Internet Appendix to
Equity trading costs have fallen less than commonly thought. Evidence using alternative trading cost estimators

Valeriia Klova and Bernt Arne Ødegaard*

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1 Measures of equity trading costs

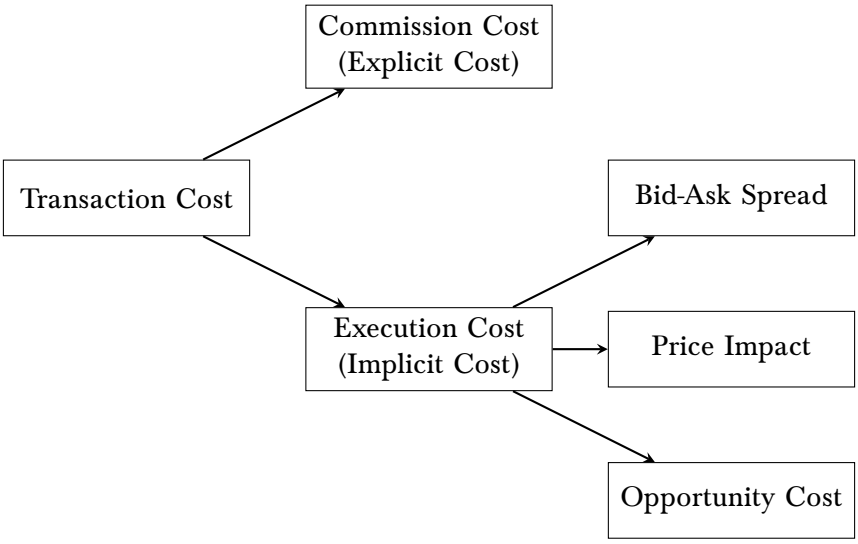
Transaction costs of investors can be decomposed into two groups: explicit costs and implicit costs. Explicit costs include brokerage commissions, order-related fees, and transaction taxes. Implicit costs represent execution-related costs, which are the bid-ask spread, price impact, and opportunity cost. For retail investors, bid-ask spreads constitute their total implicit costs, while for institutional investors additional costs could arise, e.g. price impact and opportunity cost. Price impact occurs due to execution of large orders. The orders of this magnitude impact the transaction price which applies to subsequent orders. Opportunity cost arises from the change in price during the period between order submission and order execution. The components of investors' transaction costs are depicted in Figure 1. There are a myriad of transaction cost measures proposed in the microstructure literature. These measures, however, capture only some components of transaction costs, such as the bid-ask spread and price impact.

The benchmark measure of transaction costs, typically reported in the literature, is the effective spread, which is defined as the difference between the actual transaction price and the midprice. The effective spread is a good approximation of transaction costs for retail investors, but does not fully represent costs borne by institutional investors. The difference in transaction costs between the two groups of investors arises mainly due to the difference in trade sizes. Large trades typically carried out by institutions result in stock's price change, which is essentially the price impact cost. The effective spread captures the price impact component as it uses the average transaction price in its estimation of the spread. However, it does not account for the possibility of an unfavorable change in stock's price during the period between order submission and order execution, i.e., the opportunity cost. For institutional investors the opportunity cost or price drift can be material as the order size is typically large. It may be argued that the latter concern has been partly alleviated due to substantial decrease in latency in the recent years. However, any latency decrease measured in milliseconds is not even remotely enough to beat high-frequency traders (HFTs) who trade in microseconds. Therefore, the price drift component might have actually increased rather than decreased as a result of HFT predatory activities (front-running, rebate arbitrage, slow market arbitrage) that have been growing since adoption of Reg NMS and MiFID in 2006-2007. Hence, the effective spread is not conceptually flawless, despite being a benchmark, and can potentially underestimate transaction costs of institutional investors.

*Klova (valeriia.klova@uis.no) is a PhD candidate at the University of Stavanger (UiS) Business School. Ødegaard (bernt.a.odegaard@uis.no) is a professor at the University of Stavanger (UiS) Business School.

Figure 1: Disaggregation of transaction costs

This figure illustrates the break-down of transaction costs of investors. The total transaction costs consist of both explicit and implicit costs, where the former encompasses commission costs, and the latter represents execution costs. The execution costs, in turn, can be decomposed into the bid-ask spread, price impact, and opportunity cost.



There are also several computational issues related to the estimation of the effective spread. The formula for the effective spread (in relative terms) is given below, where s_{eff} is a relative effective spread, p is a transaction price, and m is a midprice:

$$s_{eff,jt} = q_{jt} * \frac{p_{jt} - m_{jt}}{m_{jt}}, \tag{1}$$

where q is an indicator variable that denotes direction of trade,

$$q = \begin{cases} +1 & \text{(buyer-initiated)} \\ -1 & \text{(seller-initiated)}. \end{cases}$$

One issue with the effective spread is that it requires transaction-level data, which is often not available for less developed stock markets. Second, in the absence of signed transaction data, the classification of transactions is typically performed using the Lee-Ready algorithm or other classifying methods, which are not free of errors and, subsequently, may introduce bias in the effective spread (Foucault, Pagano, and Röell, 2013). Another source of imprecision comes from the inability of the effective spread to account for various transaction prices that take place when executing split orders. Order splitting is a common algorithmic trading strategy, which is used predominantly by institutional investors who want to hide their interest in a particular security and to cause as little price impact as possible. This problem can be overcome by using the average transaction price over the entire order in the effective spread calculation. In practice, however, tracing the algorithmic traders' numerous split orders routed to various trading venues is close to impossible.

Finally, the effective spread is mostly calculated using intraday transaction data from the Trade and Quote (TAQ) database, and midprices are taken at the time of trades. Goyenko, Holden, and Trzcinka (2009) argue that the effective spread based on the Rule 605 midprice, which is reported at order's time, is more precise than the TAQ effective spread. Another advantage of using the Rule 605 order's data is its informativeness about order direction. However, the Rule 605 data is

only available since 2001. The other downsides of the Rule 605 calculation of the effective spread are that re-routed orders can be double-counted, and block trades are not reported. Though, the results of Goyenko et al. (2009) are robust to the type of data underlying the computation, i.e., TAQ and Rule 605 estimates of the effective spread are comparable.

Regardless of the aforementioned estimation problems, the effective spread is an acknowledged benchmark for measuring transaction costs in the microstructure literature. It is common to compare performance of other measures against the effective spread benchmark. Another widely-used measure of transaction costs is the closing (quoted) bid-ask spread. The closing spread is a very straightforward measure compared to the effective spread. It is simply defined as the difference between the closing best ask and bid quotes, divided by the midprice:

$$s_{closing,jt} = \frac{ask_{jt} - bid_{jt}}{m_{jt}} \tag{2}$$

The closing spread is an accurate measure of implicit transaction costs for small orders that can be filled at the best quotes. However, it is not able to capture price impact or price drift components of transaction costs that may be material for large orders (Foucault et al., 2013). To gauge price impact of large orders, the weighted average bid-ask spread should be calculated from the quotes at various points in time. When liquidity dries up at the best quotes, the estimation also requires data on quotes beyond the best quotes. This data is not always readily available, which often makes estimation of the weighted average spread unfeasible. Similarly, when it comes to split orders, it is practically impossible to trace them and collect quote data from different exchanges at various points in time. Hence, both the effective spread and closing spread tend to underestimate total transaction costs of split orders.

Recently, a high-low estimator of the bid-ask spread was suggested by Corwin and Schultz (2012). As implied by the name, the high-low estimator is based on the daily high and low prices, which almost always correspond to ask and bid quotes. The spread estimator is derived from the high-low ratio that reflects both stock's volatility and its bid-ask spread. The variance component of the high-low ratio is proportional to the time interval, while the spread component is assumed to be fixed over a two-day interval. Therefore, the spread estimator can be derived as a function of high-low ratios over 1-day and 2-day intervals. The spread estimator has the following functional form (see derivation of the high-low spread in Corwin and Schultz (2012)):

$$s^{CS}_{highlow} = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}, \tag{3}$$

where α is a parameter derived using the high-low ratio.

Among the advantages of the high-low spread estimator are its computational simplicity and feasibility of estimation (only daily high and low prices are required). Furthermore, the high-low estimator is derived under very general conditions, which means that it can be applied to any market regardless of market structure. Another inherent advantage is that the high-low estimator captures transitory volatility, and hence reflects price impact of large orders. Therefore, the high-low spread can be regarded as a close approximation of the effective spread.

The high-low spread estimator, however, also exhibits several inconsistencies that may result in biased estimates. First, the estimator is derived using the expectation of the high-low ratio. As the spread is non-linearly related to the high-low ratio, taking a simple average of daily spread estimates in order to obtain the spread at a lower frequency (e.g. monthly) entails the biased estimate. To eliminate this bias, monthly spreads should be estimated using the averages of the high-low ratio parameters rather than averages of daily spread estimates. Corwin and Schultz (2012), however, claim that this adjustment does not improve the estimates in practice. Second,

by design spread estimates can take on negative values[1], which contradicts a definition of spread in theory (transaction costs cannot be negative). Corwin (2014) argue that the best solution is to set negative 2-day spreads to zero before calculating monthly averages. Third, there are some unrealistic assumptions underlying the high-low spread estimation. One assumption is that stocks are traded continuously in the market. Hence, this estimator is biased for infrequently traded stocks as the observed high and low prices are not true high and low prices for the day. For example, if the stock is not traded at all during a day, the high and low prices are taken from the previous day. This reduces the variance component to zero and may lead to overestimation of spread. Another assumption is that there is no change in stock prices when the market is closed. Typically, the opposite is true, i.e., stock prices change significantly overnight. As a result, the high-low ratio (and hence variance) for the 2-day period[2] tends to be higher than the high-low ratio for two 1-day periods. Therefore, without an overnight adjustment, the spread component will be underestimated. Corwin and Schultz (2012) suggest to correct for overnight returns by decreasing (increasing) both high and low prices for day t+1 by the amount of overnight increase (decrease) in low (high) price for day t+1 compared to the close price for day t. The simulation results in Corwin and Schultz (2012) indicate that spreads adjusted for overnight returns are more accurate than non-adjusted spreads.

Despite the aforementioned issues with estimation of the high-low spread, Corwin and Schultz (2012) show that it is highly correlated with the effective spread benchmark and appears to significantly outperform other low-frequency estimators, namely, the covariance spread estimator of Roll (1984), the effective tick estimator of Holden (2009), and the LOT measure of Lesmond, Ogden, and Trzcinka (1999). These findings hold both under the near-ideal conditions and in presence of overnight returns and infrequent trading.

The performance of the high-low spread estimator of Corwin and Schultz (2012) has been investigated in a number of recent microstructure studies. To test the accuracy of the Corwin and Schultz (2012) high-low spread estimator, Lin (2014) performs the simulation analysis under different scenarios and finds that its accuracy increases in spread size and transaction frequency, and decreases in stock volatility. This is consistent with the arguments outlined by Corwin and Schultz (2012) regarding a possible bias in high-low spreads for infrequently traded stocks and for stocks that exhibit too large volatility over a 2-day period.

A more elaborate analysis of the high-low measure's accuracy is conducted by Bleaney and Li (2015). They question the results obtained in Corwin and Schultz (2012) under the nearly perfect conditions, and construct the simulation that accounts for the numerous possible departures from the ideal case: time-varying spreads, autocorrelation in midpoint returns and trade directions, price impact, and feedback trading. They also examine the effect of sampling frequency on the accuracy of various spread estimates, including high-low. For example, they report that the high-low estimator based on low-frequency data is consistent and reliable, and outperforms other low-frequency estimators. However, the high-low estimator loses to the Roll (1984) estimator and the Huang and Stoll (1997) estimator, when the high-frequency data is used.

Karnaukh, Ranaldo, and Söderlind (2015) test the accuracy of various low-frequency spread estimators, including the high-low estimator, in foreign exchange markets. Among the spread estimators they utilize[3], the high-low estimator provides the highest correlation with the effective spread benchmark. Schestag, Schuster, and Uhrig-Homburg (2016) additionally show that the

[1] When the 2-day variance is more than twice as large as the single day variance, the high-low spread estimate becomes negative.

[2] The high-low ratio for the 2-day period reflects the range of prices during each day and overnight.

[3] Alternative low-frequency spread estimators utilized in Karnaukh et al. (2015) are the Roll (1984) estimator, the Gibbs estimator of Hasbrouck (2004), the effective tick estimator of Holden (2009), the LOT and the Zeros measures of Lesmond et al. (1999), and the FHT measure of Fong, Holden, and Trzcinka (2017).

high-low estimator performs as well as the Roll and Gibbs estimators in the bond markets.

An alternative spread estimator that bridges the Corwin and Schultz (2012) estimator and the Roll (1984) estimator was recently developed by Abdi and Ranaldo (2017). It is computationally straightforward and requires only daily close, high, and low prices. The calculation of the AR measure is performed in several steps. First, the efficient price is proxied by the midpoint of two consecutive daily mid-ranges, where mid-range is defined as the mean of the daily high and low log prices. Second, the squared distance between the close price and the midpoint proxy is calculated. This distance is shown to be composed of the efficient price variance and the squared effective spread at market close. Therefore, in order to derive the spread component, the variance component is removed from the squared distance. The obtained spread formula is as follows:

$$s^{AR}_{highlow} = 2\sqrt{\mathrm{E}[(c_t - \eta_t)(c_t - \eta_{t+1})]} \tag{4}$$

Where c is the daily close log-price, η is the daily mid-range.

