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**AN EMPIRICAL ANALYSIS OF THE ROLE OF THE
TRADING INTENSITY IN INFORMATION
DISSEMINATION ON THE NYSE**

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Discussion paper

An Empirical Analysis of the Role of the Trading Intensity in Information Dissemination on the NYSE

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Abstract

Asymmetric information models predict comovements among trade characteristics such as returns, bid-ask spread, and trade volume on one hand and the trading intensity on the other hand. In this paper we investigate empirically the two-sided causality between trade characteristics and trading intensity. We apply a VAR-model for returns, bid-ask spread, trade volume, and trading intensity to transaction data on five stocks traded on the NYSE, covering the period August 1 until October 31, 1999. Similar to Dufour and Engle (2000), we find that the price impact of a trade is larger, the higher the trading intensity. Moreover, we establish significant feedback from the trade characteristics to the trading intensity. Wide spreads, large volume, and high returns have a significantly positive impact on the trading intensity. We show that this feedback affects the price impact of large trades in transaction and in calendar time.

Keywords: market microstructure theory, VAR-models, durations, trading intensity, price impact, impulse response functions

JEL classification: C41, G14

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1 Introduction

One of the major issues in market microstructure theory is how information is incorporated into asset prices, cf. O'Hara (1995). An important component of market microstructure theories is the concept of *asymmetric information*. This phenomenon arises when both uninformed and informed traders are present at the market. Uninformed traders trade for liquidity reasons. Informed traders, however, have private information on the fundamental value of the security to be traded. They trade to take advantage of their superior knowledge. Due to the presence of informed traders, the transaction process *itself* potentially reveals information on the underlying fundamental value of the security.

Information dissemination through trading has been the subject of both theoretical and empirical research. Hasbrouck (1991a, 1991b) uses a VAR-model to jointly model returns and trade volume. He shows that trades have persistent impact on prices, which confirms that trades convey information. Recently, the information content of the trading intensity has been investigated. The trading intensity refers to the process of durations, where a duration is defined as the time that elapses between two consecutive transactions. The main question is whether the trading intensity conveys any information on the underlying value of the asset in addition to trade volume. The models developed by Diamond and Verrecchia (1987) and Easley and O'Hara (1992) predict that this is indeed the case, due to the aforementioned asymmetric information. Dufour and Engle (2000) model the trading intensity using the ACD-model proposed by Engle and Russell (1998) and subsequently analyze a bivariate VAR-model for returns and trade sign to assess the effect of the trading intensity on the price adjustment process in both transaction and calendar time. They show that the price impact of a trade is larger the higher the trading intensity, implying that trades are more informative in periods of frequent trading.

This paper extends Hasbrouck (1991a, 1991b) and Dufour and Engle (2000) by proposing a joint model for trade characteristics (returns, trade size, bid-ask spread) and the trading intensity. We allow the trade characteristics to fully interact with the trading intensity in the sense that the possibly *two-sided* causality between the trade characteristics and the trading intensity is taken into account. The results show that the expected price impact is larger ceteris paribus when the trading intensity is higher, in line with the model proposed by Easley and O'Hara (1992) and the empirical results of Dufour and Engle (2000). Moreover, we show that the entire distribution of the price impact depends upon the trading intensity. The distribution of the price change with fast trading first-order stochastically dominates the

distribution with slow trading. Additionally, as in Engle and Lunde (1998), we document significant causality from trade characteristics to the trading intensity. Wide spreads, large volume and high returns significantly increase the trading intensity. Moreover, we show that this feedback affects the distribution of the price impact of trades, both in transaction and in calendar time.

The organization of this paper is as follows. In section 2 we review some market microstructure underpinnings with the focus on the role of the trading intensity in information dissemination. Section 3 briefly discusses the market setting on the NYSE and provides a description of the data and their sample properties. Section 4 is devoted to a multivariate model for returns, trade volume and bid-ask spread that ignores the possible role for the trading intensity. Section 5 discusses the modeling of the trading intensity, while Section 6 examines the impact of trades on prices in a VAR-model that takes the possible role of the trading intensity into account. In Section 7 the trading intensity is endogenized and the effects of the endogenous trading intensity on price changes are investigated. Finally, Section 8 summarizes the main conclusions of this paper.

2 Existing models for the information content of the trading intensity

In this section we briefly review some information-based market microstructure studies that predict a relation between the trading intensity and the underlying value of the asset.

In the model of Easley and O'Hara (1992) the market maker is uncertain about the existence of an information signal; i.e. he does not know whether or not an information event has taken place. Additionally, he does not know the direction of the possible news event (high or low information signal). Whether or not an information event has taken place, a no trade outcome can occur in both cases. In the model it is more likely that a no trade will take place when no news has been released. Since the market maker knows all relevant probabilities, he will lower the probability he attaches to a news event when the trading intensity is low. Moreover, he will change his bid and ask quotes correspondingly which will lead to a lower bid-ask spread as a direct consequence of adverse selection. The empirical implications of the Easley and O'Hara (1992) model are as follows. The model predicts that lagged durations are negatively correlated to the bid-ask spread. Since the market maker associates slow trading to a decreased risk of informed trading,

lagged durations will also be negatively correlated to price volatility.

Easley and O'Hara (1992) also conjecture a role for aggregated volume. This follows directly from the fact that each trade has unit size in the model. Therefore, aggregated volume equals the number of trades up to that moment. As a consequence, lagged aggregated volume is also positively related to the bid-ask spread and the volatility of prices. However, the assumption of a market with only unit size trades is unrealistic. It is therefore useful to consider the Easley and O'Hara (1987) model. The setting of the latter model is basically the same as in Easley and O'Hara (1992). However, although there is event uncertainty, uninformed traders are not allowed to refrain from trading. Therefore, durations do not play a role in this model. However, traders are allowed to trade either a small or a large quantity. When news has been released at the beginning of a trading day, it is more likely that a large quantity will be traded. Therefore, there is no unique spread: it is positively related to trade volume. It is straightforward to combine the Easley and O'Hara (1987,1992) models, which yields a model in which durations and different trade sizes play a role. In the combined model the absence of a trade is more likely when no news has been released and a large trade is more likely in case of a high information signal.

In a different framework Diamond and Verrecchia (1987) also relate the trading intensity to the presence of news. In this model traders either own or do not own the stock. If they do not own the stock, they might wish to short-sell when there is an opportunity to trade. However, all traders fall into three groups: those who face no costs in short selling, those who are prohibited from short selling and finally, those who are restricted in short selling. In the latter case the proceeds from short-selling are delayed until the price of the asset falls. Neither the market maker, nor the traders can observe why there has been no trade and whether a sell is a short sell or not. However, every agent knows all relevant probabilities. A no trade outcome may indicate several situations. A trader may wish to refrain from trading, or he may not be able to trade due to the short-sell restrictions or prohibitions. In this specific setup of the model, the probability of no trade is higher in case of bad news. Hence, in this model slow trading is associated to bad news. The empirical implications of this model are the following. Lagged durations and spread are positively correlated. Moreover, lagged durations and price volatility are also positively correlated in the setting of this model. Finally, lagged durations and (mid)prices as well as bid/ask quotes are negatively correlated.

