DE GRUYTER OLDENBOURG Review of Economics 2022; 73(1): 57–77

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Estimating the Effect of Transaction Costs Using the Tick Size as a Proxy

https://doi.org/10.1515/roe-2021-0015
Received May 25, 2021; accepted March 1, 2022

Abstract: A method is proposed for estimating the effect of transaction costs on volatility, using the tick size as a proxy. The method involves three steps: (1) collect only the cases in which the tick size changes from one regime to another; (2) estimate the effect with and without the order book size; and (3) use local data on the tick size and volatility but instruments from international markets. The first step handles stationarity and dependence. The second step is used to infer the effect of a symmetric transaction cost as the tick size is a revenue and not a cost for liquidity providers. Regressions with and without the order book may therefore indicate the extent to which this asymmetry is likely to affect the result. The third step handles endogeneity. The method is applied to intraday data from the Norwegian Stock Exchange. The results show that both the tick size and the inferred transaction costs have no significant effect on volatility.

Keywords: finance, financial transaction tax, FTT, security transaction tax, STT, Tobin tax, tick size

JEL Classification: G12, G14, H25, G28

1 Introduction

Understanding how transaction costs affect the market is important to determine how exchanges should manage their markets in the best way possible and how governments should regulate financial markets. Furthermore, many economists and non-governmental organizations argue in favor of a financial transaction tax (FTT), which raises transaction costs. The idea is that the tax will act as “sand in the machinery” (Tobin 1978), slow the speed of transactions and thereby stabilize the market. This study will shed some light on this debate.

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The main problem with estimating the effect of transaction costs is that changes in such costs occur infrequently. A solution is to compile the few cases in which governments have imposed or removed FTTs or similar costs. The advantage of such studies is that there is a tight relationship between what is studied and what is observed, but a weakness is that a small number of observations gives limited power.

The approach taken in this study is to use the tick size, the smallest permissible difference between ask and bid quotes, as a proxy for transaction costs. With this approach, every traded stock is a natural experiment, and it provides a much richer dataset than can be obtained from event studies. However, three main challenges arise when using the tick size as a proxy for transaction costs, and providing solutions to overcome these challenges is the main contribution of this paper.

First, there is a considerable amount of non-stationarity in terms of both autocorrelation and heteroscedasticity in tick-size data. The tick size is determined by the tick-size scheme adopted by the exchange (see Table 1 in Section 3.3). This scheme defines different tick sizes for different price ranges, so the tick size is determined by the price range within which a stock's price lies. The underlying problem is therefore that, if the tick size and price do not change, the next observation is only a version of the previous one.

For this reason, only the days when the tick size changed were included. After collecting only these cases, the log change in all the involved variables was calculated. This took a heavy toll on the number of observations. Originally, 111,822 daily observations were extracted from the intraday data of the Oslo Stock Exchange (OSE) for the period 2003–2010 for 150 Norwegian shares. After filtering, 1369 observations remained. The size of the remaining sample is, however, sufficient to provide tests with good power if the observations are reasonably independent, which the diagnostics suggested to be the case. The statistics also indicated that the restrictive filtering resulted in a very dispersed sample.

Second, for the traders that submit limit orders (liquidity providers), a larger spread is a revenue and not a cost. However, we have data on the amount of liquidity provided, so it is possible to infer what would have happened if the response of the liquidity providers was reversed. Specifically, regressions with and without the order book size and a regression of the tick size on the order book size can help us to understand how a symmetric transaction cost may affect volatility in different ways. We can then infer how volatility would be affected if the interaction between the liquidity provision and the tick size was reversed, as we would expect with a symmetric transaction cost.

Third, there is an endogeneity problem. The tick size is reasonably exogenous, at least when we have the price as a control. However, there may be endogeneity

Table 1: Tick-size regimes. Type refers to the type of stocks to which the regimes apply.

Type	From date	Price from	Tick size
All	Pre-2000	0	0.01
		10	0.1
		50	0.5
		1000	1
All	June 23, 2003	0	0.01
		10	0.1
		50	0.25
		150	0.5
		1000	1
All except OBX and ETF	September 25, 2006	0	0.01
		10	0.05
		15	0.1
		50	0.25
		100	0.5
		250	1
OBX	September 25, 2006	0	0.01
		15	0.05
		50	0.1
		100	0.25
		250	0.5
		500	1
Type	**From date**	**Price from**	**Tick size**
OBX	July 6, 2009	0	0.01
OBX	August 30, 2009	0	0.0001
		0.5	0.0005
		1	0.001
		5	0.005
		10	0.01
		50	0.05
		100	0.1
		500	0.5
		1000	1
		5000	5
		10 000	10
ETF	August 30, 2009	0.01	0.01
		5	0.05
		100	0.1
		250	0.25
		500	0.5
		5000	1