This closed-form solution resembles the Roll estimator. However, there is an important distinction, namely, this estimator is based on the covariance of close-to-mid-range returns rather than the autocovariance of close-to-close price returns. The AR estimator utilizes a wider set of information that includes close, high, and low prices compared to the Roll and CS estimators. Further, unlike the Roll estimator, the AR estimator is independent of trade direction dynamics of close prices[4]. It is also superior to the CS estimator as it does not violate Jensen's inequality or require adjustments for non-trading periods (e.g., an overnight adjustment). Moreover, the AR estimator is quite accurate at estimating spreads of less liquid stocks, whereas the CS estimator tends to perform poorly[5].

The AR estimator also seems to perform better than other low-frequency spread estimators, including the CS estimator, as shown in Abdi and Ranaldo (2017). Specifically, it provides the second highest time-series correlation (after the quoted spread) and highest cross-sectional correlation with the benchmark effective spread (based on TAQ data). Abdi and Ranaldo (2017) additionally show that their estimator is only marginally sensitive to the number of trades per day and provides higher explanatory power over spreads for less liquid stocks. However, similar to the CS estimator, spread estimates can be negative and thus need to be set to zero or removed.

To summarize, microstructure literature suggests that both the Corwin and Schultz (2012) and Abdi and Ranaldo (2017) high-low spread estimators generally yield spread estimates comparable to the effective spread estimates. Furthermore, they tend to significantly outperform other low-frequency spread estimators. Lastly, the high-low spread and effective spread may be different to the extent of capturing different transitory effects.

[4]It does not need to rely on assumptions of serial independence of trades and equal likelihood of buyer/seller-initiated close prices.

[5]Due to using the average of high and low prices instead of the price range, the AR estimator is less sensitive to the number of trades per day than the CS estimator.

2 US – Liquidity measures

We provide additional data on liquidity measures for US. We focus on the measures used in the paper, namely, the relative spread and high-low measures. In addition, we look at alternative liquidity measures such as the Roll measure and the LOT measure. We use US daily stock market data from CRSP. We concentrate on stocks with the main listing at the NYSE.

2.1 Spread vs. high low measures

To confirm that the trend apparent in the GE example is general, we plot time series of crossectional averages of the same three measures of transaction costs, the relative spread and the high-low measures in Figure 2. These averages show the same pattern as the GE example, spreads are falling a lot, the high-low measures by no means to the same degree.

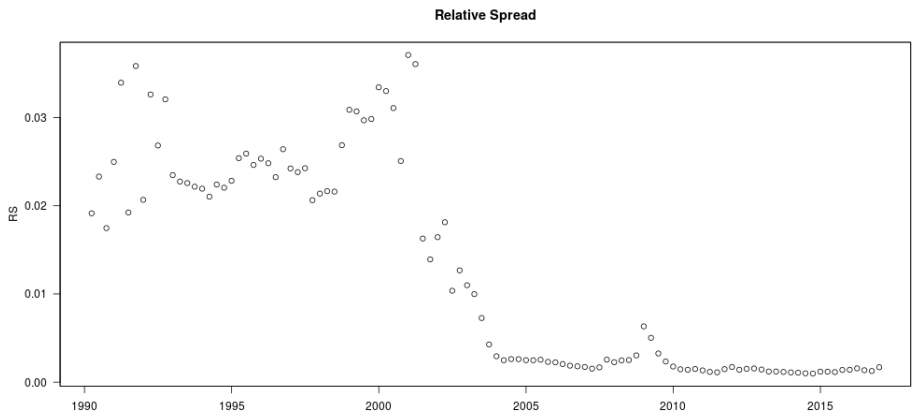
To dig a bit deeper into the US data, we also calculate similar averages, but for size sorted portfolios. In Figure 3 we show the time series evolution of averages of four size sorted portfolios, for the relative spread and high-low measures. In this illustration we concentrate on the period after 2002, as that is the one when electronic trading became the dominant method of trading. There is a striking difference between the behaviour of these two measures. The relative spread essentially "drops to the floor" in the 2002/2003 time frame, and stays there. For the smallest stocks the average relative spread is slightly larger, but still low compared to the historical numbers. The high-low measures are different along several dimensions. For one there is a much wider cross-sectional distribution of trading costs with size, which is what one expects. The downwards trend is also much less for the high-low measures. Another difference is the behaviour around the 2007/2008 financial crisis. For the spreads, the spreads of all but the smallest quartile hardly budges. This is potentially a sign of problems with this liquidity measure. There is a literature showing a link between the business cycle and stock market liquidity.[6] According to this literature, stock market liquidity dries up even before an economic downturn, and remains low during the onset of the downturn. The behaviour of the high-low measures is much more consistent with this "stylized fact", where the estimates of transaction costs more than double during the crisis. For the spread such behaviour is only marked for the smallest NYSE quartile.

[6] See Næs, Skjeltorp, and Ødegaard (2011) for some empirical evidence on the link between stock liquidity and the business cycle.

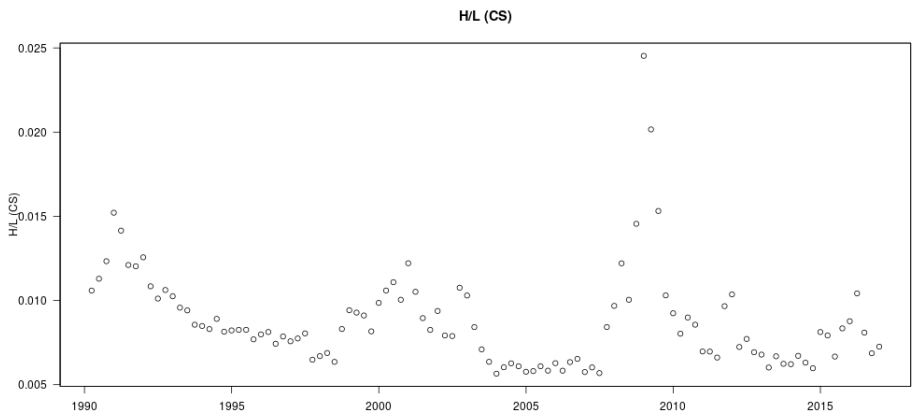
Figure 2: Time-series evolution of alternative measures of trade costs – NYSE listed shares

The figure illustrates the time series development of the quarterly average closing spread and high-low estimates. Data for NYSE-listed shares.

Panel A: Relative Spread



Panel B: High-Low measure (CS)



Panel C: High-Low measure (AR)

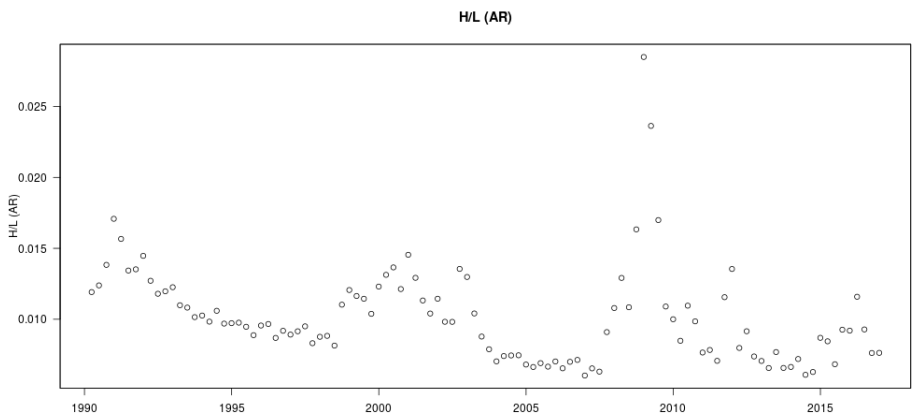
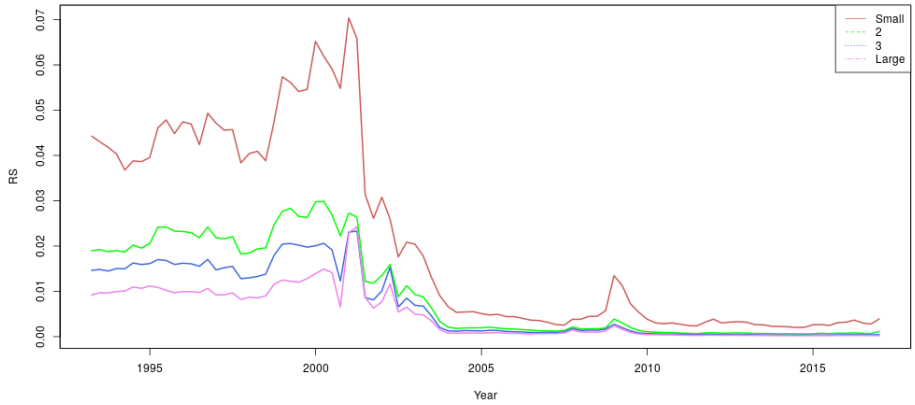


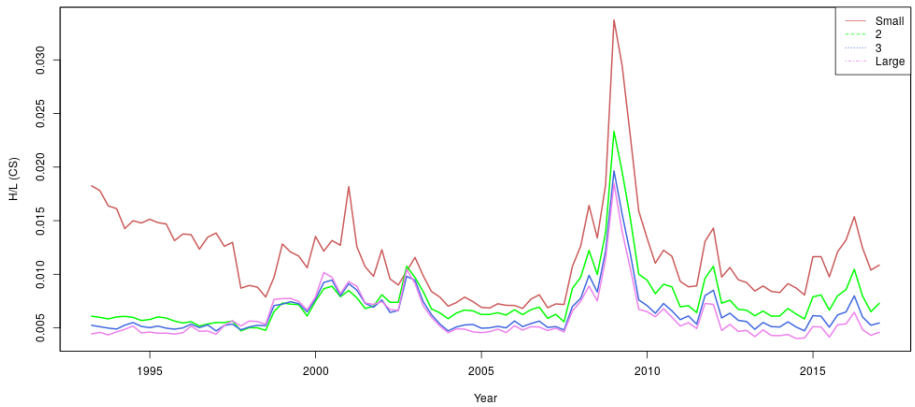
Figure 3: Time-series evolution of alternative measures of trade costs – NYSE listed shares – grouped by firm size

The figure shows the time series plots of crossectional averages for four size sorted portfolios of relative spread, the CS high-low measure, and the AR high-low measure. Data for NYSE-listed shares.

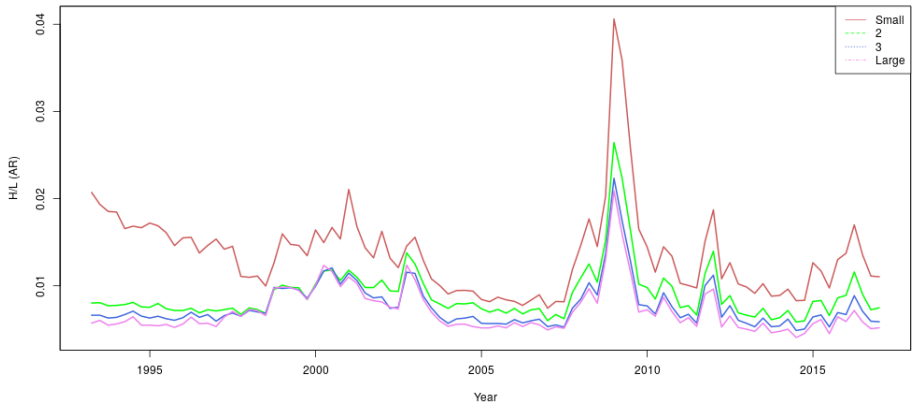
Panel A: Relative Spread



Panel B: High-Low measure (CS)



Panel C: High-Low measure (AR)



2.2 Spread vs. Roll, LOT and AR measures

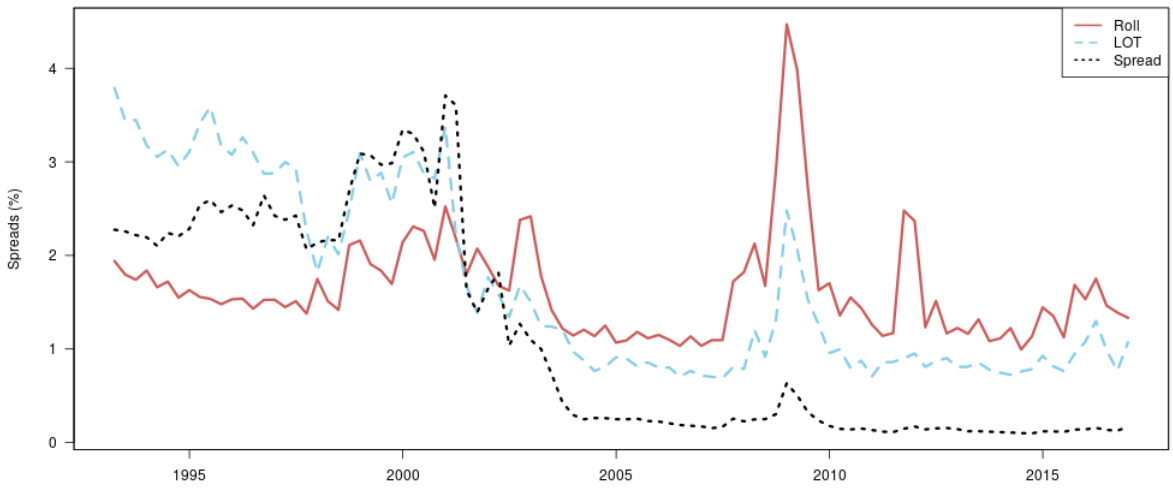
In this subsection we complement the analysis of the paper with two additional estimators of transaction costs, the Roll (1984) and Lesmond et al. (1999) measures. Figure 4 shows a comparison of the relative spread with three alternative measures, the Roll, LOT and AR measures. The alternative measures have not fallen as much as the relative spread around 2002/2003. Furthermore, these measures show less of a downward trend. Their time-series behavior appears to be related to the business cycle while the relative spread hardly budges around the 2007/2008 financial crisis.

