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The Price Impact of Trades in Illiquid Stocks in Periods of High and Low Market Activity

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Abstract

Using high frequency data on ten infrequently traded stocks during the year 1999, we measure the information content of a trade and its relation to the trading intensity. While the price impact curve for frequently traded stocks monotonically increases towards the full information price, we find impulse response functions that first 'overshoot' and subsequently decrease towards the full information price. The overshooting effect strongly depends upon the bid-ask spread and the trading intensity, which can be explained by inventory imbalances and asymmetric information of informed and uninformed traders. Furthermore, we show that the difference in price impact between periods of slow and fast trading is much larger for illiquid stocks than for frequently traded stocks. We model the overnight behavior of the trading intensity and returns and show that information contained in the trading intensity of illiquid stocks is carried over to the next day. Additionally, we show that, for infrequently traded stocks, it may take several days before the full information price that follows a trade is attained, even in periods of relatively high market activity. Moreover, the adjustment time crucially depends upon the bid-ask spread and the trading intensity.

Keywords: infrequently traded stocks, price impact, trading costs, trading intensity, durations, market microstructure, asymmetric information, inventory effects.

JEL classification: C41, G14.

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1 Introduction

An extensive literature is available on the price impact of trades in frequently traded stocks. Hasbrouck (1991a, 199b) reports that the price impact of a trade is larger when the spread is wide and is more significant for firms with smaller market capitalization. Kavajecz and Odders-White (2001) analyze how the price impact of trades depends on the information in the limit order book. Dufour and Engle (2000) argue that, for liquid stocks, the price impact of a trade is larger and convergence to its full information value faster when subsequent trades are close together in time, i.e. when the trading intensity is high.

While the analysis of the price impact of trading in liquid stocks is clearly of interest, a very substantial part of actual trading is related to less liquid stocks. Moreover, for these stocks the price impact of trades is likely to be substantially larger. Furthermore, for stocks that are typically traded a few times per hour the potential information content of fast trading seems much more important than for the most liquid stocks. Little attention seems to have been paid in the literature to modeling the microstructure properties of illiquid stocks. Manganelli (2000) jointly models trading intensity, trading volume, and volatility and concludes that the less liquid the stock the more time it takes before the price impact of a trade has died out. Easley, Kiefer, O'Hara, and Paperman (1996) show that the probability of information based trading is lower for high volume stocks and higher for low volume assets. Intuitively, since illiquid stocks are traded only occasionally, the market maker would make a large loss when he would face an informed trader. As a consequence, low volume stocks generally have wider spreads than high volume stocks to account for this risk. Hasbrouck (1991a, 199b) uses a VAR-model for returns and trade size to model the price impact of trades. Since smaller market value and traded volume are usually positively correlated and the persistent price impact of trades is directly linked to the information contents of trades, Hasbrouck (1991a, 199b)'s result that the price impact of trades is larger for firms with smaller market value is consistent in the framework of Easley et al. (1996). The same result is reported by Engle and Patton (2001) who use an error correction model for bid and ask quotes with the lagged log bid-ask spread as the error correction term.

The papers referred to above distinguish between frequently and less frequently traded stocks, but are restricted to models in transaction time and consequently do not condition on the information content that the current trading intensity might have. In this paper we analyze to what extent the cost of trading and the impact of trading differ between periods of low and high trading activity. While it has been shown e.g. in Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002) that the current trading intensity has impact on liquid stocks, intuition suggests that the impact will be much more important for the illiquid stocks that are analyzed in this paper. Moreover, inventory effects may play a more important role than for frequently traded stocks, cf. Easley et al. (1996). Finally, since illiquid stocks are usually traded only a few times a day or may not be traded for several days, the price effect of a trade may last for several days. Therefore, appropriate duration modeling for these stocks has to assess the impact of the closure of the market from 4.00 PM until 9.30 AM on returns and durations.

This paper considers the price impact of trades in illiquid stocks traded on the NYSE. A VAR-model in transaction time for returns, trade size, and bid-ask spread is combined with an ACD-model for the trading intensity in the line of Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002) to measure the information content of a trade and its relation to the trading intensity, taking overnight behavior into account. The results show that the price impact of a trade is larger for illiquid stocks than for frequently traded stocks, which is in line with Easley et al. (1996). Moreover, we establish price impact functions that first overshoot and subsequently decrease towards the full information price. We explain this using inventory and asymmetric information arguments. Adjustment to the full information price can easily take several days and the amount of overshooting and the speed of adjustment are shown to depend crucially on the current trading intensity and spread.

The organization of this paper is as follows. Section 2 provides a brief review of relevant market microstructure issues. The data are presented in Section 3. Section 4 describes the VAR-model for returns, trade volume and bid-ask spread in transaction time and its use to model the price impact of trades. The model for the trading intensity is presented in Section 5. Section 6 is devoted to the estimation of a joint model for the trade characteristics and the trading intensity, while Section 7 is focused on the price impact of a trade in this framework. Finally, Section 8 summarizes and concludes.

2 Existing models for the impact of the trading intensity on trading costs

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 information. Due to the presence of informed traders, the transaction process *itself* potentially reveals information on the underlying fundamental value of the security. In this section we first discuss a model that focuses on the risk of informed trading in infrequently traded stocks. Subsequently, we discuss some existing models that relate the existence of information to the trading intensity.

Easley, Kiefer, O'Hara and Paperman (1996) focus on the risk on informed trading in illiquid stocks. The authors empirically show that the risk of information based trading is higher for infrequently traded stocks. The absolute number of informed traders is generally higher for liquid stocks than for infrequently traded stocks. However, the problem with illiquid stocks is not that there are too many informed traders, but there are too few uninformed traders present at the market. As a consequence, illiquid stocks tend to have wider spreads than frequently traded securities. Apart from the increased risk of information based trading, Easley et al. (1996) provide two other possible explanations for this phenomenon. First, market makers trading illiquid stocks have to deal with inventory effects. Since illiquid stocks are traded only occasionally, the market makers want to be compensated for the inventory imbalances which are inherently large. Secondly, since the market maker of an infrequently traded stock inherently has a monopoly position, a market power argument can also explain why spreads of infrequently traded stocks are usually wider than the spreads of frequently traded stocks. Since the persistent price impact of trades is considered the most accurate measure of the risk of informed trading is, the price impact of a trade will be higher for infrequently traded stocks according to Easley et al. (1996).

Several market microstructure studies relate the trading intensity to 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 (good or bad news). 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. Hence, in the model of Easley and O'Hara (1992) slow trading is associated to the absence of 'news'.

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.
Admati and Pfleiderer (1988) distinguish informed 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 prefer to trade when there are many liquidity traders are 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.
In Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002) the predictions made by Easley and O'Hara (1992) have been empirically confirmed for frequently traded stocks by showing that the price impact of trades is higher in periods of fast trading, and vice versa. In this paper we will investigate the price impact of trades and the relation to the trading intensity for infrequently traded stocks.

