Empirical Studies of Market Microstructure

Empirical Studies of Market Microstructure

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Universiteit van Tilburg, op gezag van de rector magnificus, prof. dr. F.A. van der Duyn Schouten, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op

dinsdag 10 juni 2003 om 16:15 uur

door

LAURA SPIERDIJK

geboren op 16 december 1976 te Heemstede.

PROMOTORES: prof. dr. Th.E. Nijman
prof. dr. A.H.O. van Soest

En art, comme en tout autre domaine, on est toujours le fils de quelqu'un.

Henry Havard (1838–1921)

Acknowledgements

This thesis is the result of my Ph.D. project conducted at Tilburg University and the CentER for Economic Research from September 1999 until January 2003. I would like to thank several people and institutions who contributed to this project and to the other activities I undertook during this period.

First of all, I would like to thank Theo Nijman and Arthur van Soest for their excellent supervision. I benefited a lot from their ability to generate ideas and their knowledge of finance and econometrics. Furthermore, I also thank the other members of my thesis committee: Ekkehart Böhmer, Frank de Jong, Feico Drost, and Bas Werker. Additionally, I would like to thank Bas Werker for reading my working papers and giving helpful comments.

Moreover, I thank Feico Drost, John Einmahl, Bertrand Melenberg, and Gert Nieuwenhuis with whom I worked together during several courses in a very pleasant way. I am grateful to my colleague Hendri Adriaens, who provided me with the program Maketable that facilitates the creation of tables in LaTeX and who was always willing to help me with any computer problem. I would like to thank Ralph Koijen for his useful comments on my papers. I also thank the secretaries of the departments of Econometrics and Finance and of CentER. I am grateful to Rob Engle, who gave me the opportunity to spend an unforgettable month at New York University, Stern School of Business.

Furthermore, I would like to thank the Netherlands Organization for Scientific Research (NWO) for the financial support of my Ph.D. project. The financial support provided by the Department of Econometrics for my stay at New York University is gratefully acknowledged as well.

Finally, I thank my colleagues, friends, and parents for their support throughout the years.

Laura Spierdijk
March 2003

CONTENTS

CHAPTER I

Introduction

I.1 Motivation

The progress in electronic technology has made today's financial markets dependent upon 'connectivity'; i.e. the ability of communication networks to link market participants and to create markets. This development has affected, for instance, national exchanges and decentralized dealer markets, but has also created new markets such as electronic communication networks. The increased connectivity of financial markets has given a new impulse to financial research, since it has substantially changed the microstructure of financial markets. At the same time, the developments in electronic technology have led to a decrease in the costs of gathering and storing data. This has lead to the increased availability of financial high-frequency data, which can be used to explore the new research areas generated by the changes in the market microstructure. High-frequency or tick-by-tick data are not aggregated to a fixed time interval, but provide a continuous flow of information on all transactions in a particular asset. Since they preserve the microstructure features of the data, they are very suitable to analyze how the market microstructure affects the transaction process.

The part of finance that studies how trading mechanisms and market design affect the transaction process is called market microstructure analysis. Market microstructure analysis is relevant from several points of view. It allows for the comparison of different trading mechanisms and market designs to assess their relative merits, as well as the comparison of the transaction process of different types of stocks (such as frequently and infrequently traded stocks).

Market microstructure models fall into two groups: inventory models and information-based models. The first class of models tries to explain security prices from inventory imbalances. The second type of models is based on the concept of asymmetric information. Traders may have different reasons for trading a particular stock. If they trade to adjust the size or the contents of their portfolio, they are called liquidity or uninformed traders. If they possess private information on the value of the asset and trade to benefit from this, they are called informed traders. There is asymmetric information when both informed and uninformed traders are present on the market.

A consequence of asymmetric information is that trading itself conveys information. The intuition is that informed traders act strategically to benefit from the private information they possess, which causes their trades to reveal information. Since, in efficient markets, security prices move in response to the release of new information, trading itself causes prices to be revised. However, not only prices change in response to new information. For instance, after an information event, it is likely that informed traders want to benefit quickly from their superior information, which will affect the speed of trading. This suggests that the trading intensity of a stock is also affected by the release of information.

I.2 Overview

In this thesis we investigate empirically how stock prices are revised in response to (large) trades and how information is incorporated into the trading intensity of stocks, using tick-by-tick data distributed by the New York Stocks Exchange. This thesis builds on the work of − among others − Hasbrouck (1991a, 1991b), Engle and Russell (1998), Dufour and Engle (2000).

Hasbrouck (1991a, 1991b) investigates the price impact of trades using a vector autoregressive (VAR) model for returns and several variables related to trade size such as signed trading volume. Trades do not only have an immediate price effect, but may affect prices during several periods. The lagged structure of the VAR-model picks up these effects. Kraus and Stoll (1972) and Hasbrouck (1991a, 1991b) define the information content of an unexpected trade as its expected persistent impact on prices, which is directly computable from the parameters of the VAR-model. Since temporary, non-informational effects such as inventory imbalances may affect prices in the short run, the persistent (long-run) price effect is taken as a measure of the information contained in a trade.

Engle and Russell (1998) propose the autoregressive conditional duration (ACD) model for the durations between consecutive trades. This model specifies durations as the product of the conditional expected duration and a random disturbance. The conditional expected duration, in turn, is assumed to have an autoregressive structure. The recursive structure of the condi-

tional expected duration in the ACD-model is similar to the specification of the conditional variance in a generalized autoregressive conditional heteroskedasticity (GARCH) model, cf. Engle (1982) and Bollerslev (1986). The autoregressive structure is needed to capture the strong positive autocorrelation in the durations that causes trades to clump together. Engle and Russell (1998) show that part of the clustering of trades is due to information based trading, which confirms that the trading intensity conveys information.
Dufour and Engle (2000) examine the information content of trades in relation to market activity. They combine the VAR-model of Hasbrouck (1991a, 1991b) with the ACD-model of Engle and Russell (1998), by allowing the price impact of trades to depend upon the trading intensity. Although the expected persistent price impact of trades is not analytically tractable in the combined model, it is easily obtained by means of simulation.

I.3 Outline of the thesis

The setup of this thesis is as follows. In Chapter II we extend the work of Hasbrouck (1991a, 1991b) and Dufour and Engle (2000) by focusing on the entire distribution of the price impact of trades and its relation to market activity. For a sample of frequently traded stocks listed on the NYSE, we combine a vector autoregressive (VAR-) model for returns and trading volume with an autoregressive conditional duration (ACD-) model for the trading intensity. We also examine the feedback from the trade characteristics to the trading intensity and its effect on the price impact of trades.
In Chapter III the focus is on the differences in the price effects of trades between frequently and infrequently traded stocks. We extend the VAR-model of Hasbrouck (1991a, 1991b) and the ACD-model of Engle and Russell (1998) to include overnight returns and durations and apply the model to high-frequency data on ten infrequently traded stocks and one frequently traded ('benchmark') stock listed on the NYSE. Since infrequently traded stocks are generally more affected by transitory price movements such as inventory effects, we focus on both temporary and permanent impact of trades on prices.
In Chapter IV we examine again the relation between trading volume and both temporary and permanent price effects of infrequently traded stocks listed on the NYSE. Unlike the analysis in Chapters II and III, we assume in this chapter that the durations between consecutive trades have no information content. Rather than applying a parametric specification that imposes strong assumptions on the way volume affects prices, we use the more flexible semiparametric partially linear model of Engle, Granger, Rice, and Weiss

