving the results, we ran a test where we excluded the observations and computed our simulations. We found that the results are equivalent to one another, as shown in Table 10 in Appendix A.3.

In addition to the closing auction, we aggregated the data into the following intervals: 1) Ordinary intraday trading (10:00-16:00), 2) Opening (09:00-09:59) 3) “Last” 15 minutes (16:00-16:15) and 4) Last 5 minutes (16:15-16:20). The opening was defined as the first hour of trading due to many stocks had no trades in the opening auction. Defining the opening as only the auction led to 17,860 stock-day observations without any opening trades, which in turn could lead to distributional misspecifications that could cause inconsistent estimates of parameters (Hautsch, Malec & Schienle, 2013).

Interval volume for each ticker is the sum of all shares traded in the interval. We divided the interval volume by shares issued for each ticker to find the interval turnover. As illustrated in Figure 2, the distribution of auction turnover consists of some extreme values. We suspected that some observations may be considered as outliers and damage our parameter estimates. We confirmed our suspicions with a Rosner’s test (Rosner, 1983) for outliers and excluded these observations from our analysis to avoid extreme observations (e.g., 08.04.2020, where the Oslo Stock Exchange closed at 13:00 due to Easter holidays). When we calculated and plotted the fraction of aggregate daily NOK volume made at different intervals during the day in Figure 3 in Section 4.1, we included all observations for illustrative purposes. We plot the same without outliers in Figure 5 in Appendix A.4.

For each interval, the last trading price before the start of the interval and the last trading price in the interval was collected. If there were any cases where a stock did not have any trades during the time interval, we used the last trading price before the interval. 3,610 stock-days did not have any trades before 10:00. In these cases, we used the last price from the day before. We used the prices to calculate the return for each interval and the daily return.

After processing the data, we have the following variables

1. Turnover

$$Turnover_{i,j,t} = \frac{volume_{i,j,t}}{shares\ issued_{i,t}} \quad (1)$$

where $volume_{i,j,t}$ is the number of stocks traded of stock i in interval j at the date t and $shares\ issued_{i,t}$ is the number of shares issued of stock i at date t .

2. Absolute price deviation at the close (%)

$$price\ deviation_{i,t} = \left| \ln \left(\frac{p_{auc,i,t}}{p_{16:20,i,t}} \right) \right| \quad (2)$$

where $p_{auc,i,t}$ is the price in the closing auction for stock i on the date t and $p_{16:20,i,t}$ is the price in the last ordinary trade for stock i on the date t .

3. Return:

a. Daily

$$Return_{daily,i} = \ln \left(\frac{p_{last,i,t}}{p_{last,i,t-1}} \right) \quad (3)$$

where $p_{last,i,t}$ is the last trade price for stock i on the date t and $p_{last,i,t-1}$ is the last trade price for stock i the day before ($t-1$).

b. Intervals

$$Return_{i,j,t} = \ln \left(\frac{p-last_{i,j,t}}{p-last_{i,j-1,t}} \right) \quad (4)$$

where $p - last_{i,j,t}$ is the last traded price for stock i in interval j on the date t and $p - last_{i,j-1,t}$ is the last traded price for stock i in interval $j-1$ on the date t .

c. Overnight

$$Return_{overnight,i,t} = \ln \left(\frac{p_{i,10:00,t}}{p_{last,i,t-1}} \right) \quad (5)$$

where $p_{i,10:00,t}$ is the price for stock i at 10:00 on date t and $p_{last,i,t-1}$ is the last trade price for stock i the day before ($t-1$).

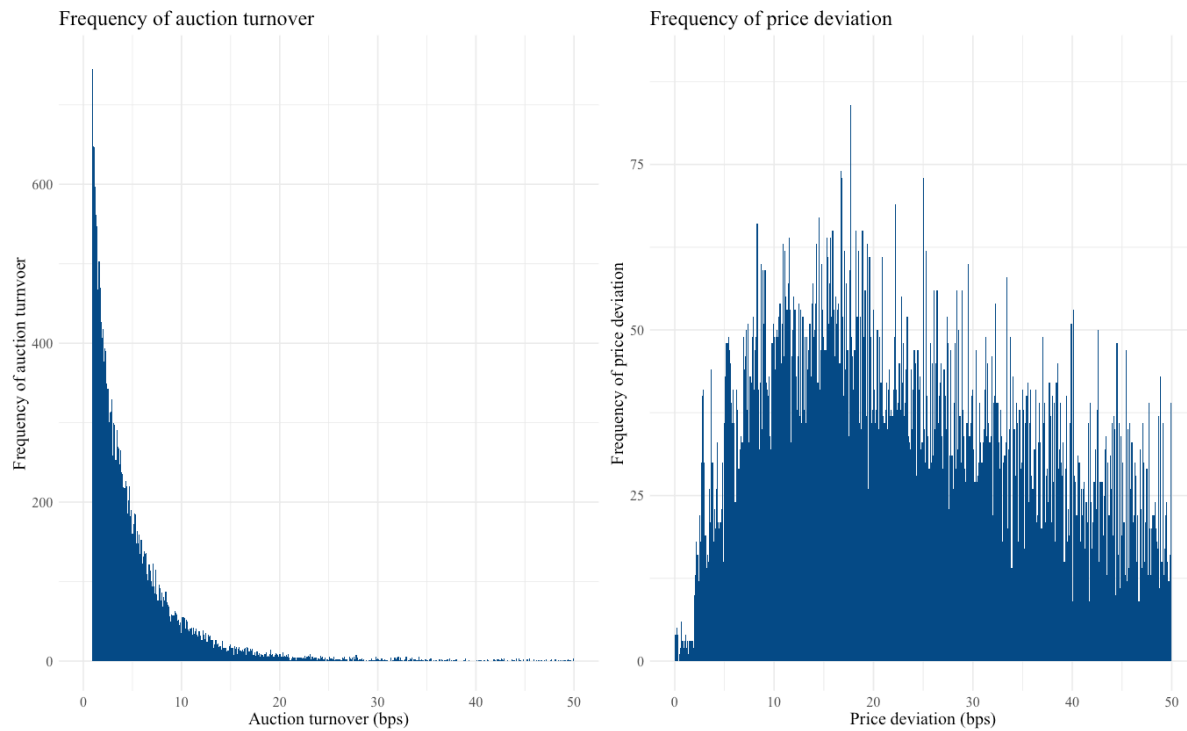


Figure 2: The figure to the left shows the frequency of auction turnover, while the figure to the right shows the frequency of price deviation.

Descriptive statistics are illustrated in Table 1 below. The group of stocks with the most cumulative trades are the OSEBX, with 216.87 million stocks trades each day, while the remaining stocks have the fewest with 49.86 million stocks trades each day. Stocks in OSEBX and OBX are naturally significantly larger, more traded and use the closing auction more widely than the remaining stocks. Nevertheless, price deviation is more substantial for the remaining stocks, with 84.11 bps on average.

Table 1: Descriptive statistics.

	ALL		OSEBX		OBX		Remaining stocks	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Daily trades	142 239.1	50 615.4	123 361.2	46 912.16	88 004.31	37 749.79	18 877.90	5 028.47
Stocks traded daily (mill.)	266.73	202.21	216.87	201.82	88.23	70.98	49.86	48.92
Average price (NOK)	116.95	130.89	122.39	123.14	145.72	133.39	81.36	168.93
Market cap. (Bill. NOK)	13 317.15	38 805.21	31 013.47	58 352.92	69 689.27	81 864.29	2 382.62	4 394.99
Auction fraction (%)	23.45	6.60	24.99	6.80	28.31	7.11	8.10	6.09
Turnover intraday 10:00-16:00 (bps)	34.04	110.15	35.71	110.00	30.49	89.04	32.33	110.28
Turnover open 09:00-09:59 (bps)	13.32	5.88	14.51	8.88	11.88	9.29	12.21	6.95
Turnover 16:00-16:15 (bps)	2.19	0.88	2.37	1.04	2.14	1.35	2.02	1.32
Turnover 16:15-16:20 (bps)	1.02	0.43	1.06	0.61	0.90	1.12	1.00	0.60
Turnover closing auction (bps)	3.37	1.89	4.72	2.03	7.17	3.17	2.01	3.08
Return daily (bps)	2.98	651.51	0.39	521.51	-4.08	522.71	5.65	762.39
Return intraday (bps)	-16.48	352.38	-7.36	273.07	1.10	201.73	-26.17	420.35
Return 16:00-16:15 (bps)	1.06	94.86	2.00	70.72	1.19	53.82	0.09	114.49
Return 16:15-16:20 (bps)	-1.36	82.54	0.43	54.97	1.05	28.68	-3.21	103.47
Return overnight (bps)	4.68	581.90	3.39	393.76	-1.59	382.61	6.05	730.50
Price deviation (bps)	64.09	130.55	41.18	98.69	24.97	57.36	84.11	148.07
Number of trades	46 085 457		39 969 021		28 513 398		6 116 436	

2.3 Bias in data

We acknowledge that there may be some limitations to our data that may impact the results of our analysis. Due to the Covid-19 pandemic, our sample period may not necessarily represent the real dynamics of the Oslo Stock Exchange. A massive market-drop in March 2020 showed an increase in stock turnover. As illustrated in Figure 3 in Section 4.1, some days in that period may be considered as outliers and have been removed to reduce the effect of this unusual activity on our parameter estimates. The market responded later in 2020 with a massive rise, which may also be considered unusual activity compared to long-term market behavior. As we do not possess data for other more “normal” years, we are not able to compare our results and check their validity in the longer term.

3. Methodology

In this section, we present the empirical methods used to examine our hypotheses. First, we describe the reasoning behind the choice of fixed versus random effects estimators on panel regressions. Second, we describe assumptions and associated measures we make to ensure the models' validity.