3 The data

We analyze a sample of illiquid stocks that are traded on the NYSE. In line with Engle and Patton (2001), we focus on stocks in the deciles two and four after ordering all NYSE stocks from least actively traded (decile one) to most actively traded (decile ten). Following many other studies we report results for a random sub sample of the stocks in that decile only. For ease of comparison, the sample of five stocks from deciles two and four that we consider is taken to be a sub sample of the sample of 25 stocks from that decile for which Engle and Patton (2001) report results. For the same reason we include the 'representative' stocks in the analysis, for which Engle and Patton (2001) report detailed results. For decile two this is Greenbrier Companies and for decile four this is Commercial Intertech Corp. (TEC). To allow for some comparison with frequently traded stocks, we moreover consider the IBM stock obtained from liquidity decile ten. Furthermore, IBM is the seventh most frequently traded stock in the year 1999 and has been extensively analyzed in the literature. The list of illiquid stocks considered in this paper is given in Table 1.

Before introducing the variables analyzed in this paper, we briefly discuss the institutional setting on the NYSE. Each security has one specialist. All trades have a specialist as intermediate party. A market order is a trade for immediate execution, while a limit order is contingent on e.g. price or time. Limit orders are registered in the market maker's limit order book which is, in general, not publicly known. The market starts at 9.30 AM with a call auction, while the remaining market is a continuous auction that ends each day at 4.00 PM. We remove all trades before 9.30 AM and after 4.00 PM. Moreover, we also delete those trades that take place before the first quotes of the day are posted.

For each trade the following associated characteristics are recorded: trade moment τ_t in seconds after midnight, trade price p_t, where t indexes subsequent transactions (i.e. t indexes 'transaction time'). The duration (in 'calendar time') between subsequent trades is defined as $y_t = \tau_t - \tau_{t-1}$. Durations which contain a night period deserve special attention. The overnight duration is defined as the duration from the last trade until 4.00 PM (closure of the market) plus the duration from 9.30 AM (opening of the market) at the next day that the stock is traded until the moment that stock is traded for the first time that day. Moreover, when the overnight period contains one or more days without any trading in the stock under consideration, we add 6.5 hours per day (the number of hours during which the market is open) of no trading to the overnight duration.

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 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: $r_t = \log(m_{t+1}/m_t)$. We express log returns in base points. Overnight returns are included in sample. We dealt with dividend payments by removing the first return in which the dividend payment is incorporated.

Since the transaction data provided by 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). To avoid the problem of zero-durations, we follow Engle and Russell (1998) and treat multiple transactions at the same time as one single transaction. We aggregate their trade volume and average prices and bid-ask spreads.

To get an idea of the sample properties of the data, we present an explorative data analysis. Table 1 shows some sample statistics (sample mean, median, and quantiles) of the durations and trade characteristics of the stocks that are included in our analysis. The mean duration for stocks in liquidity decile two and four varies from 10 minutes to 3 hours (say $4-30$ trades a day), rather than say 10 seconds (thousands of trades a day) for the most liquid stocks like IBM. The mean overnight durations $-$ which measures the time elapsed between the last trade on the previous trading day and the first trade on the next trading day $-$ are somewhat above mean of the intraday durations. Although trading takes place more frequently in the early morning and at the end of a trading day (reflected in the U-shaped pattern of the trading intensity), this can be explained by the fact that we do not take trades into account that take place before the first quotes have been posted.

By comparing sample average and sample median of the durations of each stock in the sample, we see that the distribution of the durations is much more skewed for the infrequently traded stocks than for IBM. This is due to the fact that sometimes several hours (decile four) or even several days (decile two) can elapse before a subsequent trade takes place in stocks in the lower liquidity deciles.

Although illiquid stocks usually trade only several times a day (decile 4) and may not be traded for several days (decile 2), infrequently traded stocks have periods in which they are traded relatively often.

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

In this section we assume that the price impact of trades does not depend on the trading intensity in calendar time and condition on past returns, spread, and volume only. The model that we analyze is the standard VAR-specification proposed by Hasbrouck (1991a, 199b).
We specify the VAR-model (in transaction time) for $z_t = (r_t, s_t x_t^0, x_t^0)'$ as

$$A(L)z_t = c + \upsilon_t, \mathbb{E}\upsilon_t = 0, \mathbb{V}\text{ar}\,\upsilon_t = \Sigma_t, \tag{1}$$

where $A(L)$ is an m-th order (3×3) matrix polynominal 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 model. We choose the formulation of Hasbrouck (1991a, 1991b) where trade sign and the product of trade sign and bid-ask spread contemporaneously influence returns[1]. We also assume covariance stationarity of $(z_t)_t$.
Hasbrouck (1991a, 1991b) points out that the persistent price impact of a an unexpected trade is naturally interpreted as the information content of the trade. The expected impact of an unexpected trade on prices is measured by the *impulse response function*, cf. Lütkepohl (1993). In the VAR-model of equation (1), the price impact of an unexpected buy after k transactions reduces to the coefficient of L^k in element $(1,3)$ of $A(L)^{-1}$ and the long term cumulative impulse response equals element $(1,3)$ of $A(1)^{-1}$. The impulse response function is estimated by replacing the matrix coefficients by their estimated values.

Estimation results
Following many others in the literature, e.g. Hasbrouck (1991a, 1991b), we impose a low order on the VAR-model ($m = 5$) and estimate the model using OLS. Point estimates and heteroskedasticity-consistent standard errors based on the procedure proposed by White (1980) for the representative illiquid stocks (Greenbrier Companies and Commercial Intertech) as well as for IBM are reported in Tables 2, 3 and 4. Estimation results for the other stocks under consideration are available upon request.
To investigate the specification of the models, we test several hypotheses. First of all the truncation of $A(L)$ to lag five is tested using a Ljung-Box test for autocorrelation in the residuals in each of the equations of the VAR-model. This test is asymptotically equivalent to the standard LM-test for

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

serial correlation in the residuals of a regression model and computationally far less demanding than that test. The test shows no evidence against the imposed truncation at lag five for all stocks in the sample including IBM. For each equation of the VAR-model we test whether each group of lagged (explanatory) variables Granger-causes the variable to be explained. The results are summarized in the first panel of Table 5. For IBM, for which the results are not included in Table 5 there is significant Granger-causality in all cases. The Granger-causality results show that it is important to take the feedback between the variables under consideration into account. Engle and Patton (2001) make strong assumptions on the exogeneity of the trading process and ignore this feedback. Table 5 also shows that the differences between the results for decile two and decile four are small.

The price impact of trades

As discussed above the impulse response function, which reflects the price impact of a trade, is fully determined by the VAR-model. The structure of the VAR-model implies that the price impact of a trade will also depend on returns, bid-ask spread and volume of the five last trades. Throughout these are set equal to their sample average, apart from the bid-ask spread for the trade under consideration. This is set at either the 5% or the 95% sample quantile of the spreads for that stock as reported in Table 1. These two cases will be referred to as 'low' and 'high' bid-ask spread, respectively. The estimates of the long run price impact for the stocks under consideration are reported in the first column of Table 6. For example, for Commercial Intertech the long run price impact with small spreads equals 27.8 bp and 50.6 bp with wide spreads.

The impulse response function shows that the price impact of trades in illiquid stocks is very large in comparison to trades in frequently traded stocks such as IBM. For example, for Greenbrier Companies the price impact of a trade with low spreads equals 30.8 bp, while a trade in IBM has a price effect of only 2.4 bp with low spreads. This result is consistent with Easley et al. (1996) and can be explained by the higher risk of informed trading for infrequently traded stocks. We also notice that the price impact of trades for stocks in decile two is generally higher than for stocks in decile four, which is also consistent with Easley et al. (1996).