As illustrated in Figure 5, the Roll and LOT spread estimates vary a lot with the size of the firm. The spread estimates for small firms are shown to be significantly higher compared to spread level for other firms.

Figure 4: Time-series comparison of alternative spread measures – NYSE firms

The figure illustrates the time-series development of quarterly averages of the relative spread and alternative spread measures, the Roll (1984), the Lesmond et al. (1999) and Abdi and Ranaldo (2017) measures. Data for NYSE-listed firms.

Panel A: Relative Spread vs. Roll and LOT



Panel B: Relative Spread vs. AR measure

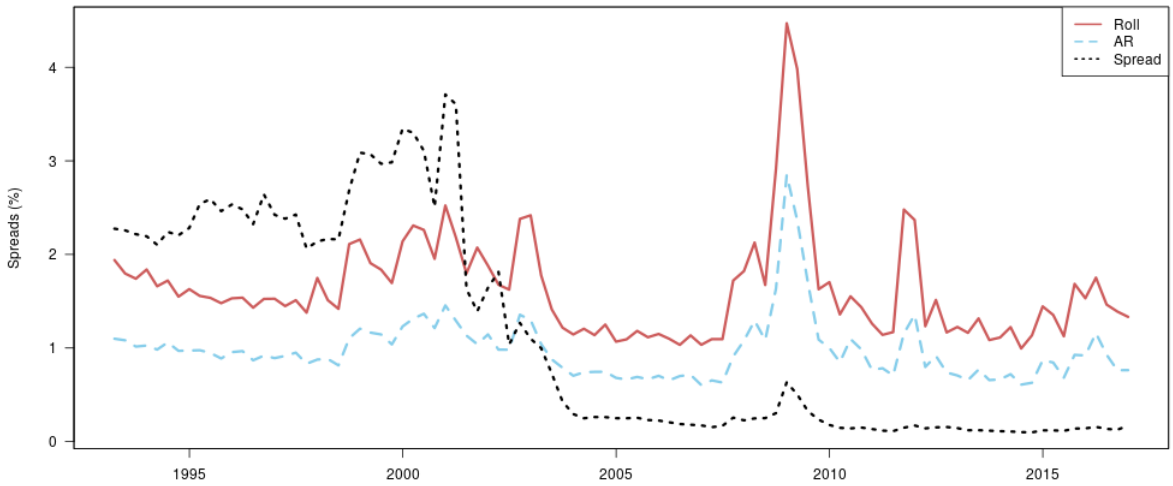
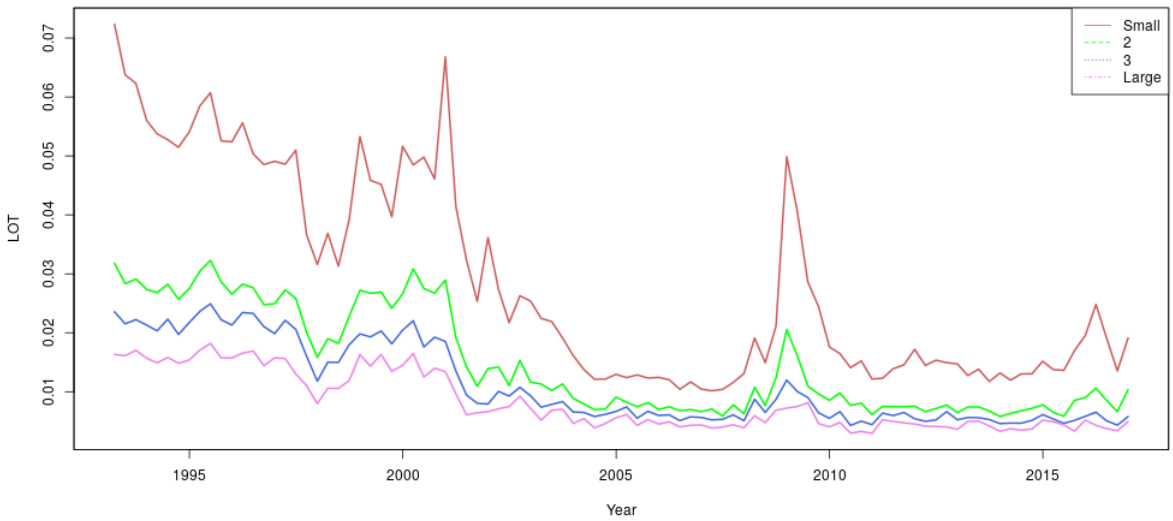


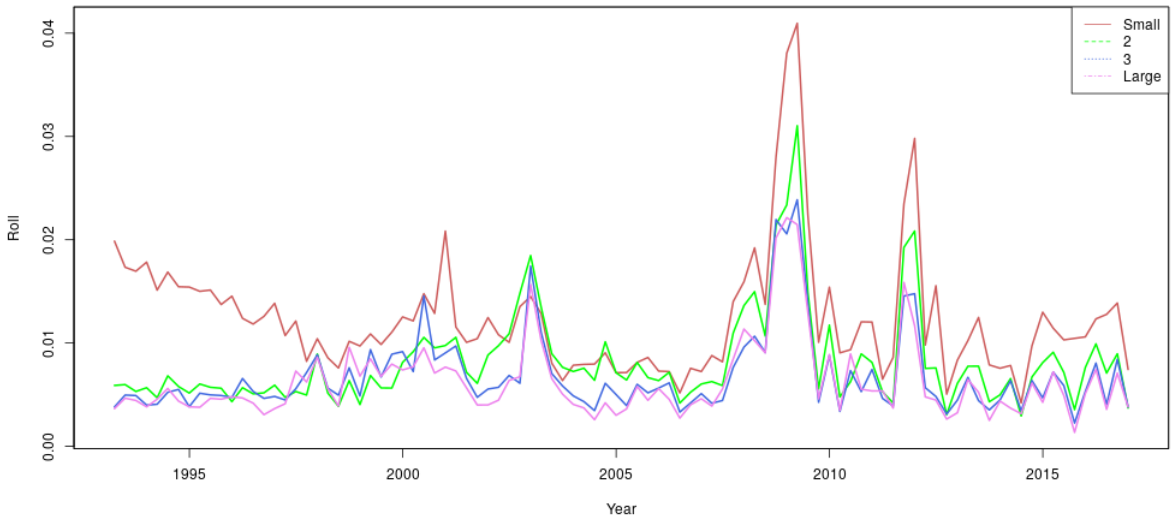
Figure 5: Alternative liquidity measures – NYSE firms – grouped by firm size

The figure shows the time-series plots of crossectional averages for four size sorted portfolios of the Roll (1984) and Lesmond et al. (1999) measures. Data for NYSE-listed firms.

Panel A: LOT measure



Panel B: Roll measure



3 Norway – Liquidity measures

In this section we look at the time-series development of alternative spread measures in the Norwegian market, which is the main market for analysis. We also take a statistical look at these measures and provide various descriptive statistics of their time-series properties.

3.1 Spread vs. alternative measures

We start with the time-series comparison of the relative spread with the alternative spread measures, the high-low measures. As shown in Figure 6, the relative spread has been steadily falling since 2003, while the high-low measures have not fallen.

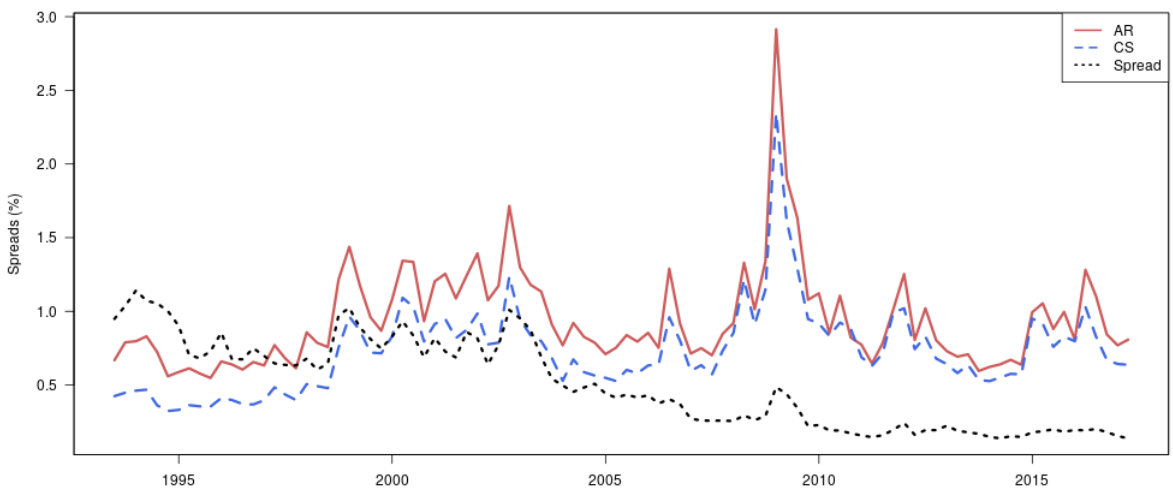
Time-series evolution of crossectional averages of transaction cost measures at the OSE is illustrated in Figure 7. These averages look somewhat different from the US case, with much more time series variation, and no such clear downward trend. One reason for this is that most of the firms listed on the OSE are much smaller than the typical NYSE firm.

The fairest comparison between the NYSE and the OSE is probably comparing the largest OSE firms with the NYSE figures. We therefore calculate averages of the 25 largest OSE firms, the constituents of the OBX index.[7] Figure 8 shows these averages. These pictures clearly correspond to the US experience, with an overall fall in spreads, while the high-low measures have stronger business cycle variation.

Figure 6: Time-series comparison of alternative spread measures – OBX firms

The figure illustrates the time-series development of quarterly averages of the relative spread and high-low measures. Data for the OBX stocks.

Panel A: Relative spread vs. high-low measures

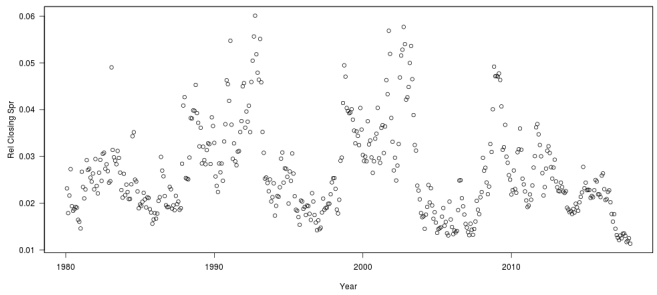


[7]The OBX index is used as basis for futures and options on the OSE. Its constituents is chosen by a joint evaluation of firm size and stock liquidity.

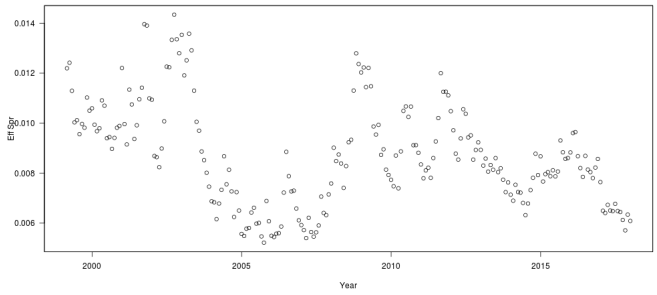
Figure 7: Time-series evolution of spread measures: OSE

The figure illustrates the time series development of the monthly averages of relative spread, effective spread and high-low spreads. Averages across all listed shares at the OSE.

