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Measuring the Impact of MiFID II on Information Asymmetries Using Microstructure Models

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Abstract

This paper evaluates the impact of the Markets in Financial Instruments Directive II (MiFID II) regulation on information asymmetries. The microstructure models of Madhavan et al. (1997) and Glosten and Harris (1988) are adapted to estimate potential changes in the adverse selection component of the spread. I use trade and quote data of 50 German stocks traded at the Cboe Europe Equities exchange. To classify trades in presence of uncertainly about the sequence of trades and quotes within a second, a robust classification method is developed. I find a short-term increase in adverse selection and transaction cost after the MiFID II implementation. A long-term reduction of information asymmetries due to the regulation is indicated and discussed.

Keywords: Market Microstructure; MiFID II / Markets in Financial Instruments Directive II; Information Asymmetry in Limit Order Books; Trade Classification; Financial Market Regulation.

1. Introduction

On efficient security markets, all market participants have the same expectation of the fundamental security value. The resulting prices immediately incorporate new public information because traders revise their beliefs about the fundamental value. In presence of information asymmetry, informed traders take advantage of their private information by buying (selling) securities if their expectation of the fundamental security value is higher (lower) than the market price. Rational uninformed traders protect themselves from informed trading by adjusting their quotes and by revising their beliefs based on actions of other market participants. This adaptation in trading strategies and behavior typically leads to less price efficiency and higher transaction costs. These consequences are called adverse selection.

Therefore, regulators such as the European Union seek to reduce information asymmetries by implementing laws and supervising financial markets. The Markets in Financial Instruments Directive II (MiFID II, 2014) and the associated Markets in Financial Instruments Regulation (MiFIR) came into force on January 3rd, 2018, to replace the previous framework MiFID I and expand the scope to non-equities.[1] [2] Improved investor protection, market resilience, efficiency and transparency for all market participants are the main goals of MiFID II (see European Securities and Market Authority, 2019). Reducing market fragmentation by limiting dark pool and Over-the-counter (OTC) trading and homogenizing tick sizes is supposed to increase competition and price efficiency while driving down transaction cost. Post-trade transparency is enhanced by extended reporting obligations for dark pool and OTC trading. The newly applied reporting standards for non-equities could also reveal relevant information for equity markets.[3]

Whether MiFID II successfully reduces information asymmetry and therefore adverse selection on equity markets is evaluated by using two market microstructure models.

I greatly appreciate the opportunity to write my thesis at the Chair of Econometrics, Statistics and Empirical Economics at the University of Tuebingen. In particular, I thank my supervisor Joachim Grammig, especially for his support in choosing an adequate model and estimation method to address the research question. I thank Johannes Bleher for his exceptional support: he collected and provided the data, developed the idea of an extended tick-rule, gave further suggestions about developing the analysis and assisted in coding the estimation procedures. Special thanks to Thomas Dimpfl for providing the idea of a rolling parameter estimation.

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[1] European Parliament and Council of the European Union (2014)

[2] From now on, MiFID II and MiFIR will be discussed together under the name MiFID II.

[3] Detailed information on the regulations impacting market transparency can be obtained from the MiFID II directive (2014) and its supplements or from the European Securities and Market Authority (2019).

The Madhavan-Richardson-Roomans model (1997) and the Glosten-Harris model (1988) state that in addition to new public information, the observed order flow is informative and reveals private information about the fundamental value of a security. While Madhavan et al. (1997) use the surprise in order flow to measure adverse selection, Glosten and Harris (1988) assume high trade volumes to be informative. The models are adapted to measure the change in adverse selection.

The paper is organized as follows. The microstructure models Section 2 explains the price formation process, the spread decomposition and the estimation procedures used. Section 3 describes and analyzes the data used for the effect estimation and discusses the method of trade classification. The model parameter and spread estimates are presented and discussed in Section 4 while the impact of the MiFID II implementation on adverse selection is evaluated in Section 5. Section 6 concludes and proposes further research ideas.

2. Microstructure Models

2.1. Model Description

Market microstructure models are able to analyze market frictions such as asymmetric information while accounting for the basic trading mechanisms. The model proposed by Roll (1984) shows that without asymmetric information, the fundamental security value μ_t fluctuates randomly due to the uncorrelated newly available public information u_t. Trade indicator models add the concept of informed trading to the basic framework provided by the Roll model. Since both informed and uninformed traders operate at the market, the order flow will provide a noisy signal about the fundamental security value μ_t. Therefore, market participants also revise their beliefs about μ_t depending on the private information revealed by the order flow.

The trade indicator variable x classifies transactions as buyer initiated ($x = 1$), seller initiated ($x = -1$) or neither buyer nor seller initiated ($x = 0$). The Madhavan et al. (1997) model assumes that surprises in the sequence of trade indicators x are informative. The revision in beliefs due to adverse selection depends on the surprise in order flow $x_t - E(x_t|x_{t-1})$ and degree of information asymmetry θ. The post-trade expected security value μ_t in Eq. (1) includes both the revision in beliefs due order flow and new public information u_t. According to the Glosten and Harris (1988) model, higher trade volumes v_t are associated with informed trades. This is captured in the adverse selection component z_t in Eq. (2).

$$\text{Madhavan et al.:} \quad \mu_t = \mu_{t-1} + \theta\big(x_t - E(x_t|x_{t-1})\big) + u_t \tag{1}$$

$$\text{Glosten-Harris:} \quad \mu_t = \mu_{t-1} + z_t x_t + u_t \tag{2}$$

Without informed trading, these processes will reduce to a random walk with parameters θ and z_t equal to zero.

Rational liquidity providers set ask (bid) quotes conditional on the trade being buyer (seller) initiated (see Madhavan et al., 1997, p.1040). The cost of providing liquidity such as direct transaction fees, specialist rent, inventory holding cost and potential profits for market makers are combined in the transitory component ϕ (Madhavan et al., 1997) or c_t (Glosten and Harris, 1988). The transitory component is uncorrelated with the fundamental value and simply added or subtracted from the conditional post-trade fundamental value depending on the trade indicator x_t (see Eq. (3)/(4)).[4]

$$\text{Madhavan et al.:} \quad P_t = \mu_t + \phi x_t \tag{3}$$

$$\text{Glosten-Harris:} \quad P_t = \mu_t + c_t x_t \tag{4}$$

Madhavan et al. (1997) include the possibility of trading at the midquote with unconditional probability $P(x_t = 0) = \lambda$. Whereas Glosten and Harris originally assume that trades are executed at the quoted bid and ask prices, the model framework also applies to trades with $x_t = 0$.