"From date" means the date on which the tick-size regime was introduced (a regime ends when a new regime is introduced). "Price from" is the lowest price for which the associated tick size is the minimum permissible spread. From September 25, 2006, the largest and most liquid stocks (the stocks included in the OBX index) were subject to a different tick-size regime. In addition, exchange traded funds (ETFs) have been subject to a separate scheme since 2009. For some periods, the tick sizes for the 15 largest companies (OBX) and for ETFs were different from the rest, as indicated by the "Type" column.

between this price and volatility and between the order book size and volatility. This problem can be addressed by using instrumental variables. As a relatively small exchange, it is unlikely that the stock prices or volatility on the Oslo Stock Exchange affect international financial data much. Data from other markets are therefore used as instruments to check whether the results are robust with respect to endogeneity.

A more trivial problem is also the well-known problem that the common measure of volatility is inflated in intraday data due to the discreteness of the pricing grid. The range volatility measure, which is well known to be very robust, can be used to overcome this problem.

The Grossman and Stiglitz (1980) (GS) model can be a useful framework for interpreting the results. In the GS model, there are noise traders, informed traders and uninformed traders. The noise traders have a destabilizing role, adding volatility to the price that would otherwise not be there. The informed traders, conversely, have a stabilizing role, keeping the price close to the fundamentals. Hence, the more informed traders there are, the less volatile the price will be. The effect of transaction costs on stability is therefore, in the GS model, determined by which trader type is most affected. If the noise traders are more discouraged by increased costs, we would expect a tax to have a stabilizing effect. If the informed traders or the uninformed traders are affected more, the relative increase in noise trading will raise the volatility and make the market less stable. The GS framework will be used to interpret the results in the discussion section.

The plan of the paper is as follows. The literature is reviewed in the next section. In Section 3, the data are described and presented. Section 4 provides the model and the results of the regressions. In Section 5, the results are discussed.

2 Literature

Both Bessembinder (2000) and Ke et al. (2004) find that volatility and the tick size are positively related, the former using intraday and the latter using daily observations. However, the effect of a tax is an issue in the study by Hau (2006), who uses the range estimator to control for microstructure noise. Hau also concludes that an increase in the tick size increases volatility. Neither of these studies discuss how interaction with the order book can be used to infer the effect of transaction costs, and neither of them consider only the cases in which stocks shift from one tick-size regime to another.

Aliber et al. (2003) use estimated transaction costs inferred from deviations in the covered interest rate parity and find that higher trading costs in terms of the spread are associated with higher volatility. However, as noted by Werner (2003), this creates an endogeneity problem. It is difficult to determine the extent to which the volatility is a cause or an effect of the spread. Lanne and Vesala (2010) attempt to mitigate this problem by controlling for fundamental volatility using the news count as a proxy.

Mulherin (1990) uses changes in the initial margin requirements and the "uptick rule" as proxies for transaction costs. He studies annual volatility and estimated trading costs in an extensive period from 1887 to 1987. He is, however, unable to find conclusive evidence in either direction.

Except for these, studies on the effect of transaction costs on volatility for the most part focus on market-wide regulatory modifications or the observed spread (as opposed to the minimum spread/tick size). The regulatory modifications may be changes in tick-size rules or changes in taxes or fees.

Clearly, those studies that focus on changes in an actual transaction tax or fee (Campbell and Froot 1994; Colliard and Hoffmann 2013; Ness et al. 2000; Saporta and Kan 1997; Umlauf 1993) have the advantage that the variable that they analyze and the phenomenon that they try to explain are more tightly connected. The main disadvantage is that such studies are often sensitive to accidental fluctuations in volatility at the time of the change.

Pomeranets and Weaver (2013) also consider a sample of several changes in market-wide regulations. They evaluate nine modifications in the New York State Securities Transaction Tax between 1932 and 1981 and find that individual stock volatility increased the volatility and widened the bid–ask spreads. There was, however, no significant effect on the volatility of portfolios.

Deng et al. (2018) consider market-wide changes in stamp duty for stocks that are cross-listed in Hong Kong and Mainland China. The transaction costs change in only one of these exchanges, providing a proper counterfactual.