Admati and Pfleiderer (1988) distinguish informed traders and liquidity traders. Liquidity traders are either nondiscretionary traders who must trade a certain number of shares at a particular time or discretionary traders who time their trades such that the expected cost of their transactions are minimized.

We consider the version of the model with endogenous information acquisition; i.e. private information is acquired at some cost and traders obtain this information if and only if their expected profit exceeds this cost. In this framework the presence of informed traders lowers the cost of trading for liquidity traders. Moreover, informed traders also prefer to trade when there are many liquidity traders present at the market. Hence, both informed and uninformed traders want to trade when the market is ‘thick’. This results in concentrated patterns of trading: informed traders and liquidity traders tend to clump together. This implies that prices are more informative in periods of frequent trading; i.e. the trading intensity positively affects volatility.

Table 1 summarizes the empirical implications of Easley and O’Hara (1987, 1992), Diamond and Verrecchia (1987) and Admati and Pfleiderer.

One of the crucial assumptions underlying the Easley and O’Hara (1987, 1992) model and Diamond and Verrecchia (1987) is the absence of feedback from the trade characteristics such as returns, bid-ask spread and trade volume to the trading intensity. Goodhart and O’Hara (1997) put forward that trade characteristics convey information on the value of the asset. Therefore, traders may learn from it and change their intensity of trading in reaction to this. Consequently, trade characteristics may affect the trading intensity. As indicated in Dufour and Engle (2000), for example, a large change in the market maker’s mid quote may be a signal to the informed traders that their information, initially unknown to other market participants, has been revealed to the market maker assuming that no new signal has been released thereafter. This means that their information is no longer superior. Therefore, the incentive to trade disappears, which decreases the trading intensity. However, from an inventory perspective, large quote changes would attract opposite-side traders, thus increasing the trading intensity. Similar effects occur when informed traders observed wide spreads or large volume trades. An additional complexity arises, however, when informed traders show strategic behavior as well, see O’Hara (1995). They will increase the probability they attach to the risk of informed trading when they notice large absolute returns, wide spreads and large trade volume and thus slow down their trading intensity in this situation. The overall effect on the trading intensity is therefore unclear when both informed and uninformed traders show strategic behavior.

3 The data

In this paper we use high frequency data on five of the most actively traded stocks listed on the NYSE, see Table 2. The data are taken from the *Trade and*

Quote (TAQ) database. For each stock, the data consist of all transactions during the months August, September and October, 1999 and consists of 64 trading days.

We remove all trades that take place outside the opening hours; i.e. before 9.30 AM and after 4.00 PM. Moreover, we also delete trades that take place before the first quotes are generated. For each stock the associated characteristics of each trade are recorded: trade moment τ_t , unsigned log trade size $|x_t|$ and¹ trade price p_t , where t indexes subsequent transactions (i.e. t indexes ‘transaction time’). All data are measured in transaction time. The duration (in ‘calendar time’) between subsequent trades is defined as $y_t = \tau_t - \tau_{t-1}$. Overnight durations are removed from the data set.

To each trade we also associate a prevailing bid and ask quote, denoted by q_t^b and q_t^a . To obtain these prevailing quotes we use the ‘five-seconds rule’ by Lee and Ready (1989) which associates each trade to the quote posted at least five seconds before the trade, since quotes can be posted more quickly than trades are recorded. The five-second rule solves the problem of potential mismatching. From the prevailing quote the prevailing bid-ask spread $s_t = q_t^a - q_t^b$ is constructed. Following many empirical studies for the NYSE, we avoid the *bid-ask bounce* (see e.g. Campbell, Lo, and McKinlay (1997), page 101), by not taking the transaction price p_t as the price of a trade. Instead, we consider the prevailing mid quote m_t as the price of a trade, where $m_t = (q_t^b + q_t^a)/2$. The return corresponding to the t -th trade is then defined as the log return over the prevailing and subsequent mid quote: $r_t = \log(m_{t+1}/m_t)$. Overnight returns are excluded from the sample. Since the transaction data provided by the NYSE are not classified according to the nature of a trade (buy or sell), we use the Lee and Ready (1991) ‘midpoint rule’ to classify a trade. With this rule, the prevailing mid quote corresponding to a trade is used to decide whether a trade is a buy, a sell, or undecided. If the price is lower (higher) than the mid quote, it is viewed as a sell (buy). If the price is exactly at the mid quote, its nature (buy or sell) remains undecided. To each trade we associate a trade indicator x_t^0 which indicates the nature of the trade: 1 (buy), -1 (sell), or 0 (undecided). From the trade size and the trade indicator we can construct signed log trade volume x_t . If a trade is unclassified, log trade volume will be zero.

To deal with zero-durations, we treat multiple transactions at the same time as one transaction and aggregate their volume and average bid-ask spreads and prices. We follow Engle and Russell (1998) and interpret multiple trades as a single transaction that is split up into several parts.

As a first exploration of our data, we compute sample mean and median

¹In the sequel we will refer for simplicity to ‘trade size’, meaning ‘log trade size’.

of several trade characteristics for each stock, see Table 2. This table shows that **IBM** is the most frequently traded stocks in the sample, with the average duration equal to 11 seconds. **Mattel** is the least frequently traded stock in the sample with an average duration of 36 seconds. Average returns are close to zero for all stocks, average bid-ask spreads vary from 0.087 to 0.160 and average log trade size varies from 0.328 to 0.857.

For the **IBM** stock, we also compute sample correlations between the following variables: unsigned log volume and bid-ask spread (positive), durations and bid-ask spread (positive), lagged absolute return and durations (negative), lagged bid-ask spread and durations (positive), lagged unsigned log volume and durations (negative). The correlations are displayed in Table 3. The positive contemporaneous correlation between volume and bid-ask spread is consistent with the Easley and O’Hara (1987) model described in Section 2. The sample correlation between lagged absolute returns and durations is negative (inventory argument of Dufour and Engle (2000)), while lagged bid-ask spread is positively correlated to durations (asymmetric information argument). Lagged volume is negatively correlated to durations (asymmetric information argument with respect to informed traders). Table 3 reports the exact value of the sample correlations and provides (asymptotic) standard errors. This table also displays the correlations between lagged and contemporaneous values of the same variable. We see that these correlations are considerably larger than the correlations between different variables. The sign of the correlations is not significant at a 5% level² for the correlation between lagged returns and contemporaneous returns and between returns and durations. We also test for Granger-causality between the variables in Table 3. The null of no Granger-causality from the variable at the left-hand-side to that at the right-hand-side is rejected at each reasonable confidence level. For the other stocks we document similar results.

4 The price impact of trades in a model in transaction time

In this section we discuss a 3-dimensional VAR-model to capture the dependence among returns, trade size and spreads. This model does not take into account the possible role of the trading intensity in calendar time. The approach is based upon on Hasbrouck (1991a, 1991b). We thus specify the

²Unless stated otherwise, we will test all hypotheses at a 5% significance level in this paper.