3.1 Panel data, fixed effects, and random effects estimators

A set of panel data consists of a time series for each cross-sectional member in the data set. The prominent feature of panel data that distinguishes them from a pooled cross-section is that the same cross-sectional units, in our case stocks, are observed throughout a given period (Wooldridge, 2016). With panel data, problems concerned with unobserved heterogeneity can be solved. Unobserved heterogeneity leads a pooled OLS estimator to be biased and inconsistent. Hence, we need a new kind of estimator.

Two main types of methods for estimating unobserved effects panel data models are the fixed effects estimator and random effects estimator. The original unobserved effects model may be

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \dots + \beta_k x_{itk} + \alpha_i + u_{it} \quad t = 1, 2, \dots, T. \quad (6)$$

The unobserved heterogeneity effect in model (6) is the term α_i , while u_{it} is the idiosyncratic error. Usually, we would allow to include time dummies among the independent variables as well. For fixed effects, the goal is to eliminate α_i because it is thought to be correlated with one or several of the x_{it} .

Model (6) becomes a random effects model when assuming that the unobserved effect α_i is uncorrelated with all independent variables in all time periods.

$$\text{Cov}(\alpha_i, x_{it}) = 0 \tag{7}$$

If the covariance is equal to zero, it is the case that both random effects and fixed effects are consistent estimators. It is then also the case that the random effects estimation is more efficient than fixed effects. The standard error of random effects should be less than the standard error which fixed effects would have obtained. If the above assumption is not true, it is not the case that fixed and random effects are consistent. Thus, only fixed effects estimation is solely consistent, while random effects is no longer consistent. Fixed effects allow arbitrary correlation between the unobserved effect and independent variables, while random effects do not. Fixed effects are widely thought to be a more convincing tool for estimating *ceteris paribus* effects (Wooldridge, 2016).

In order to test whether we should use fixed effects or random effects estimation, we performed a Hausman test. The test explicitly tests whether there is a correlation between the unobserved heterogeneity term and the independent variables. We essentially verify whether the null hypothesis, which is the above-stated assumption, is true by conducting the Hausman test. If the null hypothesis is not rejected, we conclude that random effects and fixed effects are consistent. Hence, we should use random effects estimation because of the fact that its variance is lower than that of fixed effects. Whereas if we reject the null hypothesis, we will conclude that fixed effects are the estimation strategy to go with because only fixed effects are consistent in the circumstance. The Hausman test result showed that we reject the null hypothesis on a 1% significant level. Hence, we believe the unobserved effect is correlated with at least one of the independent variables, and therefore we use fixed effects instead of random effects going forward.

3.2 One sided Welch two-sample t-test

We used the one-sided Welch two-sample t-test to test whether the turnover of stocks in the OBX and OSEBX Index is significantly higher during the closing auction relative to the remaining stocks on the Oslo Stock Exchange. Welch's t-test is an adaptation of the Student's t-test for comparing the means of two different groups, where we do not assume that the variance is the same in the two groups. The model is derived by Welch (1947) and given by

$$t = \frac{\Delta\bar{X}}{s_{\Delta\bar{X}}} = (\bar{X}_1 - \bar{X}_2) / \left(\sqrt{s_{\bar{X}_1}^2 + s_{\bar{X}_2}^2} \right) \quad (8)$$

$$s_{\bar{X}_i} = \frac{s_i}{\sqrt{N_i}}$$

where \bar{X}_i and $s_{\bar{X}_i}$ are the i^{th} sample mean and its standard error. The formula includes the variance of the two groups being compared, unlike the classic Student's t-test.

The degrees of freedom ν is estimated as

$$\nu^{-1} \approx \frac{(v_1^{-1}s_{\bar{X}_1}^4 + v_2^{-1}s_{\bar{X}_2}^4)}{s_{\Delta\bar{X}}^4} \quad (9)$$

where, $\nu_i = N_i - 1$ is the degrees of freedom associated with the i^{th} variance estimate.

3.3 Validity of the models

In order to ensure our models have valid and robust inferences and the fixed effects estimator is consistent and unbiased, the OLS estimators need to be BLUE (Best Linear Unbiased Estimator). Therefore, a set of underlying assumptions must be satisfied. Consequently, which adjustments and measures have been made and considered for valid inferences to be possible will be described in the following.

3.3.1 Normality

According to the central limit theorem, the use of our models presupposes that we face independent and identically distributed random returns in our calculations (Liu, Rekkas & Wong, 2012). Whether returns in the stock market are normally distributed has been a much-discussed topic. Hebner (2014) is among those who have researched this further and concluded that although investors can expect both positive and negative extreme values for returns in the stock market, it is reasonable to assume that these are randomly and normally distributed around an average. Nevertheless, to improve the readability of our results and to make them more easily comparable in the cross-section of stocks (OSEBX, OBX, and remaining stocks), we chose to log transform our models by taking the log of our dependent and independent variables. This helped with the normality of our observations, as the log of a variable typically has a distribution closer to normal than the variable itself (Wooldridge, 2016).

3.3.2 Strict exogeneity

The fixed effects estimator is inconsistent and unbiased without the strict exogeneity assumption. The error term must be unrelated to any explanatory variable at any given time, meaning that the conditional expected value of the residual must be zero. If the strict exogeneity assumption does not hold, endogeneity issues may arise and impact the analysis. Endogeneity issues are often caused by unobservable or observable stock characteristics and possible reverse-causality. In order to eliminate potential sources of endogeneity in our dataset, we have used a fixed effects model which eliminates time-invariant stock-specific characteristics by a within-group transformation.

3.3.3 Homoscedasticity

Homoskedasticity refers to when the error term in a regression model has constant variance conditional on the explanatory variables. While if the variance of the error term, given the explanatory variables, is not constant refers to heteroskedasticity. Without homoskedasticity, the inference is not valid; thus, the model cannot be considered efficient. We used a fixed

effects model to eliminate time-invariant stock-specific characteristics in addition to robust standard errors to account for issues related to heteroskedasticity.

3.3.4 Autocorrelation

For short intervals (less than 20 minutes), stock returns have a significant degree of autocorrelation, which refers to the correlation between the errors in different time periods in a panel data model. We used a Breusch-Godfrey test and found that at the 1% level, return for every stock has significant autocorrelation. We accounted for autocorrelation by including one lag of the stock return when calculating the auction price deviation.

3.3.5 Normally distributed residuals

The residuals must be normally distributed in order to make valid inferences from the regression. However, the central limit theorem states that the inference is valid when the number of observations is large and a minimum of 30 observations. Our dataset is sufficiently large, where the lowest amount throughout the regressions is 7,226 stock-day observations. In this way, we ensured that the residuals are normally distributed.

3.3.6 Multicollinearity

Multicollinearity is a term that refers to correlation among two or several independent variables in the regression model. Usually, it is invoked when correlations appear to be “large”, but an actual magnitude is not defined (Wooldridge, 2016). Consequently, problems in the analysis may occur in the form of increased standard errors on the regression coefficients. The coefficients may not appear statistically different from zero, even though they, in reality, are so. In the presence of multicollinearity, the regression may not be able to isolate highly correlated independent variables from each other, leading the model to be unstable. We ensured no multicollinearity by omitting variables where the correlation of the model’s independent variables is high.

3.3.7 Stationarity

Stationarity refers to time series having a constant variance and fluctuation around a constant mean over time. However, we disregarded non-stationarity issues in our dataset as we have large N (number of panel members) and T (time periods), consisting of N=174 stocks and T=324 days. In addition, we used an augmented Dickey-Fuller test on our variables to test for stationarity (Wooldridge, 2016). We discarded the null hypothesis at the 1% level, which means the series is stationary.

4. Results

In this section, we start by reporting the results from the analysis of auction turnover. Next, we report the results regarding price deviation. Lastly, a review of the results of reversals will be presented.

4.1 Auction turnover

Figure 3 illustrates the fraction of daily trades, expressed in NOK volume, intraday, and around the close. The top plot displays the fraction of daily trades made in ordinary intraday trading (10:00-16:15). The plot shows that the volume has been steady around 70%-80% of daily trades, but with some days of spikes and drops. The top right plot shows that the daily fraction of trades made in the last 5 minutes of ordinary trading (16:15-16:20) has been low and steady at below 5%, except for three days with extreme trading. The most extreme values were on the 17th of February 2020, when Akka Technologies acquired Data Respons AS, and on the 2nd of December 2020 when Entra ASA announced the decision to reevaluate their assets with the expectation of a significant rise in their net asset value. The bottom left plot in Figure 3 displays that the fraction of daily volume executed in the closing auction had a baseline of around 20% but was more volatile with more dominant spikes and fluctuations and, on some days, exceeded 60% of all trades. We see similar behavior for the opening in the last plot in Figure 4, with a baseline of around 15%-20%.

