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Time and the Price Impact of a Trade: A Structural Approach *

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Abstract:
We revisit the role of time in measuring the price impact of trades using a new empirical method that combines spread decomposition and dynamic duration modeling. Previous studies which have addressed the issue in a vector-autoregressive framework conclude that times when markets are most active are times when there is an increased presence of informed trading. Our empirical analysis based on recent European and U.S. data offers challenging new evidence. We find that as trade intensity increases, the informativeness of trades tends to decrease. This result is consistent with the predictions of Admati and Pfleiderer's (1988) rational expectations model, and also with models of dynamic trading like those proposed by Parlour (1998) and Foucault (1999). Our results cast doubt on the common wisdom that fast markets bear particularly high adverse selection risks for uninformed market participants.

JEL Classification: G10, C32

Keywords: Price Impact of Trades, Trading Intensity, Dynamic Duration Models, Spread Decomposition Models, Adverse Selection Risk

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1 Introduction

How is the time interval between transactions associated with information processing in financial markets? If a high trading intensity indicates the presence of informed traders, should a liquidity trader steer clear of an active market in order to avoid adverse selection? And is it prudent to protect non-informed agents by interrupting continuous trading in a fast market (and re-start with a call auction)? These are important questions for academics, traders and exchange operators alike, and they have spurred a growing theoretical and empirical body of literature.[1] In a seminal paper, Dufour and Engle (2000) extend Hasbrouck's (1991a, 1991b) vector-autoregressive framework to account for time-varying transaction intensity when measuring the informational content of trades. Dufour and Engle's (2000) findings are in line with a conventional wisdom of market microstructure: that fast trading means informed trading.

This paper revisits the role of time in measuring the price impact of trades. We combine Madhavan et al.'s (1997) spread decomposition model and the autoregressive conditional duration (ACD) model introduced by Engle and Russell (1998), and study how time-varying trade intensities affect the adverse selection component of the spread. Our empirical findings, based on recent European and US data, contradict the "fast trading means informed trading" paradigm. They indicate that short time intervals between trades rather reflect the activity of impatient, yet uninformed traders. Our results thus re-emphasize the empirical relevance of Admati and Pfleiderer's (1988) rational expectations model and strategic trading models like those of Parlour (1998) and Foucault (1999). Our study casts doubt on the common wisdom that fast markets bear particularly high adverse selection risks for uninformed market participants.

Classic microstructure theory delivers ambiguous predictions regarding the relation between transaction intensities and informativeness of trade events. Diamond and Verrecchia (1987) show that in the presence of short sale constraints, longer intervals of trade inactivity indicate bad news. In Easley and O'Hara's (1992) model, informed traders split up

[1] See Hasbrouck (2007) and Biais et al. (2005) for recent surveys.

their orders into smaller chunks in order to conceal their information. This behavior leads to shorter durations between trades. In the same vein, Foster and Viswanathan (1990) explain high activity by the presence of informed traders, which deters the uninformed from trading. A contradictory prediction follows from Admati and Pfleiderer's (1988) model. Here, non-informed liquidity traders cluster during certain periods of the trading day, which implies that trades in a fast market are less informative. Dufour and Engle's (2000) finding that trades occurring after short time intervals since the last transaction are associated with a larger price impact than trades following long non-trading periods thus corroborates the "fast trading means informed trading" hypothesis implied by Easley and O'Hara's (1992) model. This conclusion is supported by Furfine (2007) and Spierdijk (2004), who also use VAR approaches based on midquote returns.

We contribute to the discussion from a different methodological angle. Instead of using a multiple time series model, we draw on the class of spread decomposition models put forth by Glosten and Harris (1988), Madhavan et al. (1997) and Huang and Stoll (1997). The key parameter in Madhavan et al.'s (1997) model is the adverse selection component of the spread, which indicates how liquidity suppliers assess the price impact of incoming trades. We model the adverse selection component as a time-varying parameter which depends on the time between trades. These trade durations are highly predictable, exhibiting a pronounced diurnal pattern and a strong serial correlation (c.f. Engle and Russell 1998). Since only the unpredictable component should have new informational content, we identify the innovation component of the trade duration process using the ACD model developed by Engle and Russell (1998). We derive moment conditions that allow the joint estimation of structural and autoregressive parameters using the Generalized Method of Moments (GMM). Our methodological contribution is thus to establish a link between classic microstructure and the econometrics of ultra-high frequency data initiated by Engle (2000).

Our empirical analysis is based on a cross-section of stocks traded on one of the most important European stock markets, the Frankfurt Stock Exchange's Xetra system, as well as a matched sample of NYSE-traded U.S. stocks. Our results contradict the "fast trading means informed trading" paradigm. For both the European and the US samples we find that transactions occurring during periods of high trading activity are less informative than trades during less active periods. Moreover, the adverse selection component of the spread is considerably smaller for trades after shorter durations. This finding is in sharp contrast to the results of Dufour and Engle (2000). It is, however, in accordance with Admati and Pfleiderer's (1988) rational expectations model, and it is also consistent with the crowding-out effect described in Parlour (1998), which works - in a nutshell - as follows. When spreads are small and depth at the best quotes is high, the probability of execution of a limit order decreases and, consequently, limit orders become less advantageous. Impatient traders will thus switch to using market orders. The crowding-out of limit orders by market orders results in an increased trading frequency and shorter inter-trade durations. But periods of ample liquidity are associated with low price volatility and no asymmetric information. Thus, active markets are expected to imply small price impacts of trades.

When we estimate Dufour and Engle's (2000) VAR on our data, we are able to qualitatively confirm their findings and the resulting conclusions. The contradictory results must therefore be rooted in the way the empirical methodologies make use of the data. We argue that by thinning the sequence of quote changes at trade events, a self-selected sample is produced. The trade-event filtering performed by Dufour and Engle (2000) implies that all quote revisions in between trades are implicitly associated with the previous trade event. However, midquote changes can occur due to the processing of public information unrelated to the previous trade event. We argue, therefore, that the trade-event filtering of quote revisions drives the "fast trading means informed trading" result. The key difference between Dufour/Engle's VAR and our structural alternative is that we do not rely on filtered observed quote revisions, but assume that the suppliers of liquidity anticipate the information revealed in subsequent trades. [2]

[2] The obvious solution (at first sight) estimating the trade and quote VAR on non-filtered data is not feasible. When pure quote revision events are included in the data, the VAR parameters cannot be made dependent on the time between trades.

The remainder of the paper is organized as follows. In Section 2 we describe the market structure and the data, before going on to explain our empirical methodology in Section 3. The empirical results are then presented and discussed in Sections 4 and 5, before we conclude our analysis in Section 6.

2 Market structure and data

Our empirical analysis uses data from the first quarter of 2004 from one of the largest European Stock markets, the open limit order book system *Xetra* operating at the Frankfurt Stock Exchange (FSE) together with a matched sample of NYSE stocks. The trading process at the NYSE is well known, so we will focus on a brief description of the FSE-Xetra trading environment. In Europe, FSE-Xetra is runner up in terms of turnover after the London Stock Exchange.[3] The trading rules are similar to other limit order book markets around the world like Euronext, the Hong Kong Stock Exchange and the Australian Stock Exchange. Between an opening and a closing call auction - and interrupted by another mid day call auction - FSE-Xetra operates as a continuous double auction mechanism with automatic matching of orders based on price and time priority. The transparency of the market is only limited by the existence of hidden orders. These are (typically large) limit orders with the special provision that a portion of the volume is initially kept hidden and is thus not visible in the otherwise open book.

During the sample period, trading hours extended from 9.00 a.m. to 5.30 p.m.Central European Time. No dedicated market makers are employed for the DAX stocks.[4] FSE-Xetra competes for order flow with some regional and international exchanges. The FSE itself maintains a parallel floor trading system and some of our sample stocks were also

[3]According to data from September 2008 to September 2009 published by the World Federation of Exchanges (http://www.world-exchanges.org/statistics/ytd-monthly). The Xetra system also operates at the Irish and the Vienna Stock Exchange, the European Energy Exchange and the Shanghai Stock Exchange, China's largest securities market.

[4]For less actively traded stocks there are so-called Designated Sponsors - typically large banks - who are required to provide a minimum liquidity level by simultaneously submitting competitive buy and sell limit orders.

cross-listed at the NYSE. However, for those stocks considered in our study, FSE-Xetra clearly dominates the regional and international competitors in terms of market share.