(1986) and Robinson (1988a, 1988b) to derive the exact price-order flow relation. We compare the relation between price impact and order size obtained in the partially linear model to the price-order flow relation generated by some commonly used parametric VAR-models. We apply the approach of Whang and Andrews (1993) to test the semiparametric model specification against a wide range of alternative models, such as fully parametric and nonparametric models.
In Chapter V we investigate the comovements in the trading intensities of stocks in the same industry using a probit-pooled ACD-model, consisting of a duration model for trades in the same industry and a probit-model for the type of stock in the industry that is traded. The model is applied pair-wise to the trading intensities of stocks of five large US department-store operators listed on the NYSE. To estimate the comovements in the trading intensities of the stocks of US department-store operators, we distinguish stock-specific news that applies to one stock only and sector-specific news that is potentially relevant for stocks in the same type of industry. We provide estimates of the amounts of stock- and sector-specific news contained in the trading intensities of the stocks under consideration.
Finally, Chapter VI concludes.

This thesis is presented as a collection of papers. As a consequence, the notation differs per chapter and some definitions are repetitive. The chapters II, III, and IV, and V have been published before as Spierdijk (2002), Spierdijk, Nijman, and Van Soest (2002a), Spierdijk, Nijman, and Van Soest (2003), and Spierdijk, Nijman, and Van Soest (2002b), respectively.

CHAPTER II

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

II.1 Introduction

An important component of market microstructure theories is the concept of asymmetric information. This phenomenon arises when both uninformed and informed traders are present at the market. Uninformed traders trade for liquidity reasons. Informed traders, however, have private information on the fundamental value of the security to be traded. They trade to take advantage of their superior knowledge. Due to the presence of informed traders, the transaction process itself potentially reveals information on the value of the security.

Information dissemination through trading has been the subject of both theoretical and empirical research. Hasbrouck (1991a, 1991b) uses a VAR-model to jointly model returns and trading volume. He shows that trades contain information, since they have persistent impact on prices. Recently, the information content of the trading intensity has been investigated. The trading intensity refers to the process of durations, where a duration is defined as the time that elapses between two consecutive transactions. The main question is whether the trading intensity conveys any information in addition to trading volume. According to Diamond and Verrecchia (1987), slow trading indicates bad news. In the model of Admati and Pfleiderer (1988) fast trading refers to an increased risk of informed trading. In the model of Easley and O'Hara (1992) slow trading is associated to the lack of news. In an empirical setting, Dufour and Engle (2000) model the trading intensity using the ACD-model proposed by Engle and Russell (1998). Dufour and Engle (2000) use a bivariate VAR-model for returns and trade sign to assess the effect of the trading intensity on the price adjustment process in both transaction and calendar time. The authors show that the price impact of a trade is larger the higher the trading intensity, implying that trades are more informative in periods of frequent trading.

This chapter extends Hasbrouck (1991a, 1991b) and Dufour and Engle (2000). Using a joint model for returns on the midprice, trade size, trading intensity, and volatility we investigate the price impact of large trades and its relation to the trading intensity for a sample of frequently traded stocks listed on the New York Stock Exchange (NYSE). We show the distribution of the absolute price change with fast trading first-order stochastically dominates the distribution of the absolute price change with slow trading. As in Engle and Lunde (1998), we establish significant causality from trade characteristics to the trading intensity. Large returns slow down trading, while large trades increase the speed of trading. We show this feedback has little impact on the distribution of the price impact of trades, both in transaction and in calendar time.

The organization of this chapter is as follows. In Section II.2 we review some market microstructure underpinnings with the focus on the role of the trading intensity in information dissemination. Section II.3 provides a description of the data and their sample properties. Section II.4 is devoted to a multivariate model for returns and trading volume that ignores the possible role for the trading intensity. Section II.5 discusses the modeling of the trading intensity, while Section II.6 examines the impact of trades on prices in a VAR-model that takes the role of the trading intensity into account. In Section II.7 we allow for feedback from the trade characteristics such as returns and trading volume to the trading intensity and we investigate the effects of taking into account this feedback on the price impact of trades. Finally, Section II.8 summarizes the main results of this chapter.

II.2 Trading intensity and information

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

In the model of Easley and O'Hara (1992) an information signal is released at the beginning of the day with a certain probability. The market maker is uncertain about the existence of an information signal. He does not know whether or not an information event has taken place and he does not know the direction of the possible news event (good or bad news). The market maker acts as a Bayesian and adjusts his prices by watching the order flow. Informed traders, who have knowledge on the signal that is possibly released at the beginning of the day, buy or sell their stock in case of good and bad news, respectively. Uninformed traders are allowed to refrain from trading. When a news event has been released, a trade is more likely than a no trade outcome due to the presence of informed traders who want to trade to benefit from the private information they possess. Therefore, Easley and O'Hara (1992) associate fast trading to the existence of news and slow trading to the absence of news. Empirically, the model predicts that lagged durations are negatively correlated to the bid-ask spread. Since the market maker associates fast trading to a increased risk of informed trading, lagged durations will also be negatively correlated to price volatility.

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

In a different framework Diamond and Verrecchia (1987) also relate the trading intensity to the presence of news. Traders are either informed or uninformed and, moreover, 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. 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 but every agent knows all relevant probabilities. When they observe a no trade outcome, they know that there are several possibilities. Either a trader did not want to trade, or he could not trade due to short-sell restrictions or prohibitions. The probability of a no trade outcome is higher in case of bad news, because of the informed traders who are constrained from selling short. Therefore, Diamond and Verrecchia (1987) associate slow trading to bad news. The empirical implications of this model are as follows. Lagged durations are positively correlated to the bid-ask spread. Moreover, lagged durations and price volatility are also positively correlated. Finally, lagged durations and (mid)prices as well as bid/ask quotes are negatively correlated.

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 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. Hence, according to Admati and Pfleiderer (1988) frequent trading is associated to news. This implies that prices are more informative in periods of frequent trading; i.e. the trading intensity positively affects volatility.

Table II.1 summarizes the empirical implications of Easley and O'Hara (1987, 1992), Diamond and Verrecchia (1987) and Admati and Pfleiderer (1988).

One of the crucial assumptions underlying the Easley and O'Hara (1987, 1992) model and Diamond and Verrecchia (1987) is the absence of feedback from the trade characteristics such as returns, bid-ask spread and trading volume to the trading intensity. Goodhart and O'Hara (1997) put forward that trade characteristics convey information on the value of the asset. Therefore, traders may learn from it and adjust their speed of trading in reaction to this. As indicated in Dufour and Engle (2000), for example, a large change in the market maker's midprice may be a signal to the informed traders that their information, initially unknown to other market participants, has been revealed to the market maker assuming that no new signal has been released thereafter. This means that their information is no longer superior. Therefore, the incentive to trade disappears, which decreases the trading intensity. However, from an inventory perspective, large quote changes would attract opposite-side traders, thus increasing the trading intensity. Similar effects oc-

variables	EoH87	EoH92	AP88	DV87
duration (y_t), spread (s_{t+1})	?	−	−	+
duration (y_t), volatility (σ_{t+1})	?	−	−	+
duration(y_t), midprice (m_{t+1})	?	?	?	−
duration (y_t), bid/ask quote ($q^{a,b}_{t+1}$)	?	?	?	−
volume ($\|x_t\|$), spread (s_t)	+	?	?	?