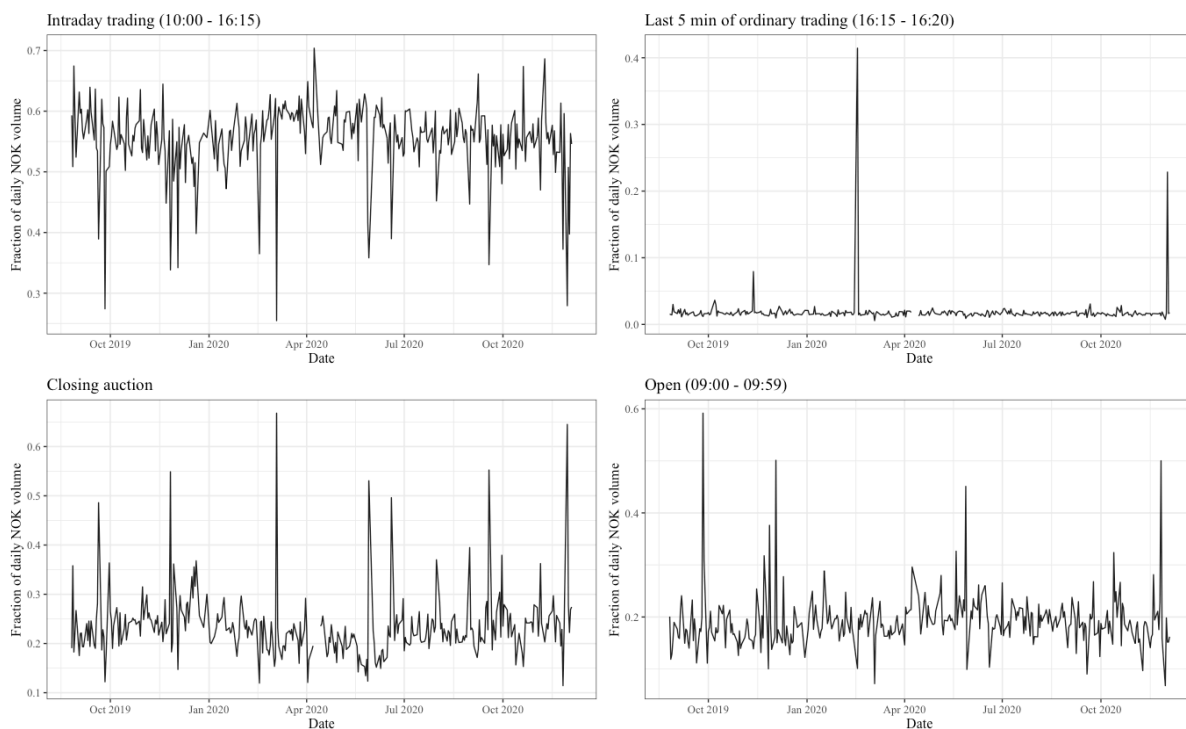


Figure 3: From the top left corner, the first figure illustrates the fraction of aggregate daily NOK volume made between 10:00 and 16:15. The second figure shows the fraction of aggregate daily NOK volume made in the last 5 min of ordinary trading (16:15-16:20). The bottom left figure displays the fraction of aggregate daily NOK volume made in the closing auction and the last figure illustrates the fraction of aggregate daily NOK volume made in the first hour of trading (09:00-09:59).

Table 8 in the Appendix A.1 confirms the results illustrated in Figure 3 and gives descriptive statistics for our sample. Auction volume was 23.46% of daily NOK volume for an average stock-day for all stocks. The auction volume was similar for stocks in the OSEBX and OBX Index with 24.99% and 28.31%, respectively. In contrast, the auction was not used to such an extent for stocks not included in the OSEBX or OBX Index, as only 8.10% of daily trade volume was executed in the closing auction, and a more considerable fraction of trading occurred in ordinary trading hours. This pattern is also shown in the share of stocks with no trades in the closing auction. Only 2.57% and 0.33% of stocks-days in the OSEBX and OBX Index had no trades in the closing auction, while 40.98% of stock-days for the remaining stocks. Nevertheless, the closing auction had a significantly higher trading volume than the last 5 minutes of ordinary trading (16:15-16:20), where only 1.86% of the daily trade was executed on an average stock-day for all stocks. The last 5 minutes trade volume changed little across sample groups: 1.71% for OSEBX, 1.58% for OBX and 2.36% for remaining stocks.

We estimated a panel regression on log turnover for all companies to find the determinants of the turnover throughout the trading day. The regression results are illustrated in Table 2 on the following page. Each column represents a stock-fixed effects model with the same variables as included in Section 2.2. We included dummies for specific calendar days to adjust for seasonalities and special trading days (e.g., the third Friday of each month is typically a stock option expiration day). To compare our estimation for auction turnover, we included equivalent regressions with pre-close/last 5 min turnover (16:15-16:20) and intraday turnover (10:00-16:15) as dependent variables. Furthermore, we included the log turnover in different intervals throughout the trading day (09:00-09:59, 16:00-16:15, and 16:15-16:20) to control for intraday changes that may not be specific to the closing auction. We controlled for volatility by including the average absolute return over the past three trading days, including the current day. Furthermore, we included the lagged return, return from 16:00-16:15, in addition to overnight and lagged return of major U.S. indices.

Table 2: Panel regression with stock fixed effects for all stocks. The log auction turnover, log turnover in the last 5 min of ordinary trading and log intraday turnover (10:00-16:15) are regressed on explanatory variables.

	Auction turnover	Last 5min Turnover	Intraday turnover
Last of month	0.406*** (0.053)	0.081 (0.057)	-0.034 (0.029)
3rd Friday	0.220*** (0.054)	-0.019 (0.058)	0.041 (0.029)
First of month	-0.178*** (0.052)	-0.146*** (0.056)	-0.025 (0.028)
log Turnover 09:00-09:59	0.228*** (0.008)	0.294*** (0.009)	
log Turnover 16:00-16:15	0.165*** (0.004)	0.261*** (0.005)	
log Turnover 16:15-16:20	0.188*** (0.004)		
log Avg Ret	0.279*** (0.016)	0.350*** (0.018)	0.617*** (0.008)
Return 16:00-16:15	-1.544 (1.120)	-3.661*** (1.203)	3.127*** (0.601)
Return(t-1)	-0.638*** (0.166)	0.182 (0.178)	0.285*** (0.089)
Return overnight	1.660** (0.706)	2.233*** (0.759)	0.333 (0.379)
Dow Jones return overnight	4.907*** (1.724)	1.372 (1.852)	5.460*** (0.926)
Nasdaq return overnight	5.203** (2.598)	1.148 (2.792)	-11.481*** (1.395)
S&P500 return overnight	-11.857*** (3.486)	-3.055 (3.746)	10.827*** (1.872)
Dow Jones return(t-1)	-1.317 (1.327)	-1.263 (1.426)	-1.603** (0.713)
Nasdaq return(t-1)	2.599* (1.360)	0.690 (1.461)	3.282*** (0.730)
Observations	43,497	43,497	43,497
R ²	0.175	0.157	0.127
Adjusted R ²	0.172	0.153	0.123
F Statistic	613.801*** (df = 15; 43308)	574.464*** (df = 14; 43309)	523.831*** (df = 12; 43311)

Note: Significance levels of 1%, 5% and 10% are denoted as ***, **, and *, respectively. The independent variables include:

- Indicators for the 3rd Friday and first and last day of month,
- log turnover for the intervals 09:00-09:59, 16:00-16:15 and 16:15-16:20,
- The absolute return averaged over the last three trading days, log Avg|Ret|,
- The return from 16:00-16:15, the lagged return (Return(t-1)) and the return made from the end of the previous until current trading day at 10:00 (Return overnight),
- Overnight returns and lagged daily return for the indices Dow Jones Industrial Average, Nasdaq and S&P 500.

As expected, the auction volume was higher on days with higher trade volume earlier in the day. We also noticed that the auction turnover was significantly larger on the last day and the third Friday of each month. At the same time, it was not the case for the last 5 minutes and intraday turnover. Additionally, we observed that the U.S. market affected the trade volume on the Oslo Stock Exchange to a great extent. The start of regular trading for the U.S. stock market is 15:30 CET, which means that Norwegian investors can monitor the opening trend (expressed as overnight return) of major U.S. indices and have time to adjust their portfolio by the end of the Oslo Stock Exchange trading day. As we can see from the panel regression in Table 2 an increase in overnight return for Dow Jones and Nasdaq is associated with a significant increase in auction turnover. We see the opposite for the S&P 500 Index. This is also the case for the intraday turnover, in addition to also being affected by the lagged return of these indices. In contrast, the effect is not significant for the turnover in the last 5 minutes of ordinary trading, meaning that U.S. indices returns do not, on average, significantly affect the pre-close turnover for the stocks on the Oslo Stock Exchange.

We allocated stocks into three groups defined by their inclusion/exclusion in the OSEBX or OBX Index to observe any differences between them. The results of the stock-fixed effects models are presented in Table 3 on the next page. We regressed log auction turnover on the same variable as in Table 2 and saw that same-day turnover had a similar positive association with auction turnover for all three groups. Day-specific indicators showed the same pattern, where the auction turnover was higher on the last day of the month and the third Friday of each month. OSEBX rebalancing days significantly impacted auction turnover for stocks included in the OBX Index but not for other stocks. OBX rebalancing days seemed to have no significant impact on any of the groups. Stocks in OSEBX and OBX are influenced by the major U.S. indices, unlike stocks that are not included (remaining stocks). Interestingly, the overnight return of the S&P 500 Index seemed to have a negative impact on the auction turnover for all groups.

Table 3: Panel regressions with stock fixed effects for stocks in OSEBX, OBX and the remaining stocks. The log auction turnover regressed on explanatory variables.