Our data contain detailed information about all market events which occurred during the first quarter of 2004. Based on these event histories, we perform a real-time reconstruction of the sequences of best bid and ask prices and associated depth, time stamps, transaction prices and trade volumes. One of the major advantages is that it is possible to unambiguously identify whether a trade is buyer- or seller-initiated (something that is not possible using the NYSE TAQ data). This avoids the biases that haunt the estimation of structural parameters when the trade classification is error-prone (c.f. Boehmer et al. 2007).

insert Table 1 about here

Table 1 reports market capitalization, daily turnover, average daily number of trades, average price, and the average quoted spread for our German sample, which consists of the thirty stocks constituting the DAX30 index. The daily turnover of an average stock is about 109 million Euros, with 2100 daily trades per stock. The mean relative effective spread amounts to 0.08 percent (3 Euro cent) and the mean relative realized spread is 0.01 percent (0.2 Euro cent), indicating a liquid market.[5] The table also displays how the securities are sorted into four groups according to their trading frequency (activity quartiles). Group one contains the most actively traded stocks, while group four is comprised of the least frequently traded stocks. We also construct a matched sample of NYSE-listed stocks using the daily trading volume as matching criterion, with the data taken from the TAQ files supplied by the NYSE. Information about the NYSE sample is provided in Table 2. Throughout the paper we focus on the German sample and treat the US sample as a robustness check, as the German data allows trades to accurately be classified as either buyer- or seller-initiated.

insert Table 2 about here

[5] We define the realized spread as the difference between the transaction price and the quote midpoint after 10 minutes, multiplied by a trade indicator variable (1 for buyer-initiated trades, -1 for seller-initiated trades).

3 Methodology

3.1 Dufour and Engle's trade and quote VAR

Before we describe our alternative methodology it is helpful to review how Dufour and Engle (2000) quantify the role of time when measuring the price impact of a trade. Drawing on Hasbrouck's (1991a, 1991b) seminal work, they specify the following bivariate vector-autoregression (VAR),

$$R_i = \sum_{j=1}^{5} a_j R_{i-j} + \gamma_{open} D_i Q_i + \sum_{j=0}^{5} b_{j,i} Q_{i-j} + v_{1,i} \tag{1}$$

$$Q_i = \sum_{j=1}^{5} c_j R_{i-j} + \gamma_{open} D_{i-1} Q_{i-1} + \sum_{j=1}^{5} d_j Q_{i-j} + v_{2,i}, \tag{2}$$

where $b_{j,i} = \gamma_j + \delta_j \ln(T_{i-j})$. The trade indicator Q_i takes the value of one if the i^{th} trade is buyer-initiated and minus one if it is seller-initiated. R_i denotes the midquote change in response to the i^{th} trade. D_i indicates the first trade of the day. T_i measures the length of the time interval between the i^{th} trade occurring at calender time t_i and the previous trade at time t_{i-1} (trade duration). The larger $b_{j,i}$ (> 0), the greater the price impact of a trade. Whether a shorter trade duration implies that a trade has increasing or decreasing informativeness depends on the parameters δ_j. Negative δ_j imply that transactions occurring after short trade durations are more informative than those after a longer non-trading interval. As the computation of Hasbrouck's (1991a) trade informativeness measure is not possible, Dufour and Engle (2000) use illustrative impulse response functions to quantify the overall effect of time between trades on trade informativeness[6]

[6]Hasbrouck (1991a) uses the MA(∞) representation of his bivariate trade and quote VAR to compute the permanent impact of a trade on the midquote. The time-varying parameters $b_{i,j}$ in (1) render Hasbrouck's trade-informativeness measure time-varying as well. We will return to this issue in Section 5.

3.2 A structural alternative

Following Dufour and Engle (2000), we formulate our alternative model in trade-event time, i.e. each trade event contributes an observation. However, instead of using a VAR framework, we draw on the class of spread decomposition models of which Glosten and Harris (1988), Madhavan et al.(1997) and Huang and Stoll(1997) are the most prominent examples. For the purpose of our paper, we adopt Madhavan et al.'s (1997) model, in which the post-trade asset value, μ_i, evolves as:

$$\mu_i = \mu_{i-1} + \theta(Q_i - E[Q_i|Q_{i-1}]) + \varepsilon_i. \tag{3}$$

The parameter θ measures the trade informativeness associated with a surprise in the order flow $Q_i - E[Q_i|Q_{i-1}]$. The orthogonal innovation ε_i accounts for public news that has accumulated since the last trade. Liquidity providers anticipate the effect of an incoming trade by setting bid quote P^a and ask quote P^b as

$$P_i^a = \mu_{i-1} + \theta(1 - \rho Q_{i-1}) + \phi + \varepsilon_i \tag{4}$$

$$P_i^b = \mu_{i-1} - \theta(1 + \rho Q_{i-1}) - \phi + \varepsilon_i, \tag{5}$$

where we have used that $E[Q_i|Q_{i-1}] = \rho Q_{i-1}$, with ρ the first-order autocorrelation of the trade indicator Q (c.f. Madhavan et al. 1997). The cost parameter ϕ accounts for order processing and inventory holding costs born by the supplier of liquidity. With transactions taking place either at the ask or bid, transaction prices are given by

$$P_i = \mu_i + \phi Q_i + \xi_i, \tag{6}$$

where ξ_i is an iid mean-zero disturbance which accounts for rounding errors due to discreteness of price changes. Combining Equations (3) and (6), transaction price changes are given by

$$\Delta P_i = \theta(Q_i - \rho Q_{i-1}) + \phi(Q_i - Q_{i-1}) + u_i. \tag{7}$$

where $u_i = \varepsilon_i + \xi_i - \xi_{i-1}$.

We account for the role of time in measuring the price impact of trade by specifying the adverse selection parameter θ as a function of the duration since the last trade. Our first specification is similar to that of Dufour and Engle's VAR in that raw trade durations (T_i) determine the price impact of trades,

$$\phi(t_i) = \gamma^\phi + \sum_{m=1}^{M} \lambda_m^\phi d_{m,i} \tag{8}$$

$$\theta(T_i, t_i) = \gamma^\theta + \sum_{m=1}^{M} \lambda_m^\theta d_{m,i} + \delta \ln T_i, \tag{9}$$

where $d_{m,i}$ equals one if the i^{th} trade occurs within the m^{th} of M time-of-day bins and is zero otherwise. $\gamma^\phi, \gamma^\theta, \lambda_m^\phi$ and λ_m^θ are parameters. Allowing the adverse selection parameter θ and the cost parameter ϕ to be time-of-day dependent accounts for the $\cup-$shaped time-of-day pattern of the spread. Our specification bears resemblance to that of Dufour and Engle (2000) in that sign and size of the parameter δ indicate whether a high trading activity is associated with increased ($\delta < 0$) or reduced trade informativeness ($\delta > 0$).

insert Figure 1 about here

However, it is only the unexpected component of the trade duration process that should carry informational content with respect to the fundamental asset value μ, as changes in μ should be unpredictable. Yet it is well known that trade durations are highly predictable (c.f. Engle and Russell 1998). They exhibit a clear-cut, inverted $\cup$-shaped intra-day (diurnal) pattern (see Figure 1), and significant serial correlation even after correcting for diurnality. In our second specification we therefore assume that rather than raw trade durations, duration *shocks*, innovations to the duration process, determine the price impact of a trade:

$$\theta(\nu_i, t_i) = \gamma^\theta + \sum_{m=1}^{M} \lambda_m^\theta d_{m,i} + \delta \ln \nu_i. \tag{10}$$

ν_i denotes the unexpected component of the trade duration process. To identify these duration shocks, we follow Engle and Russell (1998) and separate the trade duration process into a deterministic time-of-day component, $\Phi(t_i)$, an autoregressive component, ψ_i, and an innovation component, ν_i,

$$T_i = \Phi(t_i)\psi_i\nu_i, \tag{11}$$

where $E(\nu_i) = 1$. The autoregressive component ψ_i evolves as

$$\psi_i = \omega + \alpha\tilde{T}_{i-1} + \beta\psi_{i-1}, \tag{12}$$

where $\tilde{T}_i = T_i/\Phi(t_i)$. Equations 11 and 12 constitute Engle and Russell's (1998) ACD model. The conditional expected duration is given by $\Phi(t_i)\psi_i$, and ν_i is the innovation in the duration process we seek to identify. We will refer to a model where transaction price change are given by

$$\begin{aligned}\Delta P_i &= \Big(\gamma^\phi + \sum_{m=1}^{M}\lambda_m^\phi d_{m,i}\Big)Q_i - \Big(\gamma^\phi + \sum_{m=1}^{M}\lambda_m^\phi d_{m,i-1}\Big)Q_{i-1} \\ &\quad + \Big(\gamma^\theta + \sum_{m=1}^{M}\lambda_m^\theta d_{m,i} + \delta \ln \nu_i\Big)(Q_i - \rho Q_{i-1}) + u_i \end{aligned} \tag{13}$$

as the MRR-ACD model.

