Tick sizes and stock market volatility: A regression discontinuity approach

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Abstract

Increasing the tick size has been suggested as a countermeasure to high volatility on stock markets caused by growing high-frequency trading. To identify the potential effects of such an increase, we isolate the effect of the tick size change on volatility through a regression discontinuity design (RDD), utilizing the sharp increase in the tick size at 100 SEK where the tick size changes from 0.05 SEK to 0.10 SEK. The study is restricted to the Stockholm Stock Exchange, the 30 largest stocks on the market, OMXS30, and a range of share prices between 90 and 110 SEK. Volatility is measured in two ways: the level relative high-low range and the logarithm of the range, both as daily measures. While no direct causality between the tick size change and the level daily range could be isolated, the results for the log range indicate an average increase of about 10% following an increased tick size. This effect is corroborated by earlier panel studies isolating this effect. With the exception of types of volatility not controlled for in the daily range measure, such as clustered volatility, the results indicate that stock markets would not benefit, as hypothesized, from a marketwide increase in tick sizes.

Keywords: Tick size, volatility, high-frequency trading, the Stockholm Stock Exchange

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Contents

1 Introduction

On the 28^{th} of October 2011, Peter Norman, Minister for Financial Markets for the Swedish Ministry of Finance, hosted a conference on high-frequency trading (HFT). One of the topics discussed was the impact of HFT on the stock market, where an increase in volatility was mentioned as one of the drawbacks. While current research is divided on whether or not HFT have increased volatility, it was made clear during the conference that smaller investors as well as institutional investors have lost their confidence in the market, mainly due to a perceived increase in the market volatility. Concerned about their investors, marketplaces want to counter this notion. A suggested method for decreasing volatility was an increase in tick size, that is the smallest possible increase for a price of a traded equity [1]. Not limited to this conference, this countermeasure has been suggested by numerous parties earlier [2, 3]. This thesis aims to investigate what effect such an increase could have on the market volatility.

Since the late 1990s the tick sizes have gradually decreased for stock markets globally [4, 5, 6, 7]. On the Stockholm Stock Exchange, for example, the tick size has decreased with 80 to 90% between 2004 and 2011 for stocks within the 50 to 150 SEK range [8, 9]. Seeing as tick size decreases are not a new occurrence there exist several studies investigating the effect of such changes. These studies are largely parts of one of two groups: studies examining the effect of a marketwide change in the tick size at a predetermined point in time, and panel studies aiming to isolate the effect, often through a stepwise increase in tick size as the stock price increases over a certain value. Results from both types of studies are rather unequivocal concerning the sign effect on volatility. Bessembinder [10, 4] and Ronen et al. [5], among others, find that the market volatility is lower following a tick size decrease.

This study mainly differs in two ways compared to previous research. Firstly, the effect of the tick size change is analysed using data where HFT is prevalent to a large degree, conversely to earlier studies that are focused on tick size changes in the late 1990s. Seeing as an increase in the tick sizes is proposed as a countermeasure to HFT induced volatility, the prevalence of HFT should affect the impact of a tick size change. The main reason being an increased incentive of high-frequency traders to place passive orders with a higher tick size, although it is also possible that a larger tick size obfuscates stock price movements more than a smaller tick size, potentially leading to less speculation. In turn, this would lower any market volatility caused by high-frequency algorithms. Secondly, using a nonparametric approach such as regression discontinuity design (RDD) allows investigation of non-linear behaviour and isolation of any tick size effect on volatility, in the direct vicinity of the threshold.

Since previous research has indicated that effects of tick size changes are larger for stocks with more frequent trading [11] this study focus on the 30 largest stocks (OMXS30) on the Stockholm Stock Exchange. For this subset of stocks there is a discontinuity in the tick size at 100 SEK, where the tick size changes from 0.05 SEK to 0.10 SEK. These tick sizes are unchanged during the examined time period. Hence, the RDD is estimated using daily data on the Stockholm Stock Exchange (SSE) close to the 100 SEK threshold. The price range used is 90-110 SEK and observations date between January 2010 and December 2011. To control for any estimation bias caused by 15% of the observations crossing over the tick size discontinuity during a day, that is being exposed to both tick sizes, two specifications for the price are used. These are the volume weighed average price (VWAP) and the closing price, the former slightly better at estimating on which side of the discontinuity most trades were made than the latter. The dual specification allows an approximation of the bias caused by the crossover observations.

With one-period data, volatility is estimated as the difference of the highest and the lowest prices of the day relative to the volume weighted average price (VWAP), from now on denoted as range. As concluded by Garman and Klass [12], Alizadeh et al. [13] as well as Hau [14], among others, this measure is a good estimator of volatility, robust to microstructure noise and more importantly, efficient and robust to tick size changes. Furthermore, the logarithm of the range is close to Gaussian in its distribution [13]. The RDD is run with both the level and the log range, where the level range is included as a misspecification test.

Using log range as a measure for volatility, an increase in the tick size increases the range with about 10% for both price specifications. These results are robust to increases in bandwidth. Introducing the level range estimate, the results are more ambiguous. Despite the size of the treatment effect being roughly equal to that in the log range, few of these results are significant using different bandwidths with most p-values above 0.2. Hence, the null hypothesis of no change cannot be rejected for the level range. The lower significance is however expected. As the distribution of the daily range is skewed, with high variance and many outliers, the log range mitigates some of these problems and should be more indicative of the real tick size change effect.

Comparing the two price specifications, the results for the average price are more significant and show a larger effect. The difference in significance is anticipated, seeing as the VWAP is better than the closing price as a proxy for the real price during a day. This could indicate that the significance of the VWAP specification could have been better using more frequent data, lowering the number of crossover observations.

While results are weak, likely explained by the issue with crossovers, regressions indicate that an increase in tick size leads to a higher daily range. In turn this implies that market volatility would increase as a result of increasing tick sizes, conversely to the hypothesized relation. The sign effect of the tick size change is equal to that of most previous literature. However, not all effects are accounted for in this paper. For example, the daily range does not control for types of volatility such as clustered volatility and mini flash equity failures. If these are affected by a tick size change, the results of this study could be misleading. On the other hand, the daily range as a measure should capture many of the effects of volatility that a smaller investor would be subjected to, so the conclusions are still highly relevant. Furthermore, volatility effects of a marketwide tick size increase would be subject to changes in exogenous factors. Nonetheless, earlier research indicate that the effect of an event tick size decrease, and an isolated decrease is of the same sign. Hence, our results should be applicable. In conclusion, our study indicates that an increased tick size would either increase the market volatility or leave it unchanged.

The paper will be structured as follows. We will begin by giving a background to the issue, and then discuss current research on this topic. In section four an overview of the data is given, followed by section five, where a description of our methodology is outlined. This section includes how volatility is measured, background and specification of our model as well as how we test the assumptions necessary for performing a RDD. In section six descriptive statistics as well as the results are presented. We conclude with robustness checks of our findings and a conclusion where our results are put into a larger perspective and in relation to our initial question.

2 Background

To put our research into perspective, the following section presents a short description of the Stockholm Stock Exchange, its characteristics and trends, followed by an overview of tick sizes.

2.1 The Stockholm Stock Exchange and market trends

The NASDAQ OMX Stockholm Stock Exchange (SSE) is part of NASDAQ OMX Group Inc., the worlds largest exchange company. The bourse is open between 9.00 and 17.30. OMX Nordic, which the SSE is part of, lists 790 companies and on a daily basis over 287 thousand trades are executed amounting to a total value of 2.7 billion Euros [15]. Stocks on the SSE are part of one of three segments: Large Cap, Mid Cap and Small Cap. Within the Large Cap segment the OMXS30 group consist of the 30 most traded stocks, based on a market value weighted index. The index is reweighed on a semi-annual basis, every July and December. From July 1st 2009 until the end of 2011 the list has been unchanged [16].

On November 1st 2007, a new law was issued on the Swedish market. Before this all equities had to be traded on a regulated market and the SSE acted as monopoly. The introduction of the Markets of Financial Instruments Directive (MiFID) fragmented the market as it was opened up for competition [17]. In 2011 the four largest market places for Swedish equities, based on turnover, are the SSE (70%), Chi-X (15%), BATS Europe (6%) and Burgundy (6%) [18]. Trades on regulated markets represent about 84% of traded volume in Swedish equities, as an average between 2008 and 2012 [18].

One large trend, globally as well as on the SSE, is the increased algorithmic and high-frequency trading. Algorithmic trading refer to computerized trading by predetermined instructions, while high-frequency traders either take advantage of market inefficiencies by fast order execution or conduct market making. Orders are often high in number and positions are held for a short period [2]. In a survey conducted by The Ministry of Finance (FI) 80% of banks and institutions active on the Swedish equity market 2012 disclose using algorithmic trading while 14% use high-frequency trading strategies [2]. In 2011, HFT contributed to about 35% of trading for the European equity market, compared to below 15% in 2005 [19]. As for the market perception of these changes, the FI survey reports that about 50% of the Swedish banks and institutions believe that volatility has increased, out of which 42% attribute these changes to increases in HFT [2].

2.2 Tick Size

A tick size is the smallest possible increment of a stock price [10]. As such, if the tick size is 0.1, the price of a stock at 100.00 SEK may only increase to 100.01 SEK or above in similar increments, with no intermediate values. Since the late 1990s, tick sizes have gradually been lowered for many stock markets globally [4, 5, 6, 7]. On the SSE, for example, between 2004 and 2011 the tick size for the OMXS30 stocks within the 50-150 SEK price range was reduced to between one fifth and one tenth of the 2004 levels [8, 9].

In the end of October 2009, following an effort by the Federation of European Securities Exchanges (FESE) to harmonize the European stock market, the SSE adopted the FESE tick size table 2 (FESE 2) for the OMXS30 stocks. In June 2010 it was extended to the whole Large Cap segment [20]. FESE 2 employs a tiered tick size structure where the tick size changes incrementally as a function of price at certain cutoff values. For example, the tick size for equities with prices between 50.00 and 99.95 SEK is 0.05 SEK, and the tick size for stocks between 100.00 and 499.9 SEK is 0.10 SEK. Relative to the stock price, the largest tick size of this table is 0.1%, for stocks priced higher than 0.50 SEK.

Since FESE 2 was introduced there has only been smaller changes to the tick size structure. A new cutoff point was introduced at 2 SEK where the span before ranged from 1 SEK to 5 SEK and cutoff points were introduced for prices above 10 000 SEK per share. The tick size table used in the end of 2011 for all Large Cap and OMXS30 stocks is reported in Table 1.

3 Empirical research

The research on tick size is divided into two groups - studies examining the effect of a marketwide change in the tick size, and panel studies isolating the effect.

3.1 Effects of marketwide tick size changes

Several studies have analysed effects of tick size changes on transaction costs and market characteristics as a result of a stock market unilaterally decreasing tick sizes for all stocks at one point in time. Examining impacts on volatility, Ronen and Weaver find that a marketwide reduction of $1/8 ticks to $1/16 ticks on the American Stock Exchange (AMEX) in 1997 significantly decreases both daily and transitory volatility [5]. Similarly, Bessembinder studies the change of fractional pricing into decimal pricing on the New York Stock Exchange and the NASDAQ Stock Market in 2001, concluding that the intraday return volatility decreased as a result of the decreased tick size [4]. In both studies volatility is measured as the standard deviation of average returns.

In contrast, La Spada et al. observe that there is an increase in clustered volatility with a decrease in tick size [21]. Clustered volatility refers to the observation that large price changes of a stock tend to be followed by similar large price changes and vice versa for small changes [22]. The clustered volatility is measured as the autocorrelation function of 15 minute absolute returns [21]. Related, Gillemot, Farmer, and Lillo find that changes in tick size can be important in determining the persistence of volatility [23], that is the tendency that volatility sticks at a value despite external changes. Similarly, Onnela et al. observe that the tick size determines price stickiness as the proportion of zero returns increase with an increasing tick size [24].

As for other effects of a change in tick size, Ronen and Weaver [5] and Goldstein and Kavajecz [6], among others, show that the absolute bid-ask spread decreases for a marketwide tick-size reduction on AMEX and NYSE respectively. The same sign effect have been found for the relative spread, rather than the absolute spread, by Bessembinder [4] for changes on NYSE and Ahn et al. [7] on Toronto Stock Exchange (TSE). For the most illiquid stocks, Goldstein et al. find an increase in the bid-ask spread [6]. Relating the bid-ask spread to volatility, Plerou et al. [25], Lee, Mucklow and Ready [26] as well as Goodhart and O′Hara [27] conclude that the bid-ask spread and the volatility are positively related. However, it is shown that the direction of causality is such that volatility affects the spread rather than the opposite [27].

Lastly, Bacidore et al. conclude that a decrease in tick size will change the order flow so that the rate of orders is higher, but the size of orders is smaller [28]. As for the effect on volume Ahn et al. find that there is no significant change as the AMEX tick size decreased from \$1/8 ticks to \$1/16 ticks [29].

In conclusion, apart from contradictory outcomes on volatility with regards to intraday clustering there are a few general effects of a marketwide decrease in tick size: the bid-ask spread decreases, the rate of orders increase and order size decreases. Furthermore the traded volume is unaffected. It is worth noting that all these studies are performed at events where the market changes the tick size, hence these are not necessarily isolated and there may be exogenous factors causing these effects. Results of studies aiming to isolate this effect are outlined in the following section.

3.2 Panel studies on tick size changes

Bessembinder, studying the effects of stocks around the tick size change at \$10 on the NASDAQ, finds that the volatility is higher both after a tick size increase and a tick size decrease. This is explained as a result of the increase in information flow that is associated with the change [10]. When pooling the results on both sides of the discontinuity, Bessembinder finds that the median volatility is lower with a smaller tick size, irrespective of whether the tick size increases or decreases. It is also observed that the bid-ask spread decreases and the liquidity is unchanged [10].

Ke et al. examine firms that change between NS\$0.1 and NS\$0.5 tick sizes, and pools this data to isolate the effects of the tick size change. Concluding, similarly to Bessembinder, that a larger tick size results in an increased bid-ask spread, higher volatility and increased negative autocorrelation, but no difference in traded volume [30].

For the Paris Bourse, Hau investigates the stock characteristics around a tick size change, using data from 1995 to 1999 and a panel regression technique to isolate the tick size change effect, where volatility is measured by the relative range of highest and lowest prices. The range is argued to be non-biased by tick size changes. Hau finds that a 10 fold increase in the tick size, from FF 0.1 to FF 1, increases volatility with 30% and states that higher transaction costs increases volatility [14].

Niemeyer and Sandås, looking at tick size changes around the 100 SEK threshold on the Stockholm Stock Exchange, uses cross-sectional data and estimates the effect using a three-stage least squares regression. They find a positive relation between tick size and bid-ask spread and weak support that tick size negatively affects traded volume [31].

Lastly, Ascioglu et al. examine minimum tick sizes on the Tokyo Stock Exchange, finding that trade size and the number of trades are more significant determinants than price of whether the tick size is binding or not. They argue that tick sizes should be assigned using frequency of trading and price rather than just price, as it is today [11].

Combining the results from panel studies with the general effects in the event studies, most studies find that a decreased tick size lowers volatility apart from clustered volatility that is found to increase. Moreover, a decreased tick size generates a smaller bid-ask spread while the effect on volume seems to be either unchanged or slightly negative.

4 Data

The primary data is collected from NASDAQ OMX for observations before 2011 and SIX Telekurs thereafter, and is curated by Erik Eklund at the Stockholm School of Economics. The data consists of daily prices for all instruments traded on the SSE and variables include the daily highest, lowest and closing prices, end of day bid and ask prices, daily traded volume and company id. To complement this data with daily average price and number of trades as well as data on Nordea between January 3$^{\text{rd}}$ 2010 and June 15$^{\text{th}}$ 2010 that was missing, historical data for the stocks were downloaded from NASDAQ OMX Nordic [32]. The remaining issue with the dataset is that the end of day ask prices between the 3$^{\text{rd}}$ of January and the 15$^{\text{th}}$ of July 2011 are missing.