Most of the purely theoretical work either concludes that an FTT reduces volatility (Bianconia et al. 2009; Ehrenstein 2002; Ehrenstein et al. 2005; Mannaro et al. 2008; Stiglitz 1989; Westerhoff 2003; Westerhoff and Dieci 2006) or finds an ambiguous effect (Hanke et al. 2010; Shi and Xu 2009). However, not all studies reach this conclusion (Rosenthal et al. 2012).

In Kirchler et al. (2011), a lab experiment shows that, when investors are allowed to place limit orders, as is the case in most modern stock markets, a unilateral Tobin tax will increase the volatility. However, an encompassing tax has no effect. In the literature, there are a couple of examples of rational expectations models in which the effect of a transaction tax on volatility is modeled. Kupiec (1996) and Song and Zhang (2005) assume overlapping generations. Dávila and Parlatore (2019) derive the effect of transaction costs in a Grossman–Stiglitz type of model. They conclude that one cannot argue that a transaction tax will make prices informative without knowing in greater detail what sort of heterogeneity describes the marketplace.

3 Data

The data were constructed from the Oslo Stock Exchange (OSE) data feed in the period January 2003 to April 2010 and contain all the orders and trades for all the instruments available in that period. There is at present no transaction tax in the Norwegian stock market.

The choice of data was determined by availability. The Oslo Stock Exchange no longer supplies such data. This is a natural experiment study, in which the variation in the tick size is the treatment. Hence, the purpose is to study human behavior and the response to changes in transaction costs in general. By using these data, it is implicitly assumed that these behavioral mechanisms are reasonably stable over time, though technology is not.

There are considerable advantages for the analysis in that the tick size on the OSE varies across multiple price ranges and that the data include the entire order book. The dispersion of liquidity in the sample is also beneficial since liquidity and turnover are vital in this paper. Although the OSE is a peripheral exchange, foreign investors account for 88% of the trade.[1]

The total sample consisted of 111,822 daily observations for 146 different companies and 1746 trading days. Prices were sampled at 60-s intervals, which meant about 440 data points each day with uninterrupted trading throughout the entire day.

3.1 Variation in the Data

There is substantial dispersion in the companies listed on the Oslo Stock Exchange (OSE) with respect to both size and liquidity. The largest company is Statoil, which is a large corporation even by international standards, ranking as the 67th largest in the world.[2] The company has a daily average of 15,000 orders and close to 3000

1 Value weighted. http://www.vps.no/public/vps_eng/vps.no/About-us/Statistics

2 According to Fortune: http://money.cnn.com/magazines/fortune/global500/2011/full_list/

trades per day, not including transactions on the NYSE, on which it is also listed. At the opposite end of the scale, there are companies with very poor liquidity, so a minimum amount of trading activity (50 trades per day) needed to be included in the sample.

The most liquid stock in terms of trades per day was the Renewable Energy Corporation, with 3353 trades per day. The least liquid stock in the sample was Inmeta, with average trades per day equal to the minimum requirement. Hence, the sample contains a mix of liquid and quite illiquid shares, which is an advantage since the number of trades plays an important role in this paper. There is also considerable variation across time, with a substantial increase in trading activity at the end of the sample period.

3.2 Order Book Construction

The database contains the data feed that the OSE sends in real time to its clients. The feed provides information on all the changes to the order book during opening hours. To transform the data into an order book, all the order book changes during a day for a specific company were retrieved from the database. The changes were then processed using an algorithm that reconstructed the order book by sequentially adding, removing or modifying bids and asks according to the data feed.

After the reconstruction, snapshots were taken of all the levels in the order book at 60-s intervals. If no orders arrived within a 60-s interval, the snapshot would be a copy of the previous order book.

3.3 Description of the Variables

Volatility was measured using the “range” measure. Range is a well-known volatility measure that Hau (2006) proposes for this type of studies. The traditional average mean square measure is inflated if the data are restricted to a price grid, as financial data often are. The expected asymptotic bias is obtained by Ball (1988) and Gottlieb and Kalay (1985). It can be shown mathematically that the range measure does not have this bias, and our own simulations as well as those of Hau (2006) confirmed this. The range measure is defined as

$$\hat{\sigma} = \frac{1}{T}\sum_{t=1}^{T} 2 \cdot \frac{p_{\max,t} - p_{\min,t}}{p_{\max,t} + p_{\min,t}}$$

where $p_{\max,t}$ and $p_{\min,t}$ are the maximum and minimum prices observed in sub-sample t. The minima and maxima were calculated from hourly sub-samples in which the price was sampled every 60 s, providing daily observations of this volatility measure.