3.3 Estimation

We propose a two-step procedure to estimate the MRR-ACD parameters. Following Engle and Russell (1998), we first estimate the time-of-day function $\Phi(t_i)$ using a polynomial trigonometric regression (Eubank and Speckman 1990) and compute diurnally-adjusted durations as $\tilde{T}_i = T_i/\hat{\Phi}(t_i)$. In a second step, GMM estimates of the MRR-ACD parameter vector $\boldsymbol{\theta} = (\gamma^\phi, \lambda_1^\phi, \ldots, \lambda_M^\phi, \gamma^\theta, \lambda_1^\theta, \ldots, \lambda_M^\theta, \rho, \omega, \alpha, \beta, \delta)'$ are computed based on the moment conditions

$$E\begin{bmatrix} u_i \\ u_i\mathbf{d}_iQ_i \\ u_i\mathbf{d}_{i-1}Q_{i-1} \\ u_i\mathbf{z}_i \\ u_i\nu_i\mathbf{z}_i \\ Q_iQ_{i-1}-\rho \\ \nu_i-1 \\ (\nu_i-1)(\nu_{i-1}-1) \\ \vdots \\ (\nu_i-1)(\nu_{i-J}-1) \end{bmatrix} = 0, \qquad (14)$$

where $\mathbf{d}_i = (d_{1,i}, \cdots, d_{M,i})'$ and $\mathbf{z}_i = (Q_i, Q_{i-1})'$. The first block of moment conditions results from assuming orthogonality of the right-hand side variables in (13) and u_i. The moment condition $E(Q_iQ_{i-1}-\rho) = 0$ identifies ρ, the autocorrelation in the order flow. The last block of moment conditions identifies the ACD parameters ω, α and β by exploiting the ACD model assumptions $E(\nu_i) = 1$ and zero covariance between ν_i and ν_{i-j} for all $j \neq 0$ (c.f. Grammig and Wellner 2002). The MRR-ACD and the associated GMM estimation strategy is, to the best of our knowledge, the first attempt to link a structural model of the trading process to the econometrics of high frequency data.

4 Results

Table 3 reports the estimation results for the MRR-ACD model based on the FSE data, while Table 4 contains those for the matched sample of NYSE stocks.[7]

insert Tables 3 and 4 about here

The estimation results corroborate previous findings, but also provide new evidence that contradicts conventional wisdom. In particular, the adverse selection component of

[7]The results for the specification with raw durations lead to the same conclusions.

the spread λ^{θ} is considerably higher during the first half hour of the trading day. The L-shaped time-of-day pattern of the adverse selection component is most pronounced for less frequently traded stocks (see Figure 2), while the part of the adverse selection component that can be attributed to duration shocks does not exhibit a discernible diurnal pattern. The estimates of the λ^{ϕ} parameters imply that the order processing cost component is significantly higher at the end of the day, consistent with the notion that liquidity providers demand compensation for holding overnight inventory. These findings are in accordance with Madhavan et al.'s (1997) explanation of the ∪-shaped diurnal pattern of the effective spread.

insert Figure 2 about here

In order to assess the plausibility of the estimation results, in Table 5 we report the cross-sectional correlations of MRR-ACD-implied spread components with observable stock characteristics as well as with model-free estimates of spread components. The correlation between the model-implied spread and the effective spread amounts to 0.996, and the correlation between the implied adverse selection component and the price impact is 0.965. The correlation between the implied non-information-related component of the spread and the realized spread is 0.881. The negative correlations between the implied adverse selection component and market capitalization and trading activity, respectively, conform the well-known result that adverse selection effects are exacerbated for small-cap and less frequently traded stocks. All in all, these results illustrate the economic plausibility of the MRR-ACD specification.

insert Table 5 about here

The results discussed so far are both conclusive and unobtrusive. However, the estimated relation between a trade duration shock and trade informativeness contradicts the "fast trading means informed trading" paradigm. For the FSE sample, the estimates of the key parameter δ in MRR-ACD Equation (10) are positive and significantly different from zero for all stocks. In the NYSE sample, the estimate of δ is positive and significant for 25 of the 30 stocks. None of the estimates is negative (c.f. Tables 3 and 4). This implies that a shorter time interval since the last trade tends to be associated with reduced informational content pertaining to the next trade. This result, and the conclusions that can be derived from it, are in sharp contrast to the findings that Dufour and Engle (2000) report. In their VAR analysis, the estimates of the δ_j parameters (Equation (1)) are significantly negative, which suggests that shorter trade durations imply that incoming trades have a greater price impact.

Before we provide and discuss explanations for these contradictory findings, let us assess the economic significance of our estimation results. Although we focus on the FSE sample, the story for the NYSE sample is qualitatively similar.

insert Figures 3 and 4 about here

Figures 3 and 4 illustrate the importance of time in measuring the price impact of trades. To provide a concise view, we sort all trade events for a specific stock or activity quartile by the size of the duration shock. We then group the trade observations into deciles, with the first decile encompassing the trades associated with the smallest duration shocks, and decile ten the trades with the largest duration shocks. For each decile, the standardized adverse selection component is averaged across trades.[8] Figure 3 shows that for the quartile of least actively traded stocks, the standardized adverse selection component more than triples from duration decile one to duration decile ten. Figure 4 depicts the decile plots for four representative stocks, one from each of the trade activity quartiles. The negative relation between trade duration shocks and trade informativeness is very similar across the four stocks.[9]

[8]Standardization is performed by dividing the adverse selection component $\theta(\nu_i, t_i)$ by the average midquote across the sample ($\bar{P}$). Using non-standardized adverse selection components yields similar results. We use the standardized components to enhance comparability across stocks. The average midquote is quite different across the European sample stocks (see Table 1).

[9]Note that the positive relation between trade durations and the adverse selection component cannot be explained by intra-day co-movements of trade durations and the adverse selection component. Figure 2 shows that the adverse selection component of the spread is highest during the first half-hour and then flattens out. Figure 1, on the other hand, shows that trade durations exhibit an inverted $\cup$-shaped diurnal pattern. These intra-day patterns rather imply a weakening of the positive relationship between trade durations and trade informativeness.

insert Table 6 about here

Further evidence for the economic importance of time in determining the price impact of trades is provided in Table 6. Here we report the MRR-ACD implied adverse selection component as a percentage of the implied spread, the share of the implied spread that is attributable to duration shocks, and the share of the implied adverse selection component due to duration shocks. These ratios are averaged across the trades in the stocks of the four activity quartiles. Table 6 shows that the share of the MRR-ACD implied effective spread attributable to the adverse selection component is highest for the least actively traded stocks, ranging from almost 64% (least active stocks) to 45 % (most active stocks). What is new is the quantification of the role of time in the process. The share of the spread that can be attributed to duration shocks ranges from 13.4 % for the most active stocks to to 18 % (least active quartile). Roughly one quarter of the adverse selection component is explained by duration shocks, a number that is quite stable across the four activity quartiles.

5 Discussion

The results reported in the previous section contradict the conventional wisdom that fast trading means informed trading. They rather emphasize Admati and Pfleiderer's (1988) notion of clustered liquidity trading, a process that implies that intensive trading is associated with little or no trade informativeness. Our results are also consistent with the predictions from the strategic trading models developed by Foucault (1999) and Parlour (1998).

Parlour's (1998) crowding-out effect is particularly illuminating as it gives an alternative view of the relationship between transaction intensity and informed trading. Consider a market state with little information asymmetry and low volatility due to only a modicum of public information flow. In such a situation market liquidity will be ample. The spread will be narrow, possibly reduced to the minimum tick size (c.f. Foucault 1999); the inside depth will be high as patient traders queue at the best quotes. First-come-first-serve rules, however, imply that the expected time taken to fill a new limit order entered at the best quote increases. The small spread entails reduced execution costs for market order traders. Impatient market participants will become more aggressive and switch from limit order to market order trading in an attempt to get their order filled under those favorable conditions, causing trading intensity to increase. The crowding-out of limit orders by market orders thus implies small trade durations during non-informative (or not particularly informative) periods. Empirical evidence corroborating the crowding-out effect is provided by Griffiths et al. (2000), Ranaldo (2004) and Hall and Hautsch (2006).