For the unspecified Glosten-Harris model, the transitory component c_t and the adverse selection component z_t both include a constant and a volume-dependent parameter.

$$\text{Glosten-Harris:} \quad \begin{aligned} c_t &= c_0 + c_1 v_t \\ z_t &= z_0 + z_1 v_t \end{aligned}$$

Furthermore, for the Madhavan et al. (1997) model derivation 1 and 2 in the appendix show that the surprise in order flow can be written using the first-order autocorrelation of the order flow ρ.

$$\text{Madhavan et al.:} \quad E(x_t|x_{t-1}) = \rho x_{t-1} \tag{5}$$

The post-trade expected value of the security (see Eq. (1)/(2)) is combined with the transitory component (see Eq. (3)/(4)) to form the price P_t for both models. To estimate the model parameters, the price changes ΔP_t are calculated to remove the unobservable fundamental value μ_{t-1} (see derivation 3 for Madhavan et al. (1997)).[5]

$$\text{Madhavan et al.} \quad \Delta P_t = (\phi + \theta)x_t - (\phi + \rho\theta)x_{t-1} + u_t$$

$$\text{Glosten-Harris} \quad \Delta P_t = c_0 \Delta x_t + c_1 \Delta(x_t v_t) + z_0 x_t + z_1 x_t v_t + u_t$$

To model the effect of a change in adverse selection due to MiFID II, an additional adverse selection component is included after the implementation date. The dummy variable d_t is zero prior to January 3rd, 2018, and one starting from this date. Therefore, the combined adverse selection parameter include the permanent parameter (θ_0 or $z_{0,0}, z_{1,0}$) and the assumed event effect (θ_1 or $z_{0,1}, z_{1,1}$). If not mentioned,

[4] I drop the independent and identically distributed rounding error ξ with mean zero for simplicity.

[5] To be precise, u_t here includes the change in the rounding error $\Delta\xi$ instead of ξ as in Eq. (3) and (4).

all following equations will use θ, z_0 and z_1 as specified here.

$$\text{Madhavan et al.:} \quad \theta = \theta_0 + \theta_1 d_t$$

$$\text{Glosten-Harris:} \quad z_0 = z_{0,0} + z_{0,1} d_t$$
$$z_1 = z_{1,0} + z_{1,1} d_t$$

Inserting the additional adverse selection components into the basic models yields the following price changes for the extended models:

$$\text{Madhavan et al.} \quad \Delta P_t = \left(\phi + \theta_0 + \theta_1 d_t\right)x_t - \left(\phi + \rho(\theta_0 + \theta_1 d_t)\right)x_{t-1} + u_t \tag{6}$$

$$\text{Glosten-Harris} \quad \Delta P_t = c_0 \Delta x_t + c_1 \Delta(x_t v_t) + (z_{0,0} + z_{0,1} d_t)x_t + (z_{1,0} + z_{1,1} d_t)x_t v_t + u_t \tag{7}$$

The quoted bid-ask spread $s_{Q,t}$ as difference between bid and ask price is an easily observable a priori measure for potential transaction cost. The model implied quoted spread is obtained by calculating the implied quotes, which are conditioned on the trade indicator (see Eq. (1),(3) / (2),(4)). The Glosten-Harris spreads include trade volume v_t and are therefore time-dependent.

$$\text{Madhavan et al.} \quad s_Q = 2(\theta + \phi) \tag{8}$$

$$\text{Glosten-Harris} \quad s_{Q,t} = 2(c_t + z_t) \tag{9}$$

The effective spread s_E for a buyer (seller) initiated trade is defined as twice the difference between the transaction price (prevailig midquote) and the prevailing midquote (transaction price). It takes into account trading inside the spread and the effect of large orders going through multiple layers of the order book. The derivation for the Madhavan et al. (1997) model spread excluding $x = 0$ is provided by Theissen and Zehnder (2014). Since trades within the spread are supposed to execute exactly at the midquote, the effective spread is zero for $x = 0$. The resulting expected effective spreads equal the quoted spreads in Eq. (8) and (9) times the probability of a trade at the bid or ask.[6]

$$\text{Madhavan et al.} \quad s_E = 2(1-\lambda)(\theta + \phi) \tag{10}$$

$$\text{Glosten-Harris} \quad s_{E,t} = 2(1-\lambda)(c_t + z_t) \tag{11}$$

The realized bid-ask spread $s_{R,t}$ measures the cost of a round-trip and takes into account the price impact of the first transaction.[7] Due to the possibility of trading inside the spread, the realized spreads for both models depend on the trade indicator in t.[8] The computations of the expected realized spreads and the realized spreads conditional on the trade indicator are shown in the appendix (derivation 4 / 5).

$$\text{Madhavan et al.} \quad s_R = (1-\lambda)(2\phi + \theta) \tag{12}$$

$$\text{Glosten-Harris} \quad s_{R,t} = (1-\lambda)(2c_t + z_t) \tag{13}$$

Without the autocorrelation parameter ρ of Madhavan et al. (1997) model or the volume dependent components c_1 and z_1 of Glosten and Harris (1988) model, both models are equivalent to the model proposed by Huang and Stoll (1997) with a constant adverse selection and a constant transitory parameter.

2.2. Estimation

For the nonlinear extended Madhavan et al. (1997) model, the vector of model paramters $\beta_{MRR} = (\rho, \lambda, \phi, \theta_0, \theta_1)$ is estimated using the generalized method of moments (GMM). GMM requires exactly identifiable parameters and an ergodic weakly stationary stochastic process for consistent parameter estimates, but no additional assumptions about the underlying data distribution. The main idea of a method of moments estimator is to choose the estimated parameter vector $\hat{\beta}_{MRR}$ so that the sample moments match a defined set of moment equations. When the number of independent moment conditions m is equal to the number of estimated parameters k, the model is exactly identified. The unique solution of the minimization problem sets the difference of the sample moments and the moment conditions to zero given a sufficiently large sample (method of moments). For over-identified models with $m > k$, such as the extended Madhavan et al. (1997) model, one can usually only choose $\hat{\beta}_{MRR}$ to closely match sample and population moments. Hansen (1982) shows that the estimated parameters $\hat{\beta}_{MRR}$ are still consistent and asympotically normally distributed. I use iterated GMM with a Newey-West estimator[9] of the covariance matrix of moment conditions S_0 to obtain $\hat{\beta}_{MRR}$ and the heteroskedasticity consistent covariance matrix of parameters.[10]

The following 7 moment conditions are used to estimate the parameter vector β_{MRR} and a constant drift α.

$$E = \begin{pmatrix} x_t x_{t-1} - \rho x_t{}^2 \\ |x_t| - (1-\lambda) \\ u_t - \alpha \\ (u_t - \alpha)x_t \\ (u_t - \alpha)x_{t-1} \\ (u_t - \alpha)d_t x_t \\ (u_t - \alpha)d_t x_{t-1} \end{pmatrix} = 0$$

$$\text{with} \quad u_t = \Delta P_t - \left(\phi + \theta_0 + \theta_1 d_t\right)x_t + \left(\phi + \rho(\theta_0 + \theta_1 d_t)\right)x_{t-1} \tag{14}$$

[6] I denote λ also as the share of trades with $x = 0$ for the Glosten-Harris model.

[7] Madhavan et al. (1997) call this the effective spread.