Table II.1: Implications for the correlation sign

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

cur when informed traders observed large trades. An additional complexity arises, however, when uninformed traders show strategic behavior as well, see O'Hara (1995). They will increase the probability they attach to the risk of informed trading when they notice large absolute returns or large trading volume. Consequently, they will down their trading intensity. The overall effect on the trading intensity is therefore unclear when both informed and uninformed traders show strategic behavior. This issue will be investigated empirically in the sequel.

II.3 The data

We use high-frequency data on five of the most actively traded stocks listed on the NYSE, see Table II.2. The data are taken from the *Trade and Quote* (TAQ) database. For each stock, the data consist of all transactions during the months August, September and October, 1999 and covers 64 trading days.

We remove all trades that take place outside the opening hours; i.e. before 9.30 AM and after 4.00 PM. Moreover, we also delete trades that take place before the first quotes are generated.

ticker symbol	IBM	MAT	MCD	SLB	WMT
company name	Int. Business Machines Corp.	Mattel Inc.	McDonald's Corp.	Schlumberger Ltd.	WalMart Stores Inc.
# transactions	140,013	41,822	57,860	63,905	90,042
durations (seconds)					
mean	11	36	26	23	16
median	7	19	15	14	10
5% quantile	2	2	2	2	2
95% quantile	30	127	86	161	52
volume (shares)					
mean	3,055	4,305	2,512	2,187	2,957
median	1,000	1,000	900	1,000	1,000
5% quantile	100	100	100	100	100
95% quantile	11,000	20,000	10,000	9,000	11,400
returns (bp)					
mean	−0.0231	−0.1729	0.0099	−0.0238	0.0273
median	0.0000	0.0000	0.0000	0.0000	0.0000
5% quantile	−5.2562	−22.8050	−7.7131	−9.4384	−7.0646
95% quantile	5.2016	16.2101	7.7610	9.3721	7.0796

Table II.2: Ticker symbols, company names, and some sample statistics

For each stock the associated characteristics of each trade are recorded: trade moment τ_t in seconds after midnight, unsigned log trade size $|x_t|$ and transaction price p_t, where t indexes subsequent transactions (i.e. t indexes 'transaction time'). All data are measured in transaction time. The duration (in 'calendar time') between subsequent trades is defined as $y_t = \tau_t - \tau_{t-1}$. Overnight durations are removed from the data set.
To each trade we also associate a prevailing bid and ask quote, denoted by q_t^b and q_t^a. To obtain the prevailing quotes we use the 'five-seconds rule' by Lee and Ready (1991) 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. The prevailing midprice m_t is the average of the prevailing bid and ask quotes; i.e. $m_t = (q_t^b + q_t^a)/2$. The log return over the prevailing and subsequent midprice is expressed in basis points (bp) and denoted by $r_t = \log(m_{t+1}/m_t)$. Overnight returns are excluded from the sample.
Since the transaction data provided by the NYSE are not classified according to the nature of a trade (buy or sell), we use the Lee and Ready (1991) 'midquote rule' to classify a trade. With this rule, the prevailing midprice corresponding to a trade is used to decide whether a trade is a buy, a sell, or undecided. If the transaction price is lower (higher) than the midprice, it is viewed as a sell (buy). If the price is exactly at the midprice, its nature (buy or sell) remains undecided. To each trade we associate a trade indicator x_t^0 which indicates the nature of the trade: 1 (buy), -1 (sell), or 0 (undecided). From the trade size and the trade indicator we can construct signed log trading volume x_t. If a trade is unclassified, signed trading volume will be zero.
It sometimes occurs that multiple trades take place at the same second. We follow Engle and Russell (1998) and treat multiple transactions at the same time as one single transaction and aggregate their trade volume and average prices.
As a first exploration of our data, we compute sample mean and median of several trade characteristics for each stock, see Table II.2. This table shows that IBM is the most frequently traded stock in the sample, with the average duration equal to 11 seconds. Mattel is the least frequently traded stock of the sample with an average duration of 36 seconds. Average unsigned trading volume varies from 2,187 shares (Schlumberger) to 4,305 shares (Mattel) and average returns are close to zero.
For the McDonald's stock, we compute Spearman's rank correlations between the durations and several trade characteristics to get a notion of the possible dependence. We establish significantly negative correlation between lagged unsigned log trading volume $|x_{t-1}|$ and durations y_t, as well as be-

cross-correlations	estimate	std. error
return ($\|r_{t-1}\|$), duration (y_t)	0.2317	0.0043
volume ($\|x_{t-1}\|$), duration (y_t)	−0.0942	0.0042
duration (y_t), return ($\|r_t\|$)	−0.0861	0.0042
duration (y_t), volume ($\|x_t\|$)	0.0112	0.0042
autocorrelations		
return ($\|r_t\|$), return ($\|r_{t-1}\|$)	0.0395	0.0042
volume ($\|x_t\|$), volume ($\|x_{t-1}\|$)	0.1672	0.0042
duration (y_t), duration (y_{t-1})	0.0578	0.0042

Table II.3: Rank correlations

Spearman's rank correlation (with corresponding standard errors) between durations and several trade characteristics for the McDonald's stock.

tween returns $|r_t|$ and durations $|y_t|$. Moreover, we find significantly positive correlation between lagged returns $|r_{t-1}|$ and durations y_t and between durations y_t and unsigned trade size $|x_t|$. Table II.3 reports the exact value of the sample correlations and provides standard errors corresponding to the correlations. This table also displays, for comparison, the autocorrelations in each variable. The correlations reported in Table II.3 can be caused by asymmetric information or inventory effects as described in Section II.2, but they can equally well be due to other factors such as time of the day periodicities. In order to separate these effects, we will explicitly model the relation between these variables in the next sections.

II.4 The price impact of trades in transaction time

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

$z_t = (r_t, x_t)'$, expressed in transaction time, as

$$A(L)z_t = c + \upsilon_t, \tag{II.1}$$

where $A(L)$ is an m-th order (2×2) matrix polynomial in the lag operator L of the form $I - A_0 - A_1 L - \ldots - A_m L^m$. The (k, ℓ)-th element of the matrix A_j is denoted by $a_{j,(k,\ell)}$. The matrix A_0 can be normalized in various forms which do not affect the properties of the model. We choose the formulation of Hasbrouck (1991a, 1991b), such that trade size contemporaneously influences returns[1]. In expression (II.1) the variables $\upsilon_t = (\upsilon_{t,1}, \upsilon_{t,2})'$ are (2×1) vectors of mean-zero disturbances that are jointly and serially uncorrelated; i.e.

$$\mathbb{E}\upsilon_{t,i} = \mathbb{E}\upsilon_{t,i}\upsilon_{s,i} = 0 \qquad [t \neq s; i = 1, 2];$$
$$\mathbb{E}\upsilon_{t,1}\upsilon_{s,2} = 0.$$

We will measure the price impact of trades by means of the cumulative impulse response function. Given a certain history up to time τ_t, the cumulative impulse response function at time τ_{t+k} corresponding to an unexpected buy of M shares at time τ_t is defined as

$$\mathbb{E}_{t-1}(r_t + \ldots + r_{t+k} \mid \upsilon_{t,2} = \log(M)) - \mathbb{E}_{t-1}(r_t + \ldots + r_{t+k}). \tag{II.2}$$

Hence, the cumulative impulse response function represents the expected price impact of an unexpected trade, relative to the expected price impact conditional on the history only. See, for instance Koop, Pesaran, and Potter (1996). Kraus and Stoll (1972) and Hasbrouck (1991a, 1991b) point out that the persistent price impact of a an unexpected trade is naturally interpreted as the information content of the trade. The persistent impact is obtained for $k \to \infty$ in expression (II.2).