VAR-model (in transaction time) for $z_t = (r_t, s_t x_t, x_t)'$ as

$$A(L)z_t = c + v_t, \mathbb{E}v_t = 0, \text{Var } v_t = \Sigma_t, \quad (1)$$

where c is a 3-dimensional vector of constants, $A(L)$ an m -th order (3×3) matrix polynomial in the lag operator L . The contemporaneous term in this matrix polynomial, A_0 , and the possibly heteroscedastic covariance matrix of the residuals, Σ , can be normalized in various forms which do not affect the properties of the model³. We choose the normalization of Hasbrouck (1991a, 1991b) which lets trade size and the product of bid-ask spread and trade size contemporaneously influence returns. Finally, we assume covariance stationarity of $(z_t)_t$. According to the VAR-specification, the impact of trades on returns and the correlation between trade sizes depends upon the bid-ask spread. According to Easley and O'Hara (1987) we would expect that the impact of trades is larger when the bid-ask spread is wider.

Hasbrouck (1991a, 1991b) explains that the persistent price impact of a transitory shock in trade volume, is naturally interpreted as the information content of the trade. The expected price impact of a trade is measured by means of the *generalized impulse response function*, cf. Koop et al. (1996). The expected price impact of a an unexpected trade of size v after k transactions is given by the coefficient of L^k in the first element of

$$vA(L)^{-1}e_3, \quad (2)$$

where $e_3 = (0, 0, 1)'$. Moreover, the *long-term* impulse response equals the first element of $vA(1)^{-1}e_3$. We thus see that the disturbances cancel out in the expected price change. The impulse response function is easily estimated by replacing the matrix coefficients by the estimated values. The impulse response function refers to the *expected* price change of a trade, while the entire distribution of the price change is of interest. Therefore, we will also estimate several quantiles of the distribution of the price change, which will be reported in the form of $\alpha\%$ *prediction intervals*.

Estimation results

In line with Hasbrouck (1991a, 1991b) and Dufour and Engle (2000) we truncate the model at $m = 5$. We estimate the VAR-model by means of OLS and use White (1980)'s heteroskedasticity-consistent covariance matrix. We test the correctness of the truncation lag by testing for autocorrelation in the OLS-residuals using the Ljung-Box test. This test is asymptotically equivalent to the standard LM-test for serial correlation in the residuals of

³The normalization sets the elements (2, 1), (2, 3), (3, 1) and (3, 2) of A_0 equal to zero and imposes $(\Sigma_t)_{12} = 0, \mathbb{E}_t(v_t) = 0$.

a regression, but computationally less demanding. The results in Table 4 show that for all stocks, both trade size and bid-ask spread have a positive immediate impact on returns. This empirically confirms the results of Easley and O’Hara (1987) and confirms Hasbrouck (1991a, 1991b).

We test for Granger-causality for each type of variable in every equation. We do this by testing the null hypothesis that the coefficients corresponding to one type of lagged variables are jointly zero. For example, to test whether or not trade size Granger-causes returns we use a (robust⁴) Wald-test and test the null hypothesis $H_0 : a_{j,(1,2)} = 0$ for $j = 0, \dots, 5$. This null hypothesis is rejected at a 5% level for all stocks. Similarly, returns, trade size and the product of bid-ask spread and trade size Granger-cause returns, trade size and the product of bid-ask spread and trade size. This emphasizes the importance of taking into account the feedback among the trade characteristics.

The price impact of trades

To investigate the short and long run price impact of a large trade on the McDonald’s stock, we assume that the market is in a state of ‘equilibrium’. We define this as a situation in which returns, trade size, and bid-ask spread are equal to their sample average. We consider a buy consisting of 5,000 shares, which corresponds to the 95% quantile of unsigned trade volume in our data.

We compute the impulse response functions, including confidence and prediction intervals, for price changes following a trade of 5,000 shares. A parametric bootstrap from the asymptotic distribution of the OLS-estimates (with $N = 1,000$ draws) is used to obtain confidence intervals for the impulse response functions.

Figure 1 shows the impulse response function corresponding to the unexpected trade of 5,000 shares (in transaction time), including a 90% prediction interval. After 25 transactions, the impulse response equals 6.6 basis points (bp). The 95% confidence interval corresponding to the expected price change is [6.4, 6.8] bp. From Figure 1 we can see that it takes about 10 transactions before the new efficient price has been reached. Since the average duration for the McDonald’s stock is 26 seconds, it takes approximately 4.5 minutes before the new price has been attained.

To estimate prediction intervals, we need some assumptions on the distribution of the disturbances $(v_t)_t$. We do not assume any parametric distribution, but only assume constant correlation and multiplicative heteroskedasticity cf. Harvey (1976). We assume that $v_t = \Lambda_t^{1/2} \eta_t$, where $\Lambda_{(i,i),t} = \sigma_{i,t}^2 = \exp(\gamma_i \tilde{z}_{i,t})$ and $\Lambda_{t,(i,j)} = \rho_{ij} \sigma_{i,t} \sigma_{j,t}$ for $i \neq j$. Here $\tilde{z}_{i,t}$ is a $1 \times n$ row vector with regressors

⁴Robust for heteroskedasticity.

containing the same regressors as in the corresponding equation of the VAR-model. Finally, we assume that $\eta_{i,t}$ is iid white noise and independent of $\tilde{z}_{j,s}$ for all i, j and s, t . The null hypothesis of no heteroskedasticity is rejected at each reasonable confidence level for each of the three disturbances. To obtain prediction intervals we proceed as follows. We randomly draw $N = 1,000$ times from the residuals $(\eta_t)_t$ and compute the corresponding price change following the trade of 5,000 shares. The $(1 - \alpha)\%$ prediction interval is obtained by computing the $(\alpha/2)\%$ and the $(1 - \alpha/2)\%$ -quantiles of the realized price changes.

Apart from the expected price change, figure 1 also displays a 90% prediction interval for the price change following the large trade. The 90% prediction interval after 25 trades equals $[0.0, 13.0]$ bp. Thus, with 90% probability, the true price change following the unexpected trade is between 0.0 bp and 13.0 bp.

5 Modeling the trading intensity

In the VAR-model of Hasbrouck (1991a, 1991b) the price impact of trades can only be measured in *transaction time*. It is often useful to have impulse responses in *calendar time*, since this allows e.g. for the computation of the exact time it takes to reach a certain price level. In this section we therefore focus on the specification of the data generating process underlying the trading intensity. We use a version of Engle and Russell (1998)'s ACD-model for this purpose. We assume that the duration process is strongly exogenous cf. Engle, Hendry, and Richard (1983) and that $(y_t)_t$ is generated by a log ACD(1,1)-model; i.e. $y_t = \psi_t \varepsilon_t$, where $\psi_t = \mathbb{E}(y_t | \mathcal{I}_{t-1})$ and $(\varepsilon_t)_t$ identically distributed with unit mean and independent of \mathcal{I}_{t-1} (the information known up to time τ_{t-1}) and independent of $v_{i,s}$ for $i = 1, 2, 3$ and all s . The log conditional duration is specified according to

$$\log \psi_t = \omega + \alpha \log \varepsilon_{t-1} + \beta \log \psi_{t-1}.$$

The model is expressed in terms of diurnally corrected durations which are also denoted by y_t as well, with some abuse of notation. The diurnally corrected durations are obtained by proceeding as in Engle and Russell (1998), with nodes on 9.30 – 10.00, 10.00 – 11.00, ..., 14.00 – 15.00, 15.30 – 16.00 hours. We assume covariance stationarity of $(y_t)_t$, i.e. $\beta < 1$.