RelTick (*relative tick size*) is the proxy for transaction costs. RelTick is the tick size relative to the daily mean price. The advantage of using the tick size is that it is reasonably exogenous. The tick size on the Oslo Stock Exchange is determined by the price level, as shown in Table 1.

The tick-size scheme implies that a high price does not necessarily mean a small relative tick size. RelTick is given by the stock's position within the tick-size price range rather than the general price level. This ensures that the relative tick size is determined by a considerable amount of randomness. However, within each price range, there will be some correlation between the price and the relative tick size. For this reason, the mean daily price was added as a control variable, called **avgPrice**.

Since 2006, two tick-size tables have existed for ordinary stocks. The table that applies to a specific stock depends on whether the stock belongs to "OBX," an index of the most liquid stocks on the exchange. A dummy representing this was originally incorporated into the regressions, but it was insignificant and is therefore not included in this analysis.

orderBookVol (*total order book volume*) is the average total monetary amount in the order book throughout the trading day. At every instance during the day, the sum of the number of shares and prices at corresponding bid and ask levels in the order book was taken. orderBookVol represents the mean of these sums throughout the trading day.

Last, **BindFreq** represents the frequency at which the tick size is binding. That is, for each minute during the trading day, it was determined whether the spread equals the tic size. BindFreq represents the fraction of minutes for which this is the case.

3.4 Filtering

Of the full sample of 111,822 trading days, only the cases in which the minimum tick size changed from one day to another was selected, and the change in the relevant variables from the previous to the current tick-size regime was computed. To eliminate autocorrelation and heteroscedasticity as much as possible, successive shifts in and out of a tick-size regime were not included. The log difference between the variables before and after the tick-size change was then computed. There were 1929 such changes in the tick size in the sample.

In addition, the tick size was required to have been binding (spread equal to the tick size) for a certain fraction of the trading day, which was achieved by requiring BindFreq to exceed a certain threshold value. Regressions were run with different fractions in the range 0.3–0.9. The threshold was satisfied if either the lagged or the present observation satisfied it, enabling increases and decreases in BindFreq to be treated symmetrically.

Of the observations, 51.1% were increases in the tick size. This requirement reduced the sample by 560 observations to 1369 for the BindFreq ≥ 0.3 filter. After this filter was applied, the average frequency for which the tick size was binding was 45%. Since the tick size is more likely to bind when the price is low in the tick-size range, the tick size was binding more often when it increased, with an average bindingness for these observations of 70%. With the BindFreq ≥ 0.9 filter, the sample was reduced to 298.

The filtering reduced the number of unique dates from 1746 to 821 and the number of unique firms from 146 to 114. The maximum number of dates for the same firm was reduced from 1744 (99.9% of the available dates) to 40 (4.9% of the available dates). As shown in Figure 1, the number of observations was considerably smaller for most stocks. This dispersion resulted in a set of reasonably independent observations, as we shall see.

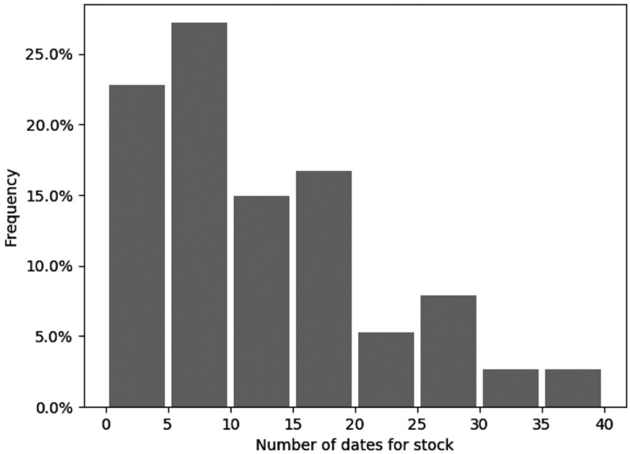

Figure 1: Frequency of observations for the stocks in the panel. The figure shows the fraction of the sample for which the number of dates of the stocks lies in the interval indicated by the *x*-axis.

3.5 Descriptive Statistics

The correlations after filtering are reported in Table 2. The correlations between the variables and the descriptive statistics are given in Table 3. The prefix "DLN" indicates that the log and the first difference of the variable were taken. As expected, there is a strong positive correlation between the bindingness (DLNBindFreq) and the tick size.

In Table 3, we can see that the relative tick size ranges from 0.005%to more than 1%. Notice also that, for the whole sample, the tick size was binding for 48% of the time on average.