Estimation results

In line with Hasbrouck (1991a, 1991b) and Dufour and Engle (2000) we truncate the VAR-model at $m = 5$. We estimate the model by means of OLS. We use the method proposed by White (1980) to obtain heteroskedasticity-consistent standard errors. We verify the correctness of the truncation lag by testing for autocorrelation in the OLS-residuals using the Ljung-Box test. This test is asymptotically equivalent to the standard LM-test for serial correlation in the residuals of a regression, but computationally less demanding. The test does not lead to any evidence that more lags should be included in the VAR-model. The estimation results are given in Table II.4. They show that for all stocks, trade size has a positive immediate impact on returns.

[1]With this normalization A_0 has one nonzero element, namely $a_{0,(1,2)}$.

		IBM		MAT		MCD		SLB		WMT	
coeff.	lag	estimate	std. error								
const	j	−0.2626	0.0092	−0.8063	0.0524	−0.1390	0.0203	−0.2736	0.0172	−0.3284	0.0165
$a_{j,(1,1)}$	1	−0.0360	0.0036	−0.0817	0.0075	−0.0581	0.0046	−0.0333	0.0052	−0.0476	0.0040
	2	0.0355	0.0038	−0.0289	0.0064	−0.0140	0.0048	0.0230	0.0053	0.0097	0.0051
	3	0.0246	0.0037	−0.0203	0.0078	0.0083	0.0048	0.0228	0.0048	0.0205	0.0044
	4	0.0242	0.0038	−0.0023	0.0070	0.0108	0.0046	0.0138	0.0047	0.0135	0.0042
	5	0.0151	0.0038	0.0141	0.0061	0.0036	0.0046	0.0132	0.0056	0.0101	0.0045
$a_{j,(1,2)}$	0	0.2279	0.0015	0.5127	0.0088	0.3733	0.0036	0.4030	0.0034	0.3067	0.0029
	1	0.0855	0.0017	0.1706	0.0091	0.0927	0.0038	0.0934	0.0040	0.1027	0.0030
	2	0.0003	0.0017	0.0623	0.0088	0.0111	0.0039	0.0059	0.0039	0.0193	0.0032
	3	−0.0086	0.0017	0.0303	0.0093	−0.0023	0.0039	−0.0057	0.0038	−0.0032	0.0031
	4	−0.0107	0.0017	0.0110	0.0091	−0.0133	0.0039	−0.0071	0.0039	−0.0039	0.0030
	5	−0.0082	0.0017	−0.0019	0.0089	−0.0049	0.0038	−0.0127	0.0039	−0.0072	0.0030
R^2		0.2215		0.1377		0.2190		0.2808		0.1798	

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

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

This empirically confirms the results of Easley and O'Hara (1987) and Hasbrouck (1991a, 1991b). We test for Granger-causality from returns to trade size and from trade size to returns. We do this by testing the null hypothesis that the corresponding coefficients in the VAR-model are jointly zero. For example, to test whether or not trade size Granger-causes returns we use a Wald-test and test the null hypothesis $H_0 : a_{j,(1,2)} = 0$ for $j = 0, \ldots, 5$. This null hypothesis is rejected at a 5% level for all stocks. Similarly, returns significantly Granger-cause trade size for all stocks in the sample. This emphasizes the importance of taking into account the feedback among the trade characteristics.

The price impact of trades

To investigate the short and long run price impact of a large trade on the McDonald's stock, we assume that the market is in a state of 'equilibrium'. We define this as a situation in which past returns and trade sizes are equal to their sample average. We consider a buy consisting of 10,000 shares. This amount of shares corresponds to the 95% sample quantile of unsigned trading volume in our data. We compute the impulse response function for an unexpected trade of 10,000 shares. The two conditional expectations in expression (II.2) are obtained by iterating the VAR-model in (II.1) k periods ahead. A parametric bootstrap from the asymptotic distribution of the OLS-estimates can be used to obtain confidence intervals for the impulse response function. After 20 transactions, the expected price impact equals 6.7 bp. The corresponding 95% confidence interval equals $[6.5, 6.9]$ bp and is based upon a bootstrap with $N = 10,000$ draws. Note that the price impact is linear in log trading volume, so the impulse response functions for other trading volumes are easily derived from the price-impact function corresponding to a trade of 10,000 shares.

To estimate the model in equation (II.1) by means of OLS, we do not need the distribution of the disturbances $(\upsilon_t)_t$. Similarly, the distribution of $(\upsilon_t)_t$ is not needed for the estimation of the expected price change of a trade, since the disturbances have mean zero and thus cancel out in expression (II.2). However, not only the expected price change of a trade is of interest. To assess the entire distribution of the price impact caused by a large trade, we have to make explicit assumptions on the distribution of the VAR-disturbances. Since returns are likely to exhibit volatility clustering, we assume that the disturbances $(\upsilon_{t,1})_t$ follow a GARCH-process; see Engle (1982) and Bollerslev (1986). In Manganelli (2002) it is shown that time-varying conditional heteroskedasticity is not only present in returns, but also in trading volume. An ARCH LM-test (see Engle (1982)) provides significant evidence for autoregressive conditional heteroskedasticity in the VAR-disturbances $(\upsilon_{t,1}, \upsilon_{t,2})'$, since the null hypothesis of no ARCH-effects in $(\upsilon_{t,1})_t$ and $(\upsilon_{t,2})_t$ is rejected at each reasonable significance level. We therefore specify a bivariate GARCH-model in transaction time for $(\upsilon_t)_t$; i.e. $\upsilon_t = \Sigma_t \eta_t$. Here Σ_t denotes a diagonal matrix with elements $\sigma_{t,1}$ and $\sigma_{t,2}$. Moreover, $(\eta_t)_t = (\eta_{t,1}, \eta_{t,2})_t$ is a bivariate sequence of mean zero, identically distributed random variables, with $\eta_{t,1}$ independent of the information known up to time τ_t and $\eta_{t,2}$ independent of the information set at time τ_{t-1} and $\eta_{t,1}$ and $\eta_{s,2}$ independent for all s, t. A specification search leads to a bivariate EGARCH$(1, 1)$ specification:

$$\begin{aligned} \log \sigma_{t,1}^2 &= \alpha_{r,1} + \alpha_{r,2}|\eta_{t-1,1}| + \alpha_{r,3}\eta_{t-1,1} + \alpha_{r,4} \log \sigma_{t-1,1}^2 \qquad \text{(II.3)} \\ &\quad + \alpha_{r,5}|x_t| + \alpha_{r,6}|x_{t-1}|; \\ \log \sigma_{t,2}^2 &= \alpha_{x,1} + \alpha_{x,2}|\eta_{t-1,2}| + \alpha_{x,3}\eta_{t-1,2} + \alpha_{x,4} \log \sigma_{t-1,2}^2. \qquad \text{(II.4)} \end{aligned}$$