For the purposes of this thesis, the analysis is limited to the stocks included in the OMXS30 index. Firstly because OMXS30 are the most liquid stocks, meaning that they tend to have comparatively smaller transaction costs than less liquid stocks, in turn making the tick size more relevant relative to other sources of transaction costs. Secondly, since Ascioglu et al. concludes that trading activity is a major determinant for whether the tick size is binding or not, the OMXS30 stocks are most suitable [11]. Information regarding what stocks are included in the OMXS30 Index is collected from the NASDAQ OMX semi-annual OMXS30 index reviews [33, 34].

The data is further limited to the time period between January 1$^{\text{st}}$ 2010 to December 31$^{\text{st}}$ 2011. During this time period, there has only been smaller changes to the FESE Table 2. The limitation to recent data allows analysis of the potential impact on any volatility caused by high-frequency trading.

This study focus on the tick size change around 100 SEK, seeing as that is the most frequently crossed threshold for the OMXS30 stocks. All observations outside a 10% interval from this threshold are dropped, that is outside the 90-110 SEK interval, based on both the VWAP and the closing price. To control for firm specific effects and to avoid selection bias, only stocks with observations both above and below the threshold are kept. The omitted stocks are ERIC-B, LUPE, SKF-B and TEL2-B. The final dataset consists of 13 stocks and a total of 2029 observations.

Even though stocks only present on one side of the cutoff are dropped, most stocks are unevenly distributed around the threshold. This is one of the potential sources of selection bias. Dropping data to even the number of observations on each side could control for the bias, but would reduce the total number of observations with about two thirds. This reduction could lower the significance of our tests. Similarly there could be time specific effects, which cannot be controlled for by the same reason as the firm specific effects. Both these biases need to be considered when analysing the results.

5 Methodology

5.1 Volatility estimation

One of the more commonly used methods of measuring volatility using one period data is the daily range, that is the difference between the highest and the lowest prices during the day. Both Beckers and Hau conclude that the range is more accurate and more efficient than the standard deviation [35, 14]. It is also robust to tick size changes [14]. Furthermore Alizadeh et al. concludes that the natural logarithm of the range is fairly close to Gaussian and robust to microstructure noise [13]. Compared to proxies such as log of absolute or squared returns it has a lower variance [13] and does account for price fluctuations during the day.

Among others, Garman and Klass have made variants of the daily range measure and argue that the estimate is made more precise when the closing and opening price is added [12]. They find that the high-low-close-open (HLCO) measure is about seven times more efficient than the standard deviation. Using the HLCO estimate would be preferable but the data used for this study does not contain information on the opening price. For this reason the original range measure will be used. While it is possible to use the closing price from the previous day, this would not account for price changes while the market is closed and could cause bias. Furthermore, the original range measure is only slightly less efficient than the HLCO estimate [12].

Inspired by Hau volatility is estimated by the log relative range [14],

$$\log(range)_i = \log\left(\frac{H_i - L_i}{VWAP_i}\right), \tag{1}$$

and the corresponding level range,

$$range_i = \frac{H_i - L_i}{VWAP_i}, \tag{2}$$

where H is the highest price and L the lowest during a day and $VWAP$ is the daily volume weighted average price. There are two notable benefits of using the log range. Firstly it is more closely Gaussian in distribution than the level range. Secondly, using the log reduce the impact of outliers on regression estimates. To account for potential misspecifications the level range is also included in our analysis.

5.2 The Regression Discontinuity Design model

The main regression of this thesis is run using the Regression Discontinuity Design (RDD). This method isolates the impact of a change in treatment by examining only a narrow interval. More specifically a RDD relaxes ceteris paribus assumptions of variables that may be uncontrollable in practical research without controlled experimental testing. Furthermore, this method has a high internal validity [36] and minimizes misspecification and endogeniety issues as well as allows for non-specified functional forms [37].

A RDD is performed by finding a discontinuity in the data, and narrowly limiting the data used in analysis to a small range above, and below the discontinuity. In essence, by doing this one can assume that the observations right above the discontinuity and just under the discontinuity are roughly equal in other aspects. That is, assuming that one cannot accurately predict or influence on which side of the discontinuity to end up. Hence, the regression can be described as a local randomized experiment.

For a sharp RDD, it is assumed that treatment, W, is allocated only as a function of one variable, and of the form:

$$W_i = \begin{cases} 1 & X_i \geq Z_0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

In a fuzzy RDD, the probability of treatment does not have to jump from 0 to 1 at the cutoff point Z_0, but there must still be a discontinuity in the probability of treatment for the method to correctly estimate the effect [36].

In relation to this, a difficulty arise with our data since a stock can fluctuate between the two different tick sizes within a day. This observation is being both treated and non treated, opposite the common sharp RDD assumption. As the data allows no definite allocation of whether these observations are treated or non-treated, a fuzzy RDD could be appropriate. However, the discontinuity in the probability of treatment is very small for our data. A stock with an average price close to the cutoff point should experience a fairly equal distribution of intraday prices around the tick size threshold at 100 SEK, leading to observations right above and right below the threshold having an approximately 50% probability of treatment. Seeing as a fuzzy RDD requires a discontinuity in the probability of treatment, in the best case, this lead to weak estimates for a fuzzy RDD but could also cause significant bias as the denominator in the local Wald estimate would be small relative to the numerator. A relatively small denominator magnifies any estimation errors. For this reason, the problem is implemented as a sharp RDD with some alterations to control for the crossover issue. For example, both the average and the closing price are used for estimating the cutoff point.

The treatment effect in the sharp regression discontinuity design is calculated as the difference in the estimates just above and right below the cutoff point Z_0, that is:

$$\tau = \lim_{\epsilon \downarrow 0} E[Y|X = Z_0 + \epsilon] - \lim_{\epsilon \uparrow 0} E[Y|X = Z_0 + \epsilon] \tag{4}$$

where Z_0 is the cutoff point, X the assignment variable price and Y the outcome variable range.

All regression discontinuity estimates are estimated using the method developed by Nichols [38], and are adapted to conform with Imbens [36], Fuji [39] and Lee [37]. The treatment effect is estimated by running local linear regressions on each side of the cutoff value since these lower bias compared to other nonparametric regression methods such as simple kernel estimators. For the calculation of the local linar regression, rectangular kernels are used as recommended by Imbens et al. with robustness testing for different bandwidths, h. In essence, using a rectangular kernel means that standard regressions are estimated over numerous small bins with size h on each side of the cutoff point, where the kernel affects the weighting of the observations. While a more advanced kernel could add attractive features such as smoothing the local linear polynomials or better control for covariates, such kernels add unnecessary complexity as most benefits are easily controlled for in a rectangular kernel design [36] and make no significant difference in asymptotic bias [37]. Following Imbens et al. the local linear polynomial regression to the left of the discontinuity (non-treated observations) is given by the optimization problem:

$$(\hat{\alpha}_l, \hat{\beta}_l) = \arg\min_{\alpha,\beta} \sum_{i:X_i<Z_0} K(\frac{X_i - Z_0}{h}) \times (Y_i - \alpha - \beta \times (X_i - Z_0))^2, \tag{5}$$

and the corresponding equation for the observations to the right (treated observations) of the discontinuity,

$$(\hat{\alpha}_r, \hat{\beta}_r) = \arg\min_{\alpha,\beta} \sum_{i:X_i\geq Z_0} K(\frac{X_i - Z_0}{h}) \times (Y_i - \alpha - \beta \times (X_i - Z_0))^2, \tag{6}$$

where the rectangular kernel is given by:

$$K(u) = \begin{cases} 1/2 & -1 \leq u \leq 1 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

The optimization problem provides the estimator for the treatment effect,

$$\hat{\tau} = \hat{\alpha}_r - \hat{\alpha}_l. \tag{8}$$

Details for the estimations used of the treatment effect variance is given in Fuji (2009) [39].

To find the optimal bandwidth, given a sharp RDD design, Imbens method is used. Optimal implies minimizing the mean square error for a RDD, and is estimated such that $\hat{h}_{opt} \propto N^{-1/5}$, where N are the number of observations. Specifics for calculation of the optimal bandwidth are presented in Imbens (2011) [40].

As recommended by Imbens et al., we report the estimate for the optimal, double the optimal and half of the optimal bandwidth. Since our regression bears characteristics of the fuzzy RDD and Imbens et al. recommend increasing the bandwidth further when using this specification, the estimate for four times the optimal bandwidth is additionally reported. While the treatment effect estimates using the smallest bandwidths will be highly biased due to the crossover observations, they are kept as a control of any bias caused by high bandwidths due to possible differences in the functional form of the outcome variable from the linear estimation of the regression.

To correctly implement and draw inference from a RDD, a small number of assumptions on the characteristics of the underlying observations needs to be controlled for. These RDD robustness checks are described in section 7, specification testing.

5.3 RDD specification

In this study, OMXS30 stocks with prices within both the 90-100 SEK and the 100-110 SEK interval in a period between 2010 and 2011 on the Stockholm Stock exchange are analysed. Thus, a 10% interval around the cutoff point Z_0 (100 SEK) is studied. Stocks below the 100 SEK threshold has a tick size of 0.05 SEK, whereas the tick size is 0.1 SEK above.

Due to the use of daily data, the RDD is not as sharp as if intraday data had been used. As discussed in the previous section, approximately 15% of the analysed observations crosses over the tick size threshold during a day, and are subjected to both tick sizes. To control for this in a sharp RDD specification, two different measures of price are used, the volume weighted average price ($VWAP$) and the closing price. The former estimate is better at estimating on which side of the discontinuity most trades were executed than the latter, allowing an estimation of the impact of the crossover observations by comparing the two specifications.

The volume weighted average price is defined as

$$VWAP_i = \frac{\sum(S_i \times P_i)}{\sum S_i}, \tag{9}$$

where S is the number of bought shares and P is the price. The closing price is the end of the day closing price.

When estimating volatility, two different measures will be used. As specified in section 5.1 a commonly used measure is the natural logarithm of the range, where range is defined as

$$range_i = \frac{H_i - L_i}{VWAP_i}. \tag{10}$$

The log $range$ will be our main estimator for volatility. As a test of robustness and to identify potential misspecifications the level range will also be reported. The regression specification can be described as,

$$Y_i = m(P_i) + \tau T_i + \upsilon_i \tag{11}$$

for an observation i where Y_i is either *range* or $\log range$, $T_i = 1(P > Z_0)$ where P is either the volume weighed average or the closing price, and $m(P_i)$ is a smooth function of price, approximated by the local linear regressions.

Summarizing, four different specifications will be tested, where each of the level range and log range volatility estimates are regressed on both the average and the closing price. For all specifications the cutoff point is defined by $Z_0 = 100$ SEK. Four different bandwidths are reported for each estimation.

5.4 RDD specification tests

5.4.1 Discontinuity in treatment variable

For a RDD to be valid there needs to be a discontinuity in the treatment variable W, tick size, at the cutoff point Z_0. This discontinuity is normally sharp and given by market directives, as described in section 2.2 Tick Size. However, due to the abstraction of using daily data, the discontinuity must be analysed.

The effect from crossover observations is tested by graphing the price on the x-axis displaying the frequency of crossover and non-crossover observations for small price intervals. This allows an estimation of the impact and the price range for which our sharp specification is valid.

5.4.2 Discontinuities away from the cutoff

To estimate any impact of spurious correlation, tests are performed to find any discontinuities in the treatment variable away from the chosen threshold 100 SEK. This is tested using the procedure for RD-regressions by Imbens et al., as specified in the RDD model section above. The regression is run separately for observations above and below the cutoff in order to eliminate any impacts from the actual discontinuity. The regression is run on both the closing and the average price, respectively for the median and the 25^{th} as well as the 75^{th} percentile, since these values increase the power of the test of finding any discontinuities [36]. Percentiles for prices are reported in Table 12. The same four bandwidths as described previously were used. In the results we look for any significant discontinuities in the relative range, using both the level and the range estimates.

5.4.3 Discontinuities in covariates

Following the procedure for testing for discontinuities in covariates by Imbens [36], sharp RDD regressions at 100 SEK are run for variables other than range. The tested variables are, $\log(trades)$, $\log(volume)$ and $\log(spread_{relative})$, where

$$spread_{relative} = 2\frac{B_i - A_i}{B_i + A_i}, \tag{12}$$

where B_i is the end of day bid price for observation i and A_i is the end of day ask price. The relative spread is used to minimize any price change effects. The log refer to the natural logarithm, which is used to make the distributions relatively more Gaussian.

The level regressions were run, but displayed rather minor differences. For this reason, these results are omitted from the reported values. In addition to current values, lagged covariates are tested in order to investigate any differences in predetermined characteristics. One day is used for lagging. Longer lag was tested, lowering the treatment effect significance further. Since these are less significant, only the one day lagged observations are reported. All covariates are tested using the four aforementioned bandwidths.

5.4.4 Assignment variable manipulation

For the RDD to correctly estimate the treatment effect, there must be no possibility of manipulation of the assignment variable. Hence, the data is tested for uniform distribution around the point of the discontinuity, using McCrary's density test [41]. Briefly, the test involves two steps. First, all observations are plotted in a histogram where the bin width is calculated following McCrary. Secondly, local linear regressions are run for the values on both sides of the discontinuity, regressing the normalized count of observations over the midpoint of the histogram bin. Standard deviations for the local linear regressions are also calculated and added to the plot. The outcome is presented as a graph where a smooth line over the threshold would indicate that there is no manipulation in the assignment variable.

6 Results

6.1 Descriptive statistics

Comparing the summary statistics for the two different price measures, the volume weighted average price (VWAP) and the closing price, the measures are seemingly equivalent. From our specification the minimum and maximum price is restricted to 90 and 110 respectively. Both price specifications have a mean price of 100.50, rounded to two decimal places. They display an average standard deviation of about 5.5 SEK and a kurtosis slightly lower than for a normal distribution, implying that they are somewhat more uniformly distributed over the price interval. Furthermore, as seen in the summary statistics in Table 2 for the average price and Table 3 for the closing price, there are stocks present on only one side of the tick size threshold, ERIC-B, TELE2-B, LUPE and SKF-B. These observations are omitted before running any regressions in order not to skew the results with any potential firm specific effects, but are kept in the descriptive statistics to allow comparison.

Analysing the data with regards to the range, the results are separated by the relative range and log of range as well as on the closing and the volume weighted average price, and are reported in Tables 4-7. The mean of the level range for most stocks are around 0.03, for both the average and the closing price as well as both above and below the cutoff point. Two notable exceptions are ELUX-B, displaying a slightly higher mean below the cutoff (0.45 for VWAP and 0.43 for close) and SCV-B, showing a slightly higher mean above the cutoff (0.45 for VWAP and 0.46 for close). On average, the mean level range for about 50% of the stocks increases after the cutoff. There is no apparent difference in standard deviation neither above nor below the cutoff point.

The observations for the level range are generally positively skewed (on average about 0.23). The extreme is NOKI-SEK, displaying a skew of 5. Stocks tend to be skewed similarly above and below the cutoff point, only being slightly lower above the cutoff than below, thus not affecting the validity of our results. The kurtosis changes around the discontinuity. The maximum kurtosis is 32.6 for NOKI-SEK below the cutoff point in the VWAP specification. Most stocks display a kurtosis close to three but the average kurtosis is high, caused by NOKI-SEK, SCA-B, SWED-A and SKA-B all having a kurtosis above 15. Due to the large kurtosis and the slight skew, these results does not follow a normal distribution. For this reason, our main specification for estimating volatility will be log range as this would benefit the local linear regressions by better satisfying the CLM assumptions and reduce the impact of outliers [42]. Descriptives for the level range can be found in Table 4 for the VWAP and Table 5 for the closing price.