Table 2: Correlation matrix of the log change in price volatility, relative tick size (RelTickSize), average price of the trading day (avgPrice), average order book volume during the trading day (orderBookVol) and frequency at which the tick size was binding (BindFreq) for BindFreq > 0.3. *N* = 1369. "DLN" indicates the log difference.

	DLNVolatility	DLNTickSize	DLNavgPrice	DLNorderBookVol	DLNBindFreq
DLNVolatility	1.00	−0.12	−0.11	0.19	−0.16
DLNTickSize	−0.12	1.00	0.29	0.08	0.67
DLNavgPrice	−0.11	0.29	1.00	−0.28	0.09
DLNorderBookVol	0.19	0.08	−0.28	1.00	0.04
DLNBindFreq	−0.16	0.67	0.09	0.04	1.00

Table 3: Descriptive statistics (before log transformations). The number of firms was 146, and the number of trading dates was 1738. The sample period was January 2003–April 2010. Amounts in USD.

	Volatility	RelTickSize	avgPrice	orderBookVol	BindFreq
Nobs	1369	1369	1369	1369	1369
Mean	−4.44	0.333%	64.29	252,387	45%
Std	0.60	0.240%	63.77	494,458	35%
Range	4.25	1.042%	523.04	9,962,226	100%
Max	−2.31	1.046%	527.28	9,966,460	100%
Min	−6.56	0.005%	4.24	4234	0%
Mode	−4.21	0.100%	15.06	171,858	0%
Median	−4.48	0.250%	50.58	106,578	48%
Skew	0.22	1.19	2.10	9	−1%
Kurtosis	3.20	4.01	8.78	132	153%

4 Model and Results

To estimate the effect of transaction costs on volatility, the log change in tick size (DLNTickSize) was regressed on the change in volatility on dates when the absolute tick size changed for a security. Selecting only the dates when there was a change in the tick size significantly reduced the problems of non-stationarity and dependence. Because a change in tick size is triggered by a change in price, which moves the stock into a different tick-size regime, the price change was added to the regression as a control variable (DLNavgPrice). In addition, if the tick size rarely binds, the effect of an increase in the tick size will frequently not resemble a transaction tax. This will add undesirable noise to the regression.

The problem was handled in two ways. First, the data were filtered depending on a minimum requirement for how often the tick size binds during a trading day. To check the robustness of this filter, regressions were run with seven different minimum bind frequencies (BindFreq), ranging from 0.3 to 0.9.

Second, the log difference of the bind frequency, DLNBindFreq, was added as a control variable to all the regressions. The results of this model are presented in Table 4. As we can see, the tick size has a very small and insignificant effect for all the bindingness filters, with an adjusted R-squared of 4% or less.

The filtering reduced the sample to only 1.2% of its original size. As indicated by the Durbin–Watson statistic in Table 4, the remaining observations are reasonably independent. The sample is sorted on firm identity, and the Durbin–Watson statistic is very close to two, suggesting that there is little correlation between observations for the same firm. As Figure 1 shows, this is probably because the number of observations for most firms is quite low.

At the outset, the low correlation between observations makes random or fixed effects unlikely. Tests of all the regressions confirmed that the random- and fixed-effect variance was close to zero. Regression results with and without panel effects were almost identical (available as an unpublished Supplementary Appendix from the author). All the regressions were therefore executed without panel effects.

A possible reason for not being able to detect effects is asymmetry. In Table 5, asymmetry is added to the model by defining the positive and negative parts of DLNTickSize as DLNTickSizeUp and DLNTickSizeDown, respectively. As we can see, neither is significant.

Table 4: Regression of the log change of the relative tick size, average price and bind frequency on the log change in the volatility on dates when the absolute tick-size level changes.

\min BindFreq Variable	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Intercept	0.069 (0.014)***	0.068 (0.015)***	0.068 (0.016)***	0.066 (0.017)***	0.055 (0.02)**	0.045 (0.022)*	0.05 (0.029)’
DLNTickSize	0.008 (0.016)	0.013 (0.017)	0.014 (0.018)	0.009 (0.019)	0.0 (0.021)	−0.011 (0.023)	−0.022 (0.033)
DLNavgPrice	−0.24 (0.094)*	−0.254 (0.102)*	−0.264 (0.117)*	−0.189 (0.11)’	−0.129 (0.091)	−0.202 (0.112)’	−0.217 (0.862)
DLNBindFreq	−0.007 (0.002)***	−0.008 (0.002)***	−0.009 (0.002)***	−0.009 (0.002)***	−0.006 (0.002)*	−0.006 (0.003)*	−0.004 (0.004)
DF	1369	1225	1082	902	712	522	298
Adj. R^2	0.03	0.04	0.04	0.03	0.01	0.03	0.01

The column headings indicate the filter condition on BindFreq, that is, the minimum allowed daily frequency at which the tick size was binding applied on the current and lagged days. Standard errors are in brackets. Significance codes: ’ = 0.1, * = 0.05, ** = 0.01, *** = 0.001.