Hence, we allow for GARCH-effects in both returns and trading volume, and, moreover, for feedback from trading volume to volatility. Since volatility is affected by the magnitude of the trade rather than its sign (buy or sell), we include unsigned trading volume in equation (II.3). Since we do not find significant evidence for feedback from the trade characteristics to the variance of trading volume, we not include any explanatory variables in equation (II.4). Using the OLS-residuals we estimate the EGARCH-model given by equations (II.3) and (II.4) by means of quasi-maximum likelihood (QML). The BHHH-algorithm of Berndt, Hall, Hall, and Hausman (1974) is used for the numerical optimization. Furthermore, we estimate the robust standard errors of Bollerslev and Wooldridge (1992) to deal with any deviations from normality in $(\eta_t)_t$.

The estimation results are displayed in Table II.5. The results show that returns are highly persistent, since the coefficients $\alpha_{r,4}$ are close to one. There is less persistence in trading volume, but the values of the coefficients $\alpha_{x,4}$ are still relatively high and thus indicate that large trades tend to clump together. For three out of five stocks (IBM, Mattel, and WalMart) the coefficients $\alpha_{r,3}$ are significantly different from zero, which means that positive and negative shocks have asymmetric impact on volatility. For all five stocks the coefficients $\alpha_{x,3}$ are significantly different from zero, which indicates that there are asymmetric effects for trading volume as well. Note that $(\alpha_{r,5} + \alpha_{r,6})(1 - \alpha_{r,4})^{-1}$ represents the 'equilibrium multiplier' and thus reflects the change in the equilibrium value of volatility caused by a ceteris paribus change in trading volume. A Wald-test shows that unsigned trading volume is positively related to volatility for two out of five stocks (IBM and Schlumberger).

	IBM		MAT		MCD		SLB		WMT	
returns	estimate	std.error								
$\alpha_{r,1}$	−0.1089	0.0057	0.0657	0.0179	0.0668	0.0149	0.0291	0.0098	−0.0226	0.0050
$\alpha_{r,2}$	0.1287	0.0056	0.1542	0.0092	0.0718	0.0068	0.0744	0.0095	0.0670	0.0046
$\alpha_{r,3}$	0.0128	0.0034	0.0169	0.0065	−0.0010	0.0037	0.0008	0.0036	−0.0103	0.0025
$\alpha_{r,4}$	0.9702	0.0036	0.9694	0.0039	0.9620	0.0056	0.9530	0.0064	0.9912	0.0016
$\alpha_{r,5}$	0.1408	0.0032	0.0401	0.0051	0.0730	0.0037	0.1414	0.0047	0.0795	0.0037
$\alpha_{r,6}$	−0.1273	0.0031	−0.0455	0.0052	−0.0733	0.0036	−0.1324	0.0051	−0.0792	0.0038
volume										
$\alpha_{x,1}$	0.7433	0.0306	0.7631	0.0459	1.2954	0.0857	1.4362	0.0838	1.4370	0.0617
$\alpha_{x,2}$	0.1747	0.0043	0.3095	0.0093	0.1690	0.0073	0.1893	0.0073	0.2173	0.0062
$\alpha_{x,3}$	−0.0143	0.0021	0.0192	0.0050	−0.0158	0.0035	−0.0185	0.0041	−0.0172	0.0031
$\alpha_{x,4}$	0.7502	0.0090	0.7060	0.0141	0.5922	0.0250	0.5287	0.0254	0.5390	0.0180

Table II.5: Estimation results for the EGARCH-model for the VAR-residuals

This table reports the results for the EGARCH-model given in equations (II.3) and (II.4). The EGARCH-model is estimated using QML. The standard errors in the columns on the right-hand-side are computed using the Bollerslev-Wooldrigde (1991)'s robust covariance matrix.

The positive impact of trading volume on volatility is in line with the model of Easley and O'Hara (1987). It is also in line with the empirical conclusions of Lamoureux and Lastrapes (1990) and Manganelli (2002). Hence, following a large trade the market maker updates his beliefs which leads to a persistent price change. In addition to this, large trades also have a positive impact on volatility. This can be explained by the fact that large trades are associated to an increased risk of informed trading, see Easley and O'Hara (1987). However, for the stocks McDonald's and WalMart the volume multiplier does not significantly differ from zero, and for Mattel the multiplier is significantly negative. Hence, the significantly positive effect of volume on volatility is restricted to two stocks only.
We estimate the distribution of the price impact using the bootstrap approach of Hasbrouck (1991b). This means that we consider an unexpected buy of M shares and simulate values of $(r_{t+k}, x_{t+k})'$ by drawing from the empirical distribution of the standardized VAR-disturbances $\upsilon_{t,i}/\sigma_{t,i}$ which are assumed iid. We do this $N = 10,000$ times and for each simulated sequence of $(r_{t+k}, x_{t+k})'$ we compute the corresponding price changes at time τ_{t+k}. We find that the 5% quantile of the price impact after 20 trades equals -0.6 bp. The 95% quantile of the price change after 20 trades is equal to 14.2 bp. Thus, with a probability of 90% the price change of a trade of 10,000 shares is in the interval $[-0.6, 14.2]$ bp. Figure II.1 shows the expected price change corresponding to the unexpected trade of 10,000 shares, including the 5% and 95% quantiles of the distribution of the price change. The remaining quantiles of the distribution of the persistent price impact of a trade of 10,000 shares are reported in the column with the caption 'no durations' in Table II.6.
Up to now we only considered impulse response functions in transaction time. From Figure II.1 we can see that it takes about 10 transactions before the new efficient price has been reached. Since the average duration for the McDonald's stock is 26 seconds, it takes slightly less than 4.5 minutes before the new efficient price has been attained.

II.5 A model for the trading intensity

In the VAR-model of Hasbrouck (1991a, 1991b) the price impact of trades can only be measured in transaction time. It is often useful to have impulse responses in calendar time, since this allows e.g. for the computation of the exact time it takes to reach a certain price level. In this section we focus on the specification of the data generating process underlying the trading intensity.