[8] In their paper, Glosten and Harris (1988) do not allow for trades between the quotes so the effective spread $s_{R,t} = 2c_t + z_t$ only depends on the traded volume.

[9] The chosen number of lags equals the nearest integer of $T^{0.25}$ with T as the number of observations (see Greene, 2003, p.142).

[10] For a detailed description of the methodology, see Hayashi (2000, pp.204-214, 454-486).

The first moment equation defines the first-order autocorrelation of the order flow, the second one the probability of trading inside the spread and the third one the constant price drift. The last four equations state orthogonality of newly available public information to the regressors x_t, x_{t-1}, $d_t x_t$ and $d_t x_{t-1}$.

The Glosten-Harris price change in Eq. (7) is estimated with ordinary least squares, which can be seen as a solved case of the method of moments method with the orthogonality assumptions as moment conditions. While Glosten and Harris (1988) state that OLS is not efficient because of round-off errors and a possibly time-dependent variance of u_t, the estimated coefficients $\hat{\beta}_{GH}$ will still be consistent and the white covariance matrix of parameters accounts for heteroskedasticity.

The implied model spreads are consistently estimated by using the estimated model parameters $\hat{\beta}$ instead of the true population parameters β for the quoted spreads in Eq. (8) and (9). However, due to a potentially different probability of trades inside the spread λ before and after MiFID II, the effective and realized spreads are calculated per observation instead of using Eq. (10), (11), (12) and (13). For the Glosten-Harris model, this additionally removes the bias of possibly correlated trade indicators and volumes.

3. Data

3.1. Source and Selection

The data was scraped from by PhD candidate Johannes Bleher from the chair of Econometrics, Statistics and Empirical Economics at the University of Tuebingen. The website netfonds.no of the Norwegian Netfonds bank AS (2018) gives users access to trading on Scandinavian, US and European exchanges. The stocks in the sample are traded via the Cboe European Equities exchange [11], which is the largest European stock exchange with 23.14% market share for DAX stocks (see Cboe European Equities, 2019a, market statistics by index). The BXE and CXE integrated books are anonymous central limit order books with both displayed and hidden liquidity for European equities. The main allowed order types for integrated books are as follows: displayed and non-displayed limit orders, displayed and non-displayed market orders within the order price collar (1% of the European Best Bid and Offer[12]), iceberg orders, displayed and non-displayed pegged orders using the Primary Best Bid and Offer[13], displayed and non-displayed post only orders for market making and sweep orders that access both the BXE and the CXE integrated order book (see Cboe European Equities, 2019b, pp.23-26). Continuous trading is possible from 9:00am to 5:30pm (CET) with an opening and a closing auction. Apart from the integrated order books, Cboe European Equities provides a periodic auction book and a seperate dark book for non-displayed orders (see Cboe European Equities, 2019b, pp.5-6).

The original sample contains separated integrated order book and transaction data on 203 German equities from October 2017 to March 2018. Securities with less than 5000 observations from December 2017 to January 2018 were removed. Since higher impacts of the aggregation methods in Section 3.2 on actively traded assets might bias the results, the 10 most liquid assets of the sample were also excluded. Therefore, the sample contains 50 stocks with 5000 to 52000 transactions from December 2017 to January 2018. To compare short- and midterm effects, model estimation is done for a two months time frame[14] (December to January) and a six months time frame (October to March).

SAS On Demand for Academics 9.4 and SAS University Edition 9.4 (basic edition) were used for data processing, model estimation and test implementation.

3.2. Trade Classification and Aggregation

The widely used method for inference of trade direction proposed by Lee and Ready (1991) requires the price P_t, the best bid P_t^b and the best ask P_t^a at transaction time t. A trade is classified as a buy (sell) if the transaction price P_t is higher (lower) than the midquote. If the transaction price is equal to the midquote, the tick test classifies the trade by tracing back to the price change: if it was an uptick (downtick), the trade is classified as a buy (sell).

Since the time variable t is only measured in seconds for the position and the trade data, time stamps with multiple quote changes do not allow to determine the prevailing quotes at the transaction time. Due to large changes in quotes within a second, using the average bid and ask quotes per second would reduce the accuracy of trade identification. Therefore, an alternative method is employed based on the highest observed bid quote $P_t^{b,max}$ and the lowest observed ask quote $P_t^{a,min}$ during a second. A trade is classified as a buy if $P_t^{b,max}$ is smaller than and $P_t^{a,min}$ is equal to or smaller than P_t. A trade is classified as sell if $P_t^{b,max}$ is equal to or greater than and $P_t^{a,min}$ is greater than P_t. The remaining trades are classified as trades neither buyer nor seller initiated with $x = 0$. This method should classify most buys and sells with ordinary order types correctly. Observations that could be a buy or a sell according to the displayed quotes are uncertain and therefore signed as neither buyer nor seller initiated.[15]

For multiple transaction within a second, the occurrence order is uncertain. As large trades are split up into multiple observations if they go through multiple layers of the order book, the trade volume v and the first-order serial correlation

[11] BATS Europe Exchange was rebranded to Cboe European Equities in 2017.

[12] The European Best Bid and Offer is the best price available in European central limit order books of regulated markets.

[13] Xetra quotes for German equities.

[14] The time frame contains 20 trading days before and 22 after the implementation of MiFID II.

[15] This method of trade classification was proposed by PhD candidate Johannes Bleher from the chair of Econometrics, Statistics and Empirical Economics at the University of Tuebingen.

of order flow ρ are biased.[16] To correct for this, a majority rule determines the trade indicator and aggregates price and volume to a single trade observation per second.[17] This method leads to unbiased model estimates if all observations within a second belong to one transaction and the trade indicators are the same. For multiple transactions within the observations of the same trade indicator, the Madhavan et al. autocorrelation coefficient ρ and the trade-volume dependent Glosten-Harris coefficients c_1 and z_1 will be downwards-biased.

Depending on the number of trades for the security, 55-80% of the trade observations are impacted by quote aggregation and 5-20% are impacted by trade aggregation. 30-45% of the trades are classified as inside the spread.

Transactions before and after the official trading hours from 9:00am to 5:30pm (CET) are deleted. Overnight price changes are removed because the opening auction price changes typically do not follow the same distribution as price changes for continuous trading (see Amihud and Mendelson, 1987).

3.3. Descriptives

Table 1 provides average mean, standard deviation, skewness and excess kurtosis for relevant variables before and after the implementation of MiFID II. Figures 5 to 16 in the appendix show the distribution of means across securities as a histogram and a as time series plot. All variables are positively skewed with positive excess kurtosis[18] except for the trade indicator.

Prices rose in December and fell slightly in January with similar standard deviation and decreasing kurtosis for price P and price change ΔP.[19] More buys (sells) than sells (buys) occurred for the period of increasing (decreasing) prices. The daily distribution for the trade indicator in Figure 10 in the appendix shows that the share of buys (sells) varied from about 40% to 60% of the transactions [20]. The Madhavan et al. assumption of $E(x) = 0$ might not hold for the time frame because of a possible correlation of the trade indicator and short term price movements.