But why do the two methodological alternatives, the Dufour/Engle-VAR and the MRR-ACD, deliver such contradictory results? A potential explanation is that the models have been applied to different data. Dufour and Engle use 1991 data from the NYSE, which then was a hybrid market, while our more recent data come from a limit order book system. In order to test whether this is a relevant factor we estimate the Dufour/Engle-VAR using our data. Table 7 shows that the results that we obtain are qualitatively similar to those reported by Dufour and Engle (2000), with the estimates of the key parameter δ_0 in Equation (1) significantly negative for all sample stocks. Different trading protocols or different sample periods therefore cannot explain the contradictory results. The reason must lie in the way the the Dufour/Engle VAR and the MRR-ACD make use of the data. Let us investigate this issue further.

insert Table 7 about here

Both the Dufour/Engle-VAR and the MRR-ACD are formulated in trade-event time, where each trade event constitutes an observation. However, the price variable in both models is different. In the Dufour/Engle-VAR it is the *midquote change* that is immediately caused by or subsequently observed after the trade event (see Equation (1)). The MRR-ACD, on the other hand, utilizes *changes in transaction prices* (see Equation (7)).

insert Table 8 about here

Sequences of transaction price and midquote changes can be markedly different, as illustrated in Table 8. At time t_0, the best ask is at 105, and the best bid at 100. At t_1 a buyer-initiated trade occurs with a volume smaller than the depth at the best ask. The transaction price is 105. The state of the market remains unchanged until the next trade occurs at t_2, when a market-to-limit buy order arrives with limit price equal to 105 and a limit volume that exceeds the depth at the best ask.[10] The market-to-limit order (MLO) first consumes the depth at the best ask, implying again a transaction price of 105. The non-executed volume is immediately entered as the new best bid price, which improves from 100 to 105. The new midquote is now 107.5. Finally, at t_3, a marked order seller, seizing the opportunity provided by the improved bid, consumes the remaining MLO volume completely. The transaction price is again 105; the midquote after the trade equals 105. Throughout this sequence of trade events, the transaction price remains the same, while the midquote changes considerably.

It is important to note that Dufour and Engle (2000) formulate their bivariate trade and quote VAR in a way that differs with respect to one crucial detail from Hasbrouck's (1991a) original formulation. Hasbrouck (1991a) also works in event time, but in his data set both trades and quote revisions are recorded as observations. As a matter of fact, quote revisions often occur without intermittent trades, simply because of public news arrival. In Hasbrouck's (1991) original formulation of the bivariate trade and quote VAR, the trade indicator Q_i is zero whenever there is a quote revision event (without a trade). By contrast, all quote revision events are filtered out in the Dufour/Engle VAR. As a matter of fact, the filtering is necessary to incorporate time between trades in the trade and quote VAR (1) and (2). If intermittent quote revision events were allowed, modeling the dependence of the VAR parameters on the time between trades would not be feasible.

[10] A market-to-limit order (MLO) is executed at the best quote on the opposite side of the market. If the volume exceeds the depth at that price, the remainder of the order is converted into a limit order with a price limit equal to that of the exhausted limit order at the opposite side of the market. An MLO thus simultaneously demands and supplies liquidity. An MLO represents a suitable instrument to implement the strategy of an impatient, yet price-sensitive trader who is not willing to accept a price worse than the specified limit. A limit order with a price limit that makes the order immediately executable and a volume that exceeds the executable volume has the same effect as an MLO.

Beltran-Lopez et al. (2010) propose an alternative method to account for time-varying trade intensity which also draws on Hasbrouck's (1991a) VAR framework. They slice their transaction level data into time intervals determined by a given number of trade events and estimate the trade and quote VAR (including quote revision events) for each of the intervals. Beltran-Lopez et al. (2010) then compute Hasbrouck's (1991a) trade informativeness measure, the long-run impact of a trade event on the midquote, for each of the time intervals, and correlate the resulting time series of trade informativeness measures with characteristics of the time intervals. They report that trade informativeness is positively correlated with volatility and spread, and negatively with order book liquidity. They also report that trade informativeness is *positively* correlated with the average duration between trades during the estimation interval. This implies that times of high trading intensity tend to be associated with low trade informativeness and ample liquidity. This result is consistent with the crowding-out story above and with the results of our MRR-ACD model.

To summarize, our explanation for the different findings obtained using the Dufour/Engle VAR methodology and the MRR-ACD model is as follows. We believe that the thinning of quote changes at trade events produces a self-selected sample. The trade-event filtering implies that all quote revisions in between two trades are implicitly associated with the previous trade event, ignoring the fact that these midquote changes may be due to the processing of public information unrelated to the trade event. Using Hasbrouck's (1991a) original VAR formulation, i.e. including interjacent quote revision events, or the structural MRR-ACD, reverses the "fast trading means informed trading" result. The key difference between the Dufour/Engle VAR and the MRR-ACD, which both work in trade-event time, is that the latter does not rely on filtered observed quote revisions, but assumes that the suppliers of liquidity anticipate the information revealed by subsequent trades when setting (or revising) their quotes.

6 Conclusion

This paper provides new evidence regarding the role of time in measuring the informational content of trades. Instead of using the vector-autoregressive methodology employed by Dufour and Engle (2000), we combine Madhavan et al.'s (1997) spread decomposition model and Engle and Russell's (1998) autoregressive conditional duration model. We estimate the resulting MRR-ACD model on a cross section of stocks traded on one of the largest Continental European stock markets, the Frankfurt Stock Exchange's Xetra system, and a matched sample of NYSE traded stocks. One of the advantages of using the German data is the excellent quality of the data, which allows us to avoid misclassification of buyer- and seller-initiated trades. This is of particular importance for both the VAR and the MRR-ACD methodology.

Dufour and Engle's (2000) paper provided strong support for the hypothesis that "fast trading means informed trading", one of the key predictions implied by Easley and O'Hara's (1992) microstructure model, and arguably part of the conventional wisdom of market microstructure. We provide new and contradictory evidence. Like Dufour and Engle (2000), we also find that time matters when measuring the informational content of trades, both from a statistical and an economic point of view. However, we do not find that the informational content of a trade increases with shorter durations since the last trade: it rather *decreases*. Our results are thus more in accordance with the predictions derived from Admati and Pfleiderer's (1988) model and with the crowding-out effect as described in Parlour (1998).

When we re-estimate Dufour and Engle's (2000) VAR model on our data set we find results consistent with theirs. The contradictory findings are thus not explained by different sample periods or differences in the microstructure of the markets under scrutiny. Instead, we argue that the difference lies in the specification of the data set. Both the VAR and the MRR-ACD model are estimated in trade time and each trade is recorded as an observation. However, estimation of the VAR is based on a trade indicator variable and changes in the quote midpoint, while estimation of the MRR-ACD is based on a trade indicator and transaction price changes. The differences between price changes and midquote changes can be substantial. In particular, market-to-limit orders and large, executable limit orders have a large impact on quote midpoints but may have little impact on transaction prices. We argue that these differences are the cause of the contradictory findings obtained when using the two estimation approaches. We further believe that estimation based on transaction prices yields more valid results. This view is corroborated by evidence reported recently in Beltran-Lopez et al. (2010).

Our results have important implications. They contradict the common wisdom that fast trading is informed trading, and rather support the predictions of models such as those of Admati and Pfleiderer (1988), Parlour (1998) and Foucault (1999). They further imply that uninformed traders are not disadvantaged in fast markets and that, therefore, there is no cause to halt trading in a fast market.

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Table 1: **Descriptive Statistics. European sample stocks.** The table reports characteristics of the FSE-Xetra traded stocks constituting the DAX index. The sample period is January 2, 2004 to March 31, 2004. *Daily turnover* is the average turnover (mill. Euros) per trading day and *Daily nb. trades* the average daily number of trades. The following indicators are averages over the trade events. $\bar{P}$ is the midquote (prevailing before the trade). *Effective Spread (%)* is the *Effective Spread* (in Euros) divided by the prevailing midquote and *Realized Spread (%)* the *Realized Spread* (in Euros) divided by the prevailing midquote. *Price Impact* (in Euros) is computed as the difference between effective and realized spread, and *Price Impact (%)* gives the price impact (difference between effective and realized spread) relative to the prevailing midquote. *Market cap.* reports the market capitalization in million Euros at the end of December 2003. Stocks are sorted into four groups according to the daily number of trades. Horizontal lines separate the four trading activity quartiles.