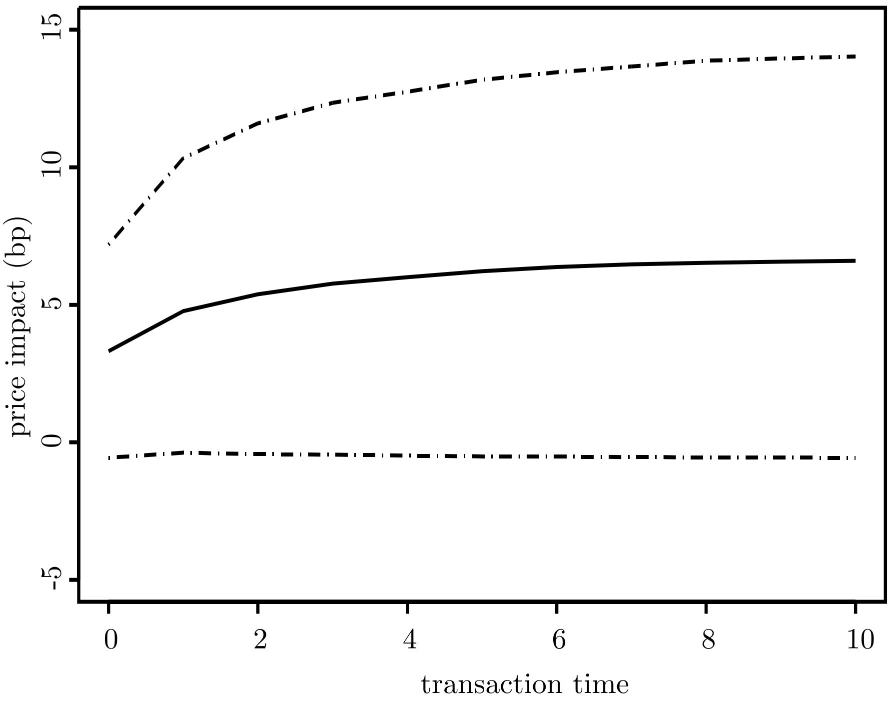

Figure II.1: Impulse response function and 90% prediction interval

This plot shows the expected price impact (solid line) and the 5% and 95% quantiles (dashed lines) of the distribution of the price impact corresponding to an unexpected trade of 10,000 shares of McDonald's stock, based on the VAR-model defined in equation (II.1).

quantile (%)	no durations	no feedback fast trading	no feedback slow trading	feedback fast trading	feedback slow trading
2.5	−1.3	−1.8	−1.1	−1.2	−0.9
5	−0.6	−0.8	−0.5	−0.3	−0.2
10	0.3	0.4	0.1	0.8	0.4
20	1.7	2.1	1.3	2.4	1.7
30	2.8	3.8	2.4	3.6	2.5
40	4.1	5.1	3.3	4.7	3.5
50	5.8	7.0	4.6	6.5	5.0
60	7.8	9.2	6.2	9.2	6.6
70	9.6	11.6	7.4	11.5	7.8
80	11.2	13.3	8.8	12.9	9.1
90	12.9	15.1	10.1	15.0	10.3
95	14.2	16.3	10.8	16.2	11.2
97.5	15.2	17.1	11.5	17.1	11.9

Table II.6: The distribution of the persistent price impact of a trade of 10,000 shares of the McDonald's stock

This table reports the estimated quantiles (in bp) of the distribution of the persistent price impact of trades implied by an unexpected trade of 10,000 shares of the McDonald's stock in several models: in the VAR-model defined in equation (II.1) without a role for the trading intensity, in the extended VAR-model with a role for the trading intensity, and in the extended VAR-model with feedback from the trade characteristics to the trading intensity.

We use a version of Engle and Russell (1998)'s ACD-model for this purpose, assuming that the duration process is strongly exogenous cf. Engle, Hendry, and Richard (1983) and that $(y_t)_t$ is generated by a log ACD(1,1)-model, cf. Bauwens and Giot (2000); i.e.

$$y_t = \psi_t \varepsilon_t, \quad \psi_t = \mathbb{E}_{t-1}(y_t), \tag{II.5}$$

with $(\varepsilon_t)_t$ a sequence of identically distributed variables with unit mean, independent of the information up to time τ_{t-1} and of $v_{i,s}$ for $i = 1, 2$ and all s. The log conditional duration is specified recursively as

$$\log \psi_t = \beta_1 + \beta_2 \log \varepsilon_{t-1} + \beta_3 \log \psi_{t-1}. \tag{II.6}$$

The model is expressed in terms of diurnally corrected durations which are also denoted by y_t as well, with some abuse of notation. The diurnally corrected durations are obtained as in Engle and Russell (1998). The expected duration given the time of the day is approximated by a piecewise linear and continuous spline with nodes set on $9.30 - 10.00, 10.00 - 11.00, \ldots, 14.00 - 15.00$, and $15.30 - 16.00$ hours. We compute the diurnally corrected durations by dividing each duration by its corresponding diurnal correction.

Estimation results
We first estimate the diurnal component separately by means of a regression, cf. Engle and Russell (1998). Subsequently, we estimate the ACD(1,1)-model by means of QML, see Engle and Russell (1998) and Drost and Werker (2001). We use the BHHH-algorithm of Berndt, Hall, Hall, and Hausman (1974) for the numerical optimization. Moreover, we compute the Bollerslev and Wooldridge (1992) robust covariance matrix to obtain standard errors that are robust against deviations in exponentiality of ε_t. The row with the caption 'no feedback' in Table II.7 shows the QML-estimation results of the ACD(1,1) model for each stock. As usual, the persistence parameter β_3 is close to one. It varies from 0.988 to 0.999. The estimation results for the diurnal correction factor are available upon request.

II.6 The price impact of trades and calendar-time effects

It is likely that the price impact of trades depends upon the trading intensity, cf. Diamond and Verrecchia (1987), Admati and Pfleiderer (1988) ,and Easley and O'Hara (1992). In this section we proceed in the line of Dufour and Engle (2000).

	IBM		MAT		MCD		SLD		WMT	
no feedback	estimate	std.error								
β_1	−0.0375	0.0014	−0.0457	0.0015	−0.0364	0.0016	−0.0468	0.0016	−0.0233	0.0010
β_2	0.0605	0.0022	0.0783	0.0026	0.0624	0.0027	0.0789	0.0027	0.0393	0.0017
β_3	0.9933	0.0006	0.9994	0.0003	0.9879	0.0011	0.9926	0.0007	0.9963	0.0004
with feedback										
β_1	−0.0396	0.0017	−0.0461	0.0021	−0.0351	0.0028	−0.0527	0.0023	−0.0279	0.0016
β_2	0.0760	0.0026	0.0887	0.0030	0.0979	0.0036	0.1068	0.0033	0.0648	0.0024
β_3	0.9904	0.0008	0.9989	0.0004	0.9708	0.0018	0.9849	0.0010	0.9898	0.0008
$\xi_{\|r\|,1}$	0.1406	0.0021	0.0746	0.0024	0.1006	0.0026	0.1596	0.0028	0.1203	0.0020
$\xi_{\|r\|,2}$	−0.1398	0.0021	−0.0738	0.0024	−0.0997	0.0025	−0.1588	0.0028	−0.1210	0.0020
$\xi_{\|x\|,1}$	−0.1105	0.0058	−0.1196	0.0084	−0.1934	0.0082	−0.2228	0.0062	−0.1457	0.0062
$\xi_{\|x\|,2}$	0.1043	0.0059	0.1161	0.0084	0.1780	0.0081	0.2186	0.0063	0.1391	0.0062
ξ_Q	−0.0002	0.0000	−0.0002	0.0001	−0.0005	0.0001	−0.0005	0.0001	−0.0003	0.0000

Table II.7: QML-estimation results for the ACD(1,1)-model

Estimation results for the ACD(1, 1)-model with and without feedback as specified in equation (II.12) and (II.13). The standard errors in this table are computed from the Bollerslev and Wooldrige (1992) robust covariance matrix.