As found in previous research, the log range should be close to Gaussian [14]. With the exception of NOKI-SEK all stocks have a kurtosis and skewness close to a normal distribution both for the average and the closing price, when log range is used. Furthermore, both the skewness and the kurtosis are more similar above and below the cutoff for individual stocks, compared to the level range values. Thus, using log range generates a more controlled setup for our main regression. Similar to the level range the mean and standard deviation for the log range of all stocks are fairly alike on both sides of the discontinuity, with a mean between -3 and -4 and a standard deviation between 0.4 and 0.5. A summary of the log range statistics can be found in Table 6 for the average price and in Table 7 for the closing price.

As data from two different years are used, the values of both the level and log range for the different years are compared in Table 8. Noticeable is that about 60% of the observations are from 2010 and that the mean range is slightly higher in 2011. Similarly the standard deviation is higher in 2011. Consistent with the statistics mentioned above, the log range follows a normal distribution whereas the level range is positively skewed and shows a high kurtosis. Both specifications are however closer to a normal distribution in 2011 than in 2010.

Lastly, descriptive statistics of covariates is reported in Tables 9-10. Both the absolute range and the relative spread are higher for observations with a larger tick size (above 100 SEK), than those with the smaller tick size. In the case of the absolute range that could be caused by the price difference between the observations. On the other hand, both trades and volume are lower for the observations with the larger tick size, than the observations with the smaller tick size. These changes are consistent for both price measures.

The descriptive statistics do indicate that there is a difference in most variables with a larger tick size compared to a smaller. While this effect is clear for the covariates and the biased absolute range measure, it is not as apparent for the relative range measures. Hence, there is a need to analyse the regression results before coming to any conclusions.

6.2 Regression results

When analysing the results attained from the RDD regressions, one general criteria is used. Even though four different bandwidths are reported, three of these are seen as more significant due to our specification generating a RDD which is somewhere in between sharp and fuzzy. As Imbens recommends to use larger bandwidths when analysing a fuzzy RDD [36] the results for half the optimal bandwidth are only reported for validation purposes. Since about 15% of our observations are both above and below the cutoff point during the same day, and these mainly lie close to the cutoff, these observations will have a proportionately larger impact on the estimate as the bandwidth decreases. This is an issue seeing as the range of these stocks will be less different than non-crossover stocks, affecting the statistical significance of the regression. As an example, consider one stock with a VWAP of 99.9 SEK, and another stock with a VWAP of 100 SEK. For practical purposes, both stocks can be assumed to having had a price below 100 SEK for 50% of the day, and above 100 SEK for the other 50% of the day. Hence, they are approximately equally treated by the larger and the smaller tick sizes respectively during the day. On average, then, their volatilities should be equal. The problem being that these stocks are identified as different. One treated and one non-treated. For apparent reasons this lowers the significance of any discontinuity that would otherwise exist. Hence, it is also believed that the lower significance of this specification does not pose a problem with the robustness of our results. Therefore larger bandwidths will be considered more representative of the real effect.

Examining the regression results in Table 11 and Figures 1-4, the effect of a tick size change is not apparent. Although the estimated effects for the level and log ranges are approximately similar, their significance is substantially different. In the text that follows, a thorough analysis of both results and implications will be presented, starting with log range as this is the main specification.

Using the log range as an estimate for volatility, a clear effect from an increase in the tick size is seen, the daily range is increased. The effect of the tick size change, on average, was 12.15% for the average price specifications, and 9.69% for the closing price specifications. Since the average absolute range was roughly 2.6 SEK, see Tables 9 and 10, for both the average price and the closing price specifications, this would correspond to an increase in the average spread of 0.32 and 0.25 SEK for the average and the closing prices respectively.

The difference between the closing price and average price specifications in the regression results is notable. The estimated treatment effect for the average price specification is slightly higher than the estimates for the closing price specification. Furthermore, the p-values for the average price specification are higher. The results are however unsurprising. As discussed in previous sections: while the density distributions of both the closing price and the average price specifications should be centred roughly around the same value, the closing price is less correlated to the actual prices during the day. Though there is some significance to the closing price explaining whether the prices during the day generally were above or below the discontinuity, there is more significance to the average price. For this reason, the closing price results in a distribution that is less sharp around the discontinuity, resulting in the lower economic and statistic significance of these specifications.

Looking at a change in the log range, using optimal and larger bandwidths, the p-values are between 0.05 and 0.08, indicating that the change is rather statistically significant. However, when half the bandwidth is used the p-value increases to 0.2. This increase in the p-value is expected, as described above. Further comparing the different bandwidth specifications, it is clear that the treatment effect initially decreases as the bandwidth is increased. Once again, the exception is half the optimal bandwidth, where the effect is slightly lower than for the optimal bandwidth. However, this difference is not significant. Looking at the VWAP specification, the treatment effect is 17% for the optimal bandwidth, decreasing to around 8% for four times the optimal bandwidth. With even larger bandwidths, such as eight and ten times the optimal, the effect converges toward 10% at a very high significance, both statistically and economically.

The pattern is similar for the closing price but the effect is more moderate. For the optimal bandwidth the treatment effect on the log range is about 12% while the effect is roughly 6% for four times the bandwidth and converges to around 9% as the bandwidth is increased further. These results would indicate that the effect of the tick size change on the range is higher right by the cutoff point and that the effect is levelled off the further away it comes, (of course excluding half the bandwidth and thus the observations in the near vicinity of the cutoff).

As a robustness check, the behaviour of the level range when the tick size changes is analysed. Consistent with the log range results, an increased tick size is associated with a higher range, looking only at the regression coefficients. On average the level range increases with about 0.4 percentage points. Given that the mean level range is 0.028 this is approximately equivalent to the 10% increase using the log range, and is true for both the average and the closing price. Yet, there is a large discrepancy in the significance of the level and the log range results. Most level range results are highly insignificant, making it impossible to reject the null of no change. However, the results using four times the optimal bandwidth for both the close price and the VWAP are highly significant. Considering that the data for level range were both skewed and showed a high kurtosis this result is expected. Not unlike the effect of the logarithm, a higher bandwidth includes more values, which lower the impact of outliers.

In summary, these results indicate that an increase in tick size increases the range as seen in the changes in the log range, when observations are sorted by the volume weighed average price. These results are somewhat robust to misspecification in the form of using close prices and the level range, though they lower the significance, albeit expectedly, for reasons discussed earlier. Similarly, the lower significance at lower bandwidths is expected due to the issue with crossover observations. As the bandwidth increases, the estimated increase in range caused by an increase in the tick size converges to about 10%, common to all specifications.

7 Specification testing

To validate the regression results, we test the specification in the light of the assumptions underlying the regression discontinuity design. In this section, we analyse the robustness of our results based on these assumptions.

7.1 Discontinuity in treatment variable

Even though the Stockholm Stock Exchange forces treatment of shares on the market when crossing a boundary, leading to a sharp discontinuity, the abstraction to daily data creates some fuzziness. There is however still a discontinuity that is sharp for a subset of observations that do not cross the tick size boundary. Even though the assumption of a discontinuity is fulfilled, as all stocks sufficiently above the discontinuity is treated and vice versa, we need to analyse the fuzziness.

As can be seen in Figures 5 and 6, there are significant numbers of crossovers roughly 2 SEK above and 2 SEK below the threshold. Outside this range, the number of crossovers decreases quickly. For this reason, any bandwidth for which this range represents a high proportion of the range in the bandwidth likely causes biased estimates. So, a lower bound for the bandwidth should be at least 2. Not surprisingly, the optimal bandwidth for many of our regressions is between 2 and 3, leading credence to the assumption that inference from half the bandwidth specification should be limited.

7.2 Discontinuities away from the cutoff

To analyse any tendency of spurious correlation, it is necessary to estimate whether there are any significant discontinuities away from Z_0. The results are reported in Tables 13-16. There are few significant discontinuities for the level range under either price specification. There is a slightly significant discontinuity at the 25^{th} percentile above the threshold, with the half and the optimal bandwidths reporting significance at a 10% level. However, this diminishes with increasing bandwidth. As such, it seems to be caused by spurious correlation. The log range specifications are slightly more significant on average, but the significant observations seems to be located around the threshold for the closing price, indicating an impact from crossover observations. As for the average price the discontinuity is harder to explain. The observation with the highest significance at the optimal bandwidth, the 25^{th} percentile, is visualized in Figure 7. As seen in the figure, there is an outlying cluster in the vicinity of the cutoff point, which if removed minimizes the discontinuity, but it is still not possible to conclude with any certainty that results may not be impacted by spurious correlation.

7.3 Discontinuities in covariates

The results from the regressions on the covariates are reported in Tables 17-18 and Figures 8-10. Few of the reported ex post treatment effects for the VWAP specification are statistically significant at all, with the exception being the number of trades when using a double or quadruple bandwidth. While this would suggest that the covariates should be equal over the cutoff, the result is surprising given the amount of research on both event and panel studies showing a definite relation between the tick size and the bid-ask spread for example. Similarly, Figure 9 clearly shows that the bid-ask spread is downwards limited by the minimum tick size. Hence, there should be a discontinuity in the estimate assuming that the upper bound after the tick size change does not change markedly. It is hypothesised that these somewhat surprising results are due to the crossover issues as discussed in previous sections. This is further validated by the rather high significance for the spread when testing the close price. Due to both the closing proce and the spread being end of day values, this regression corresponds a sharp design. Hence, it is significant of the real effect on the bid-ask spread. The difference between the closing price and VWAP specifications might indicate the breadth of the crossover problem for the main regression of this study. Also surprising is the high significance on volume for the closing price specification. It is especially notable since it is the only variable that remains quite as significant when using lagged variables.

Running the same tests for the other covariates lagged one day decreases the discontinuities to a point where none of the treatment effects are statistically significant. Given these results, even though there might be differences in the non-lag covariates, there is seemingly no difference in the lagged, adding credibility to the assumption of no difference in predetermined characteristics of the observations. Hence, any difference in the discontinuity should be caused by the tick size change and nothing else. The non-lagged variables do limit assumptions of causality, seeing as it is impossible to discern whether the tick size change causes higher volatility or e.g. the bid-ask spread or the volume is the cause, but as the predetermined characteristics are equal, there should be little doubt that it is the tick size that is the primary cause for this difference. Relating the results with earlier studies, volatility has been shown to cause higher bid-ask spreads and not vice versa, so even in the case of ex post significant characteristics, we should be able to infer causality for the VWAP specification.

7.4 Assignment variable manipulation

As can be seen in Figures 11 and 12, there is no significant discontinuity in the density at the tick size change at 100 SEK for the average price specification. For the closing price, there is a difference, in the range of one standard deviation from the other. There is a slight hump right above the discontinuity for both figures. While this might be a result of sticky pricing right above 100 SEK, it should be noted that there could potentially be a difference that our density regression does not account for. It could also just be an anomaly in the data used. As is, however, it is estimated that this does not pose a problem for the average price specification, seeing as the densities at the cutoff are relatively equal. While there should be no possibility of manipulating the stock price due to market rules and the discontinuity could be random, caution should be taken in inference from the closing price specification.

7.5 Discussion of other potential issues

One drawback of the regression specification is an assumption that every observation is independent. As such, it is assumed that there are no correlation between observations, and no firm or time fixed effects, for example. While this could lead to unbiased estimations if assuming that the observations are evenly distributed across firms, thresholds, and time, our summary statistics show that this is not necessarily true. For this reason, it would be beneficial to use a method that control for these issues, such as using a multivariate kernel instead of the uniform kernel in the estimation of the local linear polynomials in the regression discontinuity design, as described by Black et al. [43]. Including fixed effects could also help reduce the high variance of estimates, causing low significance.

Furthermore, other measures for volatility accounting for intraday changes or other effects that HFT could create could potentially generate other results. Lastly, looking at other cutoffs or other stock segments would increase the external validity of our findings in order to see how the overall market is affected by the change.

8 Conclusion

As seen in the results, an increase in the tick size generates different results for the level and the log range specifications. Though the null hypothesis of no change cannot be rejected when the level range is used, the log range specification implies a 10% increase in the range when the tick size is increased.

While the effect of the tick size change on the daily level range is weak in significance, considering both volatility estimates implies an economically as well as statistically significant change in the range that is consistent with earlier research. Assuming that the low significance of some of the specifications is caused by the problem with crossover observations, as indicated by the alternative closing price specification, and that the measure of volatility used in the regression specifications does capture any significant volatility on the market, our results imply that an increase in tick size will increase market volatility.

Under these assumptions, a tick size increase could be counterproductive if used only as a method of lowering volatility. A surprising conclusion seeing that this was suggested at the conference hosted by Peter Norman at the Ministry of Finance on the 28*th* of October 2011 [1]. Based on this study an increased tick size would thus not be recommended as a remedy for the increased volatility.

If the assumptions fail, a recommendation is made more difficult. For example, the daily range might be unable to capture volatility caused by high frequency trading as it is suspected that the daily range fails to correctly capture impacts from, for example, small flash equity failures. That is when a stock price changes by more than a certain small percentage, 0.5-1% or so, within a few seconds. If the price movement is small enough not to affect the daily range, it will be unnoticed in the range. On the other hand, volatility in the form of flash equity failures should not affect most non-HFT investors, other than psychologically. Similarly, the range might be unable to capture volatility changes such as clustered volatility. Seeing that a smaller tick size has been shown to lead to large trades being divided into smaller orders, an increased tick size could decrease the autocorrelation between orders. Autocorrelation will in turn likely decrease the clustered volatility. So, assuming that HFT disproportionately affects these types of intraday volatility rather than the range, our results will overestimate the increase in volatility for a change in tick size. To accurately predict the effect, studies should be performed using intraday data looking at volatility estimates uncontrolled for in this study.

Using intraday data would also provide a more sharp specification of treatment around the discontinuity, likely increasing the statistical significance of the results. The significance could further be increased by using multivariate kernels in the regression. The use of such kernels will allow correlation between observations, and relax the assumptions on independence between observations in this study. It would also further minimize any bias caused by sample selection where the distribution of firms are not equal across the threshold in tick size, either by number of observations, by date or other characteristics.

Furthermore, as this thesis only examines the isolated effect that an increased tick size would have on market volatility, there could be other exogenous factors affecting the impact on market volatility if the bourse decided to introduce a marketwide tick size increase. However, earlier research indicate that the impacts on volatility of a marketwide tick size decrease, and an isolated decrease is of the same sign. For this reason, it is assumed that this relationship will hold for an increase as well.

In conclusion, our results show that daily volatility increases when increasing the tick size. These results do not include all types of volatility, two exceptions being clustered volatility and mini flash equity failures. Earlier research observing a negative relationship between tick size and clustered volatility suggests that there might be a trade-off between impacts on different types of volaility. Seeing as the volatility captured in this study should affect the concerned smaller investors to a larger degree than the uncontrolled volatility, we recommend markets to be cautious of increasing the tick size.

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A Appendix

Table 1: Tick size table for Large Cap stocks on the SSE, introduced 1 April 2011

Price		
From	To	Tick size
0.0000	0.4999	0.0001
0.5000	0.9995	0.0005
1.0000	1.9990	0.0010
2.0000	4.9980	0.0020
5.0000	9,9950	0.0050
10.0000	49.9900	0.0100
50.0000	99.9500	0.0500
100.0000	499.9000	0.1000
500.0000	999.5000	0.5000
1,000.0000	4,999.0000	1.0000
5,000.0000	9,995.0000	5.0000
10,000.0000	19,990.0000	10.0000
20,000.0000	39,980.0000	20.0000
40,000.0000	49,960.0000	40.0000
50,000.0000	79,950.0000	50.0000
80,000.0000	99,920.0000	80.0000
100,000.0000		100.0000

Notes: All prices in SEK and reported with all significant figures from the market model specification. The tick size table is based on FESE tick size table 2, which is aimed to harmonize tick size regimes for the most liquid stocks in Europe. Apart from the introduction of new thresholds at 2 SEK and above 10000 SEK, this tick size structure have been in effect since October 26$^{\text{th}}$ 2009, and June 7$^{\text{th}}$, 2010 for OMXS30 and Large Cap shares at the SSE respectively.