	Auction turnover		
	OSEBX	OBX	Remaining stocks
Last of month	0.475*** (0.046)	0.289*** (0.027)	0.349*** (0.086)
3rd Friday	0.294*** (0.047)	0.282*** (0.027)	0.161* (0.087)
First of month	-0.095* (0.049)	-0.066** (0.028)	-0.226** (0.091)
log Turnover 09:00-09:59	0.136*** (0.010)	0.075*** (0.010)	0.254*** (0.011)
log Turnover 16:00-16:15	0.186*** (0.007)	0.280*** (0.011)	0.162*** (0.006)
log Turnover 16:15-16:20	0.176*** (0.006)	0.168*** (0.009)	0.188*** (0.006)
log Avg Ret	0.159*** (0.015)	0.064*** (0.010)	0.375*** (0.025)
Return 16:00-16:15	0.251 (1.368)	1.302 (1.066)	-3.335** (1.567)
Return 16:15-16:20	-2.938* (1.742)	-0.817 (1.988)	-8.425*** (1.902)
OSEBX rebalancing	0.140 (0.128)	0.192** (0.075)	-0.315 (0.234)
OBX rebalancing	-0.111 (0.119)	-0.090 (0.070)	-0.176 (0.218)
Return(t-1)	-0.406** (0.192)	-0.245** (0.111)	-0.724*** (0.235)
Dow Jones return overnight	7.027*** (1.549)	2.584*** (0.912)	4.523 (2.786)
Nasdaq return overnight	5.164** (2.313)	1.480 (1.361)	3.843 (4.157)
S&P500 return overnight	-13.354*** (3.137)	-7.168*** (1.844)	-10.762* (5.563)
Dow Jones return(t-1)	-7.480*** (1.532)	-2.580*** (0.904)	3.937 (2.750)
Nasdaq return(t-1)	4.225** (1.643)	5.237*** (0.972)	3.830 (2.965)
S&P500 return(t-1)	2.173 (2.206)	-3.069** (1.304)	-5.287 (3.968)
Observations	18,581	6,972	24,916
R ²	0.200	0.400	0.175
Adjusted R ²	0.197	0.396	0.171
F Statistic	257.587*** (df = 18; 18498)	256.401*** (df = 18; 6931)	292.175*** (df = 18; 24789)

Note: Significance levels of 1%, 5% and 10% are denoted as ***, **, and *, respectively. The independent variables include:

- Indicators for the 3rd Friday and first and last day of month,
- log turnover for the intervals 09:00-09:59, 16:00-16:15 and 16:15-16:20,
- The absolute return averaged over the last three trading days, log Avg|Ret|,
- The return from 16:00-16:15, 16:15-16:20 and the lagged return (Return(t-1)),
- OSEBX and OBX rebalancing are indicators for OSEBX and OBX rebalancing dates,
- Overnight returns and lagged daily return for the indices Dow Jones Industrial Average, Nasdaq and S&P 500.

We compared the closing auction turnover for stocks in OSEBX and OBX with the remaining stocks by performing a one-sided Welch two-sample t-test and display the test results in Appendix A.5 Figure 6. Our results showed that the auction turnover was significantly higher for stocks in OSEBX and OBX than the remaining stocks on a 1% level with t-values of 29.40 and 37.38, respectively.

4.2 Price deviation

Table 11 in Appendix A.6 reports the descriptive statistics for the closing auction price deviation for our entire sample and divided into groups defined by inclusion/exclusion in the OSEBX or OBX Index. Auction price deviation was on average 64.09 bps for all stocks and varied from 24.97 bps for stocks in OBX to 84.11 bps for the stocks not included in OSEBX or OBX (remaining stocks). The distribution was positively skewed. In 10% and 5% of stock-days, auction prices deviated by more than 155 bps (1.55%) and 240 bps (2.40%), respectively. Results showed that the spread was driven by the non-index stocks, wherein 10% and 5% of stock-days auction price deviated by more than 209 bps and 306 bps, respectively. The mean price deviation of 64.09 bps accounted for a change in the total daily trade volume of NOK 46.88 million and a NOK 85 million change in market capitalization for an average stock.

Table 4 illustrates the results of the auction price deviation panel regression model. We focused on the cross-stock variation by including date fixed effects instead of stock fixed effects. As expected, a higher auction turnover corresponded to a higher absolute price deviation. In contrast, our results showed that absolute price deviation decreased with a higher turnover earlier in the day. This held for stocks in the OSEBX and non-index stocks. Our fixed effects model for stocks in the OBX Index gave significant independent variables, but due to the low adjusted R^2 , we are careful to draw conclusions from our model. Absolute price deviation was significantly smaller for stocks in OSEBX and OBX. The price deviation was smaller for stocks with high stock prices and larger when the volatility was higher. The coefficients were quantitatively close for all stocks with significant independent variables.

Table 4: Panel regressions with date fixed effects for stocks in OSEBX, OBX and the remaining stocks. The auction price deviation is regressed on explanatory variables.

	Auction price deviation			
	All	OSEBX	OBX	Remaining stocks
log Turnover 16:15-16:20	-2.711*** (0.263)	-2.170*** (0.471)	-1.858* (1.093)	-2.300*** (0.356)
log Turnover 09:00-16:15	-7.956*** (0.568)	-4.092*** (0.873)	4.556*** (1.373)	-7.686*** (0.880)
log Turnover Auction	1.728*** (0.371)	1.177** (0.590)	6.935*** (1.257)	1.683*** (0.518)
log Price	-12.741*** (0.484)	-9.273*** (0.641)	-3.676*** (0.696)	-13.875*** (0.727)
log Avg Ret	19.705*** (0.944)	13.323*** (1.173)	3.549*** (1.291)	22.398*** (1.477)
Auction price deviation (t-1)	0.112*** (0.005)	0.062*** (0.008)	-0.001 (0.012)	0.117*** (0.008)
OBX	-6.074*** (1.973)	-11.774*** (1.706)		
OSEBX	-15.586*** (1.580)			
Observations	36,493	18,199	6,970	16,753
R ²	0.102	0.050	0.031	0.079
Adjusted R ²	0.094	0.033	-0.014	0.062
F Statistic	511.548*** (df = 8; 36180)	134.113*** (df = 7; 17888)	35.149*** (df = 6; 6660)	235.360*** (df = 6; 16443)

Note: Significance levels of 1%, 5% and 10% are denoted as ***, **, and *, respectively. The independent variables include:

- log turnover for the intervals 16:15-16:20, 09:00-16:15 and the auction,
- The logarithm of each stock's price,
- The absolute return averaged over the last three trading days, log Avg|Ret|,
- The lagged auction price deviation, Auction price deviation (t-1),
- Indicators for the stocks included in OSEBX or OBX on a given day.

We further analyzed the drivers behind the auction price deviation by plotting the VSTOXX against the value-weighted auction return in Figure 4 on the following page. The plot shows that the time series are highly correlated, meaning that auction prices are more likely to deviate when the aggregate risk is high. Most notably, the plot shows a massive spike in risk and a corresponding spike in price deviation during March 2020, as Covid-19 started to spread and countries went into lockdown. Table 5 confirms that aggregate risk, expressed as VSTOXX, drives aggregate price deviation in our sample. The results showed that the VSTOXX can account for more than 34% of the variation in value-weighted auction return/deviation. Thus, closing auction price deviations are correlated across stocks and are significant on an aggregate level.

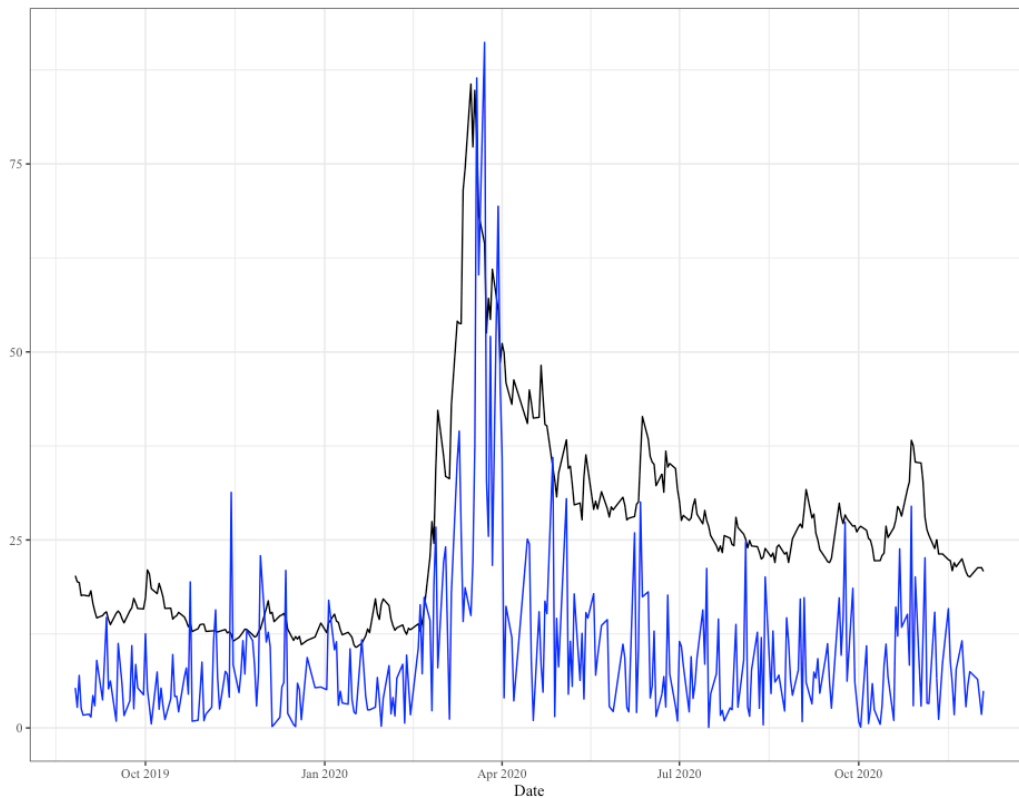


Figure 4: VSTOXX price in EUR (black) and value-weighted auction return in basis points (blue). To compute the auction deviation, we value-weighted the price deviation at the close across stocks and took an absolute value.

Table 5: Panel regressions with stock fixed effects for all stocks. The value-weighted auction return is regressed on the VSTOXX price (EUR).

	Value-weighted auction return
VSTOXX price (EUR)	0.510*** (0.040)
Intercept	-2.922** (1.132)
Observations	314
R ²	0.347
Adjusted R ²	0.345
Residual Std. Error	9.185 (df = 312)
F Statistic	165.610*** (df = 1; 312)

Note: Significance levels of 1%, 5% and 10% are denoted as ***, **, and *, respectively.