Trade volume v and the number of trades per day $tr./day$ increased from December to January, which could have various reasons such as the inactivity during the Christmas break in December or new portfolio allocations and strategies in the new year. However, the distribution of trade volume v is highly susceptible to data aggregation (see Section 3.2). The shift in mean trade volume could be caused by a higher number of trades which increases the probability of aggregating multiple trades within a second. This might also explain the positive skewness and kurtosis of trade volume (see Figure 11 in the appendix). The higher number of trades per day in January could also be caused by increased attractiveness of the Cboe trading venue. This may indicate a successful shift of trading volume to more structured market places as intended by MiFID II.

Quoted spreads decreased by 1.0 cents from December to January while effective spreads increased marginally. Standard deviations fell sharply for both measures. The low ratio of effective to quoted spread is partly caused by trades inside the spread. In addition, the fact that best bid and best ask vary within a second could lead to more sells (buys) at higher bid (lower ask) quotes while s_Q and s_E are calculated using averages. Still, the considerable difference between quoted and effective spread reduces their validity as observed measures of transaction cost. The relative spreads $r_{Q,MQ}$ and $r_{E,MQ}$ compare the spread to the midquote and are used as a standardized measure for different security prices. The relative effective spread $r_{E,MQ}$ decreased by 3.2% compared to the 4.0% increase for the effective spread. This indicates that absolute effective spreads are not proportional to security prices.

The same descriptives for the time frame from October 1st, 2017, to March 31st, 2018 are provided in Table 4 in the appendix. Price movement, trading activity and spread changes all have the same directions as for the smaller time frame. Price volatility increased for the period from January to March and effective spread volatility is constant compared to the decrease in Table 1.

From January 2nd to January 3rd, tick sizes increased for 38 securities of the sample and stayed constant for 12 securities due to the introduction of the MiFID II ticksize regime[21]. An increase in minimum tick size generally increases spreads and transaction cost (Verousis et al., 2018). Boyde et al. (2018) and a paper published by the french financial markets regulator Autorite des Marches Financiers (2018)[22] show that the minimum tick size regime of MiFID II is the main determinant of relative quoted spread changes for individual securities. Relative quoted spreads for DAX stocks with an rise in minimum tick size increased by 35.6%, the overall average increased by 8.9% (see Boyde et al., 2018, p.6). These findings are not confirmed by the decreasing relative quoted spreads for the Cboe data. Unequal sample composition and trading venues could be one reason for the deviant effect. Besides, the discrepancy could be caused by the

[16] Trade volume v is underestimated for larger trades. ρ is overestimated because one transaction splits up into multiple observations with the same trade indicator x.

[17] The volume-weighed trade indicator for all trades within the second is calculated. For $\overline{x} >= \frac{1}{3}$, the aggregated indicator x_t is set to 1, for $\frac{1}{3} > \overline{x} > \frac{1}{3}$, $x_t = 0$ and for $\overline{x} <= -\frac{1}{3}$ follows $x_t = -1$. For the aggregated trade observation per second, the accumulated volume and the volume-weighed average price of all observations with $x_{t,i} = x_t$ is used. If $x_t = 0$ and no observation fulfills $x_{t,i} = x_t$, then the accumulated volume and the volume-weighed average price of all observations within the second is used.

[18] Excess kurtosis is defined as kurtosis -3. If positive, the distributions kurtosis is higher than the kurtosis of the normal distribution.

[19] The mean price difference cannot be entirely explained by the mean price change ΔP because overnight price changes are deleted.

[20] This is a simplified interpretation of the trade indicator assuming that all trades are either buys or sells.

[21] The minimum tick size for each stock in the sample is determined by sorting the quotes in ascending order and calculating the smallest difference between quotes. Taking differences of the minimum tick size on January 3rd and January 2nd in 2018 yields the change in minimum tick size for a security assuming no significant change in price or trading activity.

[22] Authors unknown.

Table 1: Descriptive statistics (Dec. 2017 - Jan. 2018)

Note. This table presents the descriptive statistics for key variables from December 1st, 2017, to January 31st, 2018. The mean, standard deviation, skewness and excess kurtosis of the individual security distributions are reported before and after the implementation of MiFID II. The following variables are included: price P in Euro, price change between trades ΔP in cent, trade indicator x, quoted/effective spread s_Q/s_E in cent, volume per trade v in 1000 shares, transactions per day $tr./day$, relative quoted/effective spread $r_{Q,MQ}/r_{E,MQ}$ in basis points.

	Mean		Std.Dev.		Skewness		Excess kurtosis	
	before	after	before	after	before	after	before	after
P	72.244	75.48	1.465	1.423	0.498	0.195	13.369	1.191
ΔP	0.000	-0.008	3.458	3.546	-1.100	-0.498	41.386	37.200
x	0.002	-0.003	0.021	0.022	0.119	0.157	-0.156	-0.121
v	11.590	12.254	21.194	27.601	1.424	1.415	3.556	5.553
$tr./day$	502.595	580.671	135.412	136.625	0.347	0.831	0.636	4.903
s_Q	8.070	7.004	7.759	5.979	3.118	3.557	25.446	18.368
s_E	1.346	1.400	4.472	3.036	2.374	2.334	32.443	24.310
$r_{Q,MQ}$	12.060	9.620	11.646	5.091	3.145	3.557	25.654	18.436
$r_{E,MQ}$	1.955	1.893	7.076	2.525	2.504	2.320	33.376	25.054

average quoted spread calculation which is not time-weighed for the Cboe quotes.

For consistent estimation results, weakly stationarity of price changes is required. The Dickey-Fuller test rejects the null hypothesis of non-stationary price changes for all securities on a 1% significance level.

4. Empirical Results

4.1. Parameter Estimates

Table 2 shows summary statistics of the Madhavan et al. parameter estimates. Autocorrelation of order flow $\hat{\rho}$ is positive as assumed by the model. 39.22% of the trades are classified as neither buyer nor seller initiated. The transitory parameter estimate $\hat{\phi}$ with 0.69 cents is more than twice as large as the estimated adverse selection parameter before MiFID II $\hat{\theta}_0$ with 0.32 cents. The additional adverse selection parameter in January, $\hat{\theta}_1$, is comparable in size to $\hat{\theta}_0$, which leads to a combined adverse selection parameter of 0.62 cents after MiFID II. The drift estimate $\hat{\alpha}$ is economically insignificant. Without knowledge of the parameter distribution, the mean of parameter estimates $\overline{\hat{\beta}_i}$ is still assumed to be normally distributed, so a t-test on the mean parameter can be conducted. The p-value for this test shows that all parameters except the drift α are significantly different from zero on a 1% level. On an individual level, the share of significant parameters for two-sided and one-sided tests supports the overall t-test results. The first-order autocorrelation parameter ρ, the share of trades inside the spread λ and the transitory parameter ϕ are significantly greater than zero for all stocks on a 5% significance level. For the adverse selection parameters θ_0 and θ_1, the null hypothesis of a parameter value smaller or equal to zero is rejected for 58% and 66% of stocks respectively. After the MiFID II implementation, the combined adverse selection parameter θ is significantly greater than zero for 47 stocks on a 5% level.