Table 2: Descriptive statistics for the volume weighted average price within the 90 to 110 SEK interval

Ticker	N	Min	Mean	Max	Std. dev.	Skew.	Kurt.
ALFA	141	95.9300	104.1309	109.9200	3.5068	0.0328	1.8639
ATCO-A	59	95.8100	103.6512	109.6200	3.9028	-0.2005	1.8540
ATCO-B	149	90.1300	101.4679	109.7400	5.3417	-0.5025	2.2131
BOL	177	90.1900	99.2213	109.9200	5.3842	0.3568	2.2183
ELUX-B	64	95.0300	103.6716	109.0000	3.4639	-0.3950	2.5350
ERIC-B	39	90.0100	92.2759	95.6500	1.6690	0.7081	2.2877
LUPE	31	90.2500	93.1826	97.0000	2.0189	0.1592	1.7399
NOKI-SEK	63	91.5200	99.0554	109.7200	5.6638	0.5792	1.9724
SAND	175	90.0400	99.0529	109.9700	5.4612	0.1168	1.8265
SCA-B	388	90.0900	100.2342	109.8700	4.6846	-0.3421	2.0803
SCV-B	135	90.6600	100.5513	109.9200	4.5609	0.1005	2.2633
SKA-B	119	90.0800	100.9977	109.9700	5.7345	-0.2388	1.8262
SKF-B	1	109.1100	109.1100	109.1100	-	-	-
SSAB-A	213	90.3100	101.8128	109.7900	5.4236	-0.2853	1.8483
SWED-A	182	90.1300	98.6279	109.9900	6.0329	0.3499	1.7712
TEL2-B	39	102.0100	106.7113	110.0000	1.9003	-0.1665	2.5913
VOLV-B	164	90.1500	99.8849	109.9600	6.3270	0.0517	1.5451
Total	2139	90.0100	100.4901	110.0000	5.5458	-0.1352	1.8666

Notes: Hyphens indicate too few observations. The statistics are based on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price.

Table 3: Descriptive statistics for the closing price within the 90- 110 SEK interval

Ticker	N	Min	Mean	Max	Std. dev.	Skew.	Kurt.
ALFA	141	96.0000	104.1337	110.0000	3.6117	0.0674	1.8126
ATCO-A	59	96.0000	103.6466	109.4000	3.8955	-0.2631	1.8581
ATCO-B	149	90.6000	101.5658	109.6000	5.3417	-0.4987	2.1711
BOL	177	90.3500	99.1636	110.0000	5.3321	0.3766	2.2543
ELUX-B	64	95.3000	103.6930	109.7000	3.5255	-0.3855	2.4986
ERIC-B	39	90.2000	92.3423	96.2500	1.7018	0.7329	2.3321
LUPE	31	90.1500	93.4516	97.2500	2.0456	0.2455	1.9617
NOKI-SEK	63	90.7000	98.9238	109.2000	5.7303	0.5231	1.8784
SAND	175	90.1500	99.0434	110.0000	5.4852	0.1658	1.8546
SCA-B	388	90.0000	100.2347	109.8000	4.7329	-0.3601	2.0857
SCV-B	135	91.4000	100.5219	109.9000	4.5740	0.1266	2.2005
SKA-B	119	91.0000	101.1092	109.9000	5.6732	-0.1918	1.7934
SKF-B	1	109.3000	109.3000	109.3000	-	-	-
SSAB-A	213	91.2000	101.7735	110.0000	5.4261	-0.2872	1.8194
SWED-A	182	90.0500	98.6239	110.0000	6.0108	0.3523	1.7679
TEL2-B	39	101.8000	106.6000	109.9000	1.9211	-0.1587	2.6389
VOLV-B	164	90.0000	99.8143	109.9000	6.3961	0.0461	1.5527
Total	2139	90.0000	100.4861	110.0000	5.5558	-0.1266	1.8543

Notes: Hyphens indicate too few observations. The statistics are based on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price.

Table 4: Descriptive statistics for the level range, using the volume weighted average price to separate observations around 100 SEK

	Observations below 100 SEK					Observations at or above 100 SEK				
ticker	N	mean	sd	skewness	kurtosis	N	mean	sd	skewness	kurtosis
ALFA	20	0.0286	0.0122	1.1483	3.8119	121	0.0282	0.0134	1.6624	6.0293
ATCO-A	13	0.0318	0.0091	1.0272	4.1950	46	0.0255	0.0149	1.5853	5.0396
ATCO-B	47	0.0254	0.0136	1.6746	6.2226	102	0.0291	0.0146	1.4383	5.3722
BOL	103	0.0338	0.0171	1.7468	9.0381	74	0.0333	0.0164	1.1854	5.0559
ELUX-B	11	0.0450	0.0102	0.1831	2.7683	53	0.0390	0.0136	0.9822	4.6311
ERIC-B	39	0.0209	0.0074	0.7504	2.7714	-	-	-	-	-
LUPE	31	0.0312	0.0128	0.0303	2.3498	-	-	-	-	-
NOKI-SEK	39	0.0245	0.0272	5.4395	32.5930	24	0.0255	0.0217	3.8720	17.8062
SAND	94	0.0310	0.0145	1.0926	4.1719	81	0.0288	0.0124	1.9330	8.6175
SCA-B	163	0.0223	0.0130	3.1348	16.6258	225	0.0180	0.0091	3.2711	19.4049
SCV-B	67	0.0347	0.0135	0.6267	2.8516	68	0.0453	0.0230	1.8771	7.6788
SKA-B	50	0.0330	0.0146	2.2575	9.9875	69	0.0267	0.0124	2.6723	14.7219
SKF-B	-	-	-	-	-	1	0.0229	-	-	-
SSAB-A	87	0.0216	0.0093	0.9602	3.0729	126	0.0249	0.0091	0.8260	3.1692
SWED-A	104	0.0235	0.0146	2.8176	14.5141	78	0.0260	0.0103	0.7771	3.3323
TEL2-B	-	-	-	-	-	39	0.0243	0.0073	0.1958	2.5815
VOLV-B	82	0.0238	0.0105	1.0934	4.0966	82	0.0274	0.0112	1.5879	7.4845
Total	950	0.0270	0.0150	2.7018	19.7350	1189	0.0272	0.0146	2.1567	11.2416

Notes: Hyphens indicate missing or too few observations. Observations are from daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. The shares below 100 SEK have a tick size of 0.05 while shares at or above 100 SEK have a tick size of 0.1 SEK. All non-integer values are reported to four decimal places. The level range is given by,

$$range_i = \frac{H_i - L_i}{VWAP_i},$$

where H_i is the highest price during a day for an observation, L_i the lowest price and $VWAP_i$ the volume weighed average price. While stocks that are present on only one side of the threshold will be omitted from regression testing, these are included in the table for comparison.

Table 5: Descriptive statistics for the level range, using the closing price within the 90- 110 SEK interval, separated above and below the cutoff point 100 SEK

	Observations below 100 SEK					Observations at or above 100 SEK				
ticker	N	mean	sd	skewness	kurtosis	N	mean	sd	skewness	kurtosis
ALFA	20	0.0307	0.0135	0.8941	2.8652	121	0.0278	0.0132	1.7432	6.4768
ATCO-A	11	0.0359	0.0152	1.3304	4.0070	48	0.0249	0.0131	1.4824	5.0982
ATCO-B	49	0.0259	0.0136	1.5216	5.7282	100	0.0289	0.0147	1.4807	5.4508
BOL	103	0.0344	0.0172	1.6869	8.6221	74	0.0325	0.0162	1.2602	5.4930
ELUX-B	8	0.0434	0.0086	-0.7522	2.0813	56	0.0395	0.0137	0.9142	4.3104
ERIC-B	39	0.0209	0.0074	0.7504	2.7714	-	-	-	-	-
LUPE	31	0.0312	0.0128	0.0303	2.3498	-	-	-	-	-
NOKI-SEK	39	0.0250	0.0273	5.3580	31.9634	24	0.0247	0.0216	4.0260	18.7068
SAND	92	0.0309	0.0144	1.1572	4.3498	83	0.0290	0.0126	1.7925	7.9295
SCA-B	156	0.0220	0.0130	3.2934	17.7142	232	0.0183	0.0094	3.0244	16.8680
SCV-B	64	0.0339	0.0127	0.5649	2.9060	71	0.0456	0.0228	1.8150	7.5117
SKA-B	52	0.0333	0.0148	2.0738	9.0317	67	0.0263	0.0120	2.9453	17.3537
SKF-B	-	-	-	-	-	1	0.0229	-	-	-
SSAB-A	88	0.0219	0.0096	0.9446	3.0172	125	0.0247	0.0090	0.8243	3.2190
SWED-A	106	0.0236	0.0146	2.7566	14.0957	76	0.0259	0.0102	0.7656	3.4189
TEL2-B	-	-	-	-	-	39	0.0243	0.0073	0.1958	2.5815
VOLV-B	84	0.0248	0.0120	1.6432	7.0978	80	0.0265	0.0097	0.8687	3.7659
Total	942	0.0272	0.0151	2.6732	19.2360	1197	0.0271	0.0145	2.1696	11.4338

Notes: Hyphens indicate missing or too few observations. Observations are from daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. The shares below 100 SEK have a tick size of 0.05 while shares at or above 100 SEK have a tick size of 0.1 SEK. All non-integer values are reported to four decimal places. The level range is given by,

$$range_i = \frac{H_i - L_i}{VWAP_i},$$

where H_i is the highest price during a day for an observation, L_i the lowest price and $VWAP_i$ the volume weighed average price. While stocks that are present on only one side of the threshold will be omitted from regression testing, these are included in the table for comparison.

Table 6: Descriptive statistics for the log of the relative range using volume weighted average price within the 90- 110 SEK interval, separated above and below the cutoff point 100 SEK

	Observations below 100 SEK					Observations at or above 100 SEK				
ticker	N	mean	sd	skewness	kurtosis	N	mean	sd	skewness	kurtosis
ALFA	20	-3.6328	0.3955	0.3698	2.4378	121	-3.6603	0.4146	0.5361	2.9682
ATCO-A	13	-3.4827	0.2729	0.1702	3.2777	46	-3.8004	0.4988	0.6452	2.6311
ATCO-B	47	-3.7886	0.4671	0.4948	2.7242	102	-3.6479	0.4661	0.1723	2.7809
BOL	103	-3.4987	0.4730	0.1057	2.5580	74	-3.5154	0.4854	-0.0766	2.6224
ELUX-B	11	-3.1260	0.2344	-0.3322	2.5326	53	-3.3031	0.3517	-0.3556	4.0330
ERIC-B	39	-3.9286	0.3470	0.1465	2.2865	-	-	-	-	-
LUPE	31	-3.5649	0.4796	-0.6879	2.3476	-	-	-	-	-
NOKI-SEK	39	-3.8909	0.4820	2.4428	12.3230	24	-3.8242	0.4776	1.9937	7.9932
SAND	94	-3.5759	0.4526	0.0748	2.3961	81	-3.6224	0.3767	0.4749	3.2901
SCA-B	163	-3.9165	0.4531	0.5851	4.2369	225	-4.1055	0.3952	0.7018	4.6632
SCV-B	67	-3.4371	0.4004	-0.2300	2.5982	68	-3.1965	0.4464	0.3126	3.2978
SKA-B	50	-3.4834	0.3716	0.5831	4.1248	69	-3.7066	0.4007	0.1731	4.5580
SKF-B	-	-	-	-	-	1	-3.7761	-	-	-
SSAB-A	87	-3.9223	0.4100	0.2780	2.2377	126	-3.7535	0.3536	0.1265	2.3725
SWED-A	104	-3.8905	0.5119	0.2941	3.6124	78	-3.7252	0.3999	-0.1476	2.5697
TEL2-B	-	-	-	-	-	39	-3.7653	0.3241	-0.5765	3.0854
VOLV-B	82	-3.8273	0.4235	0.0954	2.5197	82	-3.6691	0.3818	0.1023	3.1995
Total	950	-3.7315	0.4822	0.2387	3.0651	1189	-3.7191	0.4715	0.2776	3.1059

Notes: Hyphens indicate missing or too few observations. Observations are from daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. The shares below 100 SEK have a tick size of 0.05 while shares at or above 100 SEK have a tick size of 0.1 SEK. All non-integer values are reported to four decimal places. The log of the relative range is given by,

$$\log(range)_i = \log\left(\frac{H_i - L_i}{VWAP_i}\right),$$

where H_i is the highest price during a day for an observation, L_i the lowest price and $VWAP_i$ the volume weighed average price. While stocks that are present on only one side of the threshold will be omitted from regression testing, these are included in the table for comparison.

Table 7: Descriptive statistics for the log of the relative range, using closing price to separate observations around 100 SEK

	Observations below 100 SEK					Observations at or above 100 SEK				
Ticker	N	Mean	St. Dev.	Skewness	Kurtosis	N	Mean	St. Dev.	Skewness	Kurtosis
ALFA	20	-3.5711	0.4217	0.2272	2.1854	121	-3.6704	0.4089	0.5649	3.0740
ATCO-A	11	-3.3951	0.3779	0.5278	3.0074	48	-3.8072	0.4651	0.5004	2.5341
ATCO-B	49	-3.7661	0.4704	0.3875	2.5287	100	-3.6561	0.4670	0.2137	2.8151
BOL	103	-3.4781	0.4671	0.1294	2.5097	74	-3.5441	0.4908	-0.0790	2.6101
ELUX-B	8	-3.1567	0.2193	-0.9126	2.3627	56	-3.2893	0.3518	-0.3700	3.9878
ERIC-B	39	-3.9286	0.3470	0.1465	2.2865	-	-	-	-	-
LUPE	31	-3.5649	0.4796	-0.6879	2.3476	-	-	-	-	-
NOKI-SEK	39	-3.8725	0.4908	2.2478	11.1723	24	-3.8541	0.4654	2.2834	9.3611
SAND	92	-3.5785	0.4480	0.1036	2.4907	83	-3.6184	0.3852	0.4131	3.0467
SCA-B	156	-3.9295	0.4500	0.6264	4.4533	232	-4.0910	0.4045	0.6914	4.4050
SCV-B	64	-3.4572	0.3905	-0.2849	2.6058	71	-3.1886	0.4448	0.2764	3.2135
SKA-B	52	-3.4787	0.3818	0.5025	3.7240	67	-3.7169	0.3898	0.1258	4.9282
SKF-B	-	-	-	-	-	1	-3.7761	-	-	-
SSAB-A	88	-3.9064	0.4141	0.2534	2.2438	125	-3.7634	0.3544	0.1196	2.3512
SWED-A	106	-3.8838	0.5123	0.2839	3.5756	76	-3.7302	0.3987	-0.1714	2.5637
TEL2-B	-	-	-	-	-	39	-3.7653	0.3241	-0.5765	3.0854
VOLV-B	84	-3.7997	0.4458	0.2115	2.8047	80	-3.6942	0.3630	-0.0774	2.7541
Total	942	-3.7267	0.4840	0.2375	3.0663	1197	-3.7230	0.4701	0.2775	3.1038

Notes: Hyphens indicate missing or too few observations. Observations are from daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. The shares below 100 SEK have a tick size of 0.05 while shares at or above 100 SEK have a tick size of 0.1 SEK. All non-integer values are reported to four decimal places. The log of the relative range is given by,

$$\log(range)_i = \log\left(\frac{H_i - L_i}{VWAP_i}\right),$$

where H_i is the highest price during a day for an observation, L_i the lowest price and $VWAP_i$ the volume weighed average price. While stocks that are present on only one side of the threshold will be omitted from regression testing, these are included in the table for comparison.