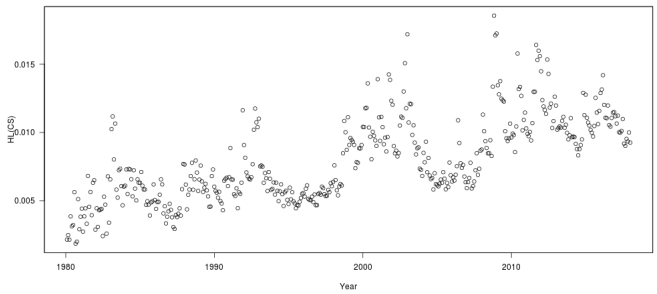
Panel A: Relative Spread



Panel B: Effective Spread



Panel C: High-Low measure (CS)



Panel D: High-Low measure (AR)

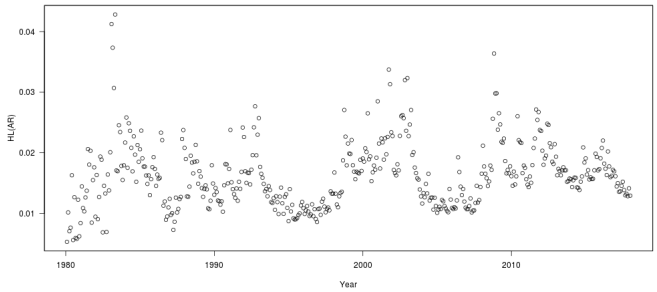
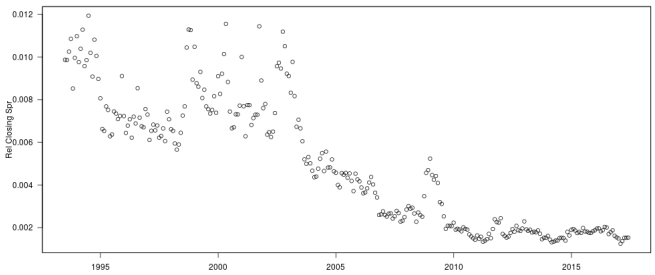


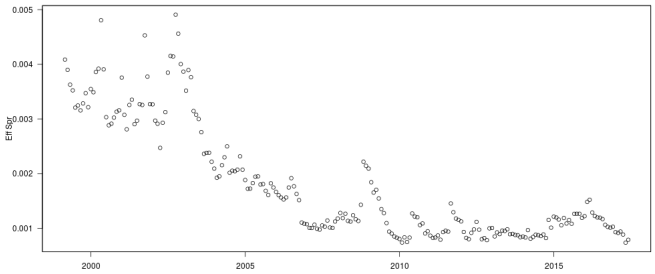
Figure 8: Time-series evolution of spread measures: OSE – constituents of OBX index

The figure illustrates the time series development of the monthly averages of relative spread, effective spread and high-low spreads. Averages are calculated for all constituents of the OBX index.

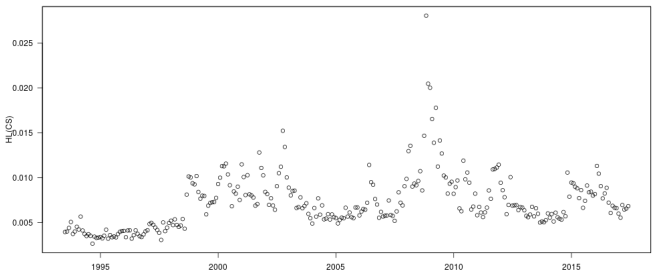
Panel A: Relative Spread



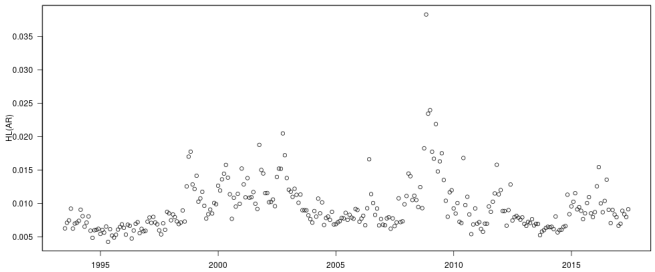
Panel B: Effective Spread



Panel C: High-Low measure (CS)



Panel D: High-Low measure (AR)



3.2 Time-series properties of spreads

We compare alternative spread measures by looking at the time-series correlations between them. The correlation matrix is given in Table 1. The time-series correlations range from moderate to strong and therefore confirm the notion about consensus between transaction costs measures. The effective spread is shown to be highly correlated with the relative spread (0.91), the AR measure (0.87), and the CS measure (0.70). The relative spread is strongly correlated with the AR measure (0.78) and moderately correlated with the CS measure (0.51). The CS measure and the AR measure are also strongly correlated with one another (0.89). The high-low measures appear to be a good approximation of transaction costs as they show high correlations with the benchmark spreads. Though, these high correlations only indicate that the measures tend to co-move over time, and do not rule out the existence of discrepancies in trends.

We additionally test whether time-series spreads are stationary using the ADF and KPSS unit root tests. Table 2 reports test results for the relative spread, effective spread, and high-low measures. Based on the test results, we cannot reject a unit root in the relative and effective spreads, while the high-low measures are shown to be trend-stationary. The Jarque-Bera test results further indicate that among spread measures only the effective spread is normally distributed.

Table 1: Time-series correlations between spread measures

The table shows time-series correlation coefficients between the spread measures: the relative spread (RS), the effective spread (ES), the CS high-low measure (CS), and the AR high-low measure (AR).

	RS	ES	CS	AR
RS	1.00			
ES	0.91	1.00		
CS	0.51	0.70	1.00	
AR	0.78	0.87	0.89	1.00

Table 2: Normality and unit root tests for spread measures

The table shows the test statistics with significance levels from the normality and unit root tests for spread measures – the relative spread, the effective spread, and the high-low measures. More specifically, the results of the following tests are reported: the Jarque-Bera (JB) normality test, the Augmented Dickey-Fuller (ADF) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The null hypotheses (H_0) are specified in the bottom panel.

Variable	**JB**	**ADF with a trend**	**KPSS without a trend**	**KPSS with a trend**
Relative spread	20.529^{***}	-3.3152	2.7183^{***}	0.22828^{***}
Effective spread	4.6	-2.3672	0.80427^{***}	0.38227^{***}
CS measure	34.651^{***}	-3.981^{***}	4.7256^{***}	0.12023
AR measure	128.8^{***}	-4.3628^{***}	0.28829^{***}	0.13262
H_0:	Normality	Unit root	Level-stationarity	Trend-stationarity

4 Descriptives, OSE

In this section we look at the statistical properties of spread measures and explanatory variables used in the regression analysis, such as stock price, stock return volatility, firm size, and trade size (in NOK and shares), in a panel data setting.

4.1 OSE stocks

In this subsection we look at descriptive statistics of the aforementioned variables calculated using all stocks at the OSE. The total size of the panel is 443499 observations. Table 3 provides summary statistics of the variables. All variables exhibit positive skewness and excess kurtosis. The average stock price of OSE stocks is 63.56 NOK. The average trade size at the OSE is 63.50 shares and 11277.13 NOK. The average spread measured by the relative spread, effective spread or CS high-low measure is 0.01. The average of the AR high-low measure, however, is 0.02, which indicates a twice larger spread. Table 4 shows the cross-sectional correlation coefficients between the variables. Cross-sectional correlations between spreads appear to be much lower compared to the time-series correlations. Trade size shows the highest correlation with the effective spread, then the relative spread, and finally the high-low measures. Trade size is also strongly correlated with the stock price. Firm size and stock price also exhibit weaker correlations with the high-low measures than the benchmark spreads. Correlation with stock volatility is comparable across spreads.

Table 3: Summary statistics

The table provides summary statistics of the variables used in the regression analysis. The mean, standard deviation, median, minimum, maximum, skewness, and kurtosis are reported.

Variable	Mean	Std. Dev.	Median	Min	Max	Skewness	Kurtosis
RelSpread	0.01	0.02	0.01	0.00	0.25	3.83	23.20
EffSpread	0.01	0.01	0.00	0.00	0.05	2.06	5.44
HighLow(CS)	0.01	0.02	0.00	0.00	0.50	3.49	27.25
HighLow(AR)	0.02	0.02	0.00	0.00	0.68	3.83	31.88
StockPrice	63.56	85.14	33.70	0.35	990.00	3.16	16.41
FirmSize	10433442122.80	33640237487.70	2043292680.00	2770556.00	672804538733.00	7.38	69.72
StockVol	0.01	0.01	0.01	0.00	0.50	15.11	356.60
TradeSize(NOK)	11277.13	39707.01	1134.00	1.00	1053618.00	10.76	159.16
TradeSize(Sh)	63.50	85.08	34.00	1.00	1075.00	3.16	16.44

Table 4: Correlation matrix

The table shows correlation coefficients between the variables used in the regression analysis: the relative spread, the effective spread, the CS measure, the AR measure, the stock price, the stock volatility, the firm size, and the trade size (in NOK and shares).

	RelSpread	EffSpread	HL(CS)	HL(AR)	StockPrice	FirmSize	StockVol	TradeSize(NOK)	TradeSize(Sh)
RelSpread	1.00	0.68	0.16	0.23	0.24	-0.45	0.17	-0.29	-0.29
EffSpread	0.68	1.00	0.22	0.29	0.34	-0.61	0.23	-0.41	-0.41
HL(CS)	0.16	0.22	1.00	0.61	0.19	-0.18	0.14	-0.21	-0.21
HL(AR)	0.23	0.29	0.61	1.00	0.16	-0.22	0.15	-0.19	-0.19
StockPrice	0.24	0.34	0.19	0.16	1.00	-0.51	0.14	-0.78	-0.78
FirmSize	-0.45	-0.61	-0.18	-0.22	-0.51	1.00	-0.16	0.68	0.68
StockVol	0.17	0.23	0.14	0.15	0.14	-0.16	1.00	-0.15	-0.15
TradeSize(NOK)	-0.29	-0.41	-0.21	-0.19	-0.78	0.68	-0.15	1.00	1.00
TradeSize(Sh)	-0.29	-0.41	-0.21	-0.19	-0.78	0.68	-0.15	1.00	1.00

4.2 OBX stocks

In this subsection we look at descriptive statistics calculated for OBX stocks, i.e. constituents of the OBX index. These stocks are the largest and most liquid stocks at the OSE. The total size of the panel is 184152 observations. Table 5 shows summary statistics of the variables. The average spread estimate for OBX stocks is consistent across the relative spread and high-low measures and equal to 0.01. The effective spread, however, is on average equal to zero. Hence, the effective spread and the AR high-low measure are lower on average for OBX stocks. Stock price, firm size, and trade size are shown to be larger for OBX stocks as expected. The average stock price of OBX stocks is 90.35 NOK, while the trade size is 90.32 in shares and 17355.86 in NOK. Table 6 shows cross-sectional correlations between the variables. The correlation between benchmark spreads and high-low measures is quite low for OBX stocks. Cross-sectional correlations between the spreads and explanatory variables are also weaker for OBX stocks.

Table 5: Summary statistics

The table provides summary statistics of the variables used in the regression analysis. The mean, standard deviation, median, minimum, maximum, skewness, and kurtosis are reported.

Variable	Mean	Std. Dev.	Median	Min	Max	Skewness	Kurtosis
RelSpread	0.01	0.01	0.00	0.00	0.25	5.12	47.45
EffSpread	0.00	0.00	0.00	0.00	0.05	3.00	13.74
HighLow(CS)	0.01	0.01	0.00	0.00	0.22	2.91	16.67
HighLow(AR)	0.01	0.02	0.00	0.00	0.57	3.36	25.00
StockPrice	90.35	95.92	64.00	0.67	990.00	2.63	11.17
FirmSize	22060491809.65	49776154324.42	5894856654.50	27024268.00	672804538733.00	4.78	28.74
StockVol	0.01	0.02	0.00	0.00	0.50	15.16	319.84
TradeSize(NOK)	17355.86	47479.72	4073.00	1.00	1053618.00	8.33	100.49
TradeSize(Sh)	90.32	95.90	64.00	1.00	1075.00	2.63	11.24

Table 6: Correlation matrix

The table shows correlation coefficients between the variables used in the regression analysis: the relative spread, the effective spread, the CS measure, the AR measure, the stock price, the stock volatility, the firm size, and the trade size (in NOK and shares).

	RelSpread	EffSpread	HL(CS)	HL(AR)	StockPrice	FirmSize	StockVol	TradeSize(NOK)	TradeSize(Sh)
RelSpread	1.00	0.69	0.09	0.14	0.15	-0.41	0.07	-0.19	-0.19
EffSpread	0.69	1.00	0.14	0.20	0.23	-0.55	0.12	-0.30	-0.30
HL(CS)	0.09	0.14	1.00	0.61	0.14	-0.15	0.08	-0.17	-0.17
HL(AR)	0.14	0.20	0.61	1.00	0.11	-0.16	0.09	-0.14	-0.14
StockPrice	0.15	0.23	0.14	0.11	1.00	-0.42	0.07	-0.74	-0.74
FirmSize	-0.41	-0.55	-0.15	-0.16	-0.42	1.00	-0.09	0.60	0.60
StockVol	0.07	0.12	0.08	0.09	0.07	-0.09	1.00	-0.08	-0.08
TradeSize(NOK)	-0.19	-0.30	-0.17	-0.14	-0.74	0.60	-0.08	1.00	1.00
TradeSize(Sh)	-0.19	-0.30	-0.17	-0.14	-0.74	0.60	-0.08	1.00	1.00

4.3 Trade size across firm size quartiles

This subsection provides descriptive statistics of trade size (in NOK and shares) across different size quartiles and subperiods. As shown in Table 7, trade size has been continuously falling over time. Furthermore, trade size is clearly an increasing function of stock size, i.e. larger stocks have larger trade sizes.