Estimation results

We first estimate the diurnal component separately by means of a regression, cf. Engle and Russell (1998). We then estimate the ACD(1,1)-model by

means of quasi maximum likelihood (QML), see Drost and Werker (2001) and use the BHHH-algorithm of Berndt, Hall, Hall, and Hausman (1974) for the numerical optimization. We assume that the usual regularity conditions for QML hold. We use the Bollerslev and Wooldridge (1992) robust covariance matrix to obtain consistently estimated standard errors. Note that the log likelihood function corresponding to QML is the same as the log likelihood function when the ε_t 's are exponentially distributed. The row with the caption 'no feedback' in Table 5 shows the QML-estimation results of the ACD(1,1) model for each stock. As usual, the persistence is high. It varies from 0.96 to 0.97. We used a Wald-test to test for higher-order effects for which there is no significant evidence. The estimation results for the diurnal correction factor are available upon request.

6 Dependence of the price impact of trades on the trading intensity

It is likely that the price impact of trades depends upon the trading intensity, cf. Diamond and Verrecchia (1987) and Easley and O'Hara (1992). In this section we follow the line set by Dufour and Engle (2000). With a bivariate VAR-model for returns and trade sign, they investigate how the trading intensity affect the price impact of trades. We will extend the model of the previous section along the same line, by incorporating a possible role for calendar time effects.

As in Section 4, we specify a VAR-model in transaction time for $z_t = (r_t, s_t x_t, x_t)'$, but now $A(L)$ is allowed to depend upon the trading intensity; i.e.

$$A(L) = A(y_t)(L).$$

The elements of A_j , for $j = 1, \dots, m$, are denoted by $(a_{j,(k,\ell)})_{k,\ell}$ [$k, \ell = 1, 2, 3$]. To test whether the duration dependence is significant or not, we choose $a_{j,(k,2)}$ of the form

$$a_{j,(k,3)} = \gamma_{(j,k)} + \delta_{(j,k)} \cdot \log y_{t-j} \quad [j = 1, \dots, 5; k = 1, 2, 3], \quad (3)$$

similar to Dufour and Engle(2000). In the present model the impact of a trade on returns depends on the trading intensity. Again we assume covariance stationarity of $(z_t)_t$.

Estimation results

Again we estimate the VAR-model using OLS with truncation at $m = 5$. The estimation results for the McDonald's stock are given in Table 6. Again

only the results for the return equation are displayed. Similar to the model of Hasbrouck (1991a, 199b) without durations, we test for Granger-causality. Again we establish significant Granger-causality from returns, trade size and the product of bid-ask spread and trade size to (contemporaneous) returns, trade size and the product of bid-ask spread and trade size. Moreover, the null hypothesis that the impact of trades does not significantly depends upon the trading intensity, is rejected for all stocks. Furthermore, we again establish significant heteroskedasticity in the VAR-disturbances.

The price impact of trades

Again we focus on the price impact of large trades (in transaction and in calendar time). As in the model of Hasbrouck (1991a, 1991b), we estimate impulse response functions to measure the price impact. Since the durations now enter the model in a nonlinear fashion, there are no analytical expressions for the impulse response function available anymore. We therefore estimate the impulse response function by simulating $N = 1,000$ future paths of durations. For each path of durations we compute price impact functions as before and finally, we average the impulse responses over the N simulations to obtain the final impulse response function.

To simulate future paths of durations, we need values of the ACD-disturbances $(\varepsilon_t)_t$. Since we used QML to estimate the coefficients of the ACD-model, we did not make any additional distributional assumptions apart from some regularity conditions. To obtain random values of the ACD-disturbances, we randomly draw from the empirical distribution of the ACD-residuals.

We again consider the McDonald's stock. We compute impulse response functions for the model of Section 5 in two different situations: in a situation of 'low' and 'high' trading intensity. We compute the 99.5% and the 0.5% quantiles of the durations in our data. Subsequently we initialize the ACD-model with these durations⁵. As we compute the impulse response functions by simulating future paths of durations, we also need to compute the diurnal correction factor. Therefore, it is necessary that we explicitly specify the time at which the large trade takes place. Consistent with the daily periodicities observed in the trading intensity, we assume that the period of slow trading takes place at 12.30 PM and the fast trading at 10.00 AM. By doing so, we capture the effect of different trading intensities on the impulse response functions. As in the model of the previous section, we assume that the trade characteristics are in a state of equilibrium.

Figure 2 shows the impulse response functions for a trade of size 5,000 with 'slow' and 'fast' trading as well as the impulse response function in the model

⁵Since we use the ACD(1,1)-model we have to initialize one lag of both durations and conditional expected durations.

of Hasbrouck (1991a, 199b) in which the trading intensity does not play a role. We see that 25 transactions after the trade of 5,000 shares, the impulse response equals 5.6 bp with slow trading and 7.3 bp with fast trading. Note that the impulse response of 6.6 bp as computed by the model of Hasbrouck (1991a, 199b) lies in between these two values. The corresponding 95% confidence intervals equal [5.1, 6.0] bp and [7.0, 7.8] bp. A 95% upper one-sided confidence interval for the difference between the price impact with slow and fast trading is $[-\infty, -2.4]$ bp, so the price impact with slow trading is significantly lower than with fast trading. Moreover, the prediction intervals show that the distribution of the price change with fast trading first-order stochastically dominates the distribution with slow trading.

To gain insight into the adjustment process of the price following a large trade, we now consider the price impact function in calendar time. The impulse response functions in calendar time⁶ show that it takes approximately 3.5 minutes to reach the new efficient price that follows the unexpected trade in case of frequent trading⁷, while this takes about 13.5 minutes in case of slow trading. See Figure 4. In the model of Hasbrouck (1991a, 199b) without durations we had estimated the time to reach the new efficient price to be approximately 4.5 minutes, which lies between the time for fast (3.5 minutes) and slow trading (13.5 minutes).

Prediction intervals and confidence intervals are estimated as in the model without durations. The only difference is that durations are averaged out as described above. The 90% prediction intervals corresponding to the large trade with slow and fast trading are [0.1, 12.7] bp and [1.5, 15.1] bp, respectively. We thus see that not only the expected price change is larger with fast trading, also the realized price changes are larger. This means that the entire distribution of the price change is different in periods of fast and slow trading and thus depends upon the trading intensity. The distribution of the price change with fast trading first-order stochastically dominates the distribution with slow trading. This effect is illustrated in Figure 3.

7 Feedback from the trade characteristics to the trading intensity

In the previous section we measured the impact of a transitory shock on prices, assuming that there is no feedback from the trade characteristics

⁶Since we simulate paths of durations for the computation of the impulse response function, we can sample each over each five seconds. We then obtain the impulse response function in calendar time.

⁷We measure the time it takes to reach 99.5% of the long-run impulse response.

to the trading intensity. In Section 2 we made clear that it is likely that there is feedback from the trade characteristics to the trading intensity. This additional feedback may affect the impulse response functions. In this section we investigate whether or not the trade characteristics affect the trading intensity and to what extent the impulse response functions are influenced by this feedback.