The parameter estimates for the six months estimation period in Table 7 in the appendix are similar for ρ, λ, θ_0 and α. The estimated transitory component $\hat{\phi}$ is 0.08 cents lower and the MiFID II adverse selection component $\hat{\theta}_1$ 0.16 cents higher for the longer estimation period. The adverse selection parameters θ_0 and θ_1 are significantly greater than zero for 76% and 86% of stocks respectively. The combined adverse selection parameter after MiFID II is significantly greater than zero for all stocks.

Compared to the Madhavan et al. (1997) estimates for a sample of 274 NYSE stocks in 1990, the parameters are notably different in size.[23] Higher autocorrelation (0.38), less trades inside the spread (30%) and substantially higher transitory (4.18) and adverse selection (3.14) parameters for the NYSE sample signifies a change in market dynamics and efficiency from 1990 to 2017. Theissen and Zehnder (2014) use signed transaction and spread data for DAX stocks traded at XETRA in 2004 to estimate the Madhavan et al. (1997) model. Their mean estimated transitory parameter $\hat{\phi}$ with 0.48 cents is slightly lower than for the Cboe sample, which could be explained by lower direct transaction costs for the highly liquid DAX-stocks. While the on average smaller capitalized stocks in the Cboe sample are expected to have higher adverse selection costs (see Frey and Grammig, 2006), $\hat{\theta}$ is higher for the DAX sample than for the Cboe sample even after the MiFID II implementation (0.70 cents to 0.62 cents). The higher DAX autocorrelation of 0.22 combined with the Madhavan et al. (1997) estimate of 0.38 supports the idea

[23] The parameters are reported over 5 intra-day trading intervals. The mean of parameters is used for comparison with the German sample.

Table 2: Parameter estimates (Madhavan et al., Dec. 2017 - Jan. 2018)

Note. The table presents summary statistics of the Madhavan et al. model parameters estimates based on data from December 1st, 2017, to January 31st, 2018. The mean of estimated parameters $\overline{\hat{\beta}_i}$ and the mean of estimated parameter standard deviations $\overline{\hat{\sigma}}_{\hat{\beta}_i}$ are given with i denoting the individual securities. The estimated standard deviation of the mean estimated parameter $\hat{\sigma}_{\overline{\hat{\beta}_i}}$ is used to compute the p-value for the two-sided t-test on $\overline{\hat{\beta}_i}$. On a single security level, the share of significant parameters for two-sided and one-sided tests on a 5% level is provided. The parameter mean and standard deviation for ϕ, θ_0, θ_1 and α are denoted in cent.

	all securities				*single securities - significant β_i*			
	$\overline{\hat{\beta}_i}$	$\overline{\hat{\sigma}}_{\hat{\beta}_i}$	$\hat{\sigma}_{\overline{\hat{\beta}_i}}$	P	$H_0:$	$\beta_i = 0$	$\beta_i >= 0$	$\beta_i <= 0$
ρ	0.1087	0.000074	0.0036	<0.01%		100%	0%	100%
λ	0.3922	0.000020	0.0042	<0.01%		100%	0%	100%
ϕ	0.6910	0.000036	0.0765	<0.01%		100%	0%	100%
θ_0	0.3207	0.000111	0.0966	0.17%		68%	12%	58%
θ_1	0.3021	0.000154	0.0768	0.03%		74%	10%	66%
α	-0.0021	0.000018	0.0048	66.21%		6%	10%	0%

that the trade aggregation process imposes a negative bias on the autocorrelation parameter ρ for the Cboe sample (see Section 3.2).

Table 5 in the appendix presents the Glosten-Harris parameter estimates for the two month time frame. The mean constant transitory parameter $\hat{c}_0$ with 0.72 cents is significantly different from zero, which is supported by the tests on a single security level. The mean volume-dependent transitory parameter $\hat{c}_1$ per 100 shares is significant according to the overall t-test, but on the individual level only 40% of stocks reject the null hypothesis of $c_1 = 0$. For the average trade volume of 12000 shares (see Table 1), the volume-dependent component is 0.08 cents, which is marginal compared to the constant transitory component. Nevertheless, since trade volume is positively skewed, some securities and observations will have sizable volume-dependent transitory components.[24] The constant transitory parameters $z_{0,0}$ and $z_{0,1}$ are both positive and significant according to the overall t-test. The test results for single stocks are less clear. Only for 68% of the sample the parameters are significantly different from zero, 68% of individual parameters for $z_{0,0}$ and 62% for $z_{0,1}$ are significantly greater than zero. The combined constant adverse selection parameter z_0 after MiFID II is equal in size to the constant transitory component and significantly greater than zero for 96% of the stocks.

The volume-dependent adverse selection parameters $\hat{z}_{1,0}$ and $\hat{z}_{1,1}$ are both negative, but $\hat{z}_{1,1}$ is statistically and economically insignificant. For the average trade volume, the volume-dependent adverse selection component is -0.38 cents which is similar to the base constant adverse selection parameter $\hat{z}_{0,0}$ in absolute value. The combined parameter z_1 is significantly different from zero for 70% of stocks after the MiFID II implementation. According to a multiple restriction Wald test, the overall adverse selection component is significantly different from zero for 41 stocks before and 48 stocks after the MiFID II implementation.[25]

The differences of the Glosten and Harris (1988) estimates for the longer time frame in Table 8 in the appendix are similar to the differences for the Madhavan et al. (1997) estimates. The constant transitory parameter $\hat{c}_0$ and the base constant adverse selection parameter $\hat{z}_{0,0}$ are 0.05 cents lower, the MiFID II constant adverse selection parameter $z_{0,1}$ is 0.12 cents higher for the longer estimation period. The combined volume-dependent adverse selection parameter $\hat{z}_1$ is closer to zero before and after MiFID II for the longer time frame, but the additional MiFID II parameter $\hat{z}_{1,1}$ is more relevant. The combined parameter z_0 after the MiFID II implementation is significantly greater than zero for all stocks. The overall adverse selection component is significantly different from zero for 48 stocks before and all stocks after the MiFID II implementation.

The model specification without c_1 and z_0 proposed by Glosten and Harris (1988) is rejected for 41 stocks before and 48 stocks after the MiFID II implementation using a Wald test. The size and direction of the volume-dependent adverse selection component for the German sample do not support support the hypothesis of higher trade volumes indicating informed trading. Both the Madhavan et al. and the Glosten-Harris overall model are significant for all stocks.