Table 7: Trade size across firm size quartiles and subperiods

The table shows the monthly trade size median across stocks in each quartile and subperiod. OSE stocks are grouped by firm size into four size quartiles: Q1 (smallest stocks), Q2, Q3, and Q4 (largest stocks). The sample period is divided into three subperiods: 1988–1998, 1999–2007, and 2008–2016.

Firm size quartile	1988-1998		1999-2007		2008-2016		Whole sample	
	Size(NOK)	Size(shares)	Size(NOK)	Size(shares)	Size(NOK)	Size(shares)	Size(NOK)	Size(shares)
Q1	1553.5	39.4	175.89	13.23	39.04	6.14	182.22	13.47
Q2	3352.55	57.87	513.55	22.51	165.55	12.90	569.07	23.82
Q3	6437.67	80.00	1889.15	43.41	445.00	21.09	1587.45	39.79
Q4	17217.71	131.10	9063.14	94.89	4514.20	67.05	10052.81	100.05
All stocks	7165.11	84.49	2200.64	46.75	469.03	21.61	2060.34	45.30

5 Regressions, extra results

In this section we provide additional regression results.

5.1 Regression results for OSE stocks

In this subsection we check robustness of our findings for OBX stocks by estimating the same regressions for all stocks at the OSE. The results are provided in Table 14 and appear to be similar to the results for OBX stocks. The main finding regarding a positive effect of trade size on the benchmark spreads and a negative effect on the high-low measures holds for the sample of OSE stocks. Moreover, the achieved adjusted R-squared is substantially higher. Further, as shown in Table 9, the difference between the benchmark spreads and high-low measures can be at least partially explained by the trade size. This result corresponds to the results for OBX stocks and our expectations.

Table 8: Trade size effect on bid-ask spread measures: OSE stocks

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for all stocks listed at the OSE over the period 1999–2016 at a daily frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0046***	0.0013***	0.0044***	0.0044***
	(0.0005)	(0.0001)	(0.0004)	(0.0006)
Volatility	0.1408***	0.0544***	0.1168***	0.1925***
	(0.0051)	(0.0018)	(0.0045)	(0.0075)
ln(MarketCap)	−0.0061***	−0.0022***	−0.0009***	−0.0029***
	(0.0001)	(0.00002)	(0.00004)	(0.0001)
TradeSize	0.0006***	0.0002***	−0.0005***	−0.0004***
	(0.00004)	(0.00001)	(0.00003)	(0.00004)
Observations	515,025	449,928	509,813	509,813
Adjusted R^2	0.1533	0.2938	0.0381	0.0463
F Statistic	23,455.3400***	46,921.6200***	5,184.4570***	6,321.3890***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 9: Trade size effect on differences between spreads

The table shows the one-way fixed-effects regression results with the absolute differences between the relative spread and the CS high-low spread (|RS-CS|), the effective spread and the CS high-low spread (|ES-CS|), the relative spread and the AR high-low spread (|RS-AR|), and the effective spread and the AR high-low spread (|ES-AR|) as the dependent variable. The independent variable is the logarithm of trade size in NOK (TradeSize). The regressions are estimated for all stocks listed at the OSE over the period 1999–2016 at a daily frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	|RS−CS|	|ES−CS|	|RS−AR|	|ES−AR|
TradeSize	-0.0016^{***}	-0.0010^{***}	-0.0019^{***}	-0.0016^{***}
	(0.00002)	(0.00001)	(0.00003)	(0.00002)
Observations	467,136	467,136	467,136	467,136
Adjusted R^2	0.0342	0.0294	0.0334	0.0266
F Statistic	$17{,}067.3500^{***}$	$14{,}676.5900^{***}$	$16{,}685.2600^{***}$	$13{,}294.2400^{***}$
Note:				*p<0.1; **p<0.05; ***p<0.01

5.2 Subsample regression results for OBX stocks

In this subsection we provide the subsample descriptive statistics and regression results for OBX stocks. The first subsample 1999–2007 encompasses the period before market fragmentation. The second subsample 2008–2016 represents the period with fragmented trading at the OSE. To remove the effect of financial crisis in the second subsample, we exclude the year 2008 observations from the regression analysis. The descriptive statistics for two subsamples for OBX stocks and OSE stocks are given in Table 10. Trade size falls substantially after 2008 for both OBX and OSE stocks. The regression results for two subsamples are presented in Tables 11 and 12. The average trade size is shown to have a significant positive effect on the relative and effective spreads and no significant effect on the high-low measures for both subsamples.

Table 10: Spreads and stock characteristics before and after 2008

The table shows the crossectional averages of spreads and stock characteristics for two subperiods 1999–2007 (before 2008) and 2008–2016 (after 2008). The crossectional averages are reported for OSE stocks and OBX stocks separately.

	OSE stocks		OBX stocks	
Variable	Before 2008	After 2008	Before 2008	After 2008
Relative Spread	0.01	0.02	0.01	0.01
Effective Spread	0.01	0.01	0.00	0.00
HighLow (CS)	0.01	0.01	0.01	0.01
HighLow (AR)	0.01	0.02	0.01	0.01
Stock Price (NOK)	76.25	50.60	101.34	76.47
Stock Volatility	0.01	0.01	0.01	0.01
Firm Size	9126574620.70	11768805267.92	17831841626.33	27404825688.77
Trade Size (NOK)	14713.78	7765.54	20878.55	12903.74
Trade Size (shares)	76.16	50.57	101.27	76.47
Observations	224,141	219,358	102,807	81,345

Table 11: Trade size effect on bid-ask spread measures: 1999–2007

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OBX stocks over the period 1999–2007 at a daily frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0056***	0.0025***	0.0033***	0.0043**
	(0.0013)	(0.0004)	(0.0010)	(0.0018)
Volatility	0.0249***	0.0134***	0.0279***	0.0619***
	(0.0024)	(0.0008)	(0.0031)	(0.0059)
ln(MarketCap)	−0.0055***	−0.0022***	−0.0010***	−0.0024***
	(0.0001)	(0.00003)	(0.0001)	(0.0002)
TradeSize	0.0006***	0.0002***	−0.0001	−0.0001
	(0.0001)	(0.00002)	(0.0001)	(0.0001)
Observations	103,992	104,079	103,284	103,284
Adjusted R^2	0.1056	0.2316	0.0071	0.0144
F Statistic	3,094.4390***	7,865.6540***	208.0825***	401.4540***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 12: Trade size effect on bid-ask spread measures: 2009–2016

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OBX stocks over the period 2009–2016 at a daily frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0073***	0.0028***	0.0003	0.0019
	(0.0007)	(0.0002)	(0.0011)	(0.0015)
Volatility	0.0243***	0.0196***	0.0520***	0.0739***
	(0.0028)	(0.0020)	(0.0064)	(0.0088)
ln(MarketCap)	−0.0061***	−0.0024***	−0.0032***	−0.0050***
	(0.0002)	(0.0001)	(0.0003)	(0.0004)
TradeSize	0.0013***	0.0005***	−0.0002	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Observations	92,999	70,115	92,226	92,226
Adjusted R^2	0.1104	0.2191	0.0305	0.0308
F Statistic	2,901.6280***	4,934.3570***	742.6451***	747.9476***
Note:				*p<0.1; **p<0.05; ***p<0.01

5.3 Regression results, monthly frequency

In this subsection we estimate trade size regressions at a monthly frequency using OBX and OSE stocks. As shown in Table 13, the effect of trade size remains positive for the relative and effective spreads and negative for the high-low measures. The results for OSE stocks, presented in Table 14, however, indicate that the AR measure is not affected by trade size at a monthly frequency. Overall, the results seem to be quite robust to data with different frequency.

Table 13: Trade size effect on bid-ask spread measures: OBX stocks

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OBX stocks over the period 1999–2016 at a monthly frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0616***	0.0493***	0.0147**	0.0226*
	(0.0234)	(0.0084)	(0.0072)	(0.0130)
Volatility	0.4087***	0.0457***	0.1532***	0.3248***
	(0.0231)	(0.0042)	(0.0083)	(0.0153)
ln(MarketCap)	−0.0083***	−0.0027***	0.0006***	−0.0011***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
TradeSize	0.0012***	0.0007***	−0.0007***	−0.0003***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	14,778	8,183	14,498	14,498
Adjusted R^2	0.3909	0.3118	0.2886	0.3334
F Statistic	2,402.7970***	953.6424***	1,502.2510***	1,844.7390***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 14: Trade size effect on bid-ask spread measures: OSE stocks

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OSE stocks over the period 1999–2016 at a monthly frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0845**	0.0227**	0.0262***	0.1018***
	(0.0355)	(0.0088)	(0.0069)	(0.0166)
Volatility	0.5913***	0.0824***	0.1140***	0.3171***
	(0.0388)	(0.0128)	(0.0121)	(0.0302)
ln(MarketCap)	−0.0107***	−0.0024***	0.0002***	−0.0018***
	(0.0003)	(0.00005)	(0.00004)	(0.0001)
TradeSize	0.0020***	0.0002**	−0.0006***	0.0002
	(0.0003)	(0.0001)	(0.0001)	(0.0002)
Observations	45,559	20,916	37,249	37,249
Adjusted R^2	0.3828	0.3207	0.1139	0.1802
F Statistic	7,219.2850***	2,578.1430***	1,350.3110***	2,199.7040***
Note:				*p<0.1; **p<0.05; ***p<0.01

5.4 Regression results, time-fixed effects

In this subsection we report the regression results from fixed-effects estimation with two-way effects (stock- and month-fixed effects). Month-fixed effects control for business cycle. Tables 15 and 16 present the regression results for OBX and OSE stocks respectively. The obtained results are similar to one-way fixed-effects results. Hence, the effect of trade size on spreads remains the same after controlling for business cycle effect.

Table 15: Trade size effect on bid-ask spread measures: OBX stocks

The table shows the two-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OBX stocks over the period 1999–2016 at a monthly frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0628***	0.0501***	0.0150**	0.0216
	(0.0238)	(0.0085)	(0.0072)	(0.0134)
Volatility	0.4087***	0.0453***	0.1533***	0.3248***
	(0.0232)	(0.0042)	(0.0083)	(0.0150)
ln(MarketCap)	−0.0083***	−0.0027***	0.0006***	−0.0011***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
TradeSize	0.0012***	0.0007***	−0.0007***	−0.0003***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	14,778	8,183	14,498	14,498
Adjusted R^2	0.3786	0.2951	0.2710	0.3163
F Statistic	2,368.8250***	931.4763***	1,465.5980***	1,794.4510***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16: Trade size effect on bid-ask spread measures: OSE stocks

The table shows the two-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for all OSE stocks over the period 1999–2016 at a monthly frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0844**	0.0240***	0.0253***	0.0994***
	(0.0359)	(0.0088)	(0.0070)	(0.0166)
Volatility	0.5913***	0.0823***	0.1142***	0.3170***
	(0.0389)	(0.0126)	(0.0121)	(0.0303)
ln(MarketCap)	−0.0107***	−0.0024***	0.0002***	−0.0018***
	(0.0003)	(0.00005)	(0.00004)	(0.0001)
TradeSize	0.0020***	0.0002**	−0.0006***	0.0001
	(0.0003)	(0.0001)	(0.0001)	(0.0002)
Observations	45,559	20,916	37,249	37,249
Adjusted R^2	0.3780	0.3152	0.1055	0.1719
F Statistic	7,164.4680***	2,564.6990***	1,337.6790***	2,172.2030***
Note:				*p<0.1; **p<0.05; ***p<0.01

5.5 Regression results across firm size quartiles

This subsection investigates the effect of trade size on spreads across different size quartiles. Fixed-effect regressions are estimated at a monthly frequency. Tables 17-20 show the regression results for four firm size quartiles, where the first and fourth quartiles represent the smallest and largest stocks respectively. As expected, the results differ across size quartiles. The effect of trade size is most pronounced for large stocks, i.e., stocks in the third and fourth quartiles. The relative and effective spreads are shown to increase with trade size, while the high-low measures either do not change or decrease with trade size. These results are therefore consistent with the results for OBX stocks and overall results for OSE stocks.