We specify the log ACD(1, 1)-model with feedback as follows. Let again $y_t = \psi_t \varepsilon_t$ for $\psi_t = \mathbb{E}(y_t | \mathcal{I}_{t-1})$ and ε_t iid with unit mean and independent of \mathcal{I}_{t-1} and independent of $v_{i,s}$ for $i = 1, 2, 3$ and all s . The information known up to time τ_{t-1} now also includes the trade characteristics up to that moment. The log conditional expectation is extended with a vector of trade characteristics in the following way

$$\log \psi_t = \omega + \alpha \log \varepsilon_{t-1} + \beta \log \psi_{t-1} + \xi \nu_{t-1}. \quad (4)$$

Here ν_{t-1} is a vector of explanatory variables consisting of trade characteristics known at time τ_{t-1} . Moreover, ξ is the corresponding vector of coefficients. Again we assume covariance stationarity of $(y_t)_t$.

According to Section 2, possible variables to include in ν_{t-1} are returns, bid-ask spread and trade volume. The effect of trade size and returns on durations is probably more related to the magnitude of these variables than their sign, so we would take these variables unsigned. Similar to durations, trade characteristics such as returns, spreads, and trade volume also show daily periodicities, cf. Engle and Lunde (1999). Therefore, they have to be diurnally corrected in the usual way to account this.

Estimation results

In the ACD-model with feedback as specified in equation (4), we take

$$\nu_{t-1} = (|r_{t-2}|, |r_{t-3}|, |s_{t-1}x_{t-1}|, |s_{t-2}x_{t-2}|, |x_{t-1}|, |x_{t-2}|, Q_{t-1})', \quad (5)$$

where

$$Q_{t-1} = |x_{t-1} + \dots + x_{t-5}|$$

represents the imbalance in unsigned volume over the five most recent transactions. Furthermore, the trade characteristics are based upon returns, spreads and trade volumes that are diurnally corrected in the usual way to account for daily periodicities. The estimation results for the diurnal components are available upon request. Again we use QML to estimate the ACD-model. We used a Wald-test to test for higher-order effects, for which there is no significant evidence.

The row with the caption ‘with feedback’ in Table 5 displays the estimation results. The estimation results for the diurnal correction factor are available

upon request. The null hypothesis of no Granger-causality from the trade characteristics to the trading intensity is rejected at each reasonable confidence level using a (robust⁸) Wald-test, making clear that there is significant feedback between the trading intensity and the various trade characteristics. To assess the effect of trade characteristics on the trading intensity, note that $(1 - \beta(1))^{-1}\xi_{\bullet}(1)$ is the ‘long-term multiplier’ corresponding to the impact on the (conditional expected) durations of a unit *ceteris paribus* change in the (diurnally corrected value of the) trade characteristic. Hence, the sign of the long run multiplier is given by $\xi_{\bullet}(1)$.

For all stocks the sign of the multiplier corresponding to returns is significantly negative. The negative effect of returns on the durations is consistent with the inventory argument explained in Dufour and Engle (2000): large returns attract opposite-side traders.

For all stocks the multiplier for trade volume is significantly negative. The negative impact of trade volume on durations suggests that informed traders increase trading when they observe large trades. They do this to quickly benefit from the private information they possess.

For all stocks except *Schlumberger* the long run multiplier corresponding to the product of trade volume and bid-ask spread is significantly positive. This suggests that for these stocks wide spreads increase the trading intensity, which can be explained using the same arguments as above. Only for *McDonald’s* and *IBM* the multiplier has a positive sign.

Finally, the coefficient of the imbalance in trade volume is significantly negative for all five stocks. The negative sign of the volume imbalance over the five most recent transactions suggests some effect of asymmetric information: when there is imbalance between the buy and the ask side of the market this may indicate the presence of good or bad news and hence, informed traders increase trading to quickly benefit from the private information they possess.

The price impact of trades with feedback

Estimation of impulse response functions in the model with feedback is more involved than in the model without feedback. In the VAR-models considered until now, the VAR-disturbances cancelled out, see expression (2). With the additional feedback taken into account in this section, we cannot set future disturbances in the VAR-model to zero as we did before. This is due to the fact that the trade characteristics enter the specification for the conditional duration in a nonlinear way. Therefore, we not only have to average out future paths of durations, but also future paths of VAR-disturbances. Moreover, the durations now depend upon the trade characteristics. This means that we

⁸We used the robust Wald-test as suggested by Bollerslev and Wooldridge (1992).

alternately have to simulate durations and trade characteristics. Regarding the disturbances in the VAR-model, we make the same distributional assumptions as in the model without feedback and proceed as before to obtain confidence and prediction intervals.

We consider the McDonald's stock one more time. We estimated impulse response functions for a trade of 5,000 shares and computed confidence and prediction intervals. The price change after 25 transactions equals 5.7 bp with 95% confidence interval [4.7, 6.6] bp and 90% prediction interval [0.0, 12.0] bp with slow trading and 7.5 bp ([6.5, 8.7] bp, [0.0, 15.5] bp) with frequent trading. In the model *without* feedback these price changes equal 5.6 bp ([5.1, 6.0] bp, [0.1, 12.7] bp) and 7.3 ([7.0, 7.8] bp, [1.5, 15.1] bp). See Figure 5 and Figure 6, which display the impulse response function in transaction time. The plots include 90% prediction intervals for a trade of size 5,000 with and without feedback in case of slow trading. The prediction intervals corresponding to the price impact functions differ in the model with and without feedback, although the distribution of the price change with fast trading still first-order stochastically dominates the price impact with slow trading. The 90% quantiles in the model with feedback are below those computed from the model without feedback. Hence, the feedback has a small effect on the distribution of the price impact of trades. Similar results are found for the other stocks, also in periods of fast trading and for other quantiles.

The price impact of trades in calendar time with feedback

Since we now have feedback from the trade characteristics to the trading intensity, we investigate the quantitative effect of the feedback on the impulse response function in calendar time. We consider the McDonald's stock one more time. To see how the trade characteristics influence the trading intensity we consider the distribution of the duration to the first transaction after the large trade. We compare the result to the distribution of the duration to the first transaction when no large trade has taken place. For this purpose we compute expected durations, with corresponding 95% confidence intervals and 90% prediction intervals. We thus compare $\mathbb{E}(y_{t+k} \mid v_t = v)$ and $\mathbb{E}(y_{t+k})$. We estimate the expected durations with the average durations over the $N = 1,000$ simulations that we used to compute the impulse response function. We consider the situation of slow trading. The average duration following the unexpected large trade equals 43 seconds with 90% prediction interval equal to [3, 130] seconds and 95% confidence interval [28, 55] seconds. The average duration equals 48 seconds without large trade, with prediction interval [3, 146] seconds and confidence interval [30, 65] seconds. The average duration directly after trade is significantly *shorter* than when no large trade has taken place. The effect of the large trade quickly dies out and the

difference between the two average durations becomes smaller. Hence, the additional feedback also has a small impact on the distribution of the durations and this in turn, affects the price impact in calendar time. For the other stocks and for periods of fast trading we report similar results.

8 Conclusions

Market microstructure theory predicts comovements among bid-ask spread, trade size, returns and durations in the process of information dissemination, see e.g. Easley and O'Hara (1987, 1992) and Diamond and Verrecchia (1987). In this paper we have investigated empirically the *two-sided* causality between trade related variables such as returns, bid-ask spread, and trade volume on one hand and the trading intensity on the other hand for five frequently traded stocks listed on the NYSE. We established the following results.