Comparing the model parameter estimates, the transitory parameters $\hat{\phi}$ an $\hat{c}_0$ are almost equal in size. This is not surprising since they both measure non-persistent effects and are incorporated in the models in the same way. The constant adverse selection parameter before MiFID II $\hat{\theta}_0$ is

[24] The upper 5% confidence interval for the daily mean trade volume in Figure 12 in the appendix is about 45000 shares per transaction, which would lead to a volume-dependent transitory component of 0.32 cents. A median volume of about 7000 shares per transaction would lead to a volume-dependent transitory component of 0.049 cents.

[25] H_0 before MiFID II: $z_{0,0} = 0$, $z_{1,0} = 0$. H_0 after MiFID II: $z_{0,0} + z_{0,1} = 0$, $z_{1,0} + z_{1,1} = 0$.

Table 3: Spread estimates (Madhavan et al., Dec. 2017 - Jan. 2018)

Note. This table presents model-implied estimated Madhavan et al. spreads and spread ratios before and after the implementation of MiFID II from December 1st, 2017, to January 31st, 2018. The mean $\overline{\hat{s}_i}$ / $\overline{\hat{r}_i}$ and the estimator of the variance across the sample $\hat{\sigma}_{\overline{\hat{s}_i}}$ / $\hat{\sigma}_{\overline{\hat{r}_i}}$ are reported in cents for the quoted spread s_Q and the effective spread s_E. The shares of implied to observed spread $r_{Q,Data}$ and $r_{E,Data}$ and the share of implied spread attributable to adverse selection r_{Adv} are denoted in percent. P-values for the paired t-test on difference in means before and after the MiFID II implementation are given in percent.

	Mean		*Std.Dev.*		Paired t-Test
	before	after	before	after	P
s_Q	2.023	2.627	2.094	2.415	0.03%
$r_{Q,Data}$	26.482	37.755	11.442	10.555	<0.01%
s_E	1.261	1.573	1.278	1.501	0.20%
$r_{E,Data}$	90.590	110.013	26.719	22.876	<0.01%
r_{Adv}	17.602	41.751	34.734	16.332	<0.01%

smaller than $\hat{z}_{0,0}$, which might partly be due to the negative volume-dependent parameter $\hat{z}_1$ that has to be compensated. The assumed MiFID II effect on adverse selection is measured by θ_1, $z_{0,1}$ and the negligible volume-dependent parameter $z_{1,1}$. Constant adverse selection components for both models are similar in size and significantly positive for two out of three stocks. For the six months estimation period, the additional adverse selection parameters are larger and significantly positive for five out of six stocks.

4.2. Spread Estimates

The economic implications of the parameter estimates are assessed by investigating the model implied spreads (see Eq. (8) to (11)) as measures for transaction cost.

Table 3 presents the Madhavan et al. implied spreads, the share of implied to observed spread and the share of implied spread attributable to adverse selection before and after the application of MiFID II. A paired t-test on difference in means before and after the implementation date is conducted and indicates a significant change in means for all variables and both models. The required normal distribution of differences plotted in Figures 3 and 4 in the appendix is unlikely to hold for all variables. Therefore, the significance of the changes in means according to the paired t-test should be evaluated with caution.

From December to January, the implied quoted spread s_Q increased from 2.02 cents to 2.63 cents, which is caused by the positive additional adverse selection parameter $\hat{\theta}_1$. The observed quoted spread is highly underestimated as shown by the low share of implied to observed quoted spread $r_{Q,Data}$. The observed quoted spread decreased after the MiFID II implementation whereas the implied quoted spread increased. Madhavan et al. (1997) argue that their systematic underestimation of the quoted spread by a third might be caused by a higher probability of midquote transactions when spreads are large.

The implied effective spread s_E is 0.31 cents higher after the MiFID II implementation while the observed spread marginally increases by 0.05 cents. Using Eq. (12), the approximated implied change in realized spread s_R from December to January is 0.18 cents ($= (1-\hat{\lambda})\hat{\theta}_1$).[26] Increasing transaction cost measured by s_E and s_R is attributed to a higher adverse selection component of the spread. The model implied effective spread underestimates the observed effective spread by 9.6% before and overestimates it by 10.0% after the implementation. In comparison to the 1.26 cents (before MiFID II) or 1.573 cents (after MiFID II), Theissen and Zehnder (2014) report average effective spreads of 2.36 cents for the DAX sample without trades inside the spread. Furthermore, Theissen and Zehnder (2014) provide evidence for a 20% downwards bias of implied spreads of trade indicator models caused by negative serial correlation of new public information and the trade indicator. This bias cannot be found for the Cboe sample. Adding the fact of reasonable parameter estimates for the Cboe sample when compared to the results of Theissen and Zehnder (2014) supports the assumption that the aggregated observed effective spreads are probably inaccurate (see Sections 3.2 and 3.3).

For the six months time frame, the assumed adverse selection effect is larger with 0.88 cents for s_Q and 0.51 cents for s_E compared to the 0.60 cents and 0.31 cents for two months (see Table 9 in the appendix). The Glosten-Harris spread estimates in Tables 6 and 10 in the appendix are comparable in size for the estimates before and after the MiFID II implementation.

5. Impact Evaluation

The validity of the measured MiFID II effect on adverse selection depends upon the capability of the chosen microstructure models to quantify adverse selection, the data quality and the ability to attribute the effect to the MiFID II changes.

[26] This simplified calculation of s_R relies on the expected realized spread in Eq. (12) rather than the conditional realized spread per observation. If λ differs in the time before and after the MiFID II implementation, the two methods do not yield the same result.

Ness et al. (2001) state that the adverse selection measures of Madhavan et al. (1997) and Glosten and Harris (1988) are related to volatility and the share of informed traders at the market, but not correlated with other adverse selection measures. Both models focus on the information content of the order flow while for instance neglecting the information revealed by the open limit order book. The Glosten and Harris (1988) idea of higher trade volume revealing private information is not supported by the results for the Cboe sample. The distribution of the volume-dependent parameter in Figure 24 in the appendix suggests that most stocks display a negative volume-dependent effect, though there is no clear direction of the effect for all stocks. This result can partly be attributed to the use of algorithms or order types such as iceberg orders that can split up large orders to reduce price impacts. The negative effect could be caused by uninformed traders who are required to move large volumes to meet their required portfolio composition or risk tolerance level without having the time or the resources to minimize price impacts. Moreover, the impact of aggregating trade volume on the measured effect (see Section 3.2) is hard to assess as it might depend on individual stock characteristics such as trading activity, price and / or volatility. The Madhavan et al. (1997) assumption of a positive serial correlation of the order flow holds for the Cboe sample. Although the assumed quote revision due to surprise in order flow $\hat{\rho}x$ seems low with 0.03 cents before and 0.07 cents after MiFID II for $x \neq 0$, Section 4.1 provides an indication of the downwards-biased autocorrelation. Furthermore, the ability to estimate adverse selection with serially correlated trade indicators is an advantage compared to the Glosten and Harris (1988) model. Hence, the Madhavan et al. (1997) results might be more appropriate as an adverse selection measure for the Cboe sample than the Glosten and Harris (1988) results.