Table 17: Trade size effect on bid-ask spread measures: Q1

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OSE stocks with firm size in the first quartile. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.2437***	0.0967***	0.0757***	0.2866***
	(0.0854)	(0.0291)	(0.0257)	(0.0612)
Volatility	0.5984***	0.1047***	0.0816***	0.3216***
	(0.0739)	(0.0150)	(0.0144)	(0.0334)
ln(MarketCap)	−0.0131***	−0.0019***	−0.0003	−0.0033***
	(0.0013)	(0.0003)	(0.0003)	(0.0007)
TradeSize	0.0014	0.0011**	−0.00004	0.0015**
	(0.0011)	(0.0004)	(0.0003)	(0.0007)
Observations	5,878	1,315	2,873	2,873
Adjusted R^2	0.2497	0.0451	0.0094	0.0863
F Statistic	528.6421***	38.5055***	45.0699***	106.0230***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: Trade size effect on bid-ask spread measures: Q2

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OSE stocks with firm size in the second quartile. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	−0.0178	−0.0336*	0.0033	0.0310
	(0.0753)	(0.0195)	(0.0171)	(0.0431)
Volatility	0.5536***	0.1119***	0.0990***	0.3077***
	(0.0686)	(0.0099)	(0.0220)	(0.0491)
ln(MarketCap)	−0.0171***	−0.0030***	−0.0004	−0.0033***
	(0.0010)	(0.0003)	(0.0003)	(0.0006)
TradeSize	−0.0006	−0.0008***	−0.0007***	−0.0010*
	(0.0009)	(0.0002)	(0.0002)	(0.0006)
Observations	9,026	3,492	6,267	6,267
Adjusted R^2	0.2776	0.1494	0.0232	0.0821
F Statistic	938.3351***	199.0570***	104.7412***	207.6141***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 19: Trade size effect on bid-ask spread measures: Q3

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OSE stocks with firm size in the third quartile. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.1163**	0.0354**	0.0067	0.0479*
	(0.0473)	(0.0172)	(0.0119)	(0.0273)
Volatility	0.7715***	0.1006***	0.1244***	0.3727***
	(0.0283)	(0.0066)	(0.0099)	(0.0277)
ln(MarketCap)	−0.0125***	−0.0039***	−0.0001	−0.0030***
	(0.0005)	(0.0002)	(0.0001)	(0.0003)
TradeSize	0.0032***	0.0006***	−0.0006***	−0.0003
	(0.0006)	(0.0002)	(0.0001)	(0.0003)
Observations	11,764	5,807	9,830	9,830
Adjusted R^2	0.3374	0.2138	0.0874	0.1503
F Statistic	1,583.9120***	454.6836***	321.0453***	520.2730***
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 20: Trade size effect on bid-ask spread measures: Q4

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OSE stocks with firm size in the fourth quartile. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0276	0.0081	0.0178**	0.0273**
	(0.0421)	(0.0158)	(0.0086)	(0.0135)
Volatility	0.3502***	0.0441***	0.1179***	0.2420***
	(0.0673)	(0.0151)	(0.0274)	(0.0553)
ln(MarketCap)	−0.0075***	−0.0020***	0.0002**	−0.0013***
	(0.0004)	(0.0001)	(0.0001)	(0.0002)
TradeSize	0.0017***	0.0003***	−0.0006***	−0.0001
	(0.0004)	(0.0001)	(0.0001)	(0.0001)
Observations	18,891	10,302	18,279	18,279
Adjusted R^2	0.2950	0.2269	0.2038	0.2336
F Statistic	2,047.4860***	804.8676***	1,239.7520***	1,462.9210***
Note:				*p<0.1; **p<0.05; ***p<0.01

5.6 Median transaction size results

In this subsection we conduct regression analysis for OBX stocks using an alternative measure of transaction size, the median transaction size. The estimation results for the effect of the median transaction size on spread measures are given in Table 21. The results for the median transaction size are similar to the results for the volume order size. It is also shown to have a significant positive effect on the relative and effective spreads, and a significant negative effect on the high-low measures. The estimation results for the effect of the median transaction size on the differences between spread measures are provided in Table 22. Similar to the volume order size results, the median transaction size has a significant negative effect on the differences between spreads and high-low measures. Hence, the regression results are robust across two alternative measures of transaction size.

Table 21: Trade size effect on bid-ask spread measures: OBX stocks

The table shows the one-way fixed-effects regression results with the relative (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. The independent variables are the inverse of a stock price (1/StockPrice), stock volatility (Volatility), the logarithm of firm size (ln(MarketCap)), and the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OBX stocks over the period 1999–2016 at a daily frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
1/StockPrice	0.0083***	0.0030***	0.0079***	0.0077***
	(0.0001)	(0.0001)	(0.0003)	(0.0002)
Volatility	0.0284***	0.0152***	0.0564***	0.0860***
	(0.0020)	(0.0008)	(0.0035)	(0.0054)
ln(MarketCap)	−0.0039***	−0.0017***	−0.0009***	−0.0022***
	(0.0001)	(0.00002)	(0.0001)	(0.0001)
TradeSize	0.0003***	0.00003**	−0.0008***	−0.0005***
	(0.00004)	(0.00001)	(0.00003)	(0.00005)
Observations	210,581	187,530	209,093	209,093
Adjusted R^2	0.3438	0.3690	0.2354	0.1391
F Statistic	27,609.5200***	27,446.3000***	16,119.0500***	8,475.9520***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 22: Trade size effect on differences between spreads

The table shows the one-way fixed-effects regression results with the absolute differences between the relative spread and the CS high-low spread (|RS-CS|), the effective spread and the CS high-low spread (|ES-CS|), the relative spread and the AR high-low spread (|RS-AR|), and the effective spread and the AR high-low spread (|ES-AR|) as the dependent variable. The independent variable is the logarithm of trade size in NOK (TradeSize). The regressions are estimated for OBX stocks over the period 1999–2016 at a daily frequency. For each model, the estimated coefficients and Driscoll and Kraay (1998) robust standard errors (adjusted for heteroscedasticity, cross-sectional and temporal dependence) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	|RS−CS|	|ES−CS|	|RS−AR|	|ES−AR|
TradeSize	-0.0016^{***}	-0.0014^{***}	-0.0015^{***}	-0.0015^{***}
	(0.00004)	(0.00003)	(0.0001)	(0.00005)
Observations	188,904	188,904	188,904	188,904
Adjusted R^2	0.0127	0.0136	0.0072	0.0065
F Statistic	$2{,}539.1420^{***}$	$2{,}713.0590^{***}$	$1{,}481.1200^{***}$	$1{,}350.0650^{***}$
Note:				*p<0.1; **p<0.05; ***p<0.01

6 Reverse Splits

In this section we provide descriptive statistics of reverse splits at the OSE. We also show the results from the analysis of liquidity reactions to reverse splits and the difference-in-differences estimation.

6.1 Reverse splits: descriptives

In this subsection we look at characteristics of splitting and nonsplitting stocks before and after the reverse split. As shown in Table 23, stock price and trade size significantly increase after the split, while stock volatility decreases for splitting stocks. The characteristics of nonsplitting stocks, however, do not change. This supports the notion that stock characteristics of splitting stocks change as a result of a split. It is also clear that splitting stocks are inherently different from nonsplitting stocks. Splitting stocks are low-priced stocks whereas nonsplitting stocks are average stocks in terms of stock price. Splitting stocks also have substantially higher volatility than nonsplitting stocks.

Figure 9 illustrates the prevalence of reverse splits across subperiods and split types. There seems to be an upward trend in reverse splits over the sample period 1999–2015. The most frequent splits are 1 for 10, 1 for 100, and 1 for 20.

Table 23: Stock characteristics before and after the reverse split

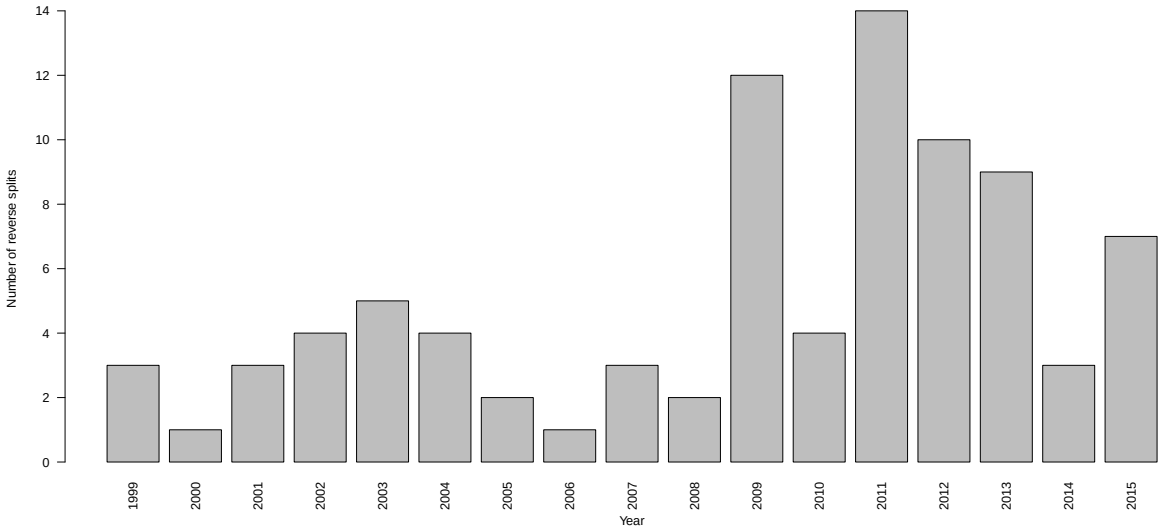
The table shows the crossectional averages of stock characteristics over the 5-day period before and the 5-day period after the reverse split for both splitting and nonsplitting stocks. The median values are given in parentheses. Stock price is specified in NOK.

Variable	Before the split	After the split
Panel A: Splitting stocks		
Stock Price	1.545	21.145
	(0.420)	(4.453)
Stock volatility	0.032	0.019
	(0.019)	(0.015)
Trade size in NOK	149.519	2780.566
	(4.150)	(19.250)
Trade size in shares	3.472	20.979
	(1.000)	(4.225)
Panel B: Nonsplitting stocks		
Stock price	91.610	91.514
	(71.048)	(71.165)
Stock volatility	0.008	0.008
	(0.006)	(0.006)
Trade size in NOK	12287.340	15599.318
	(5139.500)	(4830.250)
Trade size in shares	83.378	88.397
	(71.500)	(69.500)

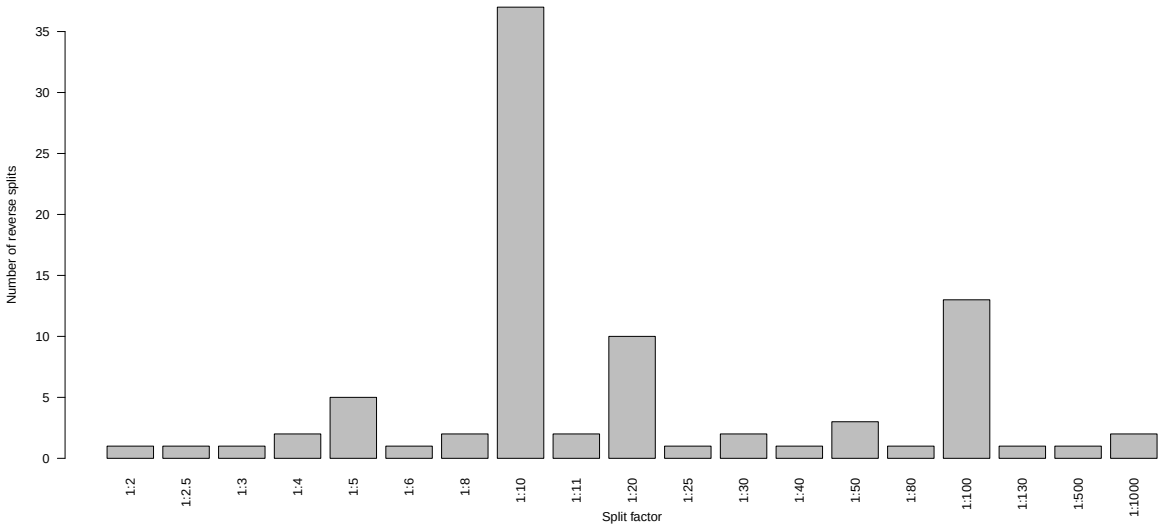
Figure 9: Frequency plots: reverse splits

The figure illustrates the frequency distribution of reverse splits (panel A) and split types (panel B) for the period 1999–2015. The sample consists of 87 reverse splits in the OSE stocks.

Panel A: Frequency of reverse splits



Panel B: Frequency of split types



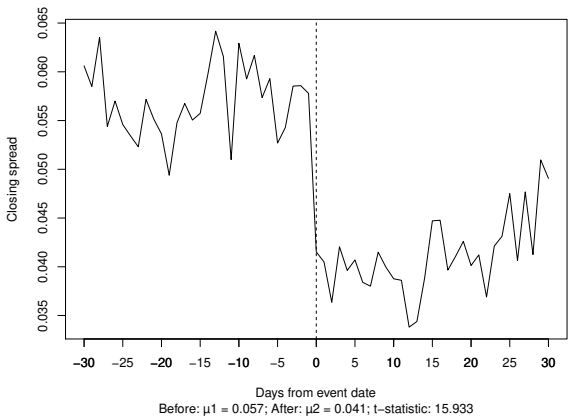
6.2 Reverse splits: analysis of liquidity before and after a split

In this subsection we report the results from a liquidity analysis around reverse splits over a 60-day event window. Figures 10 and 11 illustrate the effect of reverse split on alternative spread measures for splitting and nonsplitting stocks respectively. All spreads for splitting stocks are negatively affected by the reverse split as they drop significantly after the event date (as indicated by t-statistics). The spreads for nonsplitting stocks, however, do not change significantly after the split.