Both the short and long run impact of trades on prices can be measured by means of the impulse response function. The persistent impact on prices is naturally interpreted as the information content of the trade. In line with Dufour and Engle (2000) and Zebedee (2001), we showed that the expected price impact of a trade is larger in periods of frequent trading. In addition to this, we showed that the entire distribution of the price impact depends upon the trading intensity. The distribution of the price change with fast trading first-order stochastically dominates the distribution with slow trading.

Moreover, we established significant causality from returns, trade size, trade imbalance, and bid-ask spread to the trading intensity. *Ceteris paribus*, large returns, large trades, large trade imbalances and wide spreads tend to increase the trading intensity.

We have investigated the economic relevance of the impact of the trade characteristics on the trading intensity. The distribution of the price impact of a large trade differs in the two models, in particular for the higher quantiles. This holds both in transaction and in calendar time. Thus, the feedback from the trade characteristics to the trading intensity affects the price impact of large trades, both in transaction and in calendar time.

There are several extension for further research. Intuitively, the trading intensity is likely to play a more important role for infrequently traded stocks. Furthermore, since illiquid stocks are likely to be more affected by inventory effects than frequently traded stocks (cf. Easley, O'Hara, Kiefer and Paperman (1996)), this is likely to play a role. Another possible extension deals with the problem of optimal trading. An important issue for institutional investors is how large trades have to be split into smaller orders and how the

individual orders should be spread out over one or more days in an optimal way. This problem could be investigated using the models proposed in this paper.

variables	EoH87	EoH92	AP88	DV87
duration, spread y_t, s_{t+1}	?	-	-	+
duration, volatility y_t, σ_{t+1}	?	-	-	+
duration, mid quote y_t, m_{t+1}	?	?	?	-
duration, bid/ask quote $y_t, q_{t+1}^{a,b}$?	?	?	-
volume, spread $ x_t , s_t$	+	?	?	?

Table 1:
Implications for the correlation sign

Summary of the implications of market microstructure models for the sign of the correlation between variables. The studies are Easley and O'Hara (1987, 1992), Admati and Pfleiderer (1988), and Diamond and Verrecchia (1987), which are abbreviated by EoH87, EoH92, AP88 and DV87, respectively. A question mark indicates that the model does say anything on the sign of the correlation.

ticker symbol	IBM	MAT	MCD	SLB	WMT
company name	Int. Business Machines Corp.	Mattel Inc.	McDonald's Corp.	Schlumberger Ltd.	Wal Mart Stores Inc.
# transactions	140,013	41,822	57,860	63,905	90,042
durations (seconds)					
mean	11	36	26	23	16
median	7	19	15	14	10
returns (bp)					
mean	-0.021	-0.073	-0.002	-0.005	0.033
median	0.000	0.000	0.000	0.000	0.000
spread (\$)					
mean	0.160	0.086	0.087	0.110	0.097
median	0.125	0.0625	0.0625	0.125	0.0625
volume (log shares)					
mean	0.842	0.780	0.328	0.525	0.857
median	0.000	0.000	0.000	0.000	0.000

Table 2:
Sample statistics

Sample statistics (sample mean and median) for volume, durations, spread and returns for the period August-October, 1999.

variable/unit	correlation
volume, spread $ x_{t-1} , s_t$	0.157 (0.003)
duration, spread y_{t-1}, s_t	0.005 (0.002)
return, durations $ r_{t-2} , y_t$	-0.008 (0.009)
spread, duration s_{t-1}, y_t	0.025 (0.002)
volume, duration $ x_{t-1} , y_t$	-0.020 (0.002)
duration, duration y_{t-1}, y_t	0.062 (0.004)
return, return $ r_{t-1} , r_t $	0.003 (0.003)
volume, volume $ x_{t-1} , x_t $	0.250 (0.002)
spread, spread s_{t-1}, s_t	0.772 (0.005)

Table 3:
Sample correlations for IBM (asymptotic standard errors between parentheses)

lag	MAT	MCD	IBM	SLB	WMT
	estimate				
	std. error				
const	-0.5817	0.0229	0.0208	0.0208	0.0184
$a_{j,(1,1)}$	-0.0641	-0.0503	-0.0341	-0.0341	-0.0485
1	0.0081	0.0057	0.0050	0.0050	0.0050
2	0.0065	-0.0130	0.0065	0.0057	0.0012
3	0.0084	0.0043	0.0097	0.0057	0.0122
4	0.0064	0.0045	0.0035	0.0055	0.0090
5	0.0116	0.0024	0.0107	0.0048	0.0086
$a_{j,(1,2)}$	5.9602	0.1614	1.6573	1.6573	2.3401
0	0.4897	5.5092	0.0857	0.0857	0.0920
1	0.4658	0.1855	0.3341	0.3341	0.5360
2	0.3999	-0.0599	-0.2130	-0.2130	-0.2825
3	0.4343	-0.0174	-0.2189	-0.2189	-0.2056
4	0.3631	-0.3460	-0.1644	-0.1644	-0.0476
5	0.3382	-0.0052	-0.0758	-0.0758	-0.1534
$a_{j,(1,3)}$	0.0620	0.0128	0.2306	0.2306	0.0902
0	0.0361	-0.0676	0.0089	0.0089	0.0085
1	0.0635	0.0674	0.0529	0.0529	0.0426
2	0.0686	0.0158	0.0335	0.0335	0.0475
3	-0.0094	-0.0019	0.0192	0.0192	0.0195
4	0.0285	0.0194	0.0143	0.0143	0.0040
5	0.0514	-0.0033	-0.0026	-0.0026	0.0086

Table 4:
Estimation results for the return equation in the VAR-model

The return equation of the VAR-model defined in equation (1) is estimated using OLS. The standard errors in the columns on the right-hand-side are computed using White (1980)'s heteroskedasticity-consistent covariance matrix.

lag	MAT	MCD	IBM	SLB	WMT
	estimate				
	std. error				
const	j				
$a_{j,(1,1)}$	1	-0.1489	-0.2425	-0.2696	-0.3310
	2	-0.0480	-0.0287	-0.0300	-0.0471
	3	-0.0127	0.0222	0.0066	0.0012
	4	0.0057	0.0193	0.0097	0.0123
	5	0.0041	0.0104	0.0029	0.0090
		0.0022	0.0100	0.0098	0.0089
					0.0036
$\gamma_{(j,1)}$	0	5.4091	0.7794	1.5630	2.3242
	1	0.0676	0.0555	0.0650	0.0346
	2	0.0213	0.0137	0.0453	0.0129
	3	-0.0038	0.0113	0.0176	0.0556
	4	0.0111	0.0014	0.0060	0.0291
	5	-0.0085	-0.0030	0.0084	0.0107
					0.0112
					0.0105
$\delta_{(j,1)}$	0	-0.0319	-0.0399	-0.0342	-0.0261
	1	-0.0016	0.0024	-0.0068	0.0023
	2	-0.0024	0.0004	-0.0048	-0.0034
	3	0.0003	-0.0007	-0.0005	-0.0041
	4	0.0027	0.0004	0.0024	-0.0028
	5	0.0016	0.0024	-0.0037	0.0010
					0.0033
$a_{j,(1,3)}$	0	0.0310	0.1869	0.3359	0.1579
	1	0.1572	0.0600	0.3130	0.5176
	2	-0.0627	-0.0830	-0.2205	-0.2757
	3	-0.0160	-0.1011	-0.2112	-0.2053
	4	-0.3409	-0.0557	-0.1534	-0.0540
	5	0.0070	-0.0510	-0.0843	-0.1507
					0.0744

Table 6:
Estimation results for the return equation in the VAR-model

This table reports the results for the VAR-model defined in equation (1) with duration dependence. The return equation is estimated using OLS. The standard errors in the columns on the right-hand-side are computed using White (1980)'s heteroskedasticity-consistent covariance matrix.