The discrepancies in model implied spreads and observed spreads shown in Section 4.2 are a sign of poor model performance. However, the high share of quote observations affected by aggregation increases uncertainty of the quoted observed spread and the midquote which is used to determine the observed effective spread. Although the transactions used for the model estimation are signed by using quote data, the sign rule in Section 3.2 declares uncertain trades as inside the spread. Even if the trade aggregation process weakens the estimated effect size of serial correlation and trade volume, the models still incorporate the basic Huang and Stoll (1997) idea that order flow is informative. As a consequence, the model implied spreads based on transaction data might be more suitable to determine the prevailing spread at the time of the transaction than the aggregated observed spreads. Additionally, implied and observed effective spreads are similar and the assumed MiFID II change is positive for both.

The Madhavan et al. (1997) model parameter $\hat{\theta}_1$ of 0.3021 cents implies 0.31 cents higher effective spreads and approximately 0.18 cents higher realized spreads in January 2018 than in December 2017. For the six months estimation period, $\hat{\theta}_1$ with 0.4385 cents implies 0.51 cents higher effective and approximately 0.27 cents higher realized spreads for January to March 2018 than for October to December 2017. The direction of the measured effect is not as expected for the MiFID II regulations, which are supposed to increase market transparency and therefore reduce the adverse selection component of transaction cost.

Indeed, it cannot be followed that the measured change in adverse selection is attributable to the implementation of MiFID II on January 3rd, 2018. Other events in the estimation time frame after January 3rd might have also caused adverse selection to rise. To further evaluate this, the Madhavan et al. (1997) and Glosten and Harris (1988) extended models are estimated for event dates from November 2017 to February 2018 with a rolling estimation window of two months. The event date is the date for the activation of the additional adverse selection parameter/s.

Figures 1, 2 and 17 to 26 in the appendix show the rolling parameter estimates for both models. The mean rolling parameter estimate for the additional adverse selection parameter θ_1 in Figure 1 rises from 0.0 cents in mid-November to 0.3 cents for the last days of December and the first days of January. After that, $\hat{\theta}_1$ steadily decreases to 0.1 cents at the start of February, then drops down to -0.1 cents. The adverse selection parameter for the whole estimation time frame $\hat{\theta}_0$ in Figure 2 remains about constant for November and December. Logically, it increases from the start of January 2018 to mid-February from 0.32 cents to 0.8 cents because the dropped out additional parameter θ_1 has to be explained by θ_0 before the event. Figures 21 and 22 in the appendix show a similar relationship for the constant adverse selection parameters $\hat{z}_{0,1}$ and $\hat{z}_{0,0}$ for the Glosten and Harris (1988) model. The volume-dependent additional parameter $\hat{z}_{1,1}$ gradually increases from mid-December with -0.1 cents per 10000 shares to 0.0 cents at the year change to a high of over 0.1 cents in the last third of January and falls down to -0.1 cents afterwards.

On the one hand, the peak of the additional adverse selection parameters at the turn of the year provides evidence for a relevant change in adverse selection during that time. Positive falling parameters for the month of January imply the interpretation of long-term effects rather than additional events. Although many events at the start of January 2018 possibly impact information asymmetries for stocks, MiFID II fundamentally changes transparency and functionality of financial markets as a whole. Therefore, MiFID II is presumably the main event impacting changes in information asymmetry.

On the other hand, if only the MiFID II implementation influenced adverse selection at that time, the rise of the additional adverse selection effect would start in early December, not in mid-November. This observation could be explained by early adaptations of market participants to the regulations. Seasonality or other unrelated changes in volatility of newly available public information, share of informed traders and trading activity are likely to impact adverse selection. For instance, the approaching release of annual financial statements and new strategic announcements are plausible rea-

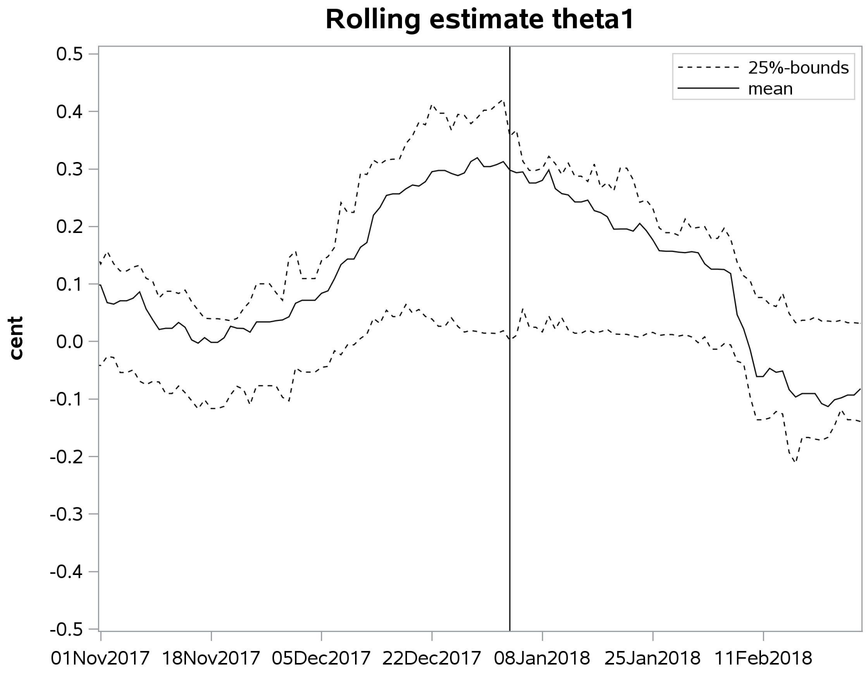

Figure 1: Rolling parameter estimate $\hat{\theta}_1$

Note. This figure plots the mean estimated Madhavan et al. (1997) parameter $\hat{\theta}_1$ for event dates from November to February with a two months estimation time frame. Starting from the event date, the additional adverse selection parameter is active. The vertical line displays the MiFID II implementation date.