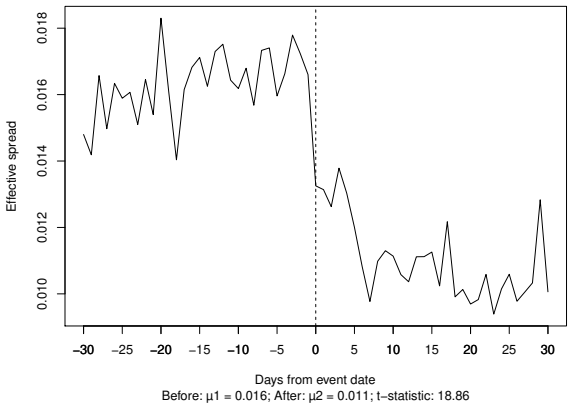
Figure 10: Analysis of liquidity before and after a slit: splitting stocks

The figure illustrates the time-series development of spread measures for splitting stocks around the reverse split date (event date). The event window of 60 trading days is used. The average spread before the event is compared with the average spread after the event using the paired two sample t-test for differences in means. The mean values of spreads in two periods (μ_1 and μ_2) and t-statistics are reported under the time-series plots.

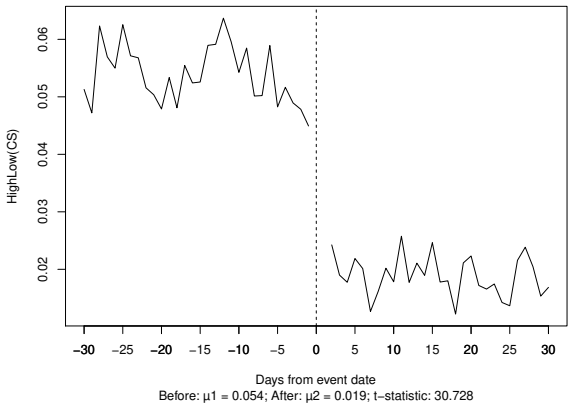
(a) Relative spread



(b) Effective spread



(c) HighLow (CS)



(d) HighLow (AR)

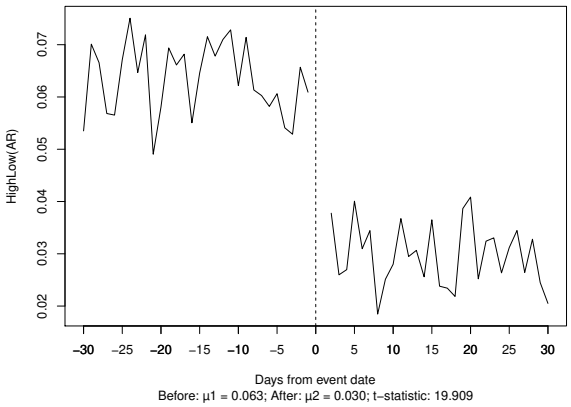
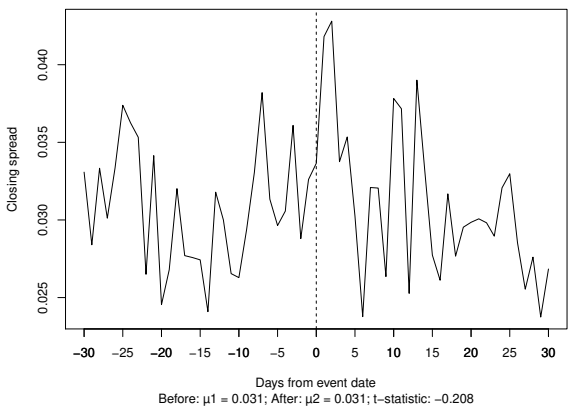


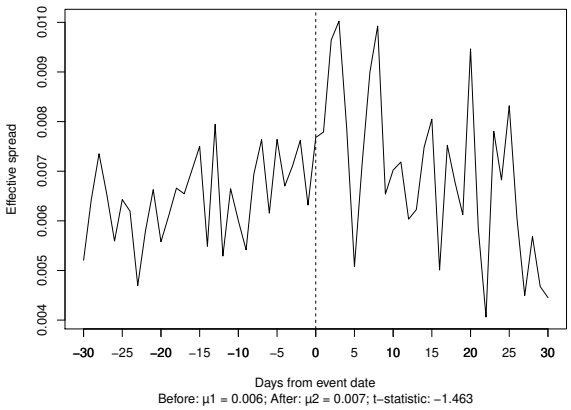
Figure 11: Analysis of liquidity before and after a slit: nonsplitting stocks

The figure illustrates the time-series development of spread measures for nonsplitting stocks around the reverse split date (event date). The event window of 60 trading days is used. The average spread before the event is compared with the average spread after the event using the paired two sample t-test for differences in means. The mean values of spreads in two periods (μ_1 and μ_2) and t-statistics are reported under the time-series plots.

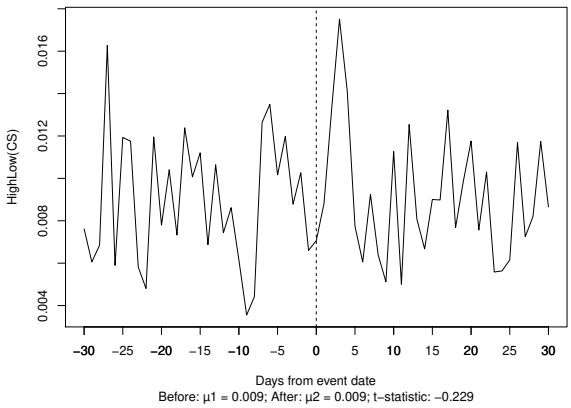
(a) Relative spread



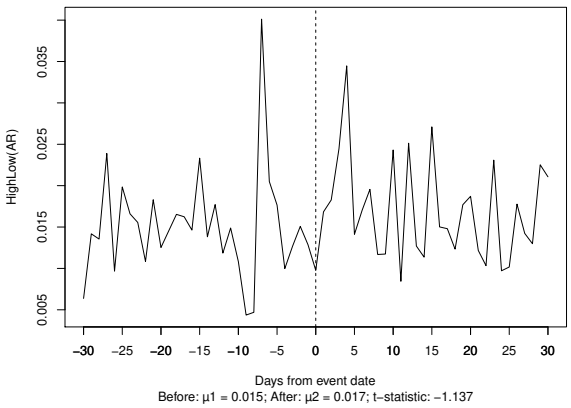
(b) Effective spread



(c) HighLow (CS)



(d) HighLow (AR)



7 Difference-in-differences results: stock splits

In this subsection we provide extra results from the differences-in-differences estimation. To test for robustness of our findings, we estimate the effect of stock splits and reverse splits over alternative event windows, namely, a 10-day window, a 20-day window, and a 60-day window. Tables 24 and 25 show the estimation results for stock splits over a 10- and 20-day windows respectively. The results for splits are consistent across different windows used in estimation. Specifically, there is a positive and significant effect of stock split on the benchmark spreads, but no significant effect on the high-low measures. Tables 26, 27, and 28 show the estimation results for reverse splits over alternative windows. The results for reverse splits indicate that all spreads are significantly negatively affected by the split. Hence, there is no difference in the effect of reverse split on the benchmark spreads and high-low measures.

Table 24: Difference-in-differences results: splits (a 10-day window)

The table shows the estimates of treatment effect coefficients from the one-way fixed-effects difference-in-differences estimation with the closing spread (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. A 10-day event window is used in the estimation. For each model, the estimated coefficients and clustered robust standard errors are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
POST	−0.00004	−0.0010*	0.0017	−0.0003
	(0.0025)	(0.0006)	(0.0020)	(0.0037)
TREAT*POST	0.0058**	0.0025***	0.0011	0.0032
	(0.0028)	(0.0007)	(0.0023)	(0.0042)
Observations	1,265	891	839	839
Adjusted R^2	−0.0891	−0.0734	−0.1282	−0.1342
F Statistic	6.2916***	17.0612***	2.9025*	0.9198
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 25: Difference-in-differences results: splits (a 20-day window)

The table presents estimates of treatment effect coefficient from the one-way fixed-effects difference-in-differences estimation with the relative spread (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. For each model, the estimated coefficients and clustered standard errors (at the stock level) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
POST	−0.0003	−0.0005	0.0008	−0.0003
	(0.0016)	(0.0005)	(0.0014)	(0.0022)
TREAT*POST	0.0056**	0.0018***	0.0007	0.0030
	(0.0026)	(0.0006)	(0.0015)	(0.0025)
Observations	2,437	1,704	1,728	1,728
Adjusted R^2	−0.0421	−0.0369	−0.0600	−0.0602
F Statistic	9.2490***	19.6724***	2.1168	1.9376
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 26: Difference-in-differences results: reverse splits (a 10-day window)

The table presents estimates of treatment effect coefficient from the one-way fixed-effects difference-in-differences estimation with the relative spread (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. For each model, the estimated coefficients and clustered standard errors (at the stock level) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
POST	0.0008	0.0008*	0.0016	0.0042
	(0.0030)	(0.0004)	(0.0026)	(0.0034)
TREAT*POST	−0.0150***	−0.0045***	−0.0292***	−0.0308***
	(0.0056)	(0.0011)	(0.0090)	(0.0104)
Observations	1,208	726	876	876
Adjusted R^2	−0.0596	−0.0423	−0.0717	−0.0925
F Statistic	19.0293***	24.7726***	20.2153***	12.4697***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 27: Difference-in-differences results: reverse splits (a 20-day window)

The table presents estimates of treatment effect coefficient from the one-way fixed-effects difference-in-differences estimation with the relative spread (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. For each model, the estimated coefficients and clustered standard errors (at the stock level) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
POST	0.0032	0.0011*	0.0005	0.0021
	(0.0029)	(0.0006)	(0.0016)	(0.0021)
TREAT*POST	−0.0191***	−0.0052***	−0.0327***	−0.0326***
	(0.0054)	(0.0011)	(0.0086)	(0.0093)
Observations	2,294	1,361	1,788	1,788
Adjusted R^2	−0.0064	0.0303	0.0141	−0.0135
F Statistic	45.6590***	62.7513***	63.3036***	38.6124***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 28: Difference-in-differences results: reverse splits (a 60-day window)

The table presents estimates of treatment effect coefficient from the one-way fixed-effects difference-in-differences estimation with the relative spread (RS), the effective spread (ES), and the high-low measures of Corwin and Schultz (2012) (CS) and Abdi and Ranaldo (2017) (AR) as the dependent variables. For each model, the estimated coefficients and clustered standard errors (at the stock level) are reported, along with the regression statistics – the number of observations, Adjusted R-squared, and F statistic.

	Dependent variable:			
	RS	ES	CS	AR
POST	0.0017	0.0008**	0.0002	0.0016
	(0.0022)	(0.0004)	(0.0007)	(0.0015)
TREAT*POST	−0.0141***	−0.0046***	−0.0361***	−0.0343***
	(0.0044)	(0.0008)	(0.0087)	(0.0090)
Observations	6,635	3,846	5,343	5,343
Adjusted R^2	0.0078	0.0560	0.0671	0.0280
F Statistic	79.1190***	156.4767***	242.7027***	127.4626***
Note:				*p<0.1; **p<0.05; ***p<0.01

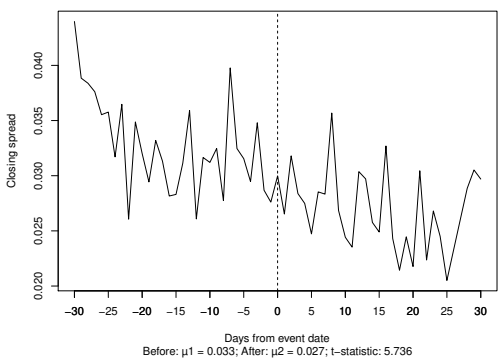
8 Lot size revisions, event study

In this section we look at liquidity changes around lot size revisions using the event study methodology. We separate lot size revisions into lot size decreases and lot size increases. In figures 12 and 13 we can see the time-series development of various measures of liquidity around lot size decreases for both revised and unrevised stocks. As revealed by the plots, spreads for revised stocks fall significantly after a decrease in lot sizes. Spreads for unrevised (control) stocks on the contrary increase significantly after a lot size decrease. Hence, it is difficult to claim causality as control stocks seem to be affected by some confounding. Similarly, in figures 14 and 15 we show liquidity changes around lot size increases for revised and unrevised stocks respectively. The relative spread for revised stocks increases significantly after a lot size increase, while other spreads do not change significantly. The unrevised stocks show no change in any of the spread measures. This implies that the increase in the relative spread for revised stocks is caused by the increase in lot size.