4.3 Reversals

Table 6 shows the panel regression model outputs for the overnight return for all stocks in our sample with stock-fixed effects. We found that a significant amount (75%) of the return from end of ordinary trading to end of auction (16:20-auction) was reversed before 10:00 the next day. We got the similar results when we controlled for return in the last 5 minutes of ordinary trading (16:15-16:20). Over 40% of the return made in the last 5 minutes of ordinary trading was also reversed by 10:00 next morning, but due to the negative adjusted R^2 we are careful to draw conclusions from this result. In Table 7 we present the results for the same regressions separated into our groups of interest. We observed that the auction returns almost fully reverted (a coefficient of -1 means that prices revert completely) for stocks in OSEBX and OBX. We found that over 95% of the price deviation in the closing auction was reversed the following morning for stocks in OSEBX and OBX. The reversals were smaller for the remaining stocks. Similarly, last 5 minutes return for stocks in the OSEBX reverted significantly by the next morning. However, as with our model for the full sample, our model for OSEBX and OBX was a poor fit for the observations.

Table 6: Panel regressions with stock fixed effects for all stocks. The overnight return from pre-close (16:20) and closing auction is regressed on return from 16:20 – auction close and the return in the last 5 minutes of ordinary trading (16:15-16:20).

	Overnight returns - Full Sample		
	Return auction-09:59	Return auction-09:59	Return 16:20-09:59
Return 16:20-auction	-0.750*** (0.018)	-0.777*** (0.018)	
Return 16:15-16:20		-0.352*** (0.035)	-0.414*** (0.035)
Observations	43,582	43,582	43,582
R^2	0.039	0.041	0.003
Adjusted R^2	0.035	0.038	-0.001
F Statistic	1,772.059*** (df = 1; 43407)	938.781*** (df = 2; 43406)	143.081*** (df = 1; 43407)

Note: Significance levels of 1%, 5% and 10% are denoted as ***, **, and *, respectively.

Table 7: Panel regressions with stock fixed effects for stocks in OSEBX, OBX and the remaining stocks. The overnight return from pre-close (16:20) and closing auction is regressed on return from 16:20 – auction close and the return in the last 5 minutes of ordinary trading (16:15-16:20).

Overnight returns - OSEBX			
	Return auction-09:59	Return auction-09:59	Return 16:20-09:59
Return 16:20-auction	-0.952*** (0.013)	-0.959*** (0.013)	
Return 16:15-16:20		-0.292*** (0.046)	-0.305*** (0.046)
Observations	18,591	18,591	18,591
R ²	0.223	0.225	0.002
Adjusted R ²	0.220	0.222	-0.001
F Statistic	5,318.697*** (df = 1; 18525)	2,685.432*** (df = 2; 18524)	44.787*** (df = 1; 18525)
Overnight returns - OBX			
	Return auction-09:59	Return auction-09:59	Return 16:20-09:59
Return 16:20-auction	-0.987*** (0.012)	-0.986*** (0.012)	
Return 16:15-16:20		0.090 (0.113)	0.087 (0.113)
Observations	6,972	6,972	6,972
R ²	0.507	0.507	0.0001
Adjusted R ²	0.506	0.506	-0.003
F Statistic	7,150.223*** (df = 1; 6948)	3,575.235*** (df = 2; 6947)	0.591 (df = 1; 6948)
Overnight returns - Remaining stocks			
	Return auction-09:59	Return auction-09:59	Return 16:20-09:59
Return 16:20-auction	-0.384*** (0.036)	-0.431*** (0.037)	
Return 16:15-16:20		-0.287*** (0.048)	-0.441*** (0.047)
Observations	24,991	24,991	24,991
R ²	0.004	0.006	0.004
Adjusted R ²	0.0001	0.001	-0.001
F Statistic	111.417*** (df = 1; 24881)	73.688*** (df = 2; 24880)	87.428*** (df = 1; 24881)

Note: Significance levels of 1%, 5% and 10% are denoted as ***, **, and *, respectively.

5. Discussion

In this section, we elaborate on our analyses and results. We follow the same order as the results section, first discussing the findings of the subject of auction turnover. Then, a discussion regarding price deviation will follow. Finally, the results regarding reversals will be discussed.

5.1 Auction turnover

Institutional investors are benchmarked with month-end prices. The investors aim to minimize tracking error by trading at the close due to their benchmarks often being set by closing prices, something that further encourages them to trade at the close. Our results are supported by Bogousslavsky and Muravyev's (2020) findings, as institutional rebalancing seems to affect turnover in the closing auction since the turnover is higher on the last day of the month, but the intraday turnover remains unchanged. Several institutional investors will meet the inflow of capital in the first days of the month (Etula, Rinne, Suominen & Vaitinen, 2020). Thus, auction turnover and pre-close turnover are significantly higher on the first day of each month. In addition, auction turnover spikes on the 3rd Friday of each month because these are typically option expiration days, and market makers will drop their stock delta-hedges after the options expire.

We find that the auction turnover is higher on days with higher trade volume earlier in the day, consistent with Bogousslavsky and Muravyev (2020), which is the case for all stock groups. Index funds rebalance their portfolio in the last minutes of ordinary trading and especially at the closing auction to minimize tracking error. In contrast to Bogousslavsky and Muravyev (2020), we find that OSEBX rebalancing days merely significantly impact stocks included in OBX, where the auction turnover increases by 19.2%. Our findings show no significant change in auction turnover on OBX rebalancing days, indicating that index investing has a weaker link to closing auction volume on the Oslo Stock Exchange.

We argue that three factors can partly explain the lack of rebalancing effect for Norwegian stocks. First, it may be from the fact that out of the 70 index funds presented by the Norwegian Fund and Asset Management Association (VFF) in 2019, only 12 have their main or sole focus on stocks listed on the Oslo Stock Exchange (VFF, 2021). Index funds tend to focus on a

global scale, with a large fraction of their portfolio in the American stock market, which can explain why the index rebalancing days have a more significant impact on the use of closing auctions in the U.S. than in Norway. Second, the Norwegian stock market is closely linked to the American stock market, and there are some obvious contagion effects. We find that auction turnover is significantly higher when the overnight return of Dow Jones and Nasdaq indices opens positively (positive overnight return) for stocks in OSEBX. The remaining stocks do not seem to be significantly affected. Consequently, if the American market opens surprisingly, Norwegian investors may use the pre-close and closing auction to adjust their portfolios. Lastly, Bogousslavsky and Muravyev (2020) found that the stock's degree of ETF ownership affects investors' use of the closing auction and that ETF ownership is highly significant for auction turnover. As of year-end 2020, there were 1,675 index-based ETFs in the United States with \$5.4 trillion in net assets, accounting for 18% of U.S.-registered investment company total net assets (ICI, 2021). In contrast, ETFs in Norway play a lesser role. Only four ETFs that track the OBX Index are traded on Euronext as of May 2021 (Euronext, 2021), with assets under management of NOK 3.12 billion, which only constitutes 0.19% of the Norwegian fund market (VFF, 2021). The small portion of ETFs in the Norwegian market can be a reason for our results showing a weaker relationship between index investing and auction turnover.

Overall, closing auction volume seems to differ relative to other periods during the day. Bogousslavsky and Muravyev (2020) argued that the closing auction has become a great trading mechanism that has increased significantly in importance and activity during recent years. Admati and Pfleiderer (1988) anticipated that clustering of trades that are not based on firm-specific information at specific times during the day would reduce costs and increase price efficiency. Furthermore, if traders clustered their trades around times of higher liquidity, intraday liquidity may deteriorate (Foster & Viswanathan, 1990). Liquidity drying up during the rest of the intraday may be a concerning trend as the opening period is crucial for pricing in overnight news (Bogousslavsky & Muravyev, 2020). An effect where liquidity induces liquidity is predicted to cause informed traders to strategically pool with these uninformed traders to minimize the price impacts of their trades (Admati & Pfleiderer, 1988), i.e., market participants are attracted to the price efficiency and the liquidity that the closing auction offers. Unfortunately, we do not have enough historical data to test if this applies to the Oslo Stock Exchange. However, we find that the auction volume is significantly larger than the opening and the last 5 minutes of ordinary trading. In addition, auction turnover is significantly higher

for stocks in OSEBX and OBX, which are the largest stocks, than the remaining stocks on the Oslo Stock Exchange, consistent with research conducted by Bogousslavsky and Muravyev (2020).

5.2 Price deviation

Our results indicate that prices deviate significantly in the closing auction, which can be compared to Bogousslavsky and Muravyev's (2020) and Wu's (2019) findings with some reservations. Bogousslavsky and Muravyev (2020) and Wu (2019) calculated price deviation from the 4 pm closing quote midpoint, while our analysis uses the final trade price before the close. Using the trade price instead of the bid-ask midpoint to compute price deviation might lead to biased results due to the illiquidity of smaller ETFs (Broman, 2016; Petajisto, 2017). However, due to the low number of ETFs on the Oslo Stock Exchange, we argue that this effect is negligible.

We know from Table 1 that stocks in OBX are, on average, larger than stocks in OSEBX, while the remaining stocks are the smallest. As illustrated in Figure 7 in Appendix A.7 we find that the price deviations are significantly higher for the smallest stocks and decrease with size, meaning that price deviations are lowest for stocks in OBX. Thus, our results are supported by Bogousslavsky and Muravyev (2020). One explanation may be that the auction improves price discovery more for the less actively traded stocks (Madhavan, 1992). In addition, liquidity shocks may have less impact on large stocks with higher market-making capacity than smaller stocks (Bogousslavsky & Muravyev, 2020).

When investigating the drivers behind the auction price deviation, we find that higher auction turnover significantly correlates with a higher price deviation. This finding is supported by Bogousslavsky and Muravyev (2020), who found that a 1% increase in turnover led to a 0.88 bps higher price deviation. In contrast to Bogousslavsky and Muravyev (2020), we find that the auction turnover has a more significant impact on stocks in OBX than smaller stocks. Wu (2019) demonstrated that passive flows increased the market-on-close orders, which impacted stock price dynamics. We argue that the larger impact on stocks in OBX is because passive funds hold the stocks in OBX and that the closing auction orders placed by passive fund

managers are so significant that one cannot guarantee immediate liquidity to be available (Wu, 2019). Liquidity providers should be compensated for meeting the high demand for liquidity to passive funds at the end of the day (Nagel, 2012; Duffie, 2010).