Table 5: Regression with asymmetry.

\min BindFreq **Variable**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Intercept	0.103 (0.03)***	0.104 (0.032)**	0.1 (0.035)**	0.106 (0.037)**	0.078 (0.043)’	0.049 (0.049)	0.013 (0.066)
DLNTickSizeUp	−0.021 (0.03)	−0.018 (0.032)	−0.014 (0.035)	−0.026 (0.037)	−0.02 (0.043)	−0.014 (0.046)	0.009 (0.061)
DLNTickSizeDown	0.039 (0.031)	0.045 (0.033)	0.043 (0.036)	0.046 (0.039)	0.021 (0.044)	−0.007 (0.049)	−0.054 (0.062)
DLNavgPrice	−0.233 (0.096)*	−0.245 (0.104)*	−0.257 (0.119)*	−0.178 (0.112)	−0.123 (0.093)	−0.202 (0.112)’	−0.23 (0.856)
DLNBindFreq	−0.007 (0.002)***	−0.008 (0.002)***	−0.009 (0.002)***	−0.009 (0.002)***	−0.006 (0.002)*	−0.006 (0.003)*	−0.004 (0.004)
DF	1369	1225	1082	902	712	522	298
Adj. R^2	0.03	0.04	0.04	0.03	0.01	0.02	0.01

Regression as in Table 4 but with separate variables for the cases in which the minimum tick size has increased. DLNTickSizeUp and DLNTickSizeDown represent the positive and negative parts of DLNTickSize, so DLNTickSizeUp > 0 and DLNTickSizeDown < 0, and the sign of both the coefficients has the same interpretation as DLNTickSize.
Significance codes: ’ = 0.1, * = 0.05, ** = 0.01, *** = 0.001.

4.1 Endogeneity

The above analysis assumed that the independent variables are exogenous with respect to the dependent variable. It is reasonable to assume that the tick-size change is exogenous when controlling for the price change, as was the case. However, the price is not necessarily exogenous with respect to volatility, and neither are the actions of liquidity providers, measured as the order book size.

Endogeneity can work in two ways. It might conceal effects that occur or it might exaggerate and cause spurious relationships between variables. To investigate the possibility of the former, an instrumental variable (IV) estimation was performed.

Since the data here are from a relatively small national exchange, international financial variables are good candidates for instruments. The problem with endogeneity is the recurring interaction that occurs if the independent variables are affected by the dependent variable. It is usually modeled by assuming that the residual depends on the independent variables (Reiersøl 1945; Wright 1928).

The bias caused by this recurring interaction may work either way, and it is impossible to know what harm is caused by just observing the endogenous variables. The only solution is to use variables that cannot be caused by the dependent variable. As a relatively small exchange, it is highly unlikely that the Oslo Stock Exchange has any significant effect on internationally observed financial time series. The following variables were therefore used as instruments for the model: the NASDAQ composite index level, volume and range (the volatility measure, with no sub-periods, i.e. using the daily high and low), the oil price and the US–EUR exchange rate.

As shown in Table 6, all the tick-size coefficients are insignificant in the IV model except for DLNTickSizeUp, which is weakly significant at the 10% level when the tick size is binding 90% of the time or more. The other *p*-values are far from any conventional level. Since we in effect ran seven tests, though not independent, significance at the 10% level should not bear much weight. It can thus be concluded that the tick size is generally far from significant.

4.2 The Effect of Transaction Costs Vs. Tick Size

Since the results show that the tick size is far from significant, it seems very unlikely that replacing the tick size with the actual transaction costs would make much difference. However, the methodology presented in this paper can be

Table 6: IV-GLS model. Regression as in Table 5 with the following instruments: the NASDAQ composite index level, volume and volatility, the petroleum price and the US–EUR exchange rate.[a]