Table 8: Descriptive statistics for range and log range, separated by year

Log of relative range							
Year	N	Min	Mean	Max	Std. Dev	Skewness	Kurtosis
2010	1253	-5.1557	-3.7881	-1.6881	0.4498	0.2864	3.4204
2011	886	-4.9833	-3.6348	-1.9271	0.4978	0.1464	2.7633
Total	2139	-5.1557	-3.7246	-1.6881	0.4762	0.2588	3.0889

Level relative range							
Year	N	Min	Mean	Max	Std. Dev	Skewness	Kurtosis
2010	1253	0.0058	0.0252	0.1849	0.0133	3.0331	24.7677
2011	886	0.0069	0.0299	0.1456	0.0163	1.8512	9.0649
Total	2139	0.0058	0.0272	0.1849	0.0148	2.4077	15.2000

Notes: Observations are from daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. The level range is given by,

$$range_i = \frac{H_i - L_i}{VWAP_i},$$

where where H_i is the highest price during a day for an observation, L_i the lowest price and $VWAP_i$ the volume weighed average price. The log range is just the natural log of the range as described above. All non-integer values are reported to 4 d.p.

Table 9: Descriptive statistics for covariates, sorted around 100 SEK by average price

	Observations below 100 SEK							
	Absolute range		Rel. spread		Trades		Volume	
Ticker	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
ALFA	2.8300	1.2115	0.1750	0.4229	3634	1504	2807697	1522991
ATCO-A	3.1269	0.8899	0.5962	0.5113	5415	1816	4941532	1909484
ATCO-B	2.4011	1.3006	0.2511	0.2223	1842	1130	1227786	842310
BOL	3.2155	1.6100	0.1398	0.1542	7163	2794	4937167	2632226
ELUX-B	4.4182	1.0167	0.1182	0.0681	6831	1848	3177000	999980
ERIC-B	1.9256	0.6890	0.0500	0.0000	8823	2417	12160454	4555016
LUPE	2.9113	1.1863	0.1107	0.0789	3882	1853	1881955	997922
NOKI-SEK	2.3397	2.6383	0.3667	0.4659	1933	2571	1731075	2639431
SAND	2.9383	1.3947	0.0856	0.0654	6514	2672	6232735	3255095
SCA-B	2.1288	1.2506	0.1018	0.1042	4003	1658	2730980	1474479
SCV-B	3.3590	1.3126	0.3052	0.4016	3322	1841	1389932	689570
SKA-B	3.1240	1.3122	0.0990	0.0786	4421	1369	2142798	761322
SKF-B	-	-	-	-	-	-	-	-
SSAB-A	2.0638	0.8721	0.0690	0.0338	3628	1495	2090864	965844
SWED-A	2.2010	1.3680	0.0756	0.0485	5391	2851	4661514	2385586
TEL2-B	-	-	-	-	-	-	-	-
VOLV-B	2.2409	0.9838	0.0741	0.0603	8479	4355	9051541	7193144
Total	2.5717	1.4296	0.1484	0.2316	5118	3128	4170428	4028164

	Observations at or above 100 SEK							
	Absolute range		Rel. spread		Trades		Volume	
Ticker	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
ALFA	2.9587	1.4208	0.2318	0.2624	2899	1441	2086382	1088381
ATCO-A	2.6772	1.5380	0.1826	0.1198	4934	2397	5416541	2749974
ATCO-B	3.0436	1.5533	0.1676	0.1358	1742	1099	1069958	549630
BOL	3.4750	1.7040	0.1164	0.0495	5982	2270	4344477	2344281
ELUX-B	4.0736	1.3912	0.1632	0.0821	5287	1330	2495540	769749
ERIC-B	-	-	-	-	-	-	-	-
LUPE	-	-	-	-	-	-	-	-
NOKI-SEK	2.6646	2.1927	0.2375	0.1974	2300	2089	2419912	2644384
SAND	2.9963	1.2909	0.1174	0.0434	5606	2133	5372304	2752118
SCA-B	1.8611	0.9273	0.1807	0.1920	2677	1137	2225065	1118607
SCV-B	4.7316	2.4115	0.1971	0.2062	4078	2388	1769086	1085304
SKA-B	2.7971	1.2626	0.1260	0.0581	3329	814	1633285	450537
SKF-B	2.5000	-	0.3000	-	2987	-	2753108	-
SSAB-A	2.6373	0.9614	0.1338	0.0533	3786	1373	2217241	991968
SWED-A	2.7205	1.0693	0.0929	0.0189	5912	1951	5419580	1921948
TEL2-B	2.5897	0.7745	0.5308	0.6237	2862	846	2076333	739159
VOLV-B	2.8884	1.1574	0.1045	0.0342	9151	2790	10452121	3805337
Total	2.8508	1.5250	0.1843	0.2168	4121	2555	3308895	2961761

Notes: Hyphens indicate missing or too few observations. The statistics are based on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. The absolute range is the difference between the highest and lowest prices of a stock during a day. The rel. spread is the difference between bid and ask prices, relative to the midprice of bid and ask. Trades is the number of executed trades in a day, and volume the number of shares traded. Trades and volume are rounded to integers, while the absolute range and spread are reported to 4 d.p.

Table 10: Descriptive statistics for covariates, sorted around 100 SEK by closing price

	Observations below 100 SEK							
	Absolute range		Rel. spread		Trades		Volume	
Ticker	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
ALFA	3.0425	1.3497	0.1775	0.4232	3487	1418	2730351	1475044
ATCO-A	3.5318	1.5252	0.6227	0.5605	5812	2521	5369615	2955264
ATCO-B	2.4643	1.3107	0.2490	0.2188	1891	1134	1260188	840667
BOL	3.2791	1.6281	0.1393	0.1549	7235	2849	4985971	2715530
ELUX-B	4.2500	0.8523	0.1125	0.0744	5976	1414	2740926	501835
ERIC-B	1.9256	0.6890	0.0500	0.0000	8823	2417	12160454	4555016
LUPE	2.9113	1.1863	0.1107	0.0789	3882	1853	1881955	997922
NOKI-SEK	2.3897	2.6462	0.3615	0.4677	1958	2575	1767123	2646196
SAND	2.9223	1.3853	0.0826	0.0640	6443	2593	6113990	3002356
SCA-B	2.0952	1.2439	0.0942	0.0933	3965	1649	2670162	1431576
SCV-B	3.2742	1.2275	0.3133	0.4092	3217	1759	1355458	628218
SKA-B	3.1596	1.3482	0.0962	0.0772	4387	1353	2127774	750859
SKF-B	-	-	-	-	-	-	-	-
SSAB-A	2.1028	0.9005	0.0724	0.0414	3613	1492	2080762	964052
SWED-A	2.2203	1.3751	0.0753	0.0483	5367	2787	4643137	2342615
TEL2-B	-	-	-	-	-	-	-	-
VOLV-B	2.3411	1.1661	0.0732	0.0599	8673	4426	9280990	7239722
Total	2.5874	1.4467	0.1462	0.2324	5118	3168	4186549	4079288

	Observations at or above 100 SEK							
	Absolute range		Rel. spread		Trades		Volume	
Ticker	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
ALFA	2.9236	1.4011	0.2314	0.2624	2924	1466	2099166	1106692
ATCO-A	2.6031	1.3606	0.1937	0.1245	4864	2206	5298647	2522097
ATCO-B	3.0255	1.5633	0.1670	0.1364	1716	1093	1050925	537356
BOL	3.3865	1.6896	0.1172	0.0465	5882	2112	4276547	2187127
ELUX-B	4.1161	1.3938	0.1616	0.0809	5492	1551	2594343	885512
ERIC-B	-	-	-	-	-	-	-	-
LUPE	-	-	-	-	-	-	-	-
NOKI-SEK	2.5833	2.1869	0.2458	0.1956	2260	2089	2361333	2648040
SAND	3.0127	1.3037	0.1206	0.0442	5706	2285	5524658	3100151
SCA-B	1.8918	0.9513	0.1819	0.1913	2743	1213	2281225	1185981
SCV-B	4.7500	2.3866	0.1944	0.2022	4142	2394	1784141	1096125
SKA-B	2.7597	1.2216	0.1300	0.0571	3322	826	1629736	455852
SKF-B	2.5000	-	0.3000	-	2987	-	2753108	-
SSAB-A	2.6144	0.9581	0.1324	0.0528	3798	1373	2225363	992350
SWED-A	2.7072	1.0570	0.1000	0.0000	5958	2037	5465160	1966669
TEL2-B	2.5897	0.7745	0.5308	0.6237	2862	846	2076333	739159
VOLV-B	2.7994	1.0227	0.1095	0.0301	8966	2654	10246214	3655929
Total	2.8366	1.5139	0.1856	0.2160	4129	2522	3301966	2911806

Notes: Hyphens indicate missing or too few observations. The statistics are based on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. The absolute range is the difference between the highest and lowest prices of a stock during a day. The rel. spread is the difference between bid and ask prices, relative to the midprice of bid and ask. Trades is the number of executed trades in a day, and volume the number of shares traded. Trades and volume are rounded to integers, while the absolute range and spread are reported to 4 d.p.

Table 11: RDD regression results

	Average price		Closing price	
	$\log range$	$range$	$\log range$	$range$
$\hat{\tau}$ $(\hat{h}_{opt})$	0.170**	0.00425	0.125*	0.00346
	(0.0889)	(0.00492)	(0.0801)	(0.00317)
	[0.056]	[0.388]	[0.118]	[0.275]
$\hat{\tau}$ $(0.5\hat{h}_{opt})$	0.164	0.0130**	0.0835	0.000817
	(0.129)	(0.00710)	(0.107)	(0.00523)
	[0.204]	[0.067]	[0.434]	[0.876]
$\hat{\tau}$ $(2\hat{h}_{opt})$	0.106**	0.00370	0.106**	0.00249
	(0.0611)	(0.00345)	(0.0579)	(0.00259)
	[0.082]	[0.283]	[0.066]	[0.337]
$\hat{\tau}$ $(4\hat{h}_{opt})$	0.0824**	0.00516***	0.0649*	0.00405***
	(0.0448)	(0.00239)	(0.0433)	(0.00192)
	[0.066]	[0.031]	[0.134]	[0.035]
N	2029	2029	2029	2029

Notes: Tests are performed on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. For a highest price, H_t, a lowest price, L_t, and a volume weighed average price $VWAP_i$ of an observation, the level range is given by

$$range_i = \frac{H_i - L_i}{VWAP_i}.$$

The log range is defined as the natural logarithm of the above range estimate. Treatment effect estimates, $\hat{\tau}$, are calculated using a RDD, regressing range on the closing price, where values on each side of the tested percentile are fitted with local linear regressions using an optimal bandwidth, $\hat{h}_{opt}$, calculated follwing Imbens (2009). For robustness, the discontinuity is tested for four different bandwidths, half the optimal value, the optimal value, twice the optimal value and four times the optimal value. Standard errors are provided in parentheses and p-values in brackets. Significance levels are marked according to, * $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$

Table 12: Percentile statistics for the volume weighted and closing price within the 90- 110 SEK interval, separated above and below the cutoff point 100 SEK. Excluding ERIC-B, LUPE, SKF-B and TELE2-B

	Percentile (SEK)			
	Observations below 100 SEK		Observations at or above 100 SEK	
Percentiles	Closing price	Average price	Closing price	Average price
1%	90.25	90.19	100.00	100.14
5%	90.90	90.92	100.50	100.56
10%	91.45	91.52	101.00	101.05
25%	93.05	93.12	102.30	102.41
50%	95.25	95.35	104.40	104.49
75%	97.55	97.68	107.00	106.82
90%	99.10	99.24	108.80	108.78
95%	99.50	99.65	109.30	109.37
99%	99.85	99.92	109.90	109.91

Observations are from daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and volume weighed average price. This data does not include stocks that are only present either above or below 100 SEK. All values are reported to 2 d.p.

Table 13: Testing for discontinuities in the level range away from 100 SEK, using the volume weighed average price

	Observations below 100 SEK			Observations at or above 100 SEK		
	93.12 SEK p25	95.35 SEK p50	97.68 SEK p75	102.41 SEK p25	104.49 SEK p50	106.82 SEK p75
$\hat{\tau}$ $(\hat{h}_{opt})$	0.00777***	0.000735	0.00122	0.00837**	0.00648	0.00542
	(0.00354)	(0.00488)	(0.00540)	(0.00470)	(0.00560)	(0.00566)
	[0.028]	[0.880]	[0.821]	[0.075]	[0.247]	[0.339]
$\hat{\tau}$ $(0.5\hat{h}_{opt})$	0.000499	-0.000395	0.00644	0.0115**	0.00950	-0.0000739
	(0.00409)	(0.00648)	(0.00799)	(0.00611)	(0.00847)	(0.00596)
	[0.903]	[0.951]	[0.420]	[0.060]	[0.262]	[0.990]
$\hat{\tau}$ $(2\hat{h}_{opt})$	-0.00190	-0.00312	-0.00294	0.00496*	0.00244	-0.00129
	(0.00273)	(0.00344)	(0.00392)	(0.00318)	(0.00364)	(0.00346)
	[0.487]	[0.364]	[0.453]	[0.118]	[0.502]	[0.709]
$\hat{\tau}$ $(4\hat{h}_{opt})$	-0.00316*	0.00278	-0.000161	0.000312	0.00269	0.00217
	(0.00225)	(0.00232)	(0.00310)	(0.00233)	(0.00255)	(0.00243)
	[0.160]	[0.231]	[0.959]	[0.893]	[0.290]	[0.371]
N	880	880	880	1149	1149	1149

Notes: Tests are performed on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. p25-p75 refer to the percentiles of volume weighed average price, $VWAP$, in the specified range, where observations, i, are categorized as below if $VWAP_i \in [90, 100)$ SEK, and categorized as above if $VWAP_i \in [100, 110]$ SEK. For a highest price, H_i and a lowest price, L_i, of an observation, the level range is given by

$$range_i = \frac{H_i - L_i}{VWAP_i}.$$

Treatment effect estimates are calculated using a RDD, regressing the level range on the volume weighed average price, where values on each side of the tested percentile are fitted with local linear regressions using an optimal bandwidth, $\hat{h}_{opt}$, calculated follwing Imbens (2009). To avoid the 100 SEK discontinuity affecting the estimates, the observations for which each regression is run is limited to only one side of the 100 SEK threshold. For robustness, the discontinuity is tested for four different bandwidths, half the optimal value, the optimal value, twice the optimal value and four times the optimal value. Standard errors are provided in parentheses and p-values in brackets. Significance levels are marked according to, * $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$

Table 14: Testing for discontinuities in the level range away from 100 SEK, using the closing price

	Observations below 100 SEK			Observations at or above 100 SEK		
	93.05 SEK (p25)	95.25 SEK (p50)	97.55 SEK (p75)	102.30 SEK (p25)	104.40 SEK (p50)	107.00 SEK (p75)
$\hat{\tau}$ $(\hat{h}_{opt})$	-0.00349	-0.000667	-0.00347	0.00527	-0.000780	-0.00158
	(0.00684)	(0.00464)	(0.00638)	(0.00423)	(0.00381)	(0.00475)
	[0.610]	[0.886]	[0.587]	[0.213]	[0.838]	[0.739]
$\hat{\tau}$ $(0.5\hat{h}_{opt})$	-0.00309	-0.0000577	-0.00217	0.00184	-0.00256	-0.00266
	(0.00795)	(0.00768)	(0.00915)	(0.00615)	(0.00525)	(0.00569)
	[0.697]	[0.994]	[0.812]	[0.765]	[0.625]	[0.640]
$\hat{\tau}$ $(2\hat{h}_{opt})$	-0.00131	0.000548	0.00339	0.000277	0.00153	-0.00325
	(0.00459)	(0.00321)	(0.00439)	(0.00323)	(0.00262)	(0.00297)
	[0.775]	[0.864]	[0.440]	[0.932]	[0.559]	[0.274]
$\hat{\tau}$ $(4\hat{h}_{opt})$	-0.00383	0.00155	0.00317	-0.00356*	0.00213	0.000439
	(0.00326)	(0.00230)	(0.00317)	(0.00244)	(0.00194)	(0.00218)
	[0.239]	[0.501]	[0.316]	[0.145]	[0.272]	[0.841]
N	872	872	872	1157	1157	1157