Ticker	Company Name	Daily Turnover (Mill.)	Market cap. (Mill.)	Daily nb. trades	Avg. $\bar{P}$ (€)	Effective Spread (€)	Effective Spread (%)	Realized Spread (€)	Realized Spread (%)	Price Impact (€)	Price Impact (%)	Trade Activity Quartile
ALV	ALLIANZ	289.98	33805	4523	100.1	0.049	0.049	0.010	0.010	0.039	0.039	
DTE	DEUTSCHE TELEKOM	350.63	34858	4445	15.7	0.011	0.072	0.005	0.031	0.006	0.041	
SIE	SIEMENS	321.70	52893	4418	64.0	0.026	0.041	0.004	0.006	0.022	0.035	
DBK	DEUTSCHE BANK	309.28	38228	3961	67.2	0.030	0.044	0.003	0.004	0.027	0.039	1
MUV2	MUENCH. RUECKVERS.	207.35	16396	3425	93.9	0.046	0.049	0.005	0.005	0.042	0.045	
DCX	DAIMLERCHRYSLER	187.74	30316	3309	36.4	0.020	0.055	0.004	0.010	0.016	0.044	
EOA	E.ON	160.63	33753	2871	52.5	0.025	0.048	0.001	0.003	0.024	0.046	
SAP	SAP	184.63	27412	2806	131.5	0.065	0.049	0.002	0.001	0.063	0.048	
IFX	INFINEON	146.46	4790	2799	11.6	0.012	0.104	0.005	0.040	0.007	0.064	
BAS	BASF	124.43	25425	2580	43.3	0.022	0.051	0.001	0.002	0.021	0.049	
VOW	VOLKSWAGEN	104.25	9688	2545	39.2	0.022	0.056	0.002	0.004	0.020	0.052	2
BAY	BAYER	88.78	15911	2400	23.1	0.017	0.076	0.003	0.012	0.015	0.064	
RWE	RWE	97.66	12653	2314	33.8	0.021	0.062	0.001	0.002	0.020	0.060	
BMW	BMW	87.85	12211	2110	34.7	0.021	0.060	0.001	0.003	0.020	0.057	
HVM	HYPO-VEREINSBANK	98.35	6629	1937	18.7	0.018	0.098	0.003	0.019	0.015	0.079	
SCH	SCHERING	51.41	7055	1523	40.8	0.029	0.071	0.002	0.004	0.027	0.067	
CBK	COMMERZBANK	53.17	7569	1450	15.4	0.015	0.100	0.004	0.023	0.012	0.077	
LHA	LUFTHANSA	43.95	4548	1352	14.2	0.016	0.111	0.003	0.022	0.012	0.088	
DPW	DEUTSCHE POST	43.84	6806	1315	18.2	0.018	0.097	0.003	0.018	0.014	0.079	3
TKA	THYSSENKRUPP	37.89	6450	1262	15.9	0.018	0.111	0.005	0.029	0.013	0.083	
MEO	METRO	38.87	5018	1235	35.0	0.031	0.089	0.000	0.000	0.031	0.090	
ALT	ALTANA	30.99	3338	1095	48.6	0.039	0.079	0.004	0.008	0.035	0.071	
TUI	TUI	26.28	2025	1063	18.7	0.023	0.125	0.003	0.015	0.020	0.109	
MAN	MAN	27.69	2434	1057	27.7	0.027	0.096	0.001	0.003	0.026	0.094	
CONT	CONTINENTAL	25.63	4060	1002	31.6	0.029	0.092	-0.003	-0.011	0.032	0.103	
DB1	DEUTSCHE BOERSE	35.70	4847	982	46.9	0.035	0.075	0.001	0.003	0.034	0.072	
ADS	ADIDAS-SALOMON	31.98	4104	980	92.6	0.065	0.070	-0.002	-0.002	0.067	0.072	4
LIN	LINDE AG	22.38	3448	896	43.6	0.035	0.080	-0.004	-0.009	0.039	0.090	
HEN3	HENKEL	18.17	3682	702	65.9	0.050	0.077	0.003	0.005	0.047	0.072	
FME	FRESENIUS MEDICAL CARE	12.85	1944	621	54.0	0.053	0.098	0.006	0.010	0.047	0.088	
	Average	108.68	14076	2099	44.5	0.030	0.076	0.002	0.009	0.027	0.067	

Table 2: **Matched sample of NYSE traded stocks.** For each DAX stock we compare the daily average traded volume to each NYSE traded stock of the S&P 500. We match the NYSE stock that minimizes the absolute difference. * Firm changed its ticker symbol in 2006. We use the 2004 ticker symbols available in our data.

Ticker	Company Name (FSE)	Daily Turnover (Mill.€)	Ticker	Company Name (NYSE)	Daily Turnover (Mill. €)
DTE	DEUTSCHE TELEKOM	350.63	XOM	EXXON MOBIL	375.45
SIE	SIEMENS	321.70	JPM	J.P. MORGAN CHASE	334.96
DBK	DEUTSCHE BANK	309.28	JNJ	JOHNSON & JOHNSON	309.25
ALV	ALLIANZ	289.98	AIG	AMERICAN INT'L.	288.35
MUV2	MUENCH. RUECKVERS.	207.35	MWD*	MORGAN STANLEY	205.98
DCX	DAIMLERCHRYSLER	187.74	MDT	MEDTRONIC	188.80
SAP	SAP	184.63	WYE	WYETH	183.87
EOA	E.ON	160.63	ABT	ABBOTT LABS	160.45
IFX	INFINEON	146.46	KSS	KOHL'S	146.28
BAS	BASF	124.43	LMT	LOCKHEED MARTIN	123.88
VOW	VOLKSWAGEN	104.25	CAH	CARDINAL HEALTH	105.51
HVM	HYPO-VEREINSBANK	98.35	STJ	ST. JUDE MEDICAL	98.50
RWE	RWE	97.66	A	AGILENT TECHNOLOGIES	97.45
BAY	BAYER	88.78	ALL	ALLSTATE	88.28
BMW	BMW	87.85	HDI*	HARLEY DAVIDSON	88.26
CBK	COMMERZBANK	53.17	CVS	CVS	53.02
SCH	SCHERING	51.41	MHS	MEDCO HEALTH SOLUTIONS	51.30
LHA	LUFTHANSA	43.95	BDX	BECTON, DICKINSON	43.99
DPW	DEUTSCHE POST	43.84	RTN	RAYTHEON	43.83
MEO	METRO	38.87	JBL	JABIL CIRCUIT	38.76
TKA	THYSSENKRUPP	37.89	JCI	JOHNSON CONTROLS	37.93
DB1	DEUTSCHE BOERSE	35.70	BBT	BB & T	35.68
ADS	ADIDAS-SALOMON	31.98	DOV	DOVER	31.97
ALT	ALTANA	30.99	BNI	BURLINGTON NORTH. SANTA FE	30.93
MAN	MAN	27.69	MBI	MBIA	27.63
TUI	TUI	26.28	BCR	BARD (C.R.)	26.33
CONT	CONTINENTAL	25.63	BDK	BLACK & DECKER	25.68
LIN	LINDE AG	22.38	CBE	COOPER INDUSTRIES	22.32
HEN3	HENKEL	18.17	DYN	DYNEGY	18.09
FME	FRESENIUS MEDICAL CARE	12.85	TMK	TORCHMARK	12.92

Table 3: **MRR-ACD estimation results: European sample.** The table reports first stage GMM parameter estimates and $p-$values averaged across stocks, as well as the number of stocks for which parameter estimates are significant and positive or negative. The significance level is $\alpha = 1\%$. GMM estimation makes use of the moment conditions in 14 with $J = 12$. The first panel (overall) reports the results including all thirty stocks; the other panels break down the statistics according to trading activity quartile. Time-of-day dummy variables are defined to mark $M = 6$ periods of the trading day: 9:00 to 9:30 a.m.; 9:30 - 11:00 a.m.; 2:00 - 3:30 p.m.; 3:30 - 5:00 p.m., and 5:00 - 5:30 p.m.. The reference period is 11:00 a.m - 2:00p.m..