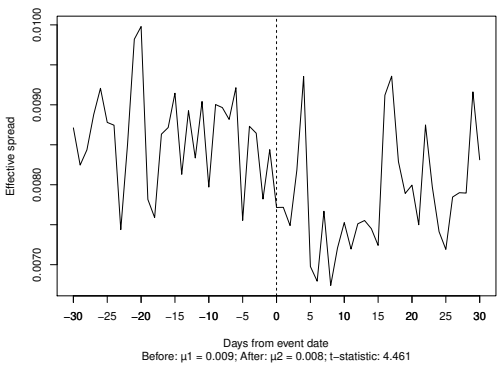
Figure 12: Analysis of liquidity before and after a lot size decrease: revised stocks

The figure illustrates the time-series development of spread measures for revised stocks around the lot size revision date (event date). The event window of 60 trading days is used. The average spread before the event is compared with the average spread after the event using the paired two sample t-test for differences in means. The mean values of spreads in two periods (μ_1 and μ_2) and t-statistics are reported under the time-series plots.

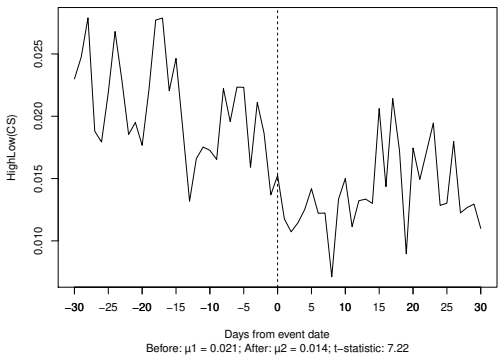
(a) Relative spread



(b) Effective spread



(c) HighLow (CS)



(d) HighLow (AR)

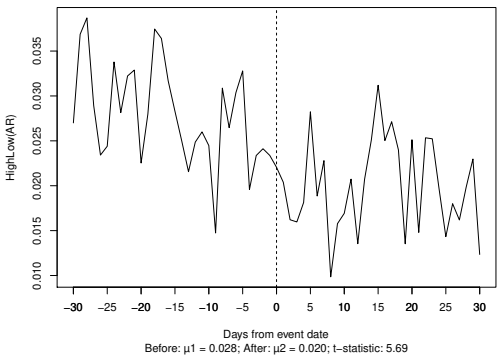
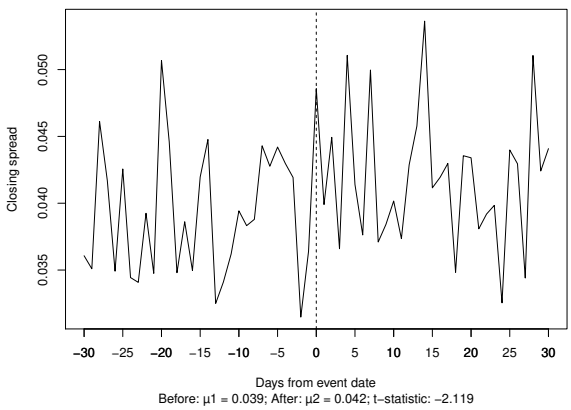


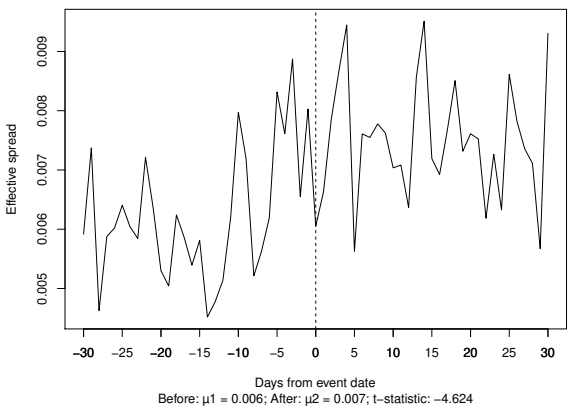
Figure 13: Analysis of liquidity before and after a lot size decrease: unrevised stocks

The figure illustrates the time-series development of spread measures for unrevised stocks around the lot size revision date (event date). The event window of 60 trading days is used. The average spread before the event is compared with the average spread after the event using the paired two sample t-test for differences in means. The mean values of spreads in two periods (μ_1 and μ_2) and t-statistics are reported under the time-series plots.

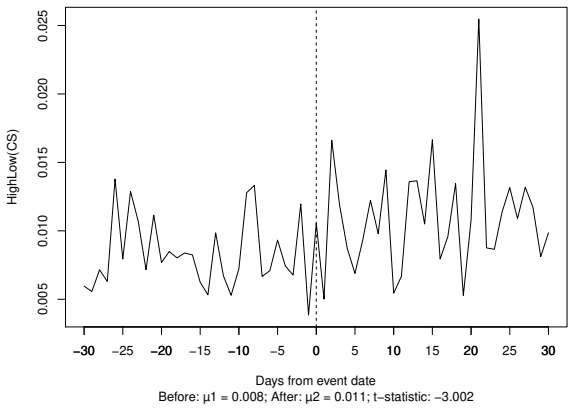
(a) Relative spread



(b) Effective spread



(c) HighLow (CS)



(d) HighLow (AR)

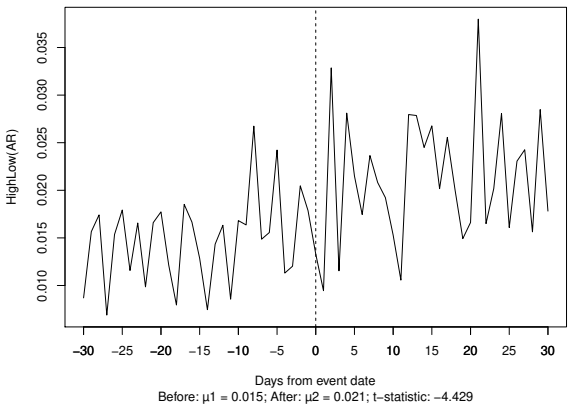
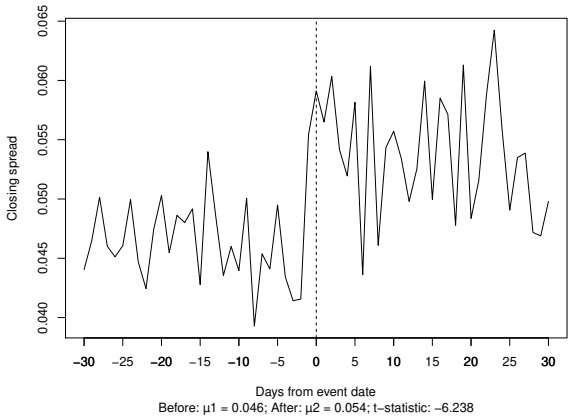


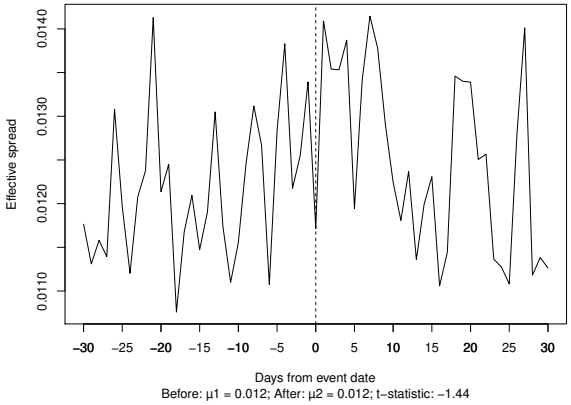
Figure 14: Analysis of liquidity before and after a lot size increase: revised stocks

The figure illustrates the time-series development of spread measures for revised stocks around the lot size revision date (event date). The event window of 60 trading days is used. The average spread before the event is compared with the average spread after the event using the paired two sample t-test for differences in means. The mean values of spreads in two periods (μ_1 and μ_2) and t-statistics are reported under the time-series plots.

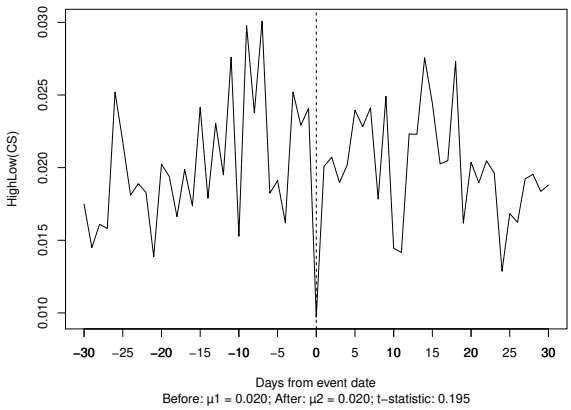
(a) Relative spread



(b) Effective spread



(c) HighLow (CS)



(d) HighLow (AR)

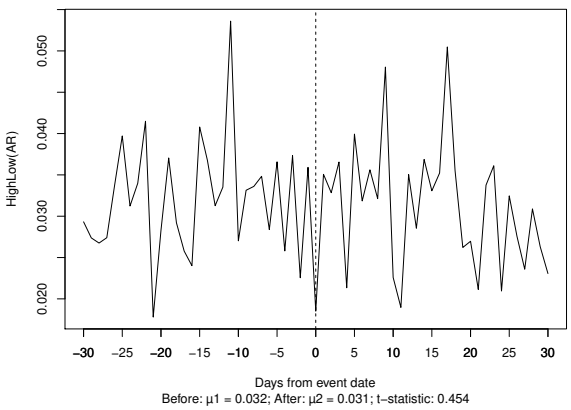
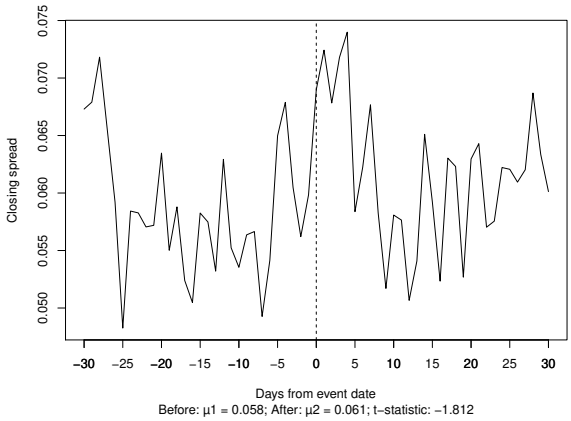


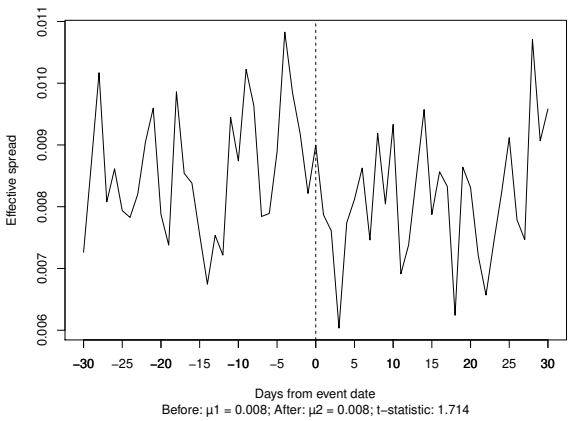
Figure 15: Analysis of liquidity before and after a lot size increase: unrevised stocks

The figure illustrates the time-series development of spread measures for unrevised stocks around the lot size revision date (event date). The event window of 60 trading days is used. The average spread before the event is compared with the average spread after the event using the paired two sample t-test for differences in means. The mean values of spreads in two periods (μ_1 and μ_2) and t-statistics are reported under the time-series plots.

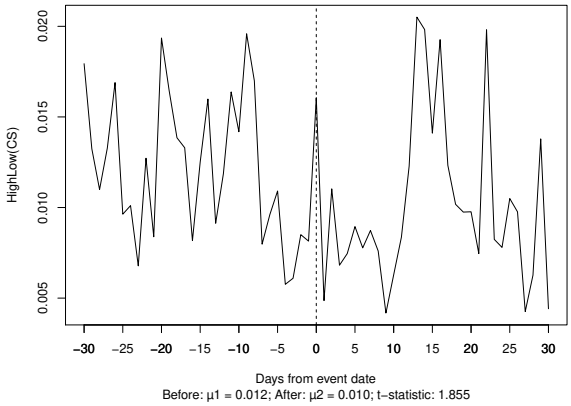
(a) Relative spread



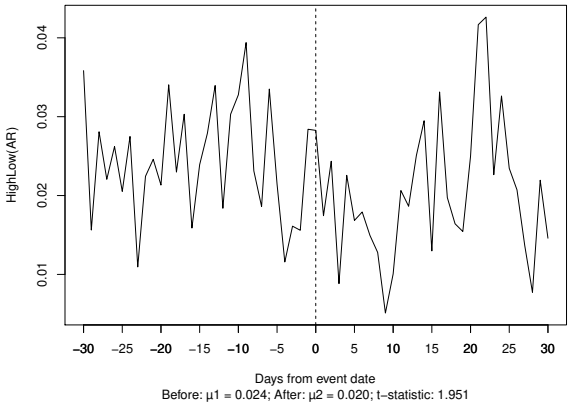
(b) Effective spread



(c) HighLow (CS)



(d) HighLow (AR)



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