Bogousslavsky and Muravyev (2020) compared aggregate price deviation and the VIX and found that they are highly correlated. We compare the aggregate price deviation of our sample to the European VSTOXX and find similar results. Prices are more likely to deviate at the closing auction when the aggregate risk is high. As Bogousslavsky and Muravyev (2020), we find that aggregate risk drives a large portion of the price deviation, meaning that price deviation is significant at the aggregate level and will also affect diversified portfolios.

5.3 Reversals

We use our model for price-reversal to investigate if the price deviation at the close is caused by information or price pressure. If the price deviation is based on information, the information hypothesis states that the prices are correct and should be permanent. On the other hand, the prices should reverse shortly if the price deviation is due to price pressure (Bogousslavsky & Muravyev, 2020). Our results show that over 75% of the price deviation at the close for all stocks reverse before 10:00 the following day. The results align with both Bogousslavsky and Muravyev (2020) and Wu and Jegadeesh (2020). The price reversal indicates that the price deviation is primarily due to price pressure and not new information. As 25% of the price deviation at the close does not reverse by the following day, there is a possibility that some of the price deviation is permanent. Wu and Jegadeesh (2020) found that 17% of the reversals remained permanent. We can interpret this lack of reversal as that market-on-close orders additionally attract significant participation of informed traders as well, consistent with theoretical implications of clustering of uninformed traders and informed traders (Admati & Pfleiderer, 1988).

Further, we find that the reversal is almost 100% for stocks in the OSEBX and OBX. As the stocks in OSEBX and OBX are, on average, the largest stocks on the Oslo Stock Exchange, our results are consistent with Bogousslavsky and Muravyev (2020), who found a complete reversal for the largest stocks. The reversal implies that overall, primary participants of the closing auction were mostly passive funds that hold the stocks in OSEBX and OBX, in addition to other uninformed traders.

6. Conclusion

The field of index investing has recently started to gain increased attention in financial literature as closing auctions across exchanges are becoming an increasingly important trading period. The aim of this thesis is to investigate the closing auction on a relatively little featured market, the Oslo Stock Exchange.

First, we analyze whether or not index investing drives closing auction turnover and if the turnover of stocks in the OSEBX and OBX Index is significantly higher during the closing auction than the remaining stocks on the Oslo Stock Exchange. Second, we examine whether prices deviate at the close and reverse overnight. Our hypotheses build on the findings of Wu (2019), Bogousslavsky and Muravyev (2020), and Wu and Jegadeesh (2020), who found that auction turnover is significantly higher on index rebalancing days and correlates to the degree of ETF ownership. To test our first hypothesis, we use a fixed effects regression model based on a sample of 174 stocks traded on the Oslo Stock Exchange over a sample period of 314 days, consisting of a total of 46,085,457 trades. We continue by using a Welch two-sample t-test to compare the stocks included in the OSEBX and OBX Index with the remaining stocks. Furthermore, we test our second hypothesis with fixed effects regression models to find the determinants of price deviation and examine if the prices reverse overnight. In addition, we model the value-weighted auction return with respect to aggregate risk, expressed as VSTOXX.

Consistent with our first hypothesis, our analysis shows that the turnover of stocks in the OSEBX and OBX are significantly higher than the remaining stocks during the closing auction. Moreover, we find that OSEBX rebalancing days merely significantly impact stocks included in OBX, where the auction turnover increases by 19.2%. However, we find no significant change in auction turnover on OBX rebalancing days, indicating that index investing has a weaker link to auction volume on the Oslo Stock Exchange than discovered in the U.S. We argue that a weak link between index investing and the use of the closing auction on the Oslo Stock Exchange is primarily due to three factors: 1) Even though index investing has experienced a rise in popularity in recent years, a vast majority of the index funds track indices other than the OSEBX and OBX, 2) the Norwegian stock market is highly linked to the U.S. market and turnover at the close is affected by the opening return of major U.S. indices

and 3) ETFs plays a much larger part of the trading in the U.S. than in Norway, as ETFs' total net asset value only constitutes 0.19% of the Norwegian fund market (VFF, 2021). To conclude, our hypothesis that auction turnover is significantly higher for stocks in OSEBX and OBX than the remaining stocks is valid. However, the use of the closing auction on the Oslo Stock Exchange might be more influenced by opening trends of the American stock market than index investing. We suggest that more research is needed to conclude that index investing drives closing auction turnover.

Our results show that prices deviate significantly in the closing auction and that a high positive correlation with auction turnover exists. Prices are more likely to deviate at the closing auction when the aggregate risk is high. Further, we find that more than 75% of the price deviation at the close for all stocks reverses before 10:00 the following day, and the reversal is almost 100% for stocks in the OSEBX and OBX. Hence, our second hypothesis that prices deviate at the close and reverse overnight is verified. The price reversal indicates that the price deviation is primarily due to price pressure and not new information. Consistent with Wu (2019), our results may indicate that if the increase of auction trades induces closing prices to distort and stock prices to deviate from the fundamental values, some index funds may benefit from accepting larger tracking errors by trading at other times than during the closing auction.

For further research, we believe it would be interesting to conduct similar analyses on a more extensive sample period to investigate whether investor behavior has changed over time. A larger data sample would allow for comparison of auction volume and price deviation with the influx of capital to index investment funds. The results may potentially change when including “normal” years that are not affected by a pandemic. From an investor’s point of view, it would also be interesting to evaluate the possibility of developing an investment strategy that takes advantage of the price deviation at the close on the Oslo Stock Exchange.

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A. Appendix

A.1 Trading volume statistics

Table 8: Descriptive statistics for the trading volume.

	All stocks			OSEBX			OBX			Remaining stocks		
	Mean	Median	StdDev	Mean	Median	StdDev	Mean	Median	StdDev	Mean	Median	StdDev
Auction vol. share (%)	23.45	22.65	6.60	24.99	24.21	6.80	28.31	27.51	7.11	8.10	6.77	6.09
16:15-16:20 vol. share (%)	1.86	1.60	2.55	1.71	1.57	1.35	1.58	1.52	0.57	2.36	1.77	4.94
10:00-16:15 vol. share (%)	74.77	75.50	6.94	73.39	74.18	7.01	70.20	71.06	7.25	89.58	90.79	7.53
Price (NOK)	116.95	79.76	130.89	122.39	88.70	123.14	145.72	129.50	133.39	81.36	23.26	168.93
Daily trade vol. (m. shares)	266.73	213.98	202.21	216.87	161.77	201.82	88.23	65.55	70.98	49.86	36.45	48.92
No 09:00-16:15 vol. (%)		0.00			0.00			0.00			0.23	
No 16:15-16:20 vol. (%)		30.25			4.71			0.35			46.10	
No auction volume (%)		26.31			2.57			0.33			40.98	
Non-complete dataset (%)		31.61										
Num. trades	46 085 457			39 969 021			28 513 398			6 116 436		

A.2 Descriptive statistics for stocks in dataset

Table 9: Descriptive statistics for all stocks included in the sample.