	Overall			1^{st} Quartile (most active)			2^{nd} Quartile			3^{rd} Quartile			4^{th} Quartile (least active)		
	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]
δ	0.0043	(0.00)	[30, 0]	0.0040	(0.00)	[7, 0]	0.0034	(0.00)	[8, 0]	0.0031	(0.00)	[8, 0]	0.0069	(0.00)	[7, 0]
γ^{ϕ}	0.0052	(0.00)	[30, 0]	0.0063	(0.00)	[7, 0]	0.0048	(0.00)	[8, 0]	0.0045	(0.00)	[8, 0]	0.0056	(0.00)	[7, 0]
λ_1^{ϕ}	0.0030	(0.01)	[28, 0]	0.0020	(0.00)	[7, 0]	0.0017	(0.00)	[8, 0]	0.0024	(0.00)	[7, 0]	0.0060	(0.03)	[6, 0]
λ_2^{ϕ}	0.0003	(0.23)	[12, 0]	0.0003	(0.26)	[4, 0]	0.0004	(0.12)	[5, 0]	0.0004	(0.14)	[3, 0]	0.0002	(0.45)	[0, 0]
λ_3^{ϕ}	-0.0003	(0.29)	[3, 4]	-0.0002	(0.32)	[1, 1]	-0.0001	(0.32)	[2, 1]	-0.0005	(0.17)	[0, 1]	-0.0006	(0.37)	[0, 1]
λ_4^{ϕ}	-0.0005	(0.23)	[1, 7]	-0.0008	(0.34)	[0, 3]	-0.0002	(0.21)	[1, 1]	-0.0006	(0.05)	[0, 3]	-0.0004	(0.33)	[0, 0]
λ_5^{ϕ}	0.0007	(0.16)	[14, 2]	0.0003	(0.20)	[4, 1]	0.0006	(0.02)	[6, 0]	0.0001	(0.28)	[0, 1]	0.0018	(0.13)	[4, 0]
γ^{θ}	0.0040	(0.00)	[30, 0]	0.0033	(0.00)	[7, 0]	0.0033	(0.00)	[8, 0]	0.0031	(0.00)	[8, 0]	0.0066	(0.00)	[7, 0]
λ_1^{θ}	0.0051	(0.03)	[28, 0]	0.0032	(0.03)	[6, 0]	0.0029	(0.09)	[7, 0]	0.0043	(0.00)	[8, 0]	0.0103	(0.00)	[7, 0]
λ_2^{θ}	0.0012	(0.15)	[14, 2]	0.0011	(0.02)	[4, 1]	0.0004	(0.37)	[1, 1]	0.0009	(0.17)	[4, 0]	0.0024	(0.01)	[5, 0]
λ_3^{θ}	0.0002	(0.23)	[3, 5]	0.0003	(0.12)	[2, 1]	0.0000	(0.23)	[0, 1]	0.0002	(0.10)	[1, 3]	0.0003	(0.47)	[0, 0]
λ_4^{θ}	0.0002	(0.29)	[5, 4]	0.0009	(0.14)	[3, 1]	-0.0001	(0.34)	[0, 2]	0.0002	(0.36)	[1, 1]	0.0000	(0.32)	[1, 0]
λ_5^{θ}	-0.0003	(0.28)	[1, 11]	-0.0003	(0.08)	[0, 5]	-0.0008	(0.09)	[0, 5]	0.0003	(0.40)	[1, 1]	-0.0005	(0.55)	[0, 0]
ρ	0.2204	(0.00)	[30, 0]	0.2203	(0.00)	[7, 0]	0.2067	(0.00)	[8, 0]	0.2113	(0.00)	[8, 0]	0.2465	(0.00)	[7, 0]
ω	0.0721	(0.00)	[30, 0]	0.0842	(0.00)	[7, 0]	0.0714	(0.00)	[8, 0]	0.0641	(0.00)	[8, 0]	0.0700	(0.00)	[7, 0]
α	0.1252	(0.00)	[30, 0]	0.1544	(0.00)	[7, 0]	0.1354	(0.00)	[8, 0]	0.1121	(0.00)	[8, 0]	0.0994	(0.00)	[7, 0]
β	0.8050	(0.00)	[30, 0]	0.7659	(0.00)	[7, 0]	0.7960	(0.00)	[8, 0]	0.8248	(0.00)	[8, 0]	0.8320	(0.00)	[7, 0]

Table 4: **MRR-ACD estimation results: NYSE sample.** The table reports first-stage GMM parameter estimates and $p-$values averaged across stocks, as well as the number of stocks for which parameter estimates are significant and positive or negative. The significance level is $\alpha = 1\%$. GMM estimation makes use of the moment conditions of Equation (14) with $J = 12$. Following Madhavan et al. (1997), time-of-day dummy variables are defined to mark $M = 5$ periods of the trading day: the first half hour, 9:30 to 10:00 a.m; 10:00 to 11:30 a.m; 2:00 to 3:30 p.m; and the final half hour, 3:30 to 4:00 p.m. The reference period is 11:30 a.m. to 2:00 p.m..

	Overall		
	Avg. est.	Avg. p-val	# sig [pos, neg]
δ	0.0009	(0.06)	[25, 0]
γ^{ϕ}	0.0021	(0.00)	[30, 0]
λ_1^{ϕ}	0.0007	(0.05)	[19, 0]
λ_2^{ϕ}	0.0001	(0.20)	[13, 1]
λ_4^{ϕ}	0.0001	(0.20)	[7, 2]
λ_5^{ϕ}	0.0005	(0.09)	[19, 2]
γ^{θ}	0.0029	(0.00)	[30, 0]
λ_1^{θ}	0.0018	(0.03)	[25, 0]
λ_2^{θ}	0.0006	(0.05)	[19, 1]
λ_3^{θ}	-0.0001	(0.31)	[2, 6]
λ_4^{θ}	-0.0006	(0.05)	[0, 24]
ρ	0.2731	(0.00)	[30, 0]
ω	0.0457	(0.03)	[26, 0]
α	0.0468	(0.01)	[28, 0]
β	0.9077	(0.00)	[30, 0]

Table 5: **Cross-sectional correlations of MRR-ACD spread components with stock characteristics. European sample.** The table reports cross-sectional correlations of MRR-ACD spread components with relative effective and realized spread, relative price impact, market capitalization and trading frequency (see caption of Table 1 for definitions of these indicators). To account for cross-sectional differences in the level of stock prices, standardized spread components implied by the MRR-ACD are computed as $\theta(\nu_i, t_i)/\bar{P}$ (adverse selection component), and $\phi(t_i)/\bar{P}$ (non-informational component), where $\bar{P}$ denotes the average midquote of the stock across the sample. $\phi(t_i)$ and $\theta(\nu_i, t_i)$ are defined in Equations (8) and (10), respectively. IS_i denotes the relative implied spread computed as $2[\theta(\nu_i, t_i) + \phi(t_i)]/\bar{P}$. Spread components, spreads and price impacts are averaged over the trades in each stock. Cross-sectional correlations are computed using the data for the 30 sample stocks. The numbers in parentheses are $p-$values.

	Effective Spread (%)	Realized Spread (%)	Price Impact (%)	Market cap. (Mill.)	Daily nb. trades
$\theta(\nu_i, t_i)/\bar{P}$	0.782	-0.144	0.965	-0.802	-0.893
	(0.000)	(0.448)	(0.000)	(0.000)	(0.000)
$\phi(t_i)/\bar{P}$	0.763	0.881	0.373	-0.351	-0.153
	(0.000)	(0.000)	(0.043)	(0.057)	(0.419)
IS_i	0.996	0.505	0.845	-0.730	-0.653
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)

Table 6: **Components of the MRR-ACD implied spread.** The table reports the share of the implied spread explained by the adverse selection component $\frac{\theta(\nu_i,t_i)}{\theta(\nu_i,t_i)+\phi(t_i)}$, where $\phi(t_i)$ and $\theta(\nu_i,t_i)$ are defined in Equations (8) and (10), respectively. It also shows the share of the implied spread attributable to duration shocks $\frac{\delta \ln \nu_i}{\theta(\nu_i,t_i)+\phi(t_i)}$, and the share of the adverse selection component attributable to duration shocks $\frac{\delta \ln \nu_i}{\theta(\nu_i,t_i)}$. The ratios are averaged over all trades in the stocks belonging to same trade activity quartile, as well as over all trades in all sample stocks (last row). The numbers in the table are percentages.

	$\frac{\theta(\nu_i,t_i)}{\theta(\nu_i,t_i)+\phi(t_i)}$	$\frac{\delta \ln \nu_i}{\theta(\nu_i,t_i)+\phi(t_i)}$	$\frac{\delta \ln \nu_i}{\theta(\nu_i,t_i)}$
1^{st} Quartile (most active)	45.0	13.4	26.4
2^{nd} Quartile	48.2	14.1	26.6
3^{rd} Quartile	50.7	14.0	25.3
4^{th} Quartile (least active)	63.8	18.0	26.5
All stocks	48.8	14.2	26.3

Table 7: **Estimation results for Dufour and Engle (2000) model estimated on European sample.** The table reports the estimation results for the quote revision equation in the Dufour and Engle (2000) model, $R_i = \sum_{j=1}^{5} a_j R_{i-j} + \gamma_{open} D_i Q_i + \sum_{j=0}^{5} b_j Q_{i-j} + v_{1,i}$ where $b_j = \gamma_j + \delta_j \ln(T_{t-j})$ estimated on the FSE-Xetra sample. We focus on the δ parameters which capture the duration impact as well as γ_{open}. The first two columns report OLS parameter estimates and $p-$values based on Newey-West standard errors averaged across all stocks. The third column reports the number of significant ($\alpha = 1\%$) parameters across the thirty FSE-Xetra stocks. The other panels report these statistics broken down according to trading activity quartile.