Notes: Tests are performed on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. p25-p75 refer to the percentiles of of closing price, Pc, in the specified range, where observations, i, are categorized as below if $Pc_i \in [90, 100)$ SEK, and categorized as above if $Pc_i \in [100, 110]$ SEK. For a highest price, H_i, a lowest price, L_i, and a volume weighed average price $VWAP_i$ of an observation, the level range is given by

$$range_i = \frac{H_i - L_i}{VWAP_i}.$$

Treatment effect estimates are calculated using a RDD, regressing range on the closing price, where values on each side of the tested percentile are fitted with local linear regressions using an optimal bandwidth, $\hat{h}_{opt}$, calculated follwing Imbens (2009). To avoid the 100 SEK discontinuity affecting the estimates, the observations for which each regression is run is limited to only one side of the 100 SEK threshold. For robustness, the discontinuity is tested for four different bandwidths, half the optimal value, the optimal value, twice the optimal value and four times the optimal value. Standard errors are provided in parentheses and p-values in brackets. Significance levels are marked according to, * $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$

Table 15: Testing for discontinuities in the log range away from 100 SEK, using the volume weighed average price

	Observations below 100 SEK			Observations at or above 100 SEK		
	93.12 SEK p25	95.35 SEK p50	97.68 SEK p75	102.41 SEK p25	104.49 SEK p50	106.82 SEK p75
$\hat{\tau}$ $(\hat{h}_{opt})$	-0.0877	-0.000944	0.00952	0.110	0.115*	0.0779
	(0.0933)	(0.120)	(0.110)	(0.0990)	(0.0882)	(0.0844)
	[0.347]	[0.994]	[0.931]	[0.264]	[0.191]	[0.356]
$\hat{\tau}$ $(0.5\hat{h}_{opt})$	0.219**	0.0519	0.0521	0.180	0.0967	-0.131
	(0.121)	(0.187)	(0.167)	(0.146)	(0.128)	(0.131)
	[0.069]	[0.782]	[0.755]	[0.216]	[0.451]	[0.318]
$\hat{\tau}$ $(2\hat{h}_{opt})$	-0.152***	0.114*	0.0690	0.00463	0.0937*	0.0131
	(0.0749)	(0.0812)	(0.0864)	(0.0733)	(0.0610)	(0.0688)
	[0.042]	[0.162]	[0.424]	[0.950]	[0.125]	[0.850]
$\hat{\tau}$ $(4\hat{h}_{opt})$	-0.174***	0.101*	0.167***	0.0351	0.116***	0.0582
	(0.0682)	(0.0643)	(0.0796)	(0.0648)	(0.0571)	(0.0651)
	[0.011]	[0.115]	[0.036]	[0.588]	[0.041]	[0.371]
N	880	880	880	1149	1149	1149

Notes: Tests are performed on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. p25-p75 refer to the percentiles of volume weighed average price, $VWAP$, in the specified range, where observations, i, are categorized as below if $VWAP_i \in [90, 100)$ SEK, and categorized as above if $VWAP_i \in [100, 110]$ SEK. For a highest price, H_i and a lowest price, L_t, of an observation, the log range is given by

$$\log(range)_i = \log\left(\frac{H_i - L_i}{VWAP_i}\right).$$

Treatment effect estimates are calculated using a RDD, regressing the log range on the volume weighed price, where values on each side of the tested percentile are fitted with local linear regressions using an optimal bandwidth, $\hat{h}_{opt}$, calculated follwing Imbens (2009). To avoid the 100 SEK discontinuity affecting the estimates, the observations for which each regression is run is limited to only one side of the 100 SEK threshold. For robustness, the discontinuity is tested for four different bandwidths, half the optimal value, the optimal value, twice the optimal value and four times the optimal value. Standard errors are provided in parentheses and p-values in brackets. Significance levels are marked according to, * $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$

Table 16: Testing for discontinuities in the log range away from 100 SEK, using the closing price

	Observations below 100 SEK			Observations at or above 100 SEK		
	93.05 SEK p25	95.25 SEK p50	97.55 SEK p75	102.30 SEK p25	104.40 SEK p50	107.00 SEK p75
$\hat{\tau}$ $(\hat{h}_{opt})$	-0.0203	0.162*	0.118	-0.0638	0.0508	-0.120
	(0.103)	(0.102)	(0.103)	(0.0863)	(0.0869)	(0.100)
	[0.844]	[0.113]	[0.253]	[0.460]	[0.559]	[0.229]
$\hat{\tau}$ $(0.5\hat{h}_{opt})$	-0.00707	0.0258	0.134	0.131	-0.118	-0.194*
	(0.151)	(0.151)	(0.151)	(0.127)	(0.131)	(0.138)
	[0.963]	[0.864]	[0.375]	[0.302]	[0.367]	[0.159]
$\hat{\tau}$ $(2\hat{h}_{opt})$	-0.0857	0.0675	0.200***	-0.112*	0.0347	0.0642
	(0.0797)	(0.0691)	(0.0854)	(0.0698)	(0.0606)	(0.0740)
	[0.282]	[0.329]	[0.019]	[0.109]	[0.567]	[0.386]
$\hat{\tau}$ $(4\hat{h}_{opt})$	-0.129**	0.0716	0.215***	-0.147***	0.0656	0.114**
	(0.0727)	(0.0634)	(0.0796)	(0.0628)	(0.0551)	(0.0610)
	[0.075]	[0.259]	[0.007]	[0.019]	[0.234]	[0.062]
N	872	872	872	1157	1157	1157

Notes: Tests are performed on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price. p25-p75 refer to the percentiles of closing price, Pc, in the specified range, where observations, i, are categorized as below if $Pc_i \in [90, 100)$ SEK, and categorized as above if $Pc_i \in [100, 110]$ SEK. For a highest price, H_i, a lowest price, L_i, and a volume weighed average price $VWAP_i$ of an observation, the log range is given by

$$\log(range)_i = \log\left(\frac{H_i - L_i}{VWAP_i}\right).$$

Treatment effect estimates are calculated using a RDD, regressing the log range on the closing price, where values on each side of the tested percentile are fitted with local linear regressions using an optimal bandwidth, $\hat{h}_{opt}$, calculated follwing Imbens (2009). To avoid the 100 SEK discontinuity affecting the estimates, the observations for which each regression is run is limited to only one side of the 100 SEK threshold.For robustness, the discontinuity is tested for four different bandwidths, half the optimal value, the optimal value, twice the optimal value and four times the optimal value. Standard errors are provided in parentheses and p-values in brackets. Significance levels are marked according to, * $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$

Table 17: Testing for covariate discontinuities at 100 SEK, average price

	Ex post characteristics (t_n)			Ex ante characteristics (t_{n-1})		
	$\ln trades$	$\ln spread$	$\ln volume$	$\ln trades$	$\ln spread$	$\ln volume$
$\hat{\tau}$ $(\hat{h}_{opt})$	0.0879	0.0530	0.216**	0.103	0.0670	0.161*
	(0.0967)	(0.155)	(0.119)	(0.100)	(0.147)	(0.123)
	[0.364]	[0.733]	[0.069]	[0.304]	[0.649]	[0.188]
$\hat{\tau}$ $(0.5\hat{h}_{opt})$	-0.135	0.0592	-0.195	-0.177	0.0733	-0.269*
	(0.133)	(0.221)	(0.162)	(0.140)	(0.209)	(0.171)
	[0.312]	[0.789]	[0.229]	[0.207]	[0.725]	[0.115]
$\hat{\tau}$ $(2\hat{h}_{opt})$	-0.106*	0.0961	0.0862	-0.0548	0.0440	0.0701
	(0.0696)	(0.110)	(0.0855)	(0.0707)	(0.106)	(0.0869)
	[0.127]	[0.384]	[0.313]	[0.438]	[0.679]	[0.420]
$\hat{\tau}$ $(4\hat{h}_{opt})$	-0.130***	0.0579	0.0251	-0.0805*	-0.0114	0.0401
	(0.0512)	(0.0778)	(0.0629)	(0.0510)	(0.0767)	(0.0627)
	[0.011]	[0.457]	[0.689]	[0.114]	[0.881]	[0.522]
N	2029	1636	2029	2022	1626	2022

Notes: The assigment variable, average price, is calculated as the volume weighed average price. Spread refer to the relative spread, that is the spread in percentage terms of the midprice of the bid and ask prices. Number of observations for testing spread is lower than the other tests due to missing ask prices between January 3$^{\text{rd}}$ 2011 and June 15$^{\text{th}}$ 2011. The ex ante characteristics are represented by one day lagged variables. Treatment effect estimates, $\hat{\tau}$, are calculated using a RDD, regressing each covariate on the volume weighed average price, where values on each side of the tested percentile are fitted with local linear regressions using an optimal bandwidth, $\hat{h}_{opt}$, calculated follwing Imbens (2009). For robustness, the discontinuity is tested for four different bandwidths, half the optimal value, the optimal value, twice the optimal value and four times the optimal value. Standard errors are provided in parentheses and p-values in brackets. Coefficients and standard errors reported to 3 s.f., and p-values to 3 d.p. Significance levels are marked according to, * $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$. Tests are performed on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price.

Table 18: Testing for covariate discontinuities at 100 SEK, closing price

	Ex post characteristics (t_n)			Ex ante characteristics (t_{n-1})		
	$\ln trades$	$\ln spread$	$\ln volume$	$\ln trades$	$\ln spread$	$\ln volume$
$\hat{\tau}$ $(\hat{h}_{opt})$	0.127*	0.372***	0.339***	0.170**	0.341***	0.242***
	(0.0979)	(0.156)	(0.116)	(0.0960)	(0.150)	(0.116)
	[0.195]	[0.017]	[0.004]	[0.076]	[0.023]	[0.036]
$\hat{\tau}$ $(0.5\hat{h}_{opt})$	0.0973	0.434***	0.191	0.125	0.0887	0.136
	(0.126)	(0.211)	(0.152)	(0.132)	(0.201)	(0.154)
	[0.439]	[0.039]	[0.211]	[0.341]	[0.660]	[0.379]
$\hat{\tau}$ $(2\hat{h}_{opt})$	0.0968*	0.223***	0.198***	0.0479	0.117	0.175***
	(0.0749)	(0.111)	(0.0867)	(0.0720)	(0.113)	(0.0852)
	[0.196]	[0.045]	[0.023]	[0.506]	[0.301]	[0.040]
$\hat{\tau}$ $(4\hat{h}_{opt})$	-0.0440	0.141**	0.0716	-0.0211	-0.0399	0.0802*
	(0.0568)	(0.0801)	(0.0642)	(0.0523)	(0.0798)	(0.0625)
	[0.439]	[0.078]	[0.265]	[0.687]	[0.617]	[0.200]
N	2029	1636	2029	2022	1626	2022

Notes: The assigment variable by which treatment is indicated is the closing price. Spread refer to the relative spread, that is the spread in percentage terms of the midprice of the bid and ask prices. Number of observations for testing spread is lower than the other tests due to missing ask prices between January 3^{rd} 2011 and June 15^{th} 2011. The ex ante characteristics are represented by one day lagged variables. Treatment effect estimates, $\hat{\tau}$, are calculated using a RDD, regressing each covariate on the closing price, where values on each side of the tested percentile are fitted with local linear regressions using an optimal bandwidth, $\hat{h}_{opt}$, calculated follwing Imbens (2009). For robustness, the discontinuity is tested for four different bandwidths, half the optimal value, the optimal value, twice the optimal value and four times the optimal value. Standard errors are provided in parentheses and p-values in brackets. Coefficients and standard errors reported to 3 s.f., and p-values to 3 d.p. Significance levels are marked according to, * $p < 0.2$, ** $p < 0.1$, *** $p < 0.05$. Tests are performed on daily 2010-2011 data for OMXS30 stocks, where all observations are within the interval $[90, 110]$ SEK based both on closing price and average price.

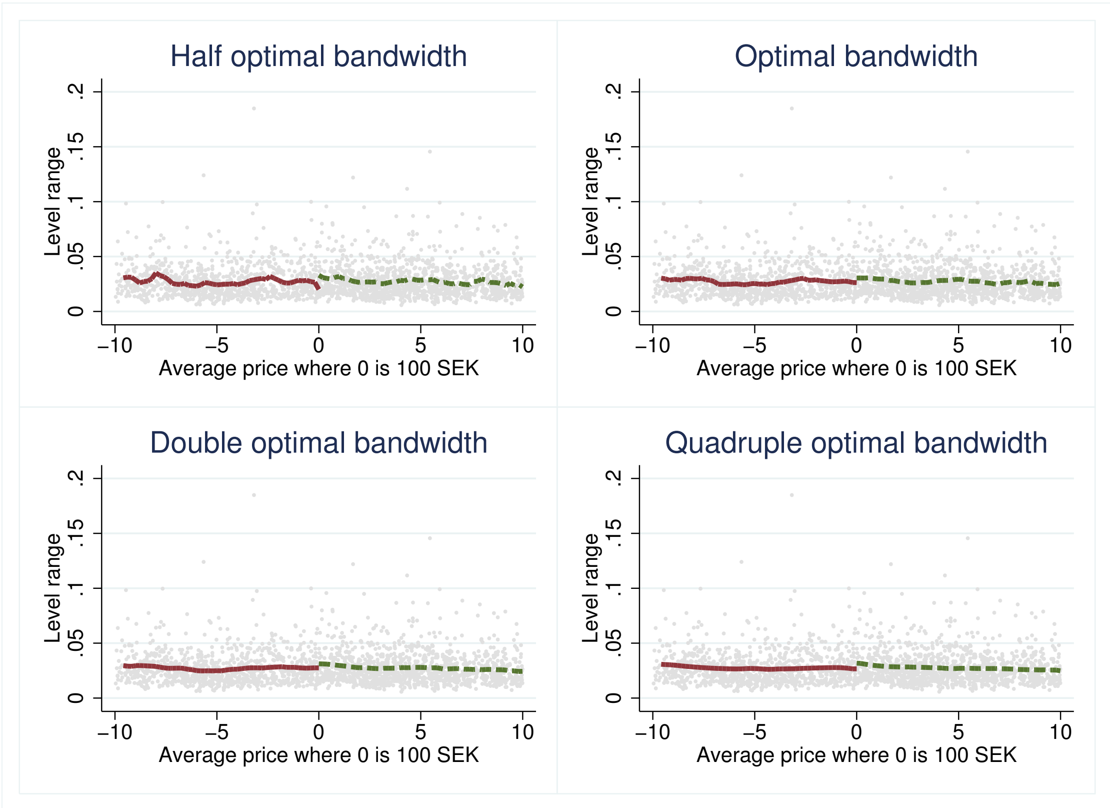

Figure 1: RDD results for the average price and level range, using four different bandwidths. Where the optimal bandwidth is calculated using Imbens (2009) method.