#	Company	Ticker	Average trade size	Nr. of trades	Sample period (days)	No closing auction	Changes
1	Adevinta Ser. A	ADEA	231.38	19 841	40	0	Share collapse of class A and B on 24.10.19. (1)
2	Adevinta Ser. B	ADEB	333.01	23 783	40	0	Share collapse of class A and B on 24.10.19. (1)
3	AF Gruppen	AFG	207.23	45 348	324	2	
4	Arendals Fossekompani	AFK	21.55	9 603	322	231	
5	Akastor	AKA	3 024.52	54 720	304	3	
6	Aker	AKER	85.02	566 092	324	1	
7	Aker BP	AKERBP	235.82	1 463 349	304	1	
8	Aker Solutions	AKSO	1 467.44	772 546	324	1	
9	AKVA Group	AKVA	618.57	10 467	324	144	
10	American Shipping Co	AMSC	664.48	38 984	324	25	
11	AqualisBraemar LOC	AQUA	3 553.01	8 537	318	259	
12	Archer	ARCHER	3 949.69	42 091	304	40	
13	Arcus	ARCUS	592.71	25 595	324	109	
14	ABG Sundal Collier Holding	ASC	4 713.40	42 133	304	51	Changed ticker to ABG on 30.11.20. (2)
15	Asetek	ASETEK	404.68	50 278	304	35	
16	ATEA	ATEA	302.78	130 584	324	1	
17	Atlantic Petroleum	ATLA	464.11	808	170	161	
18	Austevoll Seafood	AUSS	270.47	328 994	324	1	
19	Avance Gas Holding	AVANCE	840.16	394 190	304	1	
20	Awilco Drilling PLC	AWDR	1 093.55	16 227	324	153	
21	Axactor	AXA	2 481.98	201 896	324	1	
22	B2Holding	B2H	2 813.48	207 407	324	1	
23	Bakkafrost	BAKKA	84.91	693 012	324	1	
24	Borr Drilling Limited	BDRILL	980.62	474 010	304	1	
25	Belships	BEL	11 751.94	1 980	291	277	
26	BerGenBio	BGBIO	632.41	288 531	324	25	
27	Biotec Pharmacon	BIOTE	1 478.58	30 576	185	78	Rebranded to Articzymes Tech. (AZT) 17.06.2020. (3)
28	Bygma	BMA	272.94	1 179	254	239	
29	Bonheur	BON	191.70	122 906	304	1	
30	Borgestad	BOR	1 736.62	5 213	320	279	
31	Bouvet	BOUVET	141.26	24 359	304	77	
32	Borregaard	BRG	283.13	140 788	324	1	
33	BW LPG	BWLPG	516.02	601 195	324	1	
34	BW Offshore	BWO	584.57	538 692	324	1	
35	Carasent	CARA	1 415.74	37 561	324	146	
36	ContextVision	COV	316.05	37 556	304	140	
37	Crayon Group Holding	CRAYON	450.70	160 226	304	1	
38	Cxense	CXENSE	4 140.08	238	28	18	Acquired by Piano on 03.10.19. (4)
39	Data Respons	DAT	5 235.38	17 047	167	13	Acquired by AKKA Technologies 05.05.20. (5)
40	DNB	DNB	461.82	1 825 874	324	1	
41	DOF	DOF	7 568.93	55 215	324	127	
42	Eidesvik Offshore	EIOF	3 205.66	7 409	309	270	
43	Element	ELE	2 402.06	73 618	324	69	
44	Elkem	ELK	1135.91	340 910	324	1	
45	ElectroMagnetic GeoServices	EMGS	4 918.90	25 535	324	172	
46	ENDUR	ENDUR	8 082.82	57 800	323	158	
47	Entra	ENTRA	462.10	445 287	324	1	
48	Europris	EPR	620.51	345 314	324	1	
49	Equinor	EQNR	464.24	3 000 149	324	1	
50	Evry	EVRY	730.28	15 389	55	1	Merged with Tieto (TIETOO) on 05.12.19. (6)
51	Fjord1	FJORD	3 750.75	16 399	322	70	
52	Fjordkraft Holding	FKRAFT	536.51	177 332	304	1	
53	Flex LNG	FLNG	366.33	228 276	324	1	
54	Frontline	FRO	420.59	982 609	324	1	
55	Funcom	FUNCOM	2 185.57	68 919	221	17	Acquired by Tencent on 22.07.20. (7)
56	Gaming Innovation Group	GIG	1 634.27	49 935	324	65	
57	Gjensidige Forsikring	GJF	212.44	757 832	324	1	
58	Goodtech	GOD	1 881.61	22 752	317	243	
59	Golden Ocean Group	GOGL	591.30	499 880	324	1	
60	Grieg Seafood	GSF	264.86	450 225	324	1	
61	Gyldendal	GYL	19.82	665	173	159	
62	Havila Shipping	HAVI	1 483.84	11 185	322	243	
63	Hexagon Composites	HEX	569.07	297 659	324	1	
64	Hiddn Solutions	HIDDEN	5 025.54	29 832	284	151	Changed name to Arribatec Solutions on 12.10.20. (8)
65	Hoegh LNG Holdings	HLNG	762.06	51 236	324	29	
66	Havyard Grup	HYARD	1 737.84	38 116	316	225	
67	I dex Biometrics	IDEX	8 972.78	276 005	324	4	
68	Incus Investor	INC	5 876.38	3 194	163	141	Changed name to Scana 11.05.2020. (9)
69	Infront	INFRNT	2 171.28	6 453	301	214	
70	Insr Insurance Group	INSR	7 919.04	51 276	322	165	

Table 9 (continued):

#	Company	Ticker	Average trade size	Nr. of trades	Sample period (days)	No closing auction	Changes
71	InterOil Exploration and Production	IOX	4 413.42	31 791	324	126	
72	Itera	ITE	1 233.22	8 999	301	211	
73	JinHui Shipping and Transportation	JIN	2 363.85	15 403	324	97	
74	Kid	KID	420.93	59 710	324	80	
75	Kitron	KIT	1 359.14	106 785	324	6	
76	Kongsberg Automotive Holdings	KOA	48 746.93	614 475	324	1	
77	Kongsberg Gruppen	KOG	229.93	226 887	324	1	
78	Komplett Bank	KOMP	2 300.78	71 374	324	24	
79	Kværner	KVAER	1 505.62	182 595	304	1	
80	Leroy Seafood Group	LSG	438.69	823 939	324	1	
81	Medistim	MEDI	192.30	39 410	324	42	
82	Magnora	MGN	1 869.92	42 986	319	133	
83	MOWI	MOWI	321.31	1 615 410	324	1	
84	MPC Container Ships	MPCC	3 218.22	66 549	324	52	
85	Magseis Fairfield	MSEIS	5 459.50	81 120	324	43	
86	Multiconsult	MULTI	546.48	10 694	321	219	
87	Nordic Nanovector	NANO	692.47	292 759	304	1	
88	Napatech	NAPA	1 999.57	70 674	324	57	
89	Norwegian Air Shuttle	NAS	3 963.82	2 533 570	324	2	
90	Navamedic	NAVA	924.53	10 274	324	214	
91	NEL	NEL	3 482.16	2 032 866	324	1	
92	Next Biometrics Group	NEXT	3 175.70	55 608	324	51	
93	Norsk Hydro	NHY	1 472.88	1 617 577	324	1	
94	Nekkar	NKR	4 583.89	28 919	324	184	
95	Nordic Semiconductor	NOD	521.55	447 947	324	1	
96	Northern Drilling	NODL	903.83	72 675	323	30	
97	Norwegian Finans Holding	NOFI	443.58	367 778	324	1	
98	Norwegian Energy Co	NOR	162.02	30 090	324	34	
99	Norbit	NORBIT	1 429.23	12 058	304	199	
100	Norwegian Property	NPRO	6 215.36	13 199	324	116	
101	NRC Group	NRC	733.98	70 459	324	10	
102	Norway Royal Salmon	NRS	117.85	167 658	324	1	
103	NTS	NTS	352.31	4 325	316	266	
104	Ocean Yield	OCY	653.89	216 859	324	1	
105	Odfjell Ser. A	ODF	1 417.37	6 920	320	173	
106	Odfjell Ser. B	ODFB	1 490.67	2 395	291	244	
107	Odfjell Drilling	ODL	1 436.79	184 918	324	1	
108	Okea	OKEA	1 089.78	20 915	324	122	
109	Olav Thon Eiendomsselskap	OLT	279.62	31 785	324	24	
110	Orkla	ORK	504.03	1 184 492	324	1	
111	Otello Corp	OTELLO	1 460.55	49 004	304	4	
112	Oceanteam	OTS	4 787.82	11 653	320	222	
113	Pareto Bank	PARB	804.77	46 204	324	81	
114	PCI Biotech Holding	PCIB	465.75	217 557	324	12	
115	Panoro Energy	PEN	1 711.91	119 822	324	1	
116	PGS	PGS	2 199.46	645 442	324	1	
117	PhotoCure	PHO	366.52	340 191	324	1	
118	Polarcus	PLCS	13 848.40	44 221	324	63	
119	poLight	PLT	324.75	101 132	324	65	
120	Polaris Media	POL	1 587.74	3 053	300	268	
121	Protector Forsikring	PROTCT	547.17	54 697	304	5	
122	Prosafe	PRS	3 104.34	69 652	324	121	
123	Petrolia	PSE	1 344.54	12 713	297	194	
124	Questerre Energy Corp	QEC	9 403.33	55 572	324	84	
125	Q-Free	QFR	2 948.97	11 399	312	199	
126	Rak Petroleum	RAKP	2 585.75	5 764	317	231	
127	Reach Subsea	REACH	5 130.17	11 407	306	239	
128	REC Silicon	REC	4 483.43	455 149	304	1	
129	GC Rieber Shipping	RISH	725.76	2 775	271	236	
130	SalMar	SALM	82.28	935 654	324	1	
131	Salmones Camanchaca	SALMON	1 428.90	3 820	295	238	
132	SAS	SAS	1 854.52	74 836	304	119	
133	Sbanken	SBANK	343.242	149 792	324	1	
134	Star Bulk Carriers Corp.	SBLK	322.30	8 186	223	161 Delisted from OSE 31.07.20. (10)	
135	Selvaag Bolig	SBO	322.40	102 447	324	1	
136	SeaBird Exploration	SBX	14 448.82	51 033	324	107	
137	Schibsted Ser. A	SCHA	95.38	836 126	323	2	
138	Schibsted Ser. B	SCHB	131.23	345 557	323	2	
139	Seadrill	SDRL	1 430.23	279 837	324	19	
140	S.D Standard Drilling	SDSD	18 228.04	31 755	324	83	

Table 9 (continued):

#	Company	Ticker	Average trade size	Nr. of trades	Sample period (days)	No closing auction	Changes
141	Shelf Drilling	SHLF	3 457.23	46 789	324	43	
142	Siem Offshore	SIOFF	3 512.74	4 528	284	230	
143	Stolt-Nielsen	SNI	171.10	55 933	324	1	
144	Solstad Offshore	SOFF	5 406.22	96 760	324	135	
145	Solon Eiendom	SOLON	1 768.19	13 927	324	84	
146	SpareBank 1 SR Bank	SRBANK	317.68	280 614	304	1	
147	The Scottish Salmon Co	SSC	2 464.47	19 706	130	20	Acquired by Bakkafrost 05.03.2020. (11)
148	Self Storage Group	SSG	2 866.05	17 836	324	96	
149	Scanship Holding	SSHIP	1 246.78	36 789	92	0	Name changed to Vow (VOW) on 13.01.20. (12)
150	Scatec Solar	SSO	260.21	731 706	324	1	
151	Storebrand	STB	572.32	1 196 615	324	1	
152	Storm Real Estate	STORM	1 852.20	7 544	296	266	
153	StrongPoint	STRONG	1 531.53	18 564	304	174	
154	Subsea 7	SUBC	350.80	1 174 342	324	1	
155	Team Tankers International	TEAM	4 354.14	1 924	216	185	Delisted from OSE from 01.10.2020. (13)
156	Techstep	TECH	3 780.32	14 645	324	189	
157	Telenor	TEL	442.29	1 341 730	324	1	
158	TGS-NOPEC Geophysical Co	TGS	167.53	984 027	324	1	
159	Thin Film Electronics	THIN	27 615.49	190 378	324	41	
160	Tomra Systems	TOM	135.45	1 023 084	324	1	
161	Treasure	TRE	2 396.00	5 792	313	243	
162	Targovax	TRVX	2 147.61	76 851	324	94	
163	Ultimovacs	ULTIMO	426.49	36 205	304	118	
164	Veidekke	VEI	317.53	155 230	324	1	
165	Vistin Pharma	VISTIN	1 975.70	36 662	304	131	
166	Voss Veksel- og Ladmandsbank	VVL	211.62	1 498	285	264	
167	Wallenius Wilhelmsen	WALWIL	947.29	165 521	304	1	
168	Wilson	WILS	709.24	1 102	214	209	
169	Webstep	WSTEP	1 781.59	5 356	305	224	
170	Wilh. Wilhemsen Holding Ser. A	WWI	250.25	16 710	324	93	
171	Wilh. Wilhemsen Holding Ser. B	WWIB	374.19	6 652	315	173	
172	XXL	XXL	1 176.87	468 218	324	1	
173	Yara International	YAR	163.12	1 448 826	324	1	
174	Zalaris	ZAL	1 270.98	11 274	321	212	