\min BindFreq Variable	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Intercept	0.059 (0.05)	0.09 (0.054)’	0.093 (0.06)	0.112 (0.06)’	0.082 (0.105)	0.046 (0.071)	−0.006 (0.082)
DLNTickSizeUp	0.125 (0.347)	0.011 (0.292)	−0.06 (0.318)	−0.143 (0.365)	−0.197 (0.236)	0.082 (0.129)	0.332 (0.197)’
DLNTickSizeDown	0.125 (0.318)	0.055 (0.255)	−0.01 (0.326)	−0.054 (0.358)	−0.123 (0.269)	0.078 (0.145)	0.165 (0.146)
DLNavgPrice	−1.262 (1.029)	−0.515 (0.946)	−0.273 (0.861)	0.095 (0.788)	0.422 (1.071)	−0.679 (0.924)	−3.255 (2.045)
DLNBindFreq	−0.019 (0.049)	−0.01 (0.042)	−0.0 (0.054)	0.009 (0.065)	0.021 (0.052)	−0.021 (0.03)	−0.06 (0.036)’
DF	1369	1225	1082	902	712	522	298
Adj. R^2	0.02	0.01	0.01	0.01	0.00	0.01	0.01

Significance codes: ’ = 0.1, * = 0.05, ** = 0.01, *** = 0.001. [a]Brent, https://datahub.io/core/oil-prices.

applied to other data. If different results emerge, it would be useful to have a method for predicting the effect of a tax, given the data on transaction costs. Such a prediction can be obtained by assuming that liquidity providers adopt exactly the opposite behavior when facing changes in the transaction costs rather than changes in the tick size. This will be assumed in the following.

Say that, counterfactually, we were able to substitute the tick size with the transaction costs in our sample and observe the change in behavior. We can gain an idea of how this may affect the results by running a regression with the order book as a control variable and thereby obtain estimates that are cleansed for the indirect effect of liquidity provision.

This regression is presented in Table 7. It follows from standard regression theory that adding the order book size to the regression means that its interaction with volatility through the tick size is removed from the tick-size coefficient since the effect is now delivered directly from the order book size. I in what follows, estimated effects will be used to illustrate the point, but it is of course acknowledged that these effects are not significant.

The positive tick-size effect for bind frequency 0.9 is $tz = 0.332$ in Table 6. In Table 7, we can see that the corresponding tick size, controlled for liquidity provision, is $tz_{\sim LP} = 0.235$. We can now split the tick size effect into a part that is due to liquidity provision, tz_{LP}, and a part that is not, $tz_{\sim LP}$. The total effect is then

$$tz = tz_{LP} + tz_{\sim LP} = 0.332 \tag{1}$$

This implies that

$$tz_{LP} = tz - tz_{\sim LP} = 0.332 - 0.235 = 0.097 \tag{2}$$

In Table 8, the change in tick size is regressed on the order book size. The significantly positive coefficients of DLNTickSizeUp and DLNTickSizeDown indicate that a larger tick size raises the quantity in the order book, as expected, confirming a positive indirect effect.

If the impact of a transaction cost is now exactly the opposite, the part of the tick size effect contributed by liquidity providers would be $tz^C_{LP} = -0.097$ rather than $tz_{LP} = 0.097$ in (2) when the tick size is replaced by a tax. In that case, we can recalculate the total effect in (1) as

$$tz = tz^C_{LP} + tz_{\sim LP} = -0.097 + 0.235 = 0.138 \tag{3}$$

Under the assumption of exactly the opposite response by liquidity providers, we can potentially obtain an estimate of the effect of transaction costs, such as a tax. With insignificant coefficients, the likely effect of a hypothetical transaction cost is, however, also insignificant.

Table 7: Instrumental variables generalized least squares (IV-GLS) model with the order book.

\min BindFreq **Variable**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Intercept	0.043 (0.067)	0.078 (0.068)	0.092 (0.061)	0.113 (0.059)’	0.117 (0.087)	0.028 (0.072)	−0.04 (0.094)
DLNTickSize							
DLNTickSizeUp	0.286 (0.404)	0.136 (0.367)	0.052 (0.357)	−0.056 (0.37)	−0.092 (0.216)	0.031 (0.13)	0.235 (0.213)
DLNTickSizeDown	0.273 (0.364)	0.167 (0.315)	0.106 (0.355)	0.033 (0.352)	0.025 (0.215)	0.033 (0.146)	0.068 (0.178)
DLNavgPrice	−1.35 (1.011)	−0.523 (0.968)	−0.268 (0.87)	0.143 (0.819)	0.846 (1.027)	−0.379 (0.967)	−3.176 (2.041)
DLNBindFreq	−0.045 (0.063)	−0.031 (0.06)	−0.022 (0.063)	−0.009 (0.068)	−0.014 (0.043)	−0.025 (0.03)	−0.055 (0.036)
DLNorderBookVol	0.217 (0.646)	0.191 (0.682)	0.156 (0.512)	0.121 (0.451)	0.304 (0.404)	0.56 (0.405)	0.537 (0.576)
DF	1369	1225	1082	902	712	522	298
Adj. R^2	0.01	0.01	0.01	0.01	0.00	0.01	0.01

Regression as in Table 6 but with the order book as a variable. Significance codes: ’ = 0.1, * = 0.05, ** = 0.01, *** = 0.001.