	Overall			1^{st} Quartile (most active)			2^{nd} Quartile			3^{rd} Quartile			4^{th} Quartile (least active)		
	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]	Avg. est.	Avg. p-val	# sig [pos, neg]
δ_0	-0.0010	(0.00)	[0, 30]	-0.0009	(0.00)	[0, 7]	-0.0009	(0.00)	[0, 8]	-0.0010	(0.00)	[0, 8]	-0.0011	(0.00)	[0, 7]
δ_1	0.0002	(0.16)	[15, 0]	0.0003	(0.03)	[6, 0]	0.0003	(0.00)	[7, 0]	0.0002	(0.23)	[2, 0]	0.0001	(0.40)	[0, 0]
δ_2	0.0002	(0.14)	[16, 0]	0.0002	(0.00)	[7, 0]	0.0002	(0.09)	[5, 0]	0.0002	(0.13)	[3, 0]	0.0001	(0.35)	[1, 0]
δ_3	0.0001	(0.17)	[9, 0]	0.0001	(0.03)	[5, 0]	0.0002	(0.06)	[4, 0]	0.0001	(0.32)	[0, 0]	0.0001	(0.27)	[0, 0]
δ_4	0.0001	(0.15)	[10, 0]	0.0001	(0.07)	[5, 0]	0.0002	(0.03)	[3, 0]	0.0001	(0.22)	[0, 0]	0.0002	(0.30)	[2, 0]
δ_5	0.0002	(0.14)	[17, 0]	0.0002	(0.13)	[5, 0]	0.0002	(0.14)	[5, 0]	0.0003	(0.06)	[5, 0]	0.0002	(0.22)	[2, 0]
γ_{open}	0.0128	(0.00)	[30, 0]	0.0055	(0.00)	[7, 0]	0.0083	(0.00)	[8, 0]	0.0159	(0.00)	[8, 0]	0.0218	(0.00)	[7, 0]

Table 8: Effect of three trades on midquote (MQ) and transaction prices (P)

	t_0	t_1	t_2	t_3
	initial state	small buyer-initiated trade (P=105)	market-to-limit buy order with limit price $P = 105$ takes best ask and improves the best bid	remaining volume of MLO consumed by seller-initiated trade ($P = 105$)
2^{nd} ask	110	110		
best ask	105	105	110	110
MQ	102.5	102.5	107.5	105
best bid	100	100	105	100
2^{nd} bid	90	90	100	90
3^{rd} bid			90	
Δ MQ		0	4.9%	-2.3%
ΔP		0	0	0

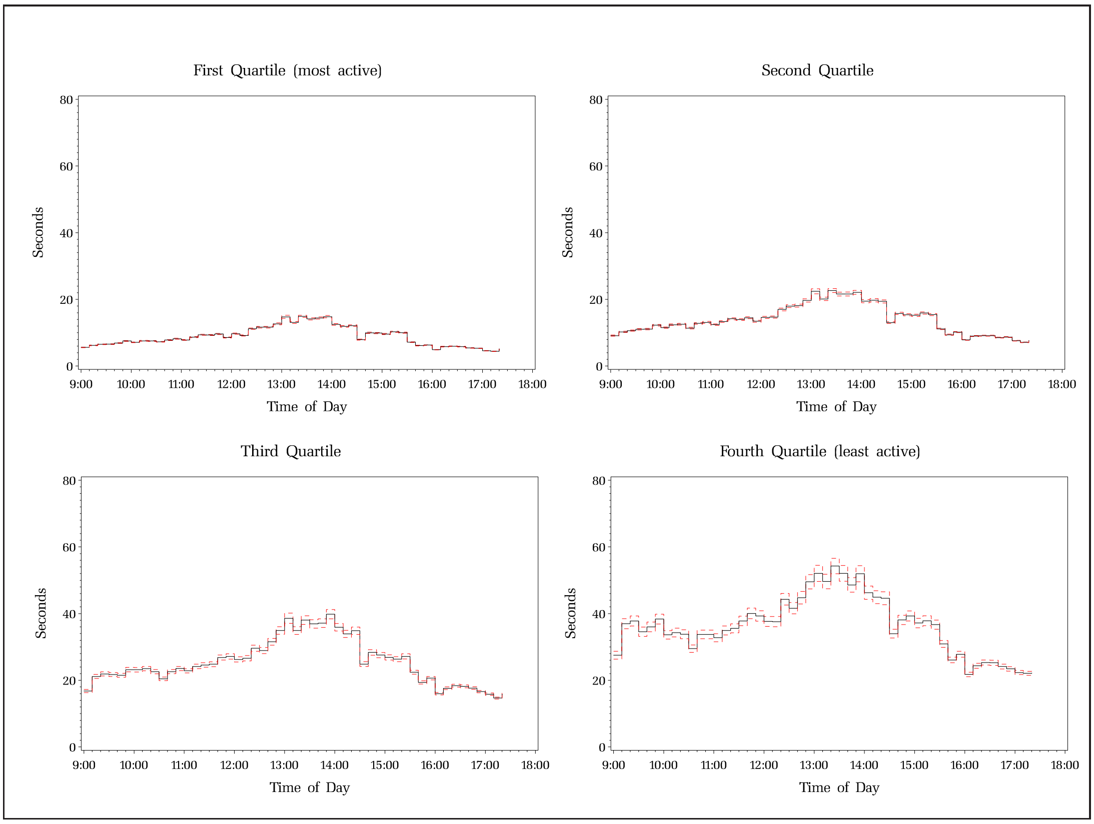

Figure 1: **Intra-day pattern of trade durations: European sample.** We compute for each ten-minute interval the average trade duration (in seconds) and plot each mean against the respective interval. All trade events of the stocks belonging to the same trading activity quartile are pooled. The panels above display the results for each of the four trading activity quartiles, with the first and last quartiles representing those for the groups of most and least frequently traded stocks respectively. The dashed lines are the 95% confidence intervals.

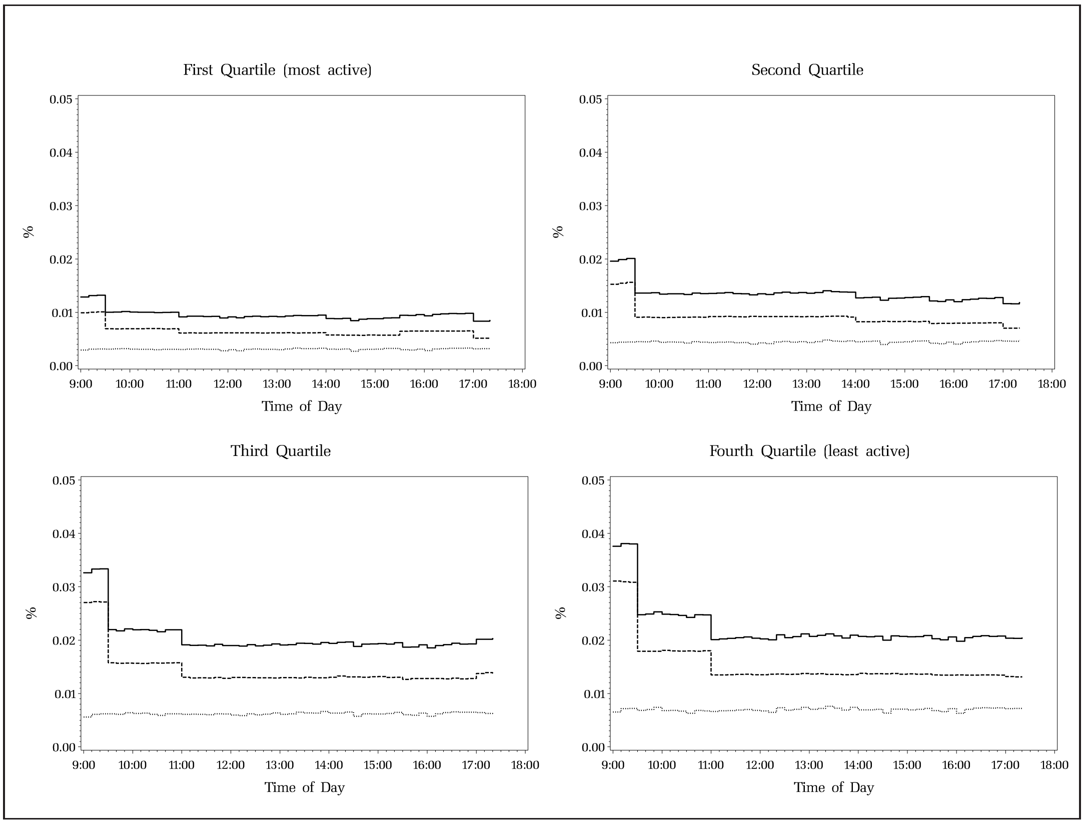

Figure 2: **Intra-day patterns of the MRR-ACD adverse selection component.** We split the MRR-ACD adverse selection parameter $\theta(\nu_i, t_i)$ defined in Equation (10) into a deterministic time-of-day component $\theta(t_i) = \gamma^\theta + \sum_{m=1}^{M} \lambda_m^\theta d_{m,i}$ and a component attributable to duration shocks, $\delta \ln \nu_i$. To ensure cross-sectional comparability, we divide these statistics by the stock-specific average midquote across the sample $\bar{P}$. The trading day is subdivided in ten-minute bins, and we compute bin averages across the trade events in the stocks belonging to each of the four trading activity quartiles using the parameter estimates in Table 3. The dotted line depicts the bin averages of $\delta \ln \nu_i / \bar{P}$; the dashed line depicts the bin averages of $\theta(t_i)/\bar{P}$, and the solid line depicts the bin averages of $\theta(\nu_i, t_i)/\bar{P}$. Numbers are multiplied by 100 such they may be interpreted as percentages.