Note:

- (1) <https://newsweb.oslobors.no/message/487788>
- (2) <https://newsweb.oslobors.no/message/519158>
- (3) <https://newsweb.oslobors.no/message/508082>
- (4) <https://www.cxense.com/blog/piano-acquires-cxense>
- (5) <https://www.akka-technologies.com/press-release/data-respons-asa-akka-technologies-se-announces-compulsory-acquisition/>
- (6) <https://newsweb.oslobors.no/message/490921>
- (7) <https://aksjelive.e24.no/article/JoVnAX>
- (8) <https://newsweb.oslobors.no/message/515241>
- (9) <https://scana.no/en/2020/05/11/incus-investor-becomes-scana/>
- (10) <https://newsweb.oslobors.no/message/508184>
- (11) <https://newsweb.oslobors.no/message/508184>
- (12) <https://newsweb.oslobors.no/message/493226>
- (13) <https://newsweb.oslobors.no/message/510655>

A.3 Fixed effects model without added trade

Table 10: Panel regression with stock fixed effects for all stocks without adding one trade to all closing auctions. The log auction turnover, log turnover in the last 5 min of ordinary trading and log intraday turnover (09:00-16:15) are regressed on explanatory variables.

	Auction turnover	Last 5min Turnover	Intraday turnover
Last of month	0.345*** (0.036)	0.039 (0.036)	-0.001 (0.022)
3rd Friday	0.225*** (0.038)	0.018 (0.038)	0.011 (0.024)
First of month	-0.143*** (0.037)	-0.031 (0.037)	0.006 (0.023)
log Turnover 09:00-09:59	0.169*** (0.007)	0.215*** (0.007)	
log Turnover 16:00-16:15	0.204*** (0.007)	0.304*** (0.006)	
log Turnover 16:15-16:20	0.183*** (0.006)		
log Avg Retl	0.159*** (0.012)	0.207*** (0.012)	0.571*** (0.007)
Return 16:00-16:15	0.902 (0.859)	0.599 (0.856)	1.991*** (0.530)
Return(t-1)	-0.267** (0.127)	0.023 (0.127)	0.607*** (0.078)
Return 16:15-16:20	1.118 (1.009)	-4.489*** (1.006)	0.805 (0.622)
Return 16:20-close	-2.616*** (0.462)	0.807* (0.461)	0.015 (0.285)
Dow Jones return overnight	3.051*** (1.184)	2.328** (1.180)	5.281*** (0.730)
Nasdaq return overnight	3.439* (1.814)	-3.226* (1.808)	-10.233*** (1.118)
S&P500 return overnight	-7.304*** (2.362)	3.037 (2.355)	7.923*** (1.457)
Dow Jones return(t-1)	-3.737*** (0.937)	-0.016 (0.934)	-3.515*** (0.578)
Nasdaq return(t-1)	4.211*** (0.960)	-0.206 (0.957)	4.053*** (0.592)
Observations	29,441	29,441	29,441
R ²	0.194	0.195	0.217
Adjusted R ²	0.189	0.190	0.213
F Statistic	440.417*** (df = 16; 29257)	473.589*** (df = 15; 29258)	625.121*** (df = 13; 29260)

Note: Significance levels of 1%, 5% and 10% are denoted as ***, **, and *, respectively.

A.4 Fraction of trades without outliers

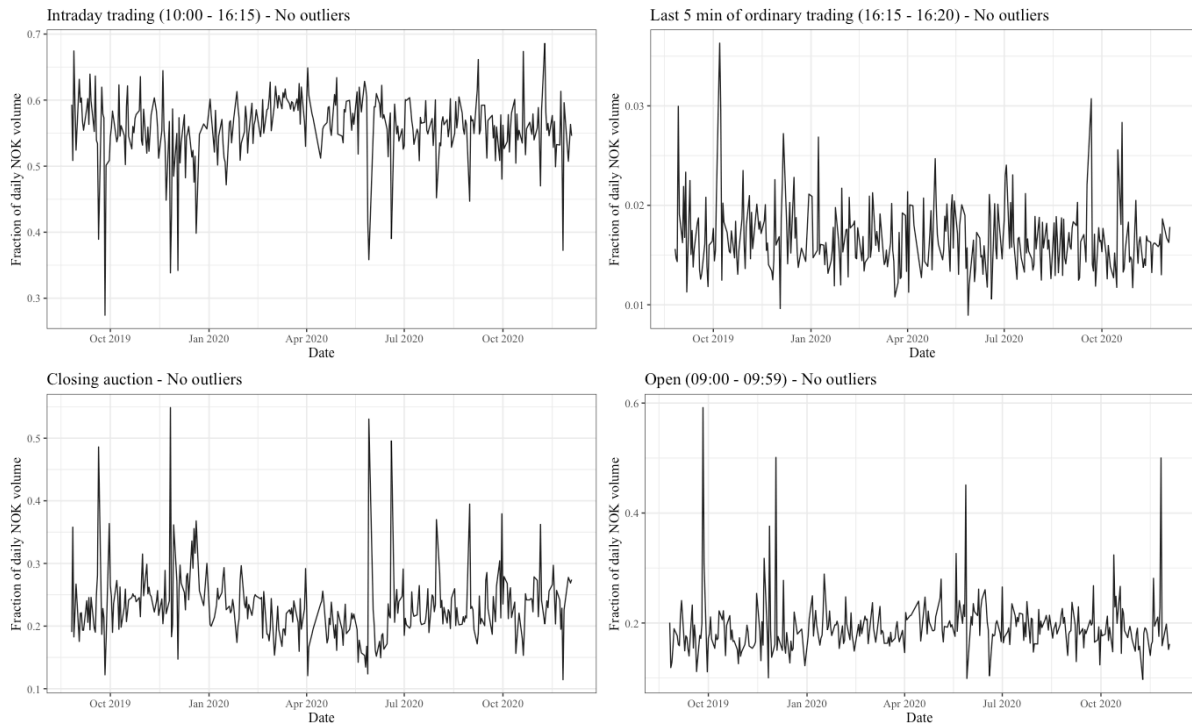


Figure 5: Outliers removed. From the top left corner, the first figure illustrates the fraction of aggregate daily NOK volume made between 10:00 and 16:15. The second figure shows the fraction of aggregate daily NOK volume made in the last 5 min of ordinary trading (16:15-16:20). The bottom left figure displays the fraction of aggregate daily NOK volume made in the closing auction and the last figure illustrates the fraction of aggregate daily NOK volume made in the first hour of trading (09:00-09:59).

A.5 Auction turnover - Welch two-sample t-test

```

Welch Two Sample t-test

data: df_OSEBX$turnover_closing and df_rest$turnover_closing
t = 29.402, df = 52432, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.0003544411      Inf
sample estimates:
 mean of x   mean of y
0.0005018904 0.0001264450

```

```

Welch Two Sample t-test

data: df_OBX$turnover_closing and df_rest$turnover_closing
t = 37.379, df = 15870, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.0006117805      Inf
sample estimates:
 mean of x   mean of y
0.0007663873 0.0001264450

```

Figure 6: Results of the one-sided Welch two-sample t-tests for OSEBX – Remaining stocks (top) and OBX – Remaining stocks (bottom) on auction turnover.

A.6 Price deviation statistics

Table 11: Descriptive statistics for the auction price deviations in basis points.

	All	OSEBX	OBX	Remaining stocks
Mean	64.09	41.18	24.97	84.11
Median	29.62	22.56	16.89	42.62
StdDev	130.55	98.69	57.36	148.07
p0.05	0.00	0.00	0.00	0.00
p0.5	29.62	22.56	16.89	42.62
p0.8	88.42	55.71	36.01	126.58
p0.9	155.04	89.54	51.36	209.07
p0.95	242.93	134.59	71.99	306.28
Count	37 750	19 088	7 226	16 766

A.7 Price deviation - Welch two-sample t-test

```
Welch Two Sample t-test

data: df_prices_dev_rest$deviation_close_bp and df_prices_dev0SEBX$deviation_close_bp
t = 34.879, df = 31781, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 44.16082      Inf
sample estimates:
mean of x mean of y
 87.52171  41.17515
```

```
Welch Two Sample t-test

data: df_prices_dev_rest$deviation_close_bp and df_prices_dev0BX$deviation_close_bp
t = 47.821, df = 25864, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 60.39638      Inf
sample estimates:
mean of x mean of y
 87.52171  24.97387
```

Figure 7: Results of the one-sided Welch two-sample t-tests for Remaining stocks – OSEBX (top) and Remaining stocks - OBX (bottom) on price deviation.