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

$$A(L) = A(y_t)(L). \tag{II.7}$$

The impact of past trading volumes on returns and current trade size depends upon the trading intensity in the following way:

$$a_{j,(k,2)} = \gamma_{(j,k)} + \delta_{(j,k)} \cdot \log y_{t-j}, \tag{II.8}$$

similar to Dufour and Engle (2000). With this specification, the impact of a trade on returns depends upon the trading intensity. For example, when the coefficient $\delta_{(j,1)}$ is negative (positive), the impact of a trade on returns is lower (higher) when the corresponding duration is long (short). Moreover, with this specification the correlation between consecutive trading volumes depends on the durations in a similar way.

The price impact of trades

As before, we estimate the VAR-model using OLS with truncation at $m = 5$. The estimation results for the McDonald's stock are given in Table II.8. Only the results for the return equation are displayed. Similar to the model of Hasbrouck (1991a, 1991b) without durations, we test for Granger-causality. Again we establish significant Granger-causality from returns to trade size and vice versa. Moreover, the null hypothesis that the impact of trades does not depend upon the trading intensity is rejected for all stocks.

As in the VAR-model without a role for the trading intensity, we estimate the impulse response functions to measure the price impact. Since the durations enter the model in a nonlinear fashion, we have to average out the durations. Therefore, we estimate the impulse response function by simulating $N = 10,000$ future paths of durations. For each path of durations we compute price-impact functions as before and finally, we average the impulse responses over the $N = 10,000$ simulations to obtain the final impulse response function.

To simulate future paths of durations, we need random values of the ACD-disturbances $(\varepsilon_t)_t$. Since we used QML to estimate the coefficients of the ACD-model, we did not make any additional distributional assumptions apart from some regularity conditions. We therefore assume that the ACD-disturbances are independent and identically distributed according to the corresponding empirical law. Hence, to obtain random values of the ACD-disturbances, we randomly draw from the empirical distribution of the ACD-residuals.

		IBM		MAT		MCD		SLB		WMT	
coeff.	lag	estimate	std. error								
const	j	−0.2617	0.0092	−0.8232	0.0525	−0.1428	0.0203	−0.2742	0.0172	−0.3305	0.0164
$a_{j,(1,1)}$	1	−0.0308	0.0035	−0.0821	0.0076	−0.0545	0.0046	−0.0257	0.0051	−0.0453	0.0040
	2	0.0350	0.0038	−0.0300	0.0064	−0.0132	0.0048	0.0234	0.0053	0.0100	0.0050
	3	0.0238	0.0037	−0.0213	0.0078	0.0083	0.0048	0.0216	0.0048	0.0203	0.0044
	4	0.0244	0.0038	−0.0029	0.0070	0.0101	0.0046	0.0119	0.0047	0.0133	0.0042
	5	0.0154	0.0038	0.0128	0.0061	0.0032	0.0046	0.0113	0.0056	0.0103	0.0045
$\gamma_{(j,1)}$	0	0.3082	0.0051	0.7409	0.0237	0.5048	0.0102	0.5339	0.0093	0.3860	0.0080
	1	0.0681	0.0048	0.2244	0.0234	0.1022	0.0097	0.1161	0.0092	0.0958	0.0079
	2	−0.0065	0.0045	0.1119	0.0224	0.0169	0.0097	0.0133	0.0092	0.0186	0.0078
	3	−0.0059	0.0047	0.0546	0.0228	−0.0087	0.0097	−0.0093	0.0091	0.0036	0.0077
	4	−0.0122	0.0046	−0.0135	0.0222	−0.0224	0.0097	−0.0189	0.0089	0.0032	0.0078
	5	−0.0128	0.0047	0.0161	0.0221	−0.0081	0.0094	−0.0081	0.0089	−0.0053	0.0076
$\delta_{(j,1)}$	0	−0.0355	0.0021	−0.0757	0.0070	−0.0463	0.0033	−0.0468	0.0031	−0.0312	0.0030
	1	0.0056	0.0020	−0.0227	0.0068	−0.0068	0.0031	−0.0131	0.0029	0.0007	0.0029
	2	0.0029	0.0019	−0.0185	0.0065	−0.0031	0.0031	−0.0043	0.0029	0.0000	0.0029
	3	−0.0010	0.0019	−0.0098	0.0065	0.0017	0.0030	0.0005	0.0029	−0.0028	0.0028
	4	0.0006	0.0019	0.0066	0.0064	0.0032	0.0030	0.0042	0.0028	−0.0031	0.0028
	5	0.0020	0.0020	−0.0061	0.0064	0.0012	0.0030	−0.0013	0.0028	−0.0011	0.0028
R^2		0.2237		0.1411		0.2212		0.2842		0.1810	

Table II.8: Estimation results for the return equation in the VAR-model

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

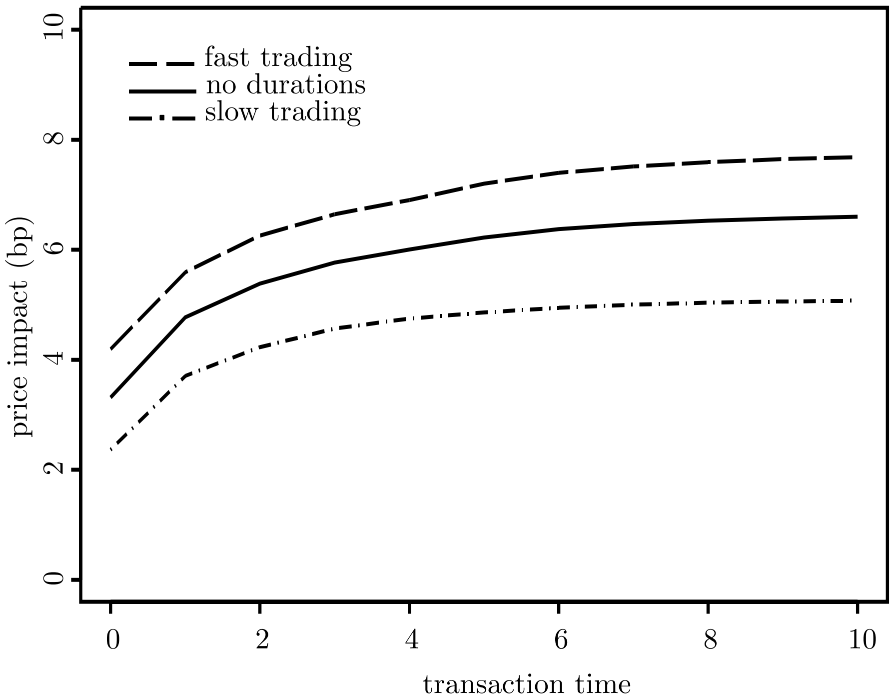

Figure II.2: Impulse response function: slow versus fast trading

This plot shows the price-impact functions corresponding to an unexpected trade of 10,000 shares of the McDonald's stock, based on the VAR-model defined in equation (II.1) without duration dependence and with fast and slow trading.