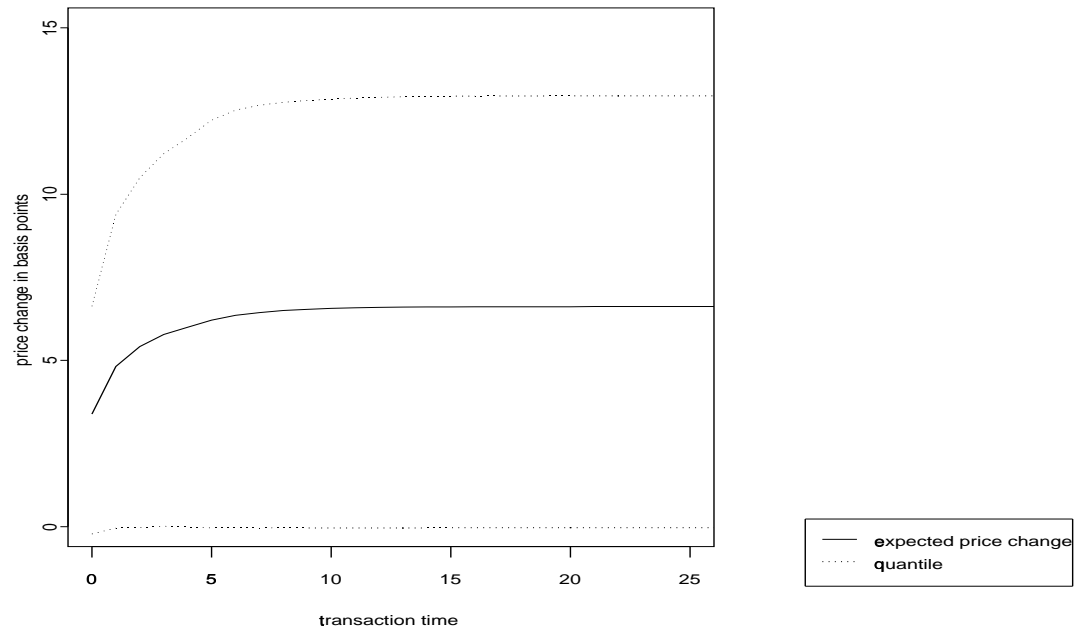


Figure 1:
Price impact: no durations

Impulse response function and 90% prediction intervals following an unexpected trade of 5,000 shares of the VAR-model defined in equation (1).

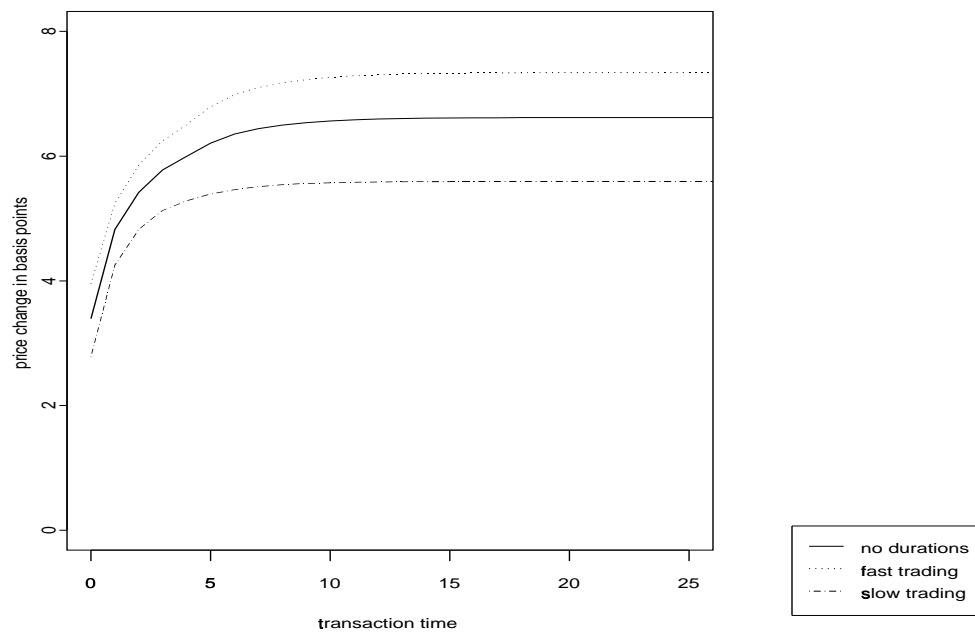


Figure 2:
Price impact with and without durations

Impulse response functions (trade of 5,000 shares) in the VAR-model defined in equation (1) with and without durations, applied to the McDonald's stock.

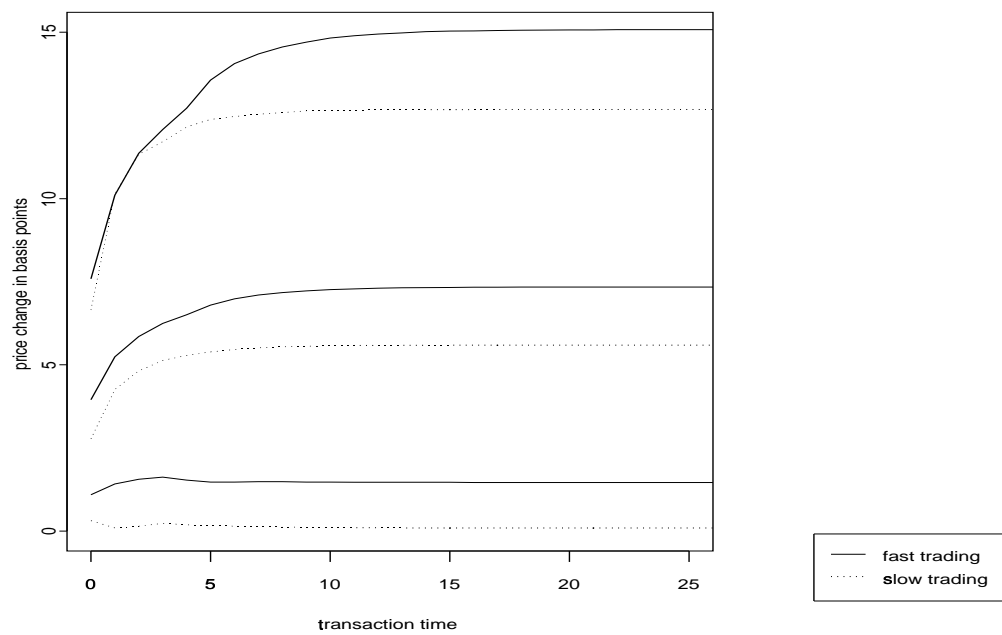


Figure 3:
Price impact with durations: slow trading versus fast trading

Impulse response functions and 90% prediction intervals following an unexpected trade of 5,000 shares in the VAR-model defined in equation (1) with durations. Periods of slow and fast trading are considered, applied to the McDonald's stock.