Table 8: Effect of the order book on the relative tick size.

\min BindFreq **Variable**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
Intercept	0.061 (0.032)’	0.059 (0.034)’	0.05 (0.037)	0.048 (0.041)	0.044 (0.05)	0.032 (0.063)	0.042 (0.091)
DLNTickSizeUp	0.093 (0.036)**	0.109 (0.039)**	0.137 (0.041)***	0.151 (0.047)**	0.188 (0.056)***	0.206 (0.067)**	0.252 (0.094)**
DLNTickSizeDown	0.121 (0.03)***	0.13 (0.033)***	0.139 (0.035)***	0.146 (0.038)***	0.164 (0.046)***	0.187 (0.058)**	0.209 (0.093)*
DLNavgPrice	−0.88 (0.15)***	−0.935 (0.15)***	−0.976 (0.152)***	−0.967 (0.178)***	−1.039 (0.191)***	−1.019 (0.271)***	−1.118 (1.346)
DLNBindFreq	−0.004 (0.002)*	−0.005 (0.002)*	−0.007 (0.002)***	−0.008 (0.002)***	−0.009 (0.003)***	−0.013 (0.003)***	−0.014 (0.004)***
DF	1369	1225	1082	902	712	522	298
Adj. R^2	0.11	0.12	0.14	0.14	0.15	0.16	0.13

Regression of the log change in the order book volume on the log change in the relative tick size. The column headings indicate the filter condition on BindFreq, that is, the minimum allowed daily frequency at which the tick size was binding, applied to the current and lagged days. Standard errors are in brackets. Significance codes: ’ = 0.1, * = 0.05, ** = 0.01, *** = 0.001.

5 Summary and Conclusion

This study shows that the tick size and transaction costs have surprisingly little impact on the market volatility. It follows immediately from Grossman and Stiglitz (1980) that the price volatility depends on the ratio of noise traders to informed and uninformed traders. Let us call the latter two types, for lack of a better word, the "rational" traders. In the original model, the number of rational traders is normalized to one, which means that the right-hand side of the demand–supply relationship represents the number of noise traders per rational trader. It is straightforward from the Grossman and Stiglitz (1980) model that the price volatility increases with the demand volatility of noise trading when the number of traders that acquire information is endogenous. The volatility of noise trading is in turn related to the number of noise traders per rational trader due to normalization and the basic statistical theory.

It follows from this that, if transaction costs raise the number of noise traders more than the number of rational traders, then the volatility will increase. If the opposite case applies, increased costs will have a stabilizing effect. In the framework of Grossman and Stiglitz, the results suggest that either neither of the trader types reacts much to the transaction costs or tick size or they are affected in similar ways so that the ratio of noise to rational traders does not change much.

Multiple steps were taken to ensure that the effect of transaction costs was investigated as thoroughly as possible. Only those cases in which the tick size actually changes were included in the sample. Both the price and the extent to which the tick size is binding were used as controls. In addition, the study investigated whether asymmetry or endogeneity may conceal the effect, but no effect was found. It is therefore concluded that the effect is either absent or at least very weak.

Though the results in this paper relate to relatively small tick sizes or inferred transaction costs, they are still relevant to the understanding of how transaction costs affect volatility. In most cases, the transaction costs are small. With respect to the debate on a financial transaction tax, the idea is usually that this tax should be small. The French tax currently in place is 0.2%. The size in this sample is, as one can see from Table 1, up to 1% of the price.

Of course, one cannot conclude from a statistical test that an effect does not exist. Lack of significance only means that it is undetectable within a margin of error. However, with 1369 reasonably independent observations, we should have been able to pick up an effect of any economic significance. The results therefore suggest that both the tick size and the transaction costs have surprisingly little effect on volatility.

Though the results here show no significant effect of transaction costs, it would be interesting to apply the same methodology to investigate whether data from other markets would yield the same result. To have effective instruments, it is a good idea to use data from a relatively small, national exchange. The policy implication of this paper is that a transaction tax is unlikely to raise volatility by any significant amount.

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Supplementary Material: The online version of this article offers supplementary material (https://doi.org/10.1515/ROE-2021-0015).