We observe several other differences between the impulse response functions corresponding to the infrequently and frequently traded stocks. First, we see that the usual monotonically increasing shape that is found for IBM and other frequently traded stocks (see Dufour and Engle (2000) and Spierdijk (2002)) is replaced by a price impact function that first 'overshoots' and subsequently returns to the full information price level. This effect is illustrated in Figure

1. With wide bid-ask spreads, a significant overshooting effect is documented for seven out of ten infrequently traded stocks − see the again first column of Table 6 − while with low spreads three out of ten stocks overshoot[2]. For example, for Commercial Intertech the overshooting effect with small spreads equals 3.4 bp and 4.0 bp with wide spreads. Later we will discuss the convergence time to the full information price that is also reported in Table 6.

A possible explanation for the phenomenon of overshooting would be the influence of *inventory effects*. To avoid inventory costs, the market maker will keep his inventory low. Generally, his inventory will be lower the more infrequently traded the stock. When the request for a trade is posted, the market maker has to rely on other sources than his own inventory to fulfill the order demand. Liquidity is provided by other agents who, however, request a premium that is caused by the fact that they expect to buy the stock back at a lower price. The price of the stock will therefore temporarily rise to a higher level. After some time this effect dies out and the stock price converges to its full information level. The 'overshooting' effect is observed more often with wide spreads than with small spreads. Since wide spreads indicate an increased risk of informed trading, the party providing liquidity to the market maker is likely to incorporate this uncertainty in the price he or she sets. The larger overshooting effect at wide spreads may thus be the consequence of *adverse selection*.

Moreover, in the presence of wide spreads not only the overshooting effect is documented for more stocks than with low spreads, the long term price impact itself is also larger. For example, for Commercial Intertech the long-term price impact of a trade equals 27.8 bp and 50.6 bp with low and high spreads, respectively. See again Figure 1. The long term impulse response with wide spreads is significantly larger than with low small spreads for all stocks including IBM. Hasbrouck (1991a, 199b) also establishes the positive effect on the price change and explains it as follows. Since wide bid-ask spreads indicate an increased risk of informed trading, the information content of trades will be larger. Therefore, the persistent price impact of a trade will be higher in periods of wide spreads. We also note that the difference in price impact with low and wide spreads is much higher for infrequently traded stocks.

[2]We investigate the significance of the overshooting effect as follows. Using the (joint) asymptotically normal distribution of the estimated coefficients (based on White (1980)'s heteroskedasticity-consistent covariance matrix), we randomly draw values of the parameters from this distribution and compute the corresponding impulse response functions. We repeat this 1,000 times and compute the number of draws for which the impulse response function overshoots. Whenever the price impact function overshoots ($\alpha \times 100$) or more times, the effect is significant at (approximately) an $\alpha\%$ significance level.

5 Modeling the trading intensity

In the previous section we measured the price impact of trades in a VAR-model in transaction time for returns, trade volume, and bid-ask spread. However, as discussed in Section 2, the models put forward by Diamond and Verrecchia (1987) and by Easley and O'Hara (1992) predict that calendar time plays a role as well and that the price impact of trades depends upon the trading intensity. The model in Easley and O'Hara (1992) implies, e.g., that the price impact is larger in periods of frequent trading. In order to analyze this issue empirically we consider in Section 6 to what extent the parameters in the VAR-model in transaction time depend on the trading intensity, following the approach of Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002). Moreover, a model for the trading intensity allows transformation from calendar time to transaction time and vice versa, including the analysis of the time it takes until the price adjustment to the new equilibrium value is completed. In this section we consider a simple univariate ACD-model (see Engle and Russel (1998)) to model the diurnally corrected[3] duration process $(y_t)_t$. We assume that the duration process is strongly exogenous, cf. Engle, Hendry and Richard (1983)[4]. Let $\mathcal{I}_{t-1}$ denote the information known up to time $t-1$. An ACD$(1,1)$ specification assumes that the marginal process for the durations $(y_t)_t$ satisfies $y_t = \psi_t \varepsilon_t$, where $\psi_t = \mathbb{E}(y_t \mid \mathcal{I}_{t-1})$ and $(\varepsilon_t)_t$ identically distributed with unit mean and independent of $\mathcal{I}_{t-1}$. The conditional expected duration is specified according to

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

The modeling of the duration process of an infrequently traded stock gives rise to several problems. Most importantly, we need to deal with overnight durations. The usual approach to modeling the trading intensity ignores overnight duration and initializes the first duration on a new day with the unconditional duration. This assumes that information contained in the trading

[3]Throughout all durations are diurnally corrected as follows. We obtain the diurnally adjusted durations by approximating the expected duration given the time of the day by a piecewise linear and continuous spline. We therefore set nodes on $9.30-10.00, 10.00-11.00, \ldots, 14.00-15.00, 15.30-16.00$ hours. We compute the diurnally corrected durations by dividing each duration by its corresponding diurnal correction $\phi_t = \text{const} + \sum_{i=1}^{8} \lambda_i T_{i,t}$, with $T_{i,t} = (\tau_{t-1} - k_i) 1_{\{\tau_{t-1} > k_i\}}$, where k_i corresponds to the i-th time interval as defined above.

[4]In Spierdijk (2002) it is shown that there is significant feedback from trade characteristics (returns, spreads, trade volume) to the trading intensity of five frequenctly traded stocks traded at the NYSE. It is shown that this feedback affects the impulse response functions, both in transaction and in calendar time. However, the effect is quite small. Therefore, we do not take the feedback into account in the sequel.

intensity is not carried over to the next day. For infrequently traded stocks, however, we deal with this as follows. Without loss of generality, consider the ACD$(1,1)$-model with[5] $\alpha + \beta < 1$. The standard specification of the conditional expected duration can be rewritten as

$$\psi_t = \mu + \alpha(y_{t-1} - \mu) + \beta(\psi_{t-1} - \mu),$$

where $\mu = \omega/(1 - \alpha - \beta)$ is the unconditional expected duration (see Engle and Russel (1998)). To incorporate overnight effects, we now insert a dummy variable to allow the conditional duration to deviate from the unconditional expected duration at the beginning of a day; i.e.

$$\psi_t = \mu + (1 - \gamma d_{t-1})\{\alpha(y_{t-1} - \mu) + \beta(\psi_{t-1} - \mu)\}, \tag{2}$$

where d_t is a binary variable indicating whether or not the t-th duration contains an overnight period and $0 \leq \gamma \leq 1$. With this specification of the conditional expected duration, the unconditional expected duration is μ as before, provided that d_t is weakly exogenous. If $\gamma = 1$, the first duration of each day is initialized with the unconditional expected duration μ. This reduces to the common approach to frequently traded stocks. If $\gamma = 0$, however, the usual autoregressive structure of the model remains valid and hence, the overnight duration is used to compute the first duration at a new day. Finally, if $0 < \gamma < 1$, the component containing the overnight durations weighted and used for the initialization of the new day together with the unconditional expected duration μ.
A second issue is the distribution of ε_t. In case of infrequently traded stocks, the distribution of ε_t is likely to have relatively fat tails. Several distributions have been proposed to model the disturbance term ε_t, for example a Weibull-distribution (see Engle and Russell (1998)). However, in Drost and Werker (2001) it is pointed out that this may lead to inconsistent estimators in case of misspecification. We therefore prefer the approach of quasi maximum likelihood (QML). This method yields (under some regularity conditions) consistent (but generally inefficient) estimates and does not require any additional distributional assumptions. To obtain consistent estimates of the standard errors in this case, we use the Bollerslev and Wooldridge (1992) robust covariance matrix.