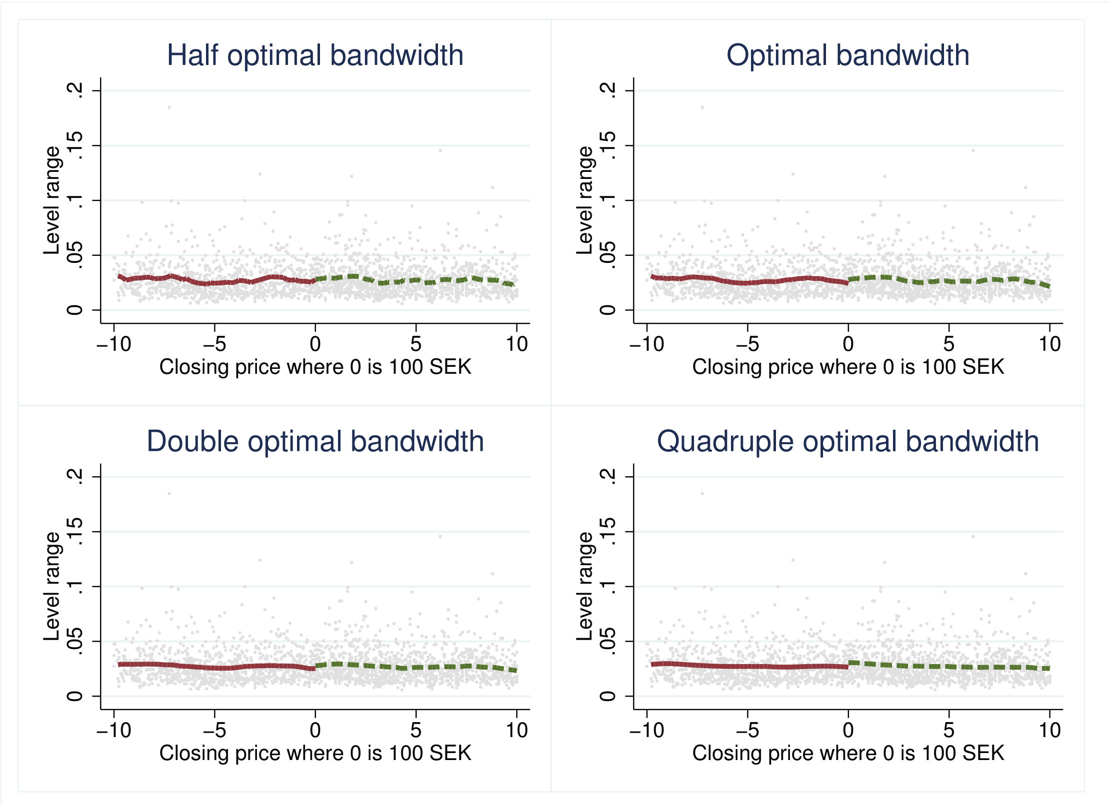

Figure 2: RDD results for closing price and level range using four different bandwidths. Where the optimal bandwidth is calculated using Imbens (2009) method.

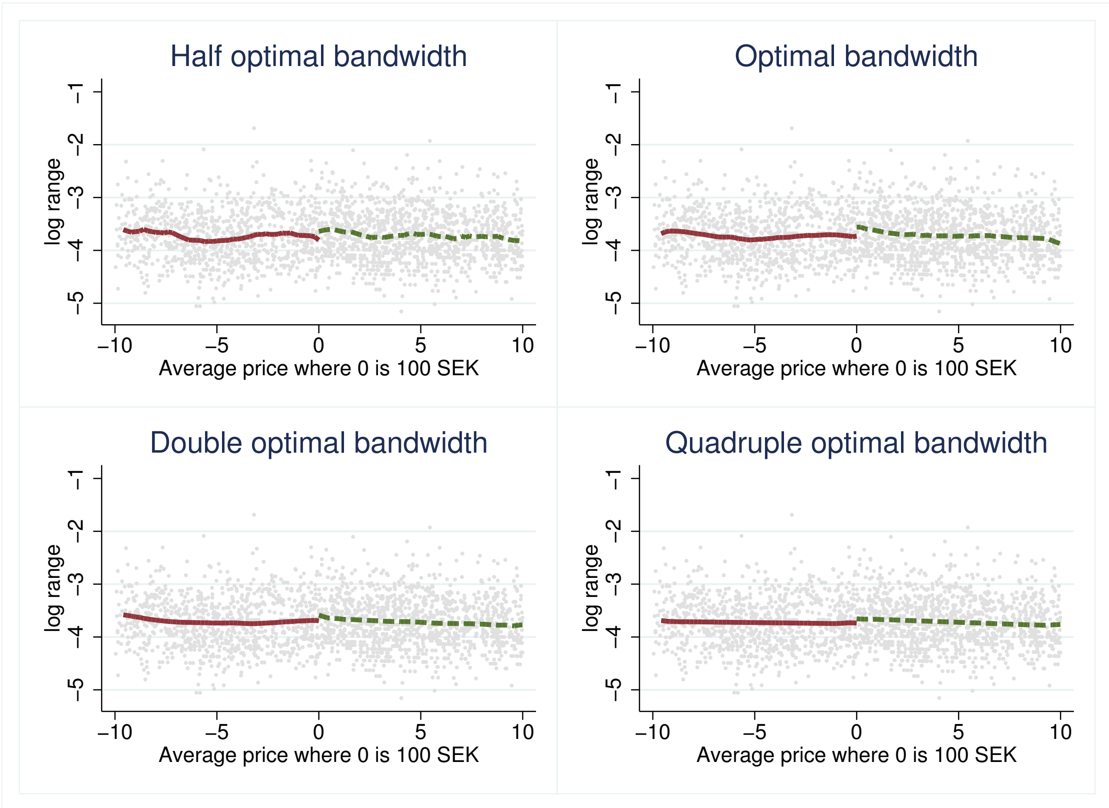

Figure 3: RDD results for average price and log range using four different bandwidths. Where the optimal bandwidth is calculated using Imbens (2009) method.

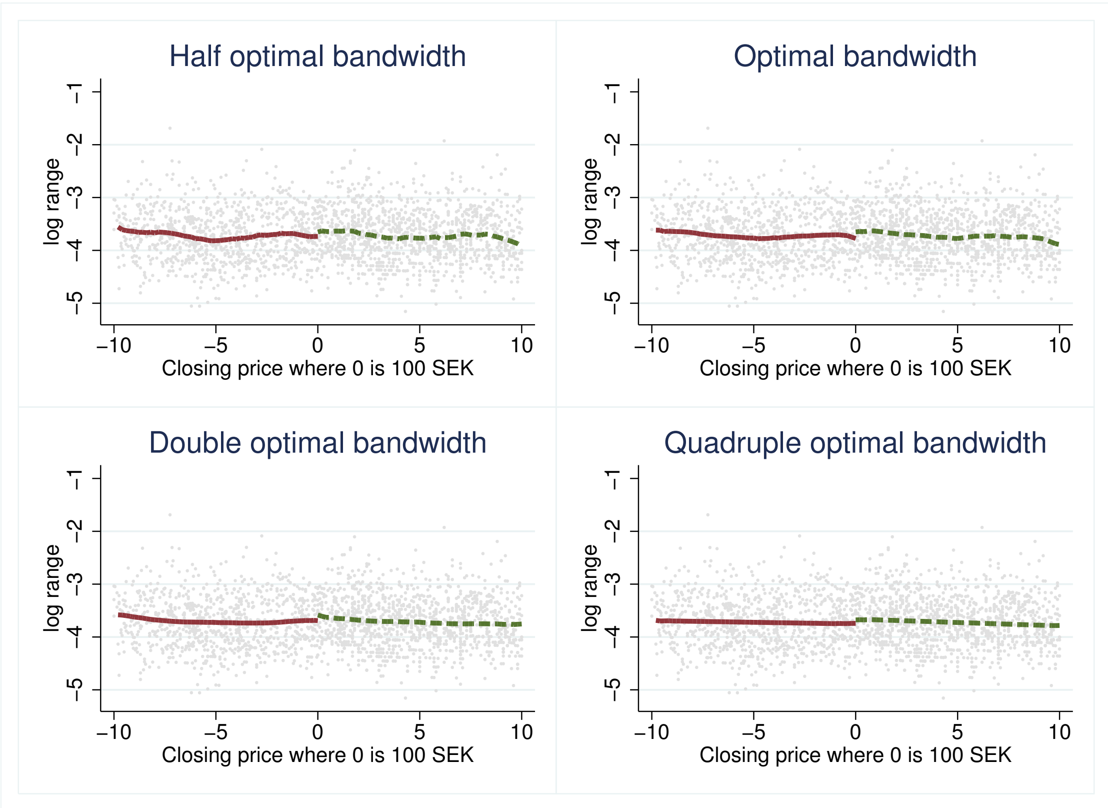

Figure 4: RDD results for closing price and log range using four different bandwidths. Where the optimal bandwidth is calculated using Imbens (2009) method.

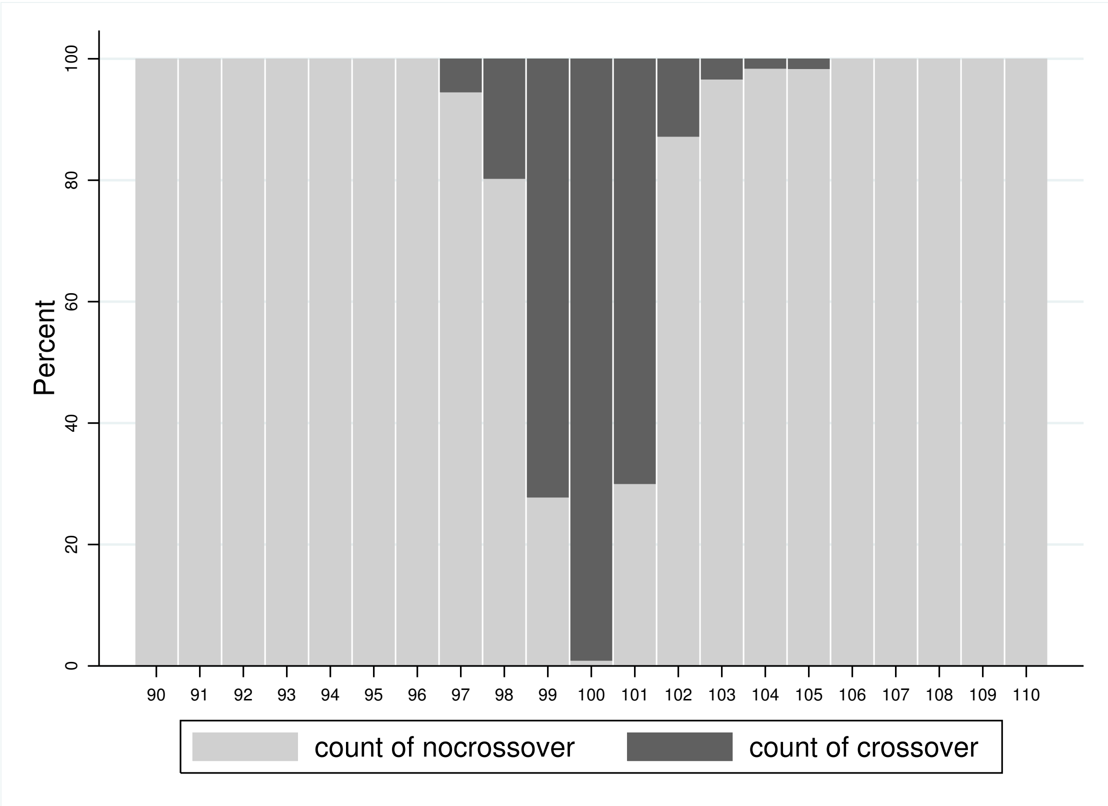

Figure 5: Number of crossover observations as a function of average price, displayed as percent of total numbers of observations within a 1 SEK interval. The ticks shown on the x-axis refers to whole numbers but is placed in the middle of ech bin.

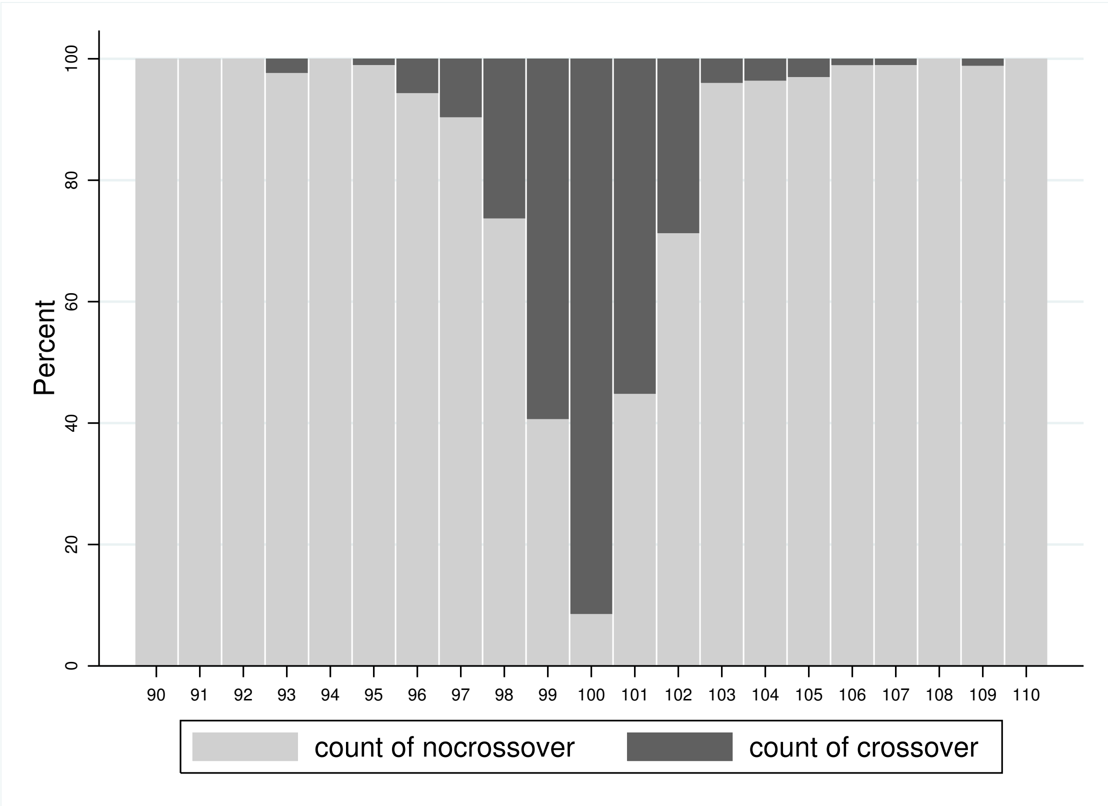

Figure 6: Number of crossover observations as a function of closing price price, displayed as percent of total numbers of observations within a 1 SEK interval. The ticks shown on the x-axis refers to whole numbers but is placed in the middle of ech bin.

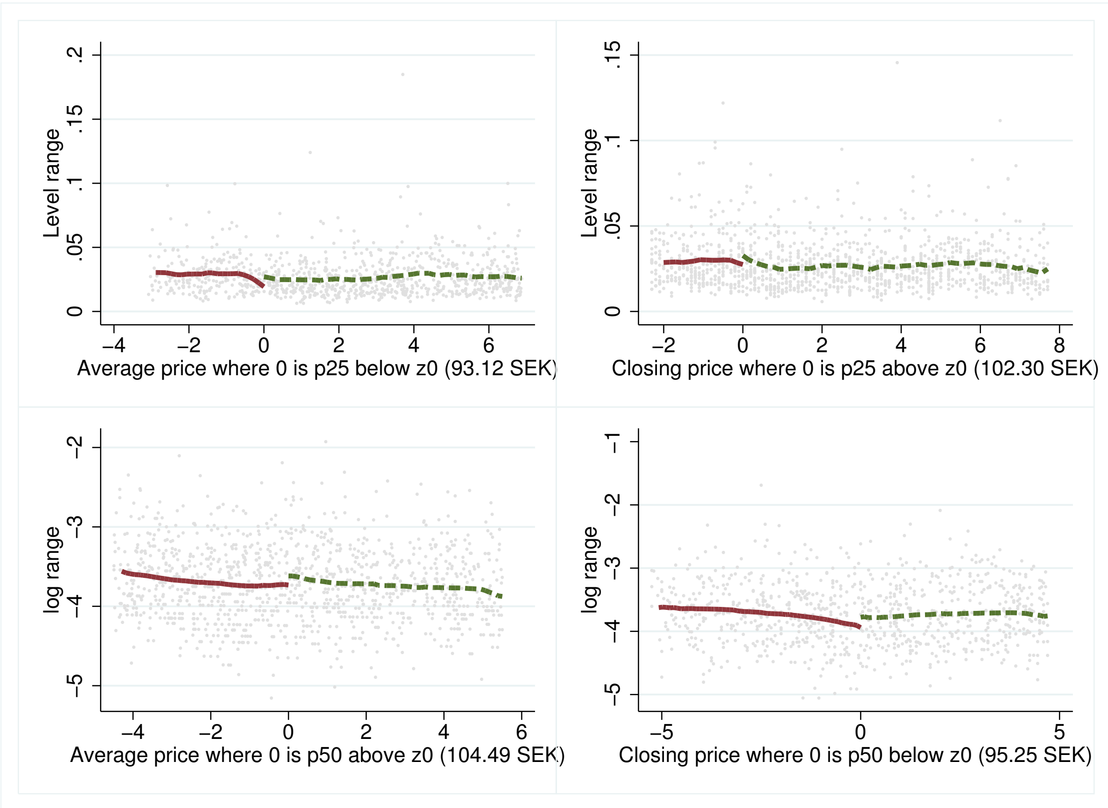

Figure 7: The most significant discontinuities away from the cutoff point Z_0 (100 SEK) for all four regression specifications, looking only at the optimal bandwidth.