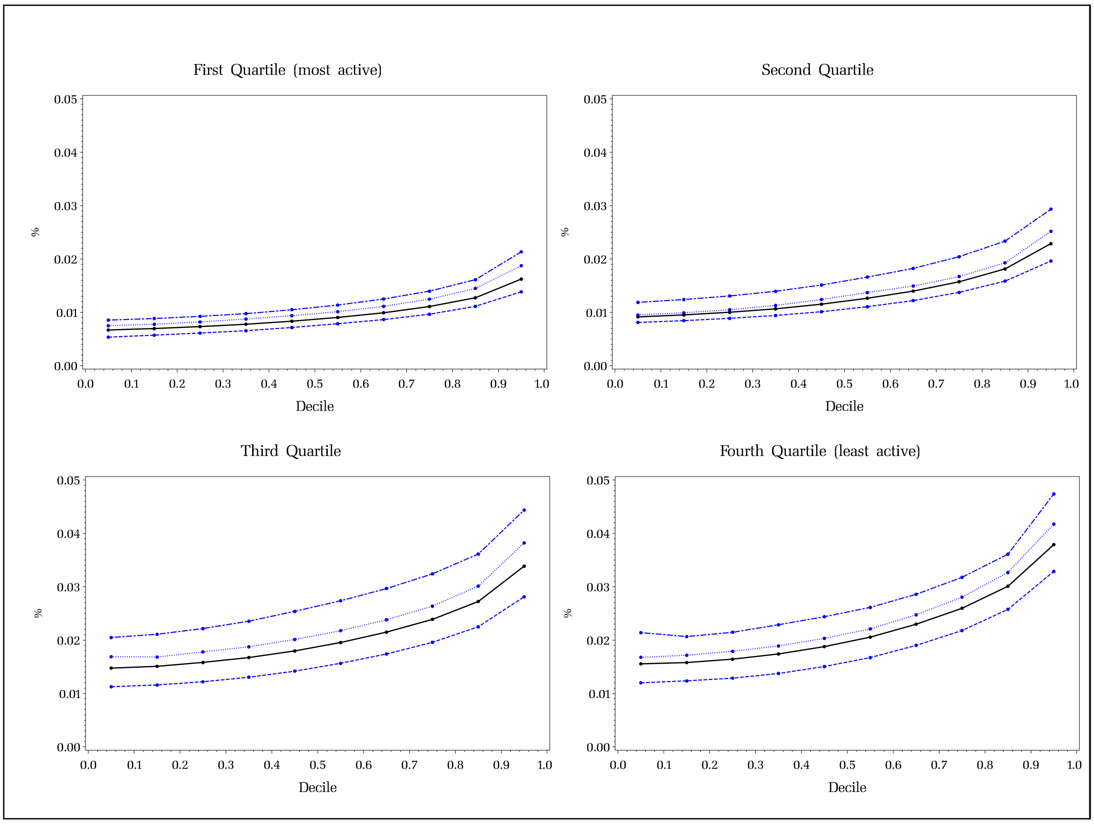

Figure 3: **Time between trades and MRR-ACD adverse selection component: European sample.** All trade events in the stocks belonging to the same trading activity quartile are pooled. We then sort the observations by the size of the duration shock (in ascending order) and group them into deciles, compute mean and 0.25, 0.75 and 0.9 quantiles of the standardized MRR-ACD adverse selection component $\theta(\nu_i, t_i)/\bar{P}$ per decile, and graphically display the results. Decile means are connected with solid lines. The dashed lines connect the 0.25 quantiles, the dotted lines the 0.75 quantiles, and the dash-dotted lines the 0.9 quantiles. The panels above display the results for each of the four trading activity quartiles, with the first and last quartiles representing those for the groups of most and least frequently traded stocks respectively.

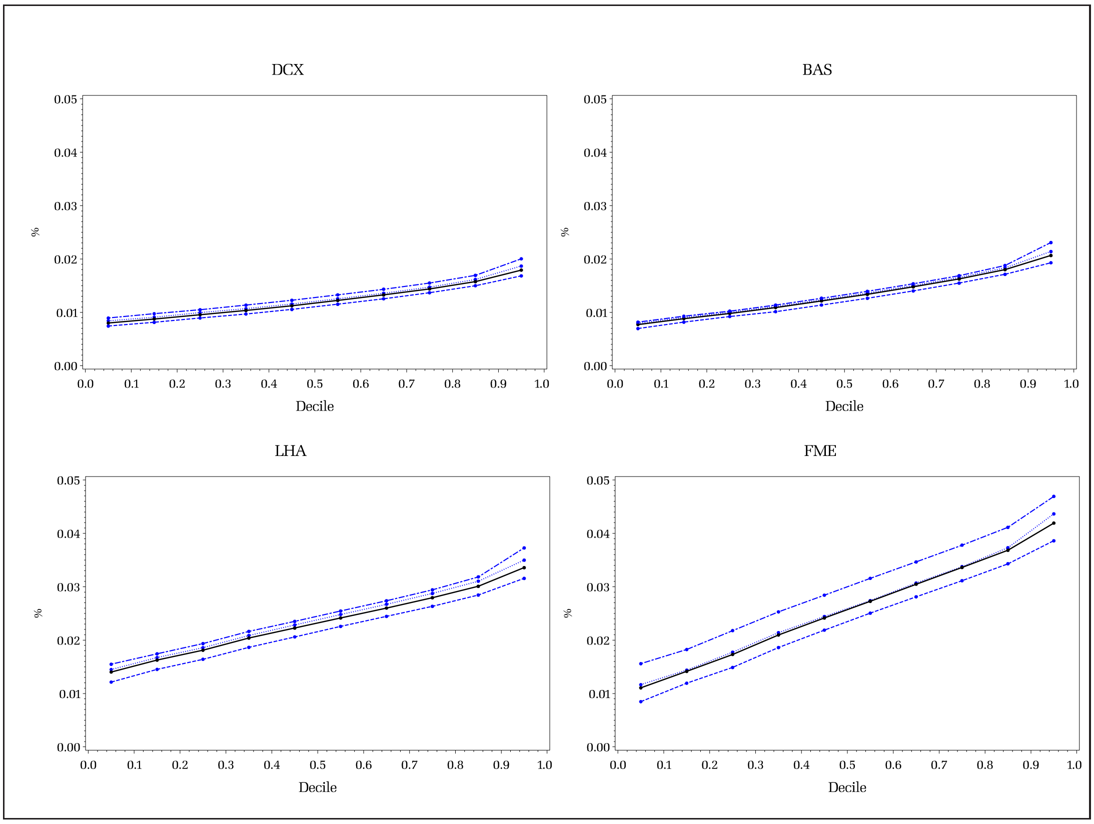

Figure 4: **Time between trades and MRR-ACD adverse selection component: Stock specific results.** We sort the observations for each stock by the size of the trade duration shock (in ascending order) and group them into deciles, compute mean and 0.25, 0.75 and 0.9 quantiles of the standardized MRR-ACD adverse selection component $\theta(\nu_i, t_i)/\bar{P}$ per decile, and graphically display the results. Decile means are connected with solid lines. The dashed lines connect the 0.25 quantiles, the dotted lines the 0.75 quantiles, and the dash-dotted lines the 0.9 quantiles. Each of the four panels above displays the results for a representative stock from one of the four trade activity quartiles respectively: (1) Daimler Chrysler (DCX); (2) BASF (BAS); (3) Lufthansa (LHA) and (4) Fresenius MedCare (FME).

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