Estimation results
We jointly estimate the ACD-model and the diurnal correction factor using QML. We apply the BHHH-algorithm to do the numerical optimization, see Berndt, Hall, Hall, and Hausman (1974). To ensure identification, we normalize the constant in the diurnal correction factor such that its expected

[5] This assumption ensures strict stationarity and finiteness of the first moment.

value equals the sample mean of the durations. Moreover, since we take the overnight durations into account, we fix the coefficient of the last node so that the diurnal correction factor is continuous from the end of one day to the next day. The estimation results for the ACD-model are shown in Table 7 (the results for the linear spline are available upon request). The persistence parameter β is generally lower for infrequently traded stocks than for liquid stocks.

For all stocks $-$ including IBM $-$ the overnight durations play a role, since the parameter γ is significantly different from one in all cases. The coefficient γ of the overnight dummy is significantly different from both zero and one (although it is close to one) for IBM. Hence, the overnight duration is taken into account for the initialization of a new day. This means that the usual approach in the literature that simply ignores the overnight durations is not fully efficient. The same holds for the approach to treat the overnight durations the same as the other durations.

The overnight durations will have different impact for liquid and illiquid stocks. The intuition is as follows. In case of frequently traded stocks such as IBM, there will be many trades during the first minutes of the opening of the market so that the effect of the information from the previous trading day $-$ if relevant $-$ would quickly disappear and would only be relevant for a small fraction of the total number of observations. The standard treatment of the overnight durations will therefore have little impact on the estimates of ω, α, and β and on the market impact of trades. However, for infrequently traded stocks there are only few trades a day. This suggests that the overnight durations could have a long lasting impact on the remaining transactions for that day or even for subsequent days. They will thus affect a large fraction of the observations as well as estimates of the market impact of trading.

We indeed see that the estimated values of γ are much lower for the infrequently traded stocks than for the frequently traded stock IBM. In fact, for four out of five stocks from decile two the overnight coefficient γ is not significant, meaning that we cannot reject that the overnight duration is taken into account entirely. For four out of five stocks from decile four γ is significantly different from both zero and one, so a weighted average of the overnight duration and the unconditional mean is used to initialize the first duration of the new day. Thus, the more illiquid the stocks, the more important the overnight duration.

The price impact of trades in calendar time

Now that we have endogenized the trading intensity, it is possible to compute the impulse response functions corresponding to the VAR-model in calendar time. We do this by fixing a moment of the day at which a trade takes place (we have taken 12.30 PM). Subsequently, we simulate $N = 1,000$ paths of durations and compute the value of the cumulative impulse response function at each second. Finally, we average the impulse responses over the N simulations which results in an estimate of the price impact function at each second. We simulate paths of durations by randomly drawing from the empirical distribution of the (consistently estimated) ACD-residuals. We compute the price impact function of a trade in periods of 'slow' trading (we initialize durations with the 95% sample quantile) and in times of 'fast' trading (5% sample quantile). We set past values of the trade characteristics equal to their equilibrium values. We do this for all stocks, including IBM. We consider 'small' and 'wide' initial spreads, as we did before. The time to reach the new efficient price is measured as the time it takes until the price has stabilized and attained 99.5% of the long-term impulse response.

The results are displayed in the first column of Table 6. For example, for Commercial Intertech it takes one hour and fourty minutes before 99.5% of the full information price has been attained in case of fast trading and small spreads. We see that it may sometimes take several days before the new efficient price has been reached. For example, with slow trading it takes approximately six hours before the new efficient price has been reached in case of the Commercial Intertech stock. Since the trade was initiated at 12.30 PM, the price will have reached the new efficient price the next day around 12.30 PM. For Huntingdon Life Science it takes more than twelve hours to reach the new efficient price in case of fast trading and small spreads. So even in periods of *fast* trading, it may take several days before the effect of a trade in a stock from decile two has died out.

6 Dependence of the price impact on the trading intensity

In Section 4 we estimated the original Hasbrouck (1991a, 199b) model in which the trading intensity does not play a role. In Section 5 we modeled the trading intensity and we now turn to VAR-model in transaction time in which the trading intensity is incorporated.

As in Section 4, we specify the VAR-model for $z_t = (r_t, s_t x_t^0, x_t^0)'$ according to equation (1) with identical assumptions regarding the disturbances $(v_t)_t$. Again we assume covariance stationarity. We no allow $A(L)$ to depend upon the trading intensity; i.e.

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

An extensive specification search shows that only impact of trades on returns significantly depends upon the trading intensity. We let the coefficient corresponding to the impact of trade sign on returns depend upon the trading intensity in the following way

$$a_{j,(1,3)} = \gamma_j + \delta_j \cdot \frac{1}{1 + y_{t-j}} \qquad [j = 0, \dots, 5]. \tag{3}$$

Although we do not have any zero-durations in our data, we still add one second in the denominator. This will appear convenient for simulation purposes[6]. This specification is in line with Dufour and Engle (2000), Zebedee (2001) and Spierdijk (2002). However, while Dufour and Engle (2000) and Spierdijk (2002) use the function $\log(1 + y)$ to model the dependence on the trading intensity and Zebedee (2001) uses $\exp(c \cdot y)$, we use the function $1/(1 + y)$ since this gives a better fit to the data.
Furthermore, we also have to deal with overnight-effects. Information may be released overnight, see Foster and Vishwanathan (1990). For this reason we want to take into account that the first trade on a day may be more informative than the other trades. Therefore, we extend equation (3) with a dummy d_t indicating whether or not the t-th transaction is the first trade of the day; i.e.

$$a_{j,(1,3)} = \gamma_j + \delta_j \cdot \frac{1}{1 + y_{t-j}} + \xi \cdot 1_{\{j=0\}} \cdot d_{t-j} \qquad [j = 0, \dots, 5].$$

We thus allow the first trade of the day to have more impact than the remaining trades, since it may contain overnight information.

Estimation results
To estimate the duration dependent VAR-model, we set again $m = 5$. We estimate the model using OLS with White (1980)'s heteroskedasticity-consistent covariance matrix.
From Table 8 we see that the durations have negative contemporaneous impact on returns. This also holds for the stocks for which the results are not reported. These results coincide with the predictions made by Easley and O'Hara (1987, 1992) and the empirical results of Dufour and Engle (2000), Zedebee (2001) and Spierdijk (2002).
For all stocks from decile four apart from Commercial Intertech the impact of the first trade of the day is significantly higher than the impact of the

[6] Simulated durations are generally not integer valued. As a consequence, simulated durations may be close to zero. To avoid numerical problem due to this, we add one second to the durations is the denominator. Adding one second does not have much impact on the estimation results.

remaining trades of the day. This means that the price impact and thus the information content of the first trade of the day is significantly larger than the other trades on that day, suggesting that information is revealed overnight (cf. Foster and Viswanathan (1990)). For IBM the price impact of the first trade of the day is also significantly higher. For all stocks in liquidity decile two the first trade of the day does not have a significantly different impact on prices. This can be explained by the fact that trading in the latter type of stocks is so infrequent that many trades in the sample are the first of that day.