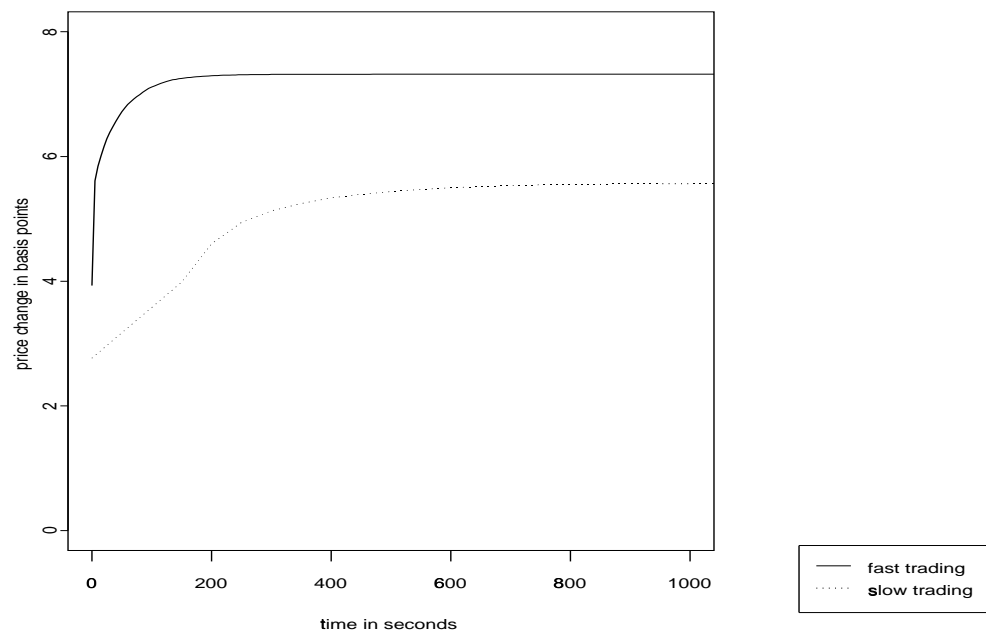


Figure 4:
Price impact with durations: convergence time

Impulse response function following an unexpected trade of 5,000 shares in the VAR-model of equation (1) with durations. Period of slow and fast trading are considered, applied to the McDonald's stock. The horizontal axes displays the time in seconds starting at the time at which the trade has been initiated.

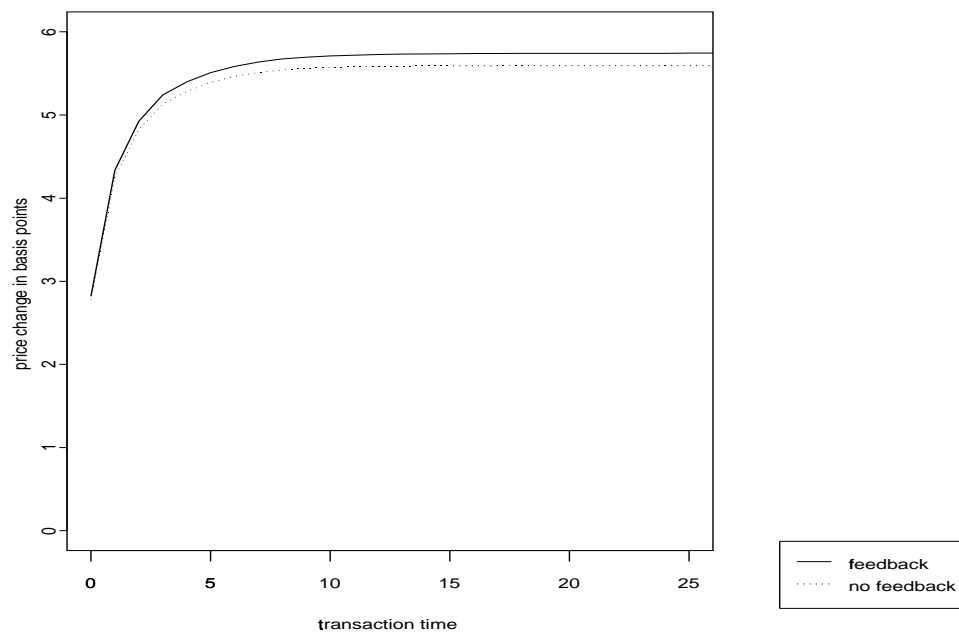


Figure 5:
Price impact with durations: feedback versus no feedback

Impulse response function following an unexpected trade of 5,000 shares in the VAR-model defined in equation (1) with durations. A period of slow trading is considered, with and without feedback, applied to the McDonald's stock.

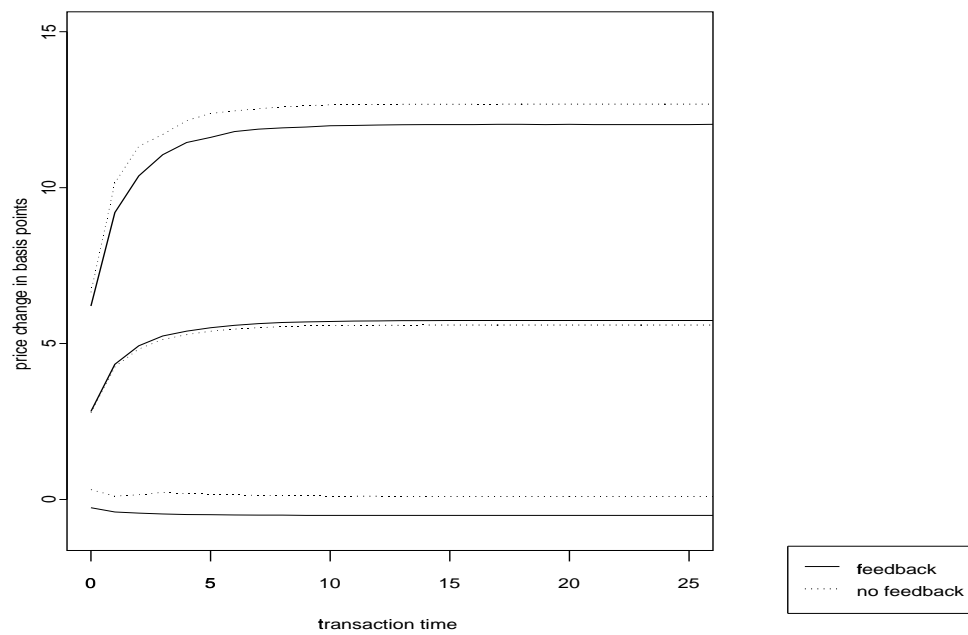


Figure 6:
Price impact with durations: feedback versus no feedback

Impulse response functions and prediction intervals following an unexpected trade of 5,000 shares in the VAR-model defined in equation (1) with durations. A period of slow trading is considered, with and without feedback, applied to the McDonald's stock.

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