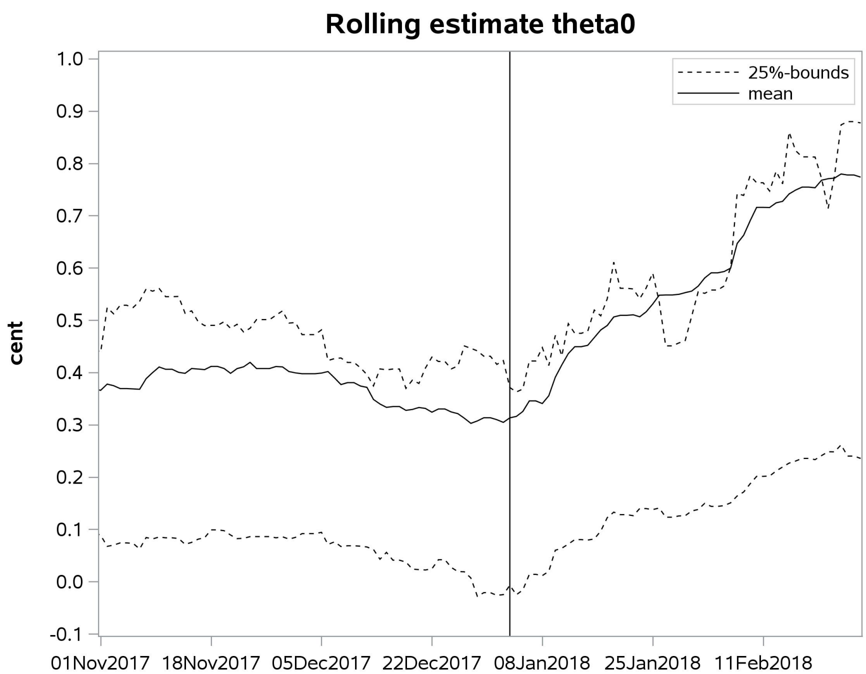

Figure 2: Rolling parameter estimate $\hat{\theta}_0$

Note. This figure plots the mean estimated Madhavan et al. (1997) parameter $\hat{\theta}_0$ for event dates from November to February with a two months estimation time frame. Starting from the event date, the additional adverse selection parameter is active. The vertical line displays the MiFID II implementation date.

sons for increased information asymmetry at the start of the year. The length of the estimation time frame does not allow to detect and control for these patterns. Additionally, effects of most regulations are unlikely to show immediately at the implementation date.[27] The drop of the additional adverse selection parameter $\hat{\theta}_1$ shown in Figure 1 at the start of February could be a long-term event effect. In the case of MiFID II, published transparency data was incomplete at first as not all market participants were prepared to fulfill the reporting requirements. For example the Double Volume Cap publication on dark pool trading volumes was delayed to March 7th by the European Securities and Markets Authority due to insufficient quality of the collected data (see European Securities and Market Authority, 2019). Also, adverse selection effects could persist longer than the actual information asymmetry since market participants cannot instantly incorporate newly available information into their trading behavior.

Collectively, despite evidence for higher adverse selection right after the MiFID II implementation, a reduction of adverse selection due to MiFID II in the long-run is more plausible than an immediate effect and cannot be rejected by the empirical results.

6. Conclusion

I evaluate the impact of the Markets in Financial Instruments Directive II (MiFID II) regulation on information asymmetries. The microstructure models of Madhavan et al. (1997) and Glosten and Harris (1988) are extended to measure the additional adverse selection effect after the MiFID II implementation date. A sample of 50 German equities traded at the Cboe European Equities exchange is used to estimate the models.

While the MiFID II transparency rules are expected to reduce information asymmetries, the results show more adverse selection after the regulation came into force on January 3rd, 2018. Estimated effective spreads are 0.31 cents higher in January 2018 than in December 2017. Rolling model estimation indicates a possible long-term reduction in adverse selection. I discuss the attribution of the adverse selection changes to MiFID II.

Further investigation of MiFID II effects could use methods to identify Granger causal effects of the MiFID II implementation. Additionally, a larger estimation time frame and increase in sample size could be valuable to detect more resilient long-run effects on adverse selection. Similarly, the change in inventory holding and direct transaction cost may be evaluated. Potential stock characteristics that determine the size of the estimated effects could be identified. Furthermore, the proposed extended microstructure models allow to examine effects of other events impacting information asymmetries on financial markets.

[27] The tick size band introduced by MiFID II is an exception because it was implemented at January 3rd and directly impacted the price formation process. The increasing sample mean transitory parameters ϕ and c_0 until the end of January imply higher inventory holding and direct transaction costs (see Figures 17 and 25 in the appendix). This is consistent with the increased minimum tick size for the majority of stocks at the MiFID II implementation date, which is included in the transitory parameter.

References

Amihud, Y. and Mendelson, H. Trading Mechanisms and Stock Returns: An Empirical Investigation. *Journal of Finance*, 42(3):533–53, 1987.

Autorite des Marches Financiers. MiFID II: Impacts of the new Tick Size Regime. *Autorite des Marches Financiers: Risk and Trends*, 2018.

Boyde, L., Yang, S., Campbell, T., and Naidoo, N. Order Book Liquidity on Primary Markets post MiFID II. *Deutsche Bank*, 2018.

Cboe European Equities. Cboe European Equities Website. https://markets.cboe.com/europe/equities/overview/, 2019a. Accessed: 2019-01-04.

Cboe European Equities. Cboe European Equities Participant Manual Draft March 2019. https://cdn.cboe.com/resources/participant_resources/CboeEE_EU_ParticipantManual.pdf, 2019b. Accessed: 2019-01-04.

European Parliament and Council of the European Union. DIRECTIVE 2014/65/EU on Markets in Financial Instruments. Official Journal of the European Union, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014L0065&from=DE, 2014. Accessed: 2019-01-04.

European Securities and Market Authority. European Securities and Market Authority Website. https://www.esma.europa.eu/policy-rules/mifid-ii-and-mifir, 2019. Accessed: 2019-01-04.

Frey, S. and Grammig, J. Liquidity supply and adverse selection in a pure limit order book market. *Empirical Economics*, 30(4):1007–1033, 2006.

Glosten, L. R. and Harris, L. E. Estimating the components of the bid/ask spread. *Journal of Financial Economics*, 21(1):123 – 142, 1988.

Greene, W. *Econometric Analysis*. NJ, Upper Saddle River, Prentice Hall, 2003.

Hansen, L. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, 50(4):1029–54, 1982.

Hayashi, F. *Econometrics*. NJ, Princeton, Princeton Univ. Press, Princeton, NJ [u.a.], 2000.

Huang, R. D. and Stoll, H. The Components of the Bid-Ask Spread: A General Approach. *Review of Financial Studies*, 10(4):995–1034, 1997.

Lee, C. and Ready, M. Inferring Trade Direction from Intraday Data. *Journal of Finance*, 46(2):733–46, 1991.

Madhavan, A., Richardson, M., and Roomans, M. Why Do Security Prices Change? A Transaction-Level Analysis of NYSE Stocks. *The Review of Financial Studies*, 10(4):1035–1064, 1997.

Ness, B. F. V., Ness, R. A. V., and Warr, R. S. How Well Do Adverse Selection Components Measure Adverse Selection? *Financial Management*, 30(3): 77–98, 2001.

Netfonds. Netfonds website. https://www.netfonds.no/, 2018. Accessed: 2018-11-05.

Roll, R. A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *Journal of Finance*, 39(4):1127–39, 1984.

Theissen, E. and Zehnder, L. S. Estimation of trading costs: Trade indicator models revisited. CFR Working Paper 14-09, Cologne, 2014.

Verousis, A., Perotti, P., and Sermpinis, G. One Size Fits All? High Frequency Trading, Tick Size Changes and the Implications for Exchanges: Market Quality and Market Structure Considerations. *Review of Quantitative Finance and Accounting*, 50(2):353–392, 2 2018.