For each equation of the VAR-model we test whether each group of lagged (explanatory) variables Granger-causes the variable to be explained. The results are summarized in Table 5. For IBM (not included in Table 5) there is significant Granger-causality in all cases. These results emphasize the importance of taking the feedback among the various variables into account, which is ignored in Engle and Patton (2001) as noticed before.

7 Trading intensity and the price impact of trades

In this section we focus on the price impact of trades in the settng of Section 6 where the trading intensity is allowed to influence the price impact of trades. Since some coefficients in the VAR-model now depend upon the trading intensity, analytical expressions for the impulse response function are no longer available. Therefore, we simulate $N = 1,000$ paths of durations in the same way as we did for the impulse response function in calendar time in Section 5. For each path of durations we obtain a price impact, which we average out over all simulations to obtain the final impulse response functions.

We present impulse response functions both in transaction and in calendar time. We compute the impact of a trade in a period of 'slow' trading and in times of 'fast' trading, as before. We again set past values of the trade characteristics equal to their equilibrium values. We consider 'small' and 'wide' initial spreads. The results are displayed in the second and third column of Table 6.

First of all, we observe large differences in the price impact between fast and slow trading for infrequently traded stocks, see also Figure 2 for the impulse response function corresponding to Commercial Intertech. This plot displays the price impact function in periods with fast and slow trading. It shows that the price impact of a trade is much larger in periods of frequent trading. For example, with small spreads the difference between fast and slow trading is significant and equals 14.8 bp for Commercial Intertech and 6.9 Greenbrier Companies. For IBM the difference is only 0.1 bp in this situation, which is not significant. This effect, but much weaker than established here, has also been reported by Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002). It confirms the intuition that, for infrequently traded stocks, the trading intensity is very informative.

As in the model without durations, we find price impact functions for illiquid stocks that first overshoot and subsequently decrease towards the full information level, see Table 6. The overshooting effect is documented more often for wide spreads than for small spreads. Both in periods of fast and slow trading the overshooting effect occurs, as shown again by Table 6. With small spreads, three out of ten stocks overshoot, while eight (seven) out of ten stocks overshoot with wide spreads and fast (slow) trading. Figure 2 displays the impulse response function for Commercial Intertech with slow and fast trading.

We interpret the relation between the trading intensity and the overshooting effect as follows. In periods of very slow trading the market maker will keep his inventory low. When a large order is posted, he has to rely almost completely on other parties to fulfill the order demand. This can cause overshooting as discussed in Section 4. In case of frequent trading, however, he will be able to fulfill the demand entirely or to a large extent with his own inventory. However, in the latter case the risk of informed trading is considered larger, cf. Easley and O'Hara (1992), and the market maker wants to rebalance his inventory quickly. This explains why the overshooting effect is documented both in periods of fast and slow trading.

To get insight in the adjustment process of the price following a large trade, we now turn to the impulse response functions in calendar time. From the second and third column of Table 6 it follows that for the least liquid stocks (decile 2) the convergence process may take several trading days, in particular in periods of slow trading. For example, with slow trading it takes about six hours for Commercial Intertech to reach the new price that follows a trade initiated around noon. This means that the new efficient price after a shock at noon is expected to be attained around noon the next day. For Huntingdon Life Science it takes almost fourteen hours to reach the full information price in case of fast trading, see Figure 3. Again we see again that even in periods of relatively *high* market activity, it may take some days before the full information price level has been reached.

8 Conclusions

In this paper we investigated the price impact of a trade and its relation to the trading intensity, taking the overnight behavior of the stock into account. We applied a VAR-model based upon Hasbrouck (1991a, 199b) to ten infrequently traded stocks and one very liquid stock (IBM) traded on the NYSE in the year 1999. We established the following results.

The price impact function of both frequently and infrequently traded stocks depends upon the trading intensity and the bid-ask spread. The higher the trading intensity and the wider the spreads, the higher the price impact of a trade. For infrequently traded stocks the difference in price impact with fast and slow trading and small and wide spreads is much larger than for frequently traded stocks. Moreover, infrequently traded stocks show the phenomenon of 'overshooting'. Prices increase to the full information level after a buy has taken place. However, before the price reaches the new higher level, it temporarily increases to a value higher than the new efficient price. Subsequently prices decrease to the new efficient price. The price of frequently traded stocks such as IBM monotonically increase to the new efficient price after a buy and do not overshoot, as is shown in our analysis and in the literature such as Dufour and Engle (2000), Zebedee (2001) and Spierdijk (2002). Furthermore, although overnight durations are significant for both liquid and illiquid stocks, we showed that its impact on the convergence to the full information price is economically negligible for IBM both in transaction and in calendar time, while the economic effect is large for the infrequently traded stocks. Hence, the information contained in the trading intensity of infrequently traded stocks is carried over to the next day. Finally, the convergence to the new efficient price that follows after a trade in an illiquid stock may last for several days.

We have analyzed ten infrequently traded stocks, taking five randomly selected stocks from decile two as well as liquidity decile four. While stocks in the decile four are traded every day, stocks in decile two may not trade for several days. According to Easley et al. (1996) we would expect to find similar results for both deciles. In fact, we established the same results for both deciles: the majority of stocks have a price impact function that overshoots, in particular when spreads are wide and trading takes place either fast or slow. For stocks in decile two and three, it may take several days before the new efficient price is attained. For stocks in decile two this even holds in periods of relatively *high* market activity.

There are various directions for further research. Since most of the stocks traded at the NYSE and other organized exchanges are illiquid[7], further research should investigate the effect of overshooting and the impact of the overnight period on (optimal) trading strategies; for example for institutional investors. 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. In this paper we have shown that the answers to these questions are likely to be very different for frequently and infrequently traded stocks. For example, the fact that the price of an infrequently traded stock may overshoot after a large trade, is likely to influence the optimal moment to post a new order after that trade. To find out about illiquid stocks and optimal trading, a model is required that includes not only trade sign but also trade size. We hope that future research will fill out the gaps.

[7]This is illustrated by the fact that only 1.6% of the listed stocks produced 58% of the total trade volume in the year 1999 at the NYSE.