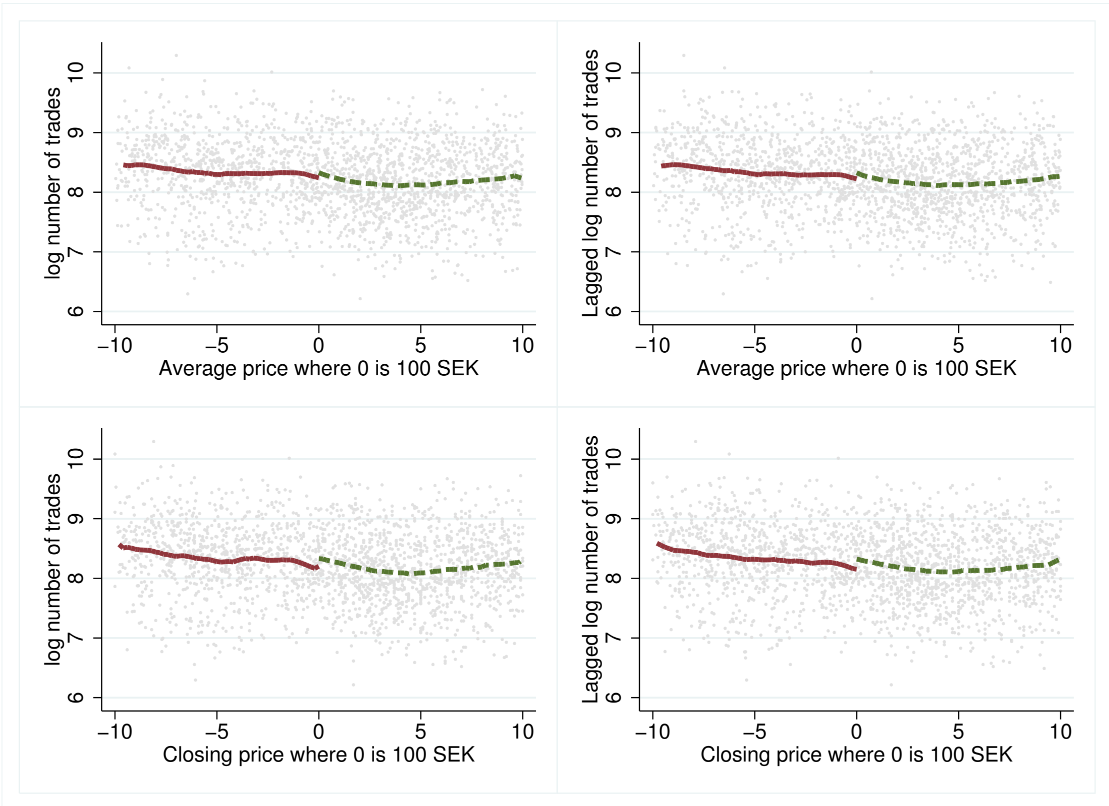

Figure 8: Testing for discontinuities for log of number of trades at Z_0 (100 SEK) for both the average and the closing price. To test for predetermined characteristics the variable is also lagged.

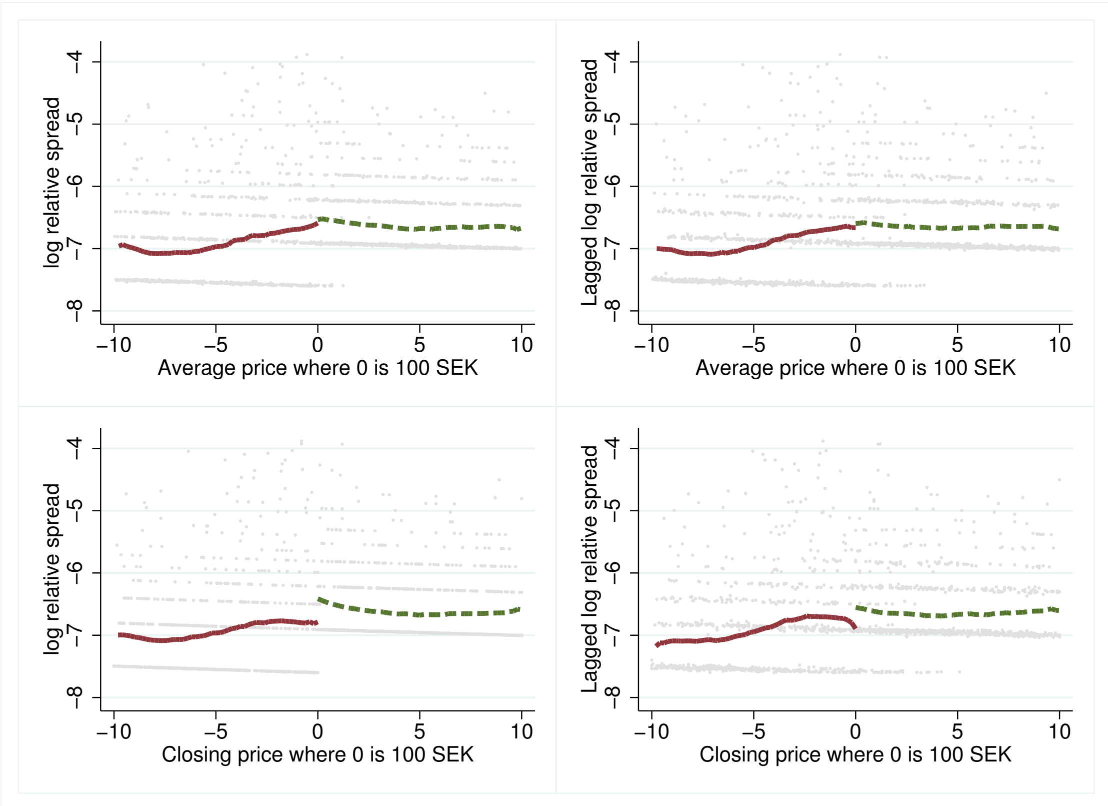

Figure 9: Testing for discontinuities for log of relative spread at Z_0, (100 SEK), for both the average and the closing price. To test for predetermined characteristics the variable is also lagged.

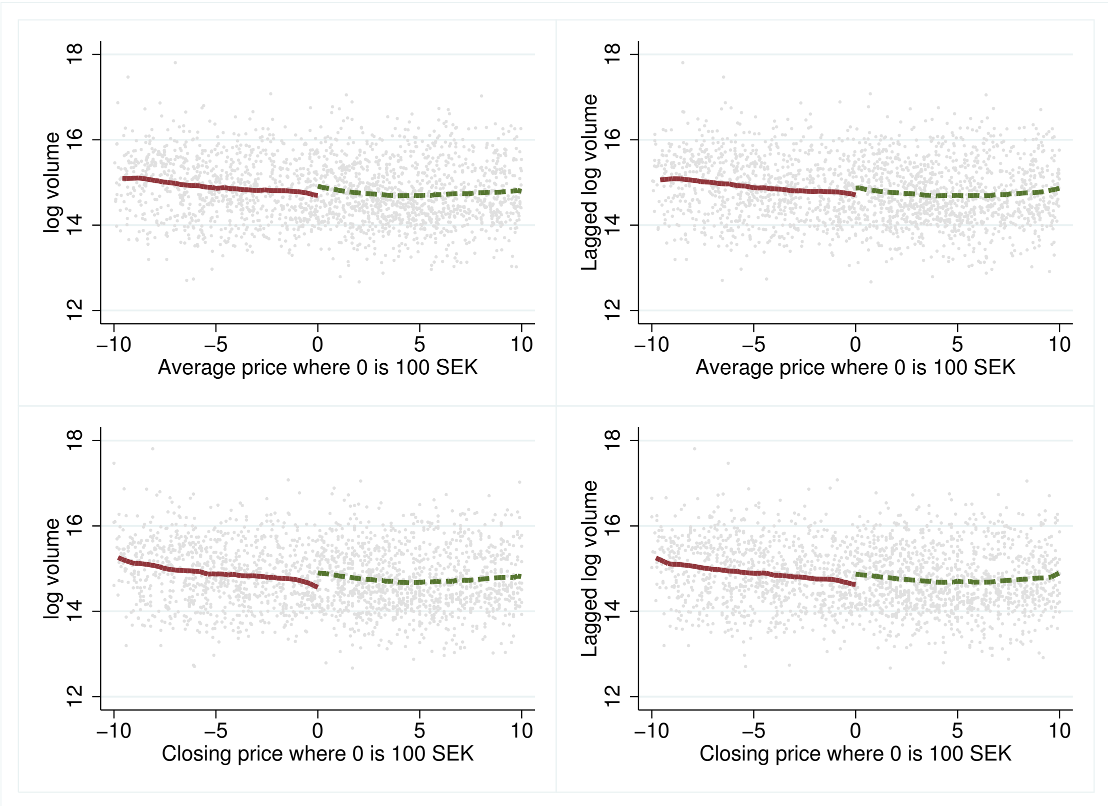

Figure 10: Testing for discontinuities for log of traded volume at Z_0, (100 SEK), for both the average and the closing price. To test for predetermined characteristics the variable is also lagged.

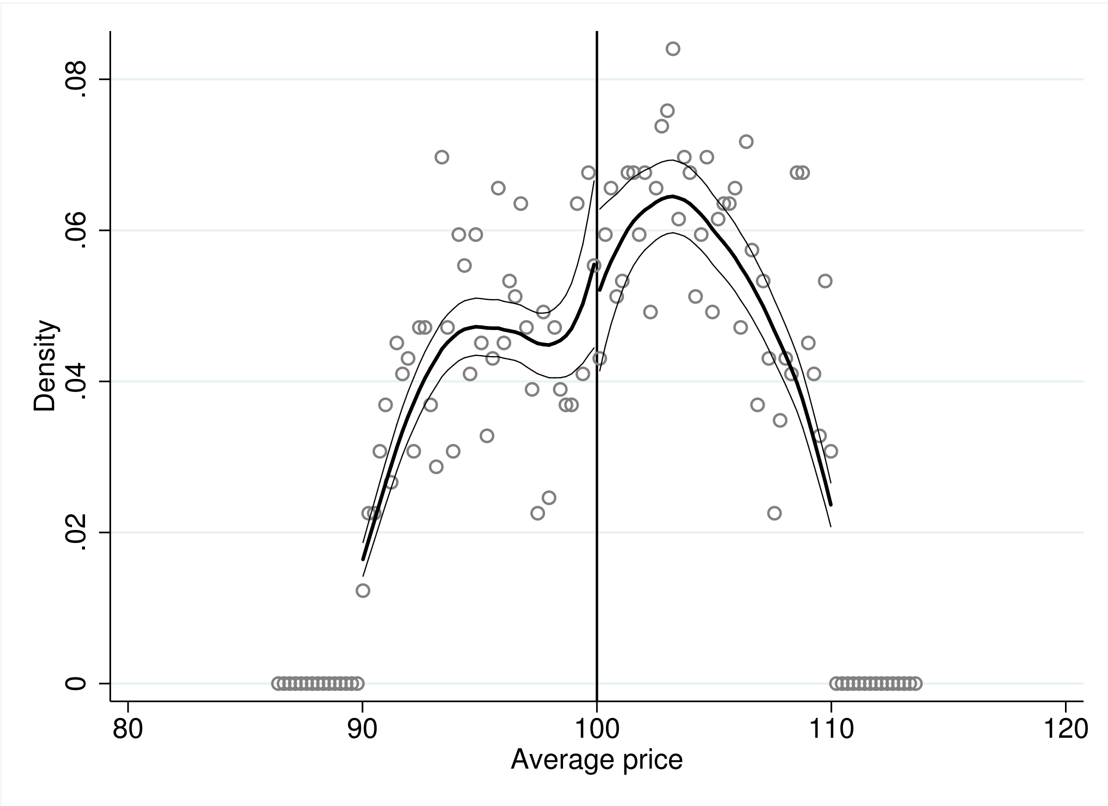

Figure 11: Estimation of the density of observations right above and just below the cutoff point Z_0, (100 SEK), for average price.

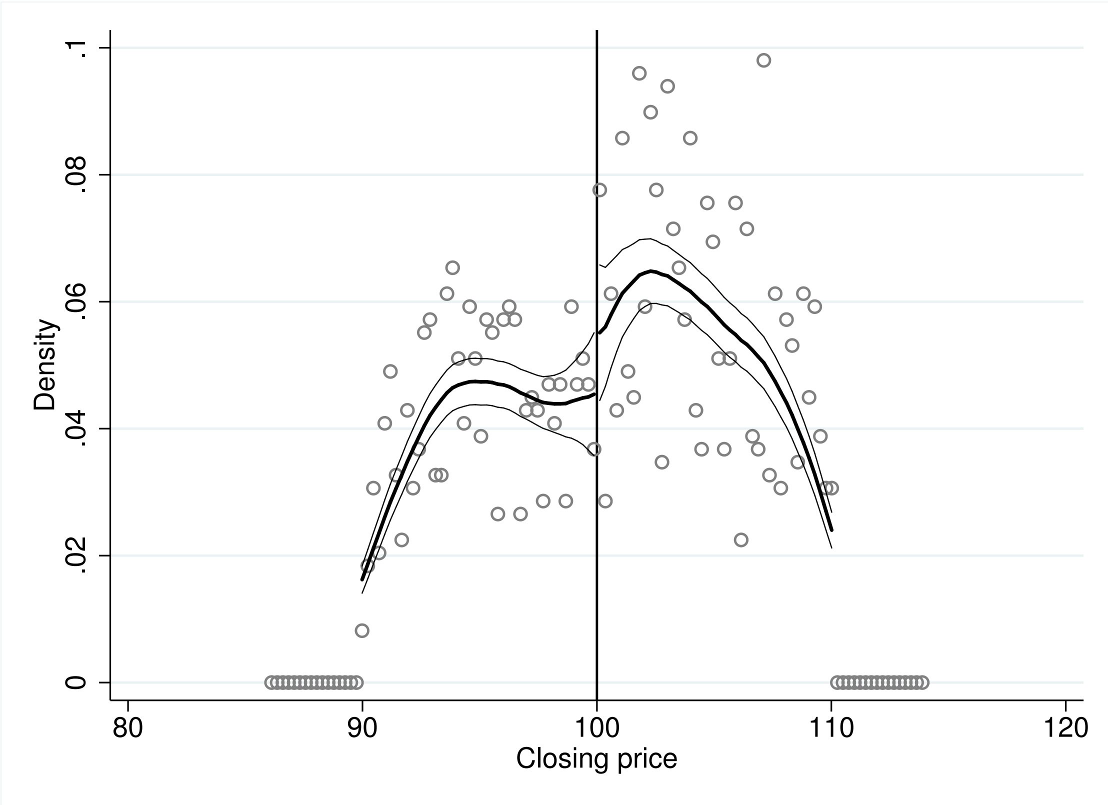

Figure 12: Estimation of the density of observations right above and just below the cutoff point Z_0, (100 SEK), for the closing price