ticker symbol	GBX	HTD	IAL	JAX	PIC	CHP	FC	FMN	TEC	XTR	IBM
company name	Greenbrier Companies Inc.	Huntingdon Life Science	International Aluminium Corp.	J.Alexander Corp.	Pichin Corp.	C&D Technologies	Franklin Covey Corp.	F&M National Corp.	Commercial Intertech Corp.	Xtra Company Corp.	International Business Machines
#transactions	2,618	726	538	961	2,116	7,802	6,898	6,122	5,105	5,632	522,580
# trading days	230	154	155	189	247	252	252	252	252	252	252
mean # trades a day	11	5	4	5	9	31	27	24	20	22	2074
durations (hh:mm:ss)											
mean	00:25:47	02:15:36	03:03:25	01:51:10	00:46:31	00:12:34	00:14:13	00:16:01	00:19:13	00:17:15	00:00:11
median	00:11:07	00:37:47	00:55:53	00:32:04	00:20:17	00:05:18	00:06:46	00:07:29	00:09:12	00:07:31	00:00:07
0.5%	00:00:01	00:00:01	00:00:01	00:00:01	00:00:01	00:00:01	00:00:01	00:00:01	00:00:01	00:00:01	00:00:01
5%	00:00:10	00:00:34	00:00:05	00:00:02	00:00:06	00:00:04	00:00:07	00:00:6	00:00:06	00:00:06	00:00:02
90%	01:03:19	06:51:11	02:51:39	05:01:35	02:10:07	00:33:10	00:36:04	00:41:41	00:49:43	00:44:53	00:00:24
95%	01:32:38	10:59:14	09:24:49	07:37:31	03:05:02	00:49:10	00:53:23	01:00:24	01:01:19	01:06:14	00:00:33
99.5%	04:50:43	26:05:31	13:51:07	21:03:43	07:22:32	02:03:35	02:02:14	02:16:27	02:46:47	02:52:40	00:01:11
spread ($)											
mean	0.1444	0.0889	0.2734	0.1340	0.1861	0.1940	0.1253	0.1631	0.1681	0.1896	0.1681
median	0.1250	0.0625	0.250	0.1250	0.1875	0.1875	0.1250	0.1250	0.1250	0.1875	0.1250
5%	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
95%	0.2500	0.1250	0.5000	0.2500	0.3750	0.3750	0.2500	0.3125	0.3125	0.4375	0.3125
return (bp)											
mean	-1.1566	-4.3027	-4.3698	-2.5989	-4.6689	0.3219	-1.1461	0.0013	0.0200	0.0440	0.0025
median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
trade sign											
mean	0.1876	-0.0399	0.2770	-0.0749	0.0047	0.0422	-0.0191	0.0601	0.0170	0.0646	0.1251
median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 1:
Sample statistics

	lag	GBX		TEC		IBM	
		estimate	st.error				
const	j	−3.9764	1.1761	−0.4204	0.7976	−0.2377	0.0078
$a_{j,(1,1)}$	1	0.0172	0.0228	0.0201	0.0201	−0.0062	0.0027
	2	0.0558	0.0226	−0.0012	0.0160	0.0293	0.0045
	3	−0.0138	0.0234	−0.0018	0.0154	0.0211	0.0045
	4	0.0153	0.0208	0.0111	0.0156	0.0182	0.0031
	5	−0.0053	0.0200	−0.0049	0.0157	0.0118	0.0035
$a_{j,(1,2)}$	0	146.8265	18.9262	99.9678	10.2178	5.9198	0.1957
	1	−0.1874	19.0183	−25.1515	8.2923	0.6625	0.2009
	2	−26.9100	17.2379	−24.7075	7.9774	−0.6383	0.1583
	3	−27.4651	18.2281	−2.1631	8.3432	−0.3953	0.1415
	4	−0.6414	17.8405	3.8334	7.6075	−0.2816	0.1257
	5	−25.7380	16.5146	−3.4959	7.6808	−0.3323	0.1182
$a_{j,(1,3)}$	0	13.1685	2.6576	13.9108	2.1807	0.5202	0.0304
	1	−1.9179	2.7249	4.5528	1.8642	0.3173	0.0284
	2	0.1766	2.5991	2.1375	1.7771	0.0744	0.0258
	3	2.1845	2.7540	−0.2219	1.8882	0.0087	0.0227
	4	−0.1012	2.5633	−2.0602	1.7012	0.0059	0.0204
	5	1.8278	2.3802	−1.9847	1.7027	−0.0227	0.0187

Table 2:
Estimation results for the return equation without duration dependence

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 from White (1980)'s heteroskedasticity-consistent covariance matrix.

	lag	GBX		TEC		IBM	
		estimate	st.error				
const	j	0.0017	0.0030	0.0019	0.0029	0.0103	0.0003
$a_{j,(2,1)}$	1	−0.0006	0.0001	−0.0007	0.0001	−0.0054	0.0006
	2	−0.0002	0.0001	−0.0003	0.0001	0.0005	0.0001
	3	0.0000	0.0001	−0.0001	0.0001	0.0004	0.0001
	4	−0.0001	0.0001	0.0000	0.0001	0.0002	0.0001
	5	−0.0001	0.0001	0.0000	0.0001	0.0002	0.0001
$a_{j,(2,2)}$	1	0.2414	0.0516	0.2527	0.0331	0.5503	0.0084
	2	0.0748	0.0482	0.1008	0.0324	−0.0093	0.0070
	3	0.0170	0.0450	0.0005	0.0317	−0.0157	0.0064
	4	0.0424	0.0441	−0.0202	0.0312	−0.0038	0.0062
	5	0.0038	0.0443	0.0278	0.0298	−0.0015	0.0055
$a_{j,(2,3)}$	1	0.0116	0.0065	0.0187	0.0058	−0.0183	0.0014
	2	0.0039	0.0068	0.0004	0.0064	0.0115	0.0011
	3	−0.0009	0.0067	0.0031	0.0064	0.0079	0.0011
	4	−0.0024	0.0067	0.0043	0.0064	0.0054	0.0010
	5	0.0117	0.0064	−0.0048	0.0062	0.0050	0.0009

Table 3:
Estimation results for the bid-ask spread/trade sign equation

The equation for bid-ask spread/trade sign 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 from White (1980)'s heteroskedasticity-consistent covariance matrix.

	lag	GBX		TEC		IBM	
		estimate	st.error				
const	j	0.0492	0.0177	0.0092	0.0123	0.0577	0.0017
$a_{j,(3,1)}$	1	−0.0036	0.0004	−0.0038	0.0002	−0.0278	0.0029
	2	−0.0007	0.0003	−0.0012	0.0002	−0.0011	0.0003
	3	0.0000	0.0003	−0.0005	0.0002	0.0009	0.0004
	4	−0.0004	0.0003	−0.0002	0.0002	0.0006	0.0004
	5	−0.0004	0.0003	−0.0002	0.0002	0.0006	0.0004
$a_{j,(3,2)}$	1	0.3367	0.2534	0.2318	0.1230	0.7383	0.0231
	2	0.0585	0.2595	0.2968	0.1247	−0.2418	0.0201
	3	0.1256	0.2513	−0.0454	0.1244	−0.1186	0.0195
	4	0.0554	0.2513	−0.1201	0.1230	−0.0784	0.0195
	5	−0.2371	0.2489	0.0074	0.1208	−0.0286	0.0179
$a_{j,(3,3)}$	1	0.2759	0.0422	0.3029	0.0287	0.2534	0.0041
	2	0.0836	0.0430	0.0084	0.0294	0.1148	0.0040
	3	−0.0135	0.0423	0.0395	0.0289	0.0603	0.0038
	4	0.0194	0.0418	0.0272	0.0288	0.0443	0.0038
	5	0.1188	0.0404	0.0033	0.0279	0.0346	0.0036

Table 4:
Estimation results for the trade sign equation

The trade sign 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 from White (1980)'s heteroskedasticity-consistent covariance matrix.

causality from causality to	returns	trade sign	spread × trade sign trade sign	trade sign × durations
VAR-model in transaction time				
decile 2				
returns	–	4	4	–
trade sign	5	–	2	–
spread × trade sign	4	1	–	–
decile 4				
returns	–	5	5	–
trade sign	5	–	5	–
spread × trade sign	5	2	–	–
extended VAR-model				
decile 2				
returns	–	5	5	5
decile 4				
returns	–	3	3	4

Table 5:

Tests for Granger-causality

This table reports the number of stocks in deciles two and four for which there is significant Granger-causality (at a 5% confidence level) in the VAR-model defined in equation (1) and in the VAR-model extended with a role for the trading intensity. This table shows, for example, that for four stocks in decile 2 there is significant Granger-causality from trade sign to returns (see the first element in the column ‘trade sign’).

stock	transaction time small, wide spreads	fast trading small, wide spreads	slow trading small, wide spreads
decile 2			
GBX			
price impact (bp)	30.5, 50.3	36.8, 54.9	29.9, 48.1
overshooting (bp)	0.0, **1.5**	0.0, **6.9**	0.0, **4.7**
convergence time (hh:mm:ss)	*fast*: 02:46:50, 02:46:40	03:20:00, 01:06:40	36:06:40, 10:50:00
	slow: 19:10:00, 08:36:40		
HTD			
price impact	93.2, 238.4	111.6, 246.8	72.6, 212.3
overshooting	**46.0**, **33.0**	**44.9.3**, **29.7**	**55.0**, **41.6**
convergence time	*fast*: 12:30:00, 08:20:00	13:36:40, 07:46:40	172:46:40, 130:00:00
	slow: 161:40:00, 118:03:20		
IAL			
price impact	21.3, 40.3	37.1, 52.3	15.1, 29.8
overshooting	0.0, 0.2	0.0, **3.5**	0.0, 0.8
convergence time	*fast*: 13:53:20, 12:46:40	23:03:20, 06:23:40	83:20:00, 69:26:40
	slow: 83:20:00, 69:26:40		
JAX			
price impact	142.0, 208.3	180.7, 214.6	136.6, 168.8
overshooting	**2.2**, **23.7**	**8.5**, **26.6**	**2.2**, **23.1**
convergence time	*fast*: 11:06:40, 13:53:20	08:03:20, 16:06:40	33:20:00, 33:20:00
	slow: 27:46:40, 27:26:40		
PIC			
price impact	61.8, 92.8	115.7, 155.3	41.8, 71.5
overshooting	0.0, **9.6**	0.0, 0.0	0.3, **17.1**
convergence time	*fast*: 01:56:40, 01:56:40	01:56:40, 01:23:20	25:00:00, 27:46:40
	slow: 22:46:40, 23:33:00		
decile 4			
CHP			
price impact	17.3, 46.2	24.0, 53.8	14.2, 43.9
overshooting	0.0, 0.0	0.0, 0.0	0.0, 0.0
convergence time	*fast*: 02:13:20, 01:40:00	01:56:40, 01:40:00	07:13:30, 06:56:40
	slow: 08:36:40, 07:13:20		
FC			
price impact	33.4, 66.4	43.0, 75.9	29.6, 61.6
overshooting	0.0, 0.0	0.0, **1.1**	0.0, 0.0
convergence time	*fast*: 01:06:40, 00:33:20	00:50:00, 00:33:20	07:46:40, 04:43:20
	slow: 07:30:00, 04:26:40		
FMN			
price impact	15.2, 31.5	19.1, 35.5	13.9, 30.6
overshooting	0.0, **2.1**	0.0, **3.5**	0.0, **2.3**
convergence time	*fast*: 02:30:00, 01:40:00	01:06:40, 00:33:20	02:13:20, 04:43:20
	slow: 09:43:20, 07:13:20		
TEC			
price impact	27.8, 50.6	38.5, 61.6	23.7, 46.6
overshooting	**3.4**, **4.0**	**4.3**, **9.5**	**2.9**, **5.4**
convergence time	*fast*: 01:40:00, 01:43:20	01:23:20, 01:23:20	05:33:20, 05:50:00
	slow: 05:50:00, 05:50:00		
XTR			
price impact	13.3, 25.1	19.3, 30.4	11.8, 22.9
overshooting	0.0,**1.7**	0.4, **2.6**	0.0, **2.8**
convergence time	*fast*: 01:40:00, 03:20:00	01:56:40, 01:23:20	07:13:30, 07:30:00
	slow: 08:03:20, 08:20:00		
decile 10			
IBM			
price impact	2.4, 4.8	2.4, 5.3	2.3, 5.2
overshooting	0.0, 0.0	0.0, 0.0	0.0, 0.0
convergence time	*fast*: 00:01:10, 00:01:30	00:01:50, 00:01:30	00:04:20,00:04:30
	slow: 00:03:30, 00:04:00		

Table 6:
Long-run impulse responses, overshooting effect and convergence time

This table reports the long-term impulse response in bp, the overshooting effect in bp and the convergence time in the VAR-model defined in equation equation (1) in transaction time and in the VAR-model extended with a role for the trading intensity. Both periods of small and wide spreads are considered. Significant overshooting effects (at a 5% level) are displayed in boldface. In the model with durations two scenarios are considered: fast and slow trading. Fast trading refers to the duration process initialized with the 5% sample quantile of the durations, while slow trading applies to the model initialized with the 95% sample quantile. The convergence reflects the time (expressed in hh:mm:ss) it takes until the price has stabilized and reached 99.5% of the long-term impulse response.

stock		TEC		GBX		IBM	
	coeff.	estimate	std.error				
ω	const	0.0036	0.0024	0.0026	0.0004	0.0090	0.0005
α	y_{t-1}	0.0446	0.0088	0.0795	0.0009	0.0281	0.0006
β	ψ_{t-1}	0.9524	0.0074	0.9191	0.0008	0.9629	0.0009
γ	d_{t-1}	0.1878	0.1115	0.0814	0.0418	0.9100	0.0361

Table 7:
Estimation results for the ACD-model

The coefficients of the ACD$(1,1)$-model as specified in equation (2) are estimated using QML. The standard errors are between parentheses and are computed from the Bollerslev and Wooldridge (1992) robust covariance matrix.

	lag	GBX		TEC		IBM	
		estimate	st.error				
const	j	−3.7775	1.1768	−0.3949	0.7895	−0.2385	0.0077
$a_{j,(1,1)}$	1	0.0227	0.0229	0.0285	0.0205	−0.0064	0.0036
	2	0.0531	0.0228	−0.0088	0.0159	0.0293	0.0044
	3	−0.0196	0.0230	−0.0048	0.0155	0.0209	0.0045
	4	0.0102	0.0208	0.0063	0.0155	0.0173	0.0031
	5	−0.0060	0.0201	−0.0036	0.0156	0.0123	0.0035
$a_{j,(1,2)}$	0	141.5759	18.8604	96.2212	10.3784	5.7349	0.1808
	1	−2.2587	19.0450	−23.6423	8.2559	0.7131	0.1890
	2	−25.3066	17.2003	−25.4846	7.9142	−0.5879	0.1579
	3	−26.9614	18.1174	0.5168	8.2477	−0.3851	0.1402
	4	−2.1111	17.8144	3.9387	7.5475	−0.3028	0.1223
	5	−26.3202	16.4724	−3.5512	7.6343	−0.2958	0.1158
γ_j	0	11.4955	2.6713	11.4691	2.2023	0.4466	0.0307
	1	−2.7788	2.7578	1.8393	1.8953	0.3251	0.0289
	2	0.1021	2.6044	2.9234	1.7922	0.0714	0.0274
	3	2.9883	2.7700	−0.5184	1.9003	0.0149	0.0242
	4	0.3102	2.5992	−1.6755	1.7174	0.0083	0.0227
	5	1.8046	2.3944	−1.7579	1.7262	−0.0154	0.0207
δ_j	0	127.7821	26.0987	145.7875	17.9367	0.5889	0.0614
	1	4.0977	23.6109	0.1759	15.3827	−0.1305	0.0686
	2	−3.7168	19.3886	−7.7590	14.0404	−0.0157	0.0607
	3	−32.7644	22.9360	−3.8229	14.2702	−0.0480	0.0609
	4	10.9712	25.5844	−5.1400	13.5868	0.0177	0.0800
	5	−2.1946	20.4632	−4.6157	12.9629	−0.0803	0.0653
ξ		7.5003	4.3659	4.6650	3.9800	31.9244	6.4514

Table 8:
Estimation results for the return equation with duration dependence

The return equation of the VAR-model defined in equation (1) with duration dependence 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.

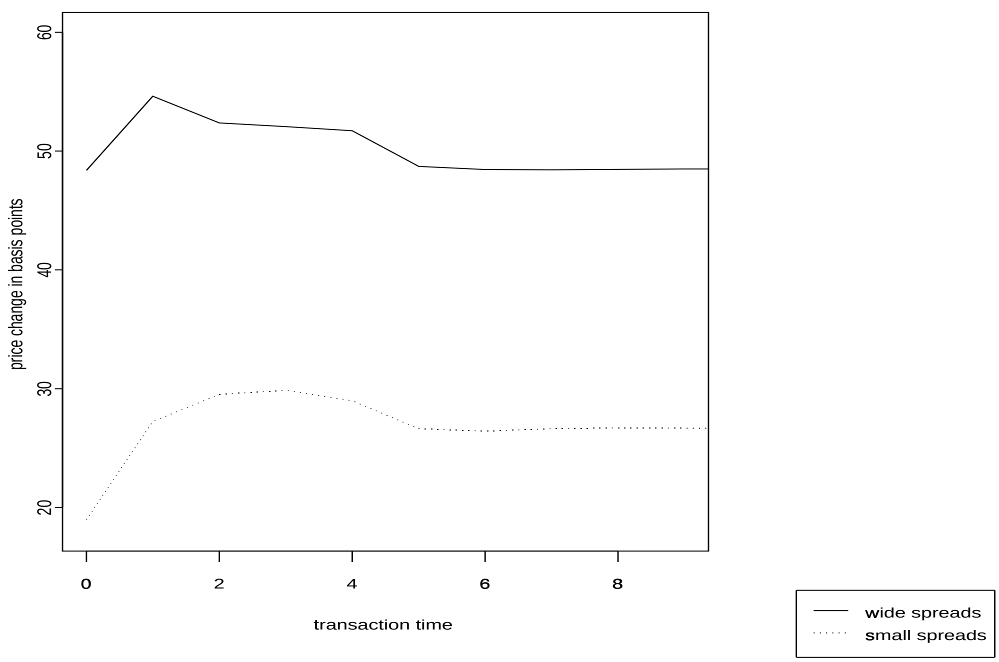

Figure 1:

Price impact of a trade in TEC: small versus wide spreads

Impulse response functions corresponding to a trade in Commercial Intertech measured in the VAR-model defined in equation (1) in periods of small and wide spreads.

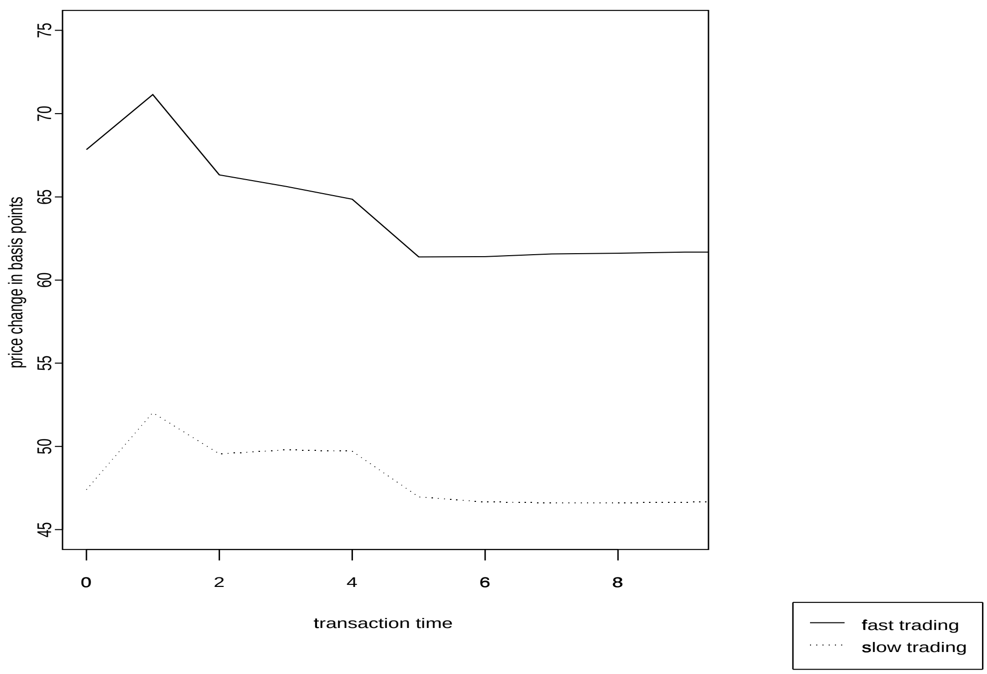

Figure 2:

Price impact of a trade in TEC: slow versus fast trading

Impulse response functions corresponding to a trade in Commercial Intertech measured in the VAR-model defined in equation (1) with duration dependence. Both periods of slow and fast trading are considered.

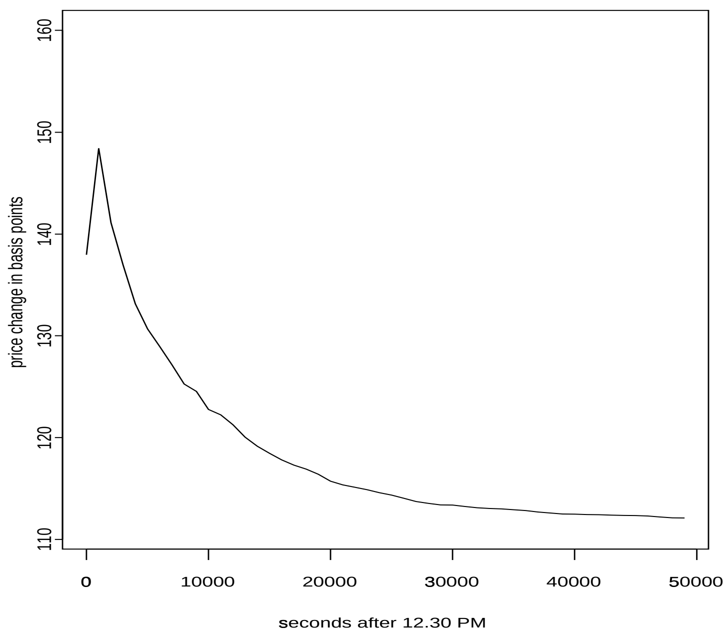

Figure 3:

Price impact of a trade in HTD: convergence time to the new efficient price

Impulse response functions corresponding to a trade in Huntingdon Life Science measured in the VAR-model defined in equation (1) with duration dependence in a period of fast trading and small spreads.

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