Again we focus on the McDonald's stock. We compute impulse response functions for the model of Section II.6 in two different situations: in a situation of 'low' and 'high' trading intensity. We compute the 99.5% and the 0.5% quantiles of the durations in our data. Subsequently we initialize the ACD-model with these durations. As we compute the impulse response functions by simulating future paths of durations, we also need to compute the diurnal correction factor. Therefore, it is necessary that we specify explicitly the time at which the large trade takes place. Consistent with the daily periodicities observed in the trading intensity, we assume that the period of slow trading takes place at 12.30 PM and the fast trading at 10.00 AM. By doing so, we capture the effect of different trading intensities on the impulse response functions. As in Section II.4, we assume that the trade characteristics are in a state of equilibrium at the time of the unexpected trade.

Figure II.2 shows the impulse response functions for a trade of size $10,000$ with 'slow' and 'fast' trading, as well as the impulse response function in the VAR-model in which the trading intensity does not play a role. We see that 20 transactions after the trade of $10,000$ shares, the impulse response equals 5.1 bp with slow trading and 7.8 bp with fast trading. Note that the expected price impact of 6.7 bp as computed by the model of Hasbrouck (1991a, 1991b) lies between these two values. The corresponding 95% confidence intervals equal $[4.5, 5.6]$ bp and $[7.4, 8.1]$ bp. A 95% upper one-sided confidence interval for the difference between the price impact with slow and fast trading is $[-\infty, -3.4]$ bp, so the price impact with slow trading is significantly lower than with fast trading.

To derive the entire distribution of the price impact, we proceed as in Section II.4 and specify an EGARCH$(1,1)$-model for the VAR-disturbances $(\upsilon_{t,1}, \upsilon_{t,2})'$. Taking into account the durations in our specification search, we arrive at the specification

$$\begin{aligned}\log\sigma_{t,1}^2 &= \alpha_{r,1} + \alpha_{r,2}|\eta_{t-1,1}| + \alpha_{r,3}\eta_{t-1,1} + \alpha_{r,4}\log\sigma_{t-1,1}^2 \\ &\quad +\alpha_{r,5}|x_t| + \alpha_{r,6}|x_{t-1}| + \alpha_{r,7}\log y_t + \alpha_{r,8}\log y_{t-1}; \end{aligned} \tag{II.9}$$

$$\log\sigma_{t,2}^2 = \alpha_{x,1} + \alpha_{x,2}|\eta_{t-1,2}| + \alpha_{x,3}\eta_{t-1,2} + \alpha_{x,4}\log\sigma_{t-1,2}^2. \tag{II.10}$$

We now also include feedback from the trading intensity to volatility, which is motivated by Easley and O'Hara (1992). As before, we estimate the EGARCH-model by means QML, applying the Bollerslev and Wooldridge (1992) robust standard errors. The estimation results are displayed in Table II.9. The equilibrium multiplier for trading volume indicates that unsigned trading volume has a positive impact on volatility for two out of five stocks (IBM and Schlumberger).

	IBM		MAT		MCD		SLB		WMT	
returns	estimate	std.error								
$\alpha_{r,1}$	−0.0670	0.0078	0.3294	0.0348	0.2239	0.0308	0.0918	0.0169	0.0255	0.0089
$\alpha_{r,2}$	0.1352	0.0059	0.1918	0.0105	0.0937	0.0081	0.0799	0.0099	0.0806	0.0050
$\alpha_{r,3}$	0.0139	0.0034	0.0354	0.0072	0.0009	0.0044	−0.0015	0.0038	−0.0107	0.0029
$\alpha_{r,4}$	0.9670	0.0039	0.9385	0.0058	0.9341	0.0081	0.9471	0.0068	0.9843	0.0021
$\alpha_{r,5}$	0.1430	0.0033	0.0432	0.0047	0.0741	0.0038	0.1401	0.0047	0.0793	0.0038
$\alpha_{r,6}$	−0.1291	0.0033	−0.0505	0.0047	−0.0750	0.0037	−0.1320	0.0050	−0.0791	0.0039
$\alpha_{r,7}$	−0.1695	0.0113	−0.1446	0.0133	−0.1376	0.0095	−0.1110	0.0096	−0.0921	0.0110
$\alpha_{r,8}$	0.1498	0.0110	0.0962	0.0129	0.1065	0.0102	0.0935	0.0096	0.0771	0.0111
volume										
$\alpha_{x,1}$	0.7169	0.0303	0.7531	0.0455	1.2954	0.0857	1.4206	0.0835	1.4116	0.0618
$\alpha_{x,2}$	0.1683	0.0043	0.3115	0.0094	0.1690	0.0073	0.1880	0.0073	0.2125	0.0061
$\alpha_{x,3}$	−0.0138	0.0021	0.0184	0.0050	−0.0158	0.0035	−0.0184	0.0041	−0.0170	0.0031
$\alpha_{x,4}$	0.7591	0.0089	0.7082	0.0140	0.5922	0.0250	0.5336	0.0253	0.5473	0.0180

Table II.9: Estimation results for the EGARCH-model for the VAR-residuals

This table reports the results for the EGARCH-model given in equations (II.3) and (II.4). The EGARCH-model is estimated using QML. The standard errors in the columns on the right-hand-side are computed using the Bollerslev and Wooldrigde (1992) robust covariance matrix.

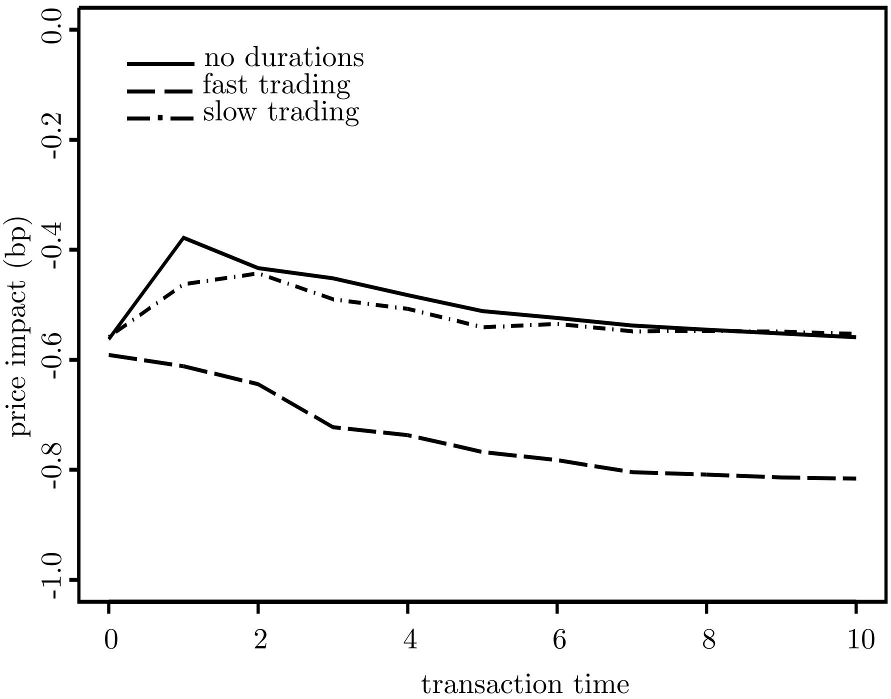

Figure II.3: Impulse response function: slow versus fast trading

This plot shows the 5% quantile of the distribution of the price change caused by a trade of 10,000 shares of the McDonald's stock, based on the VAR-model in equation (II.1) with and without a role for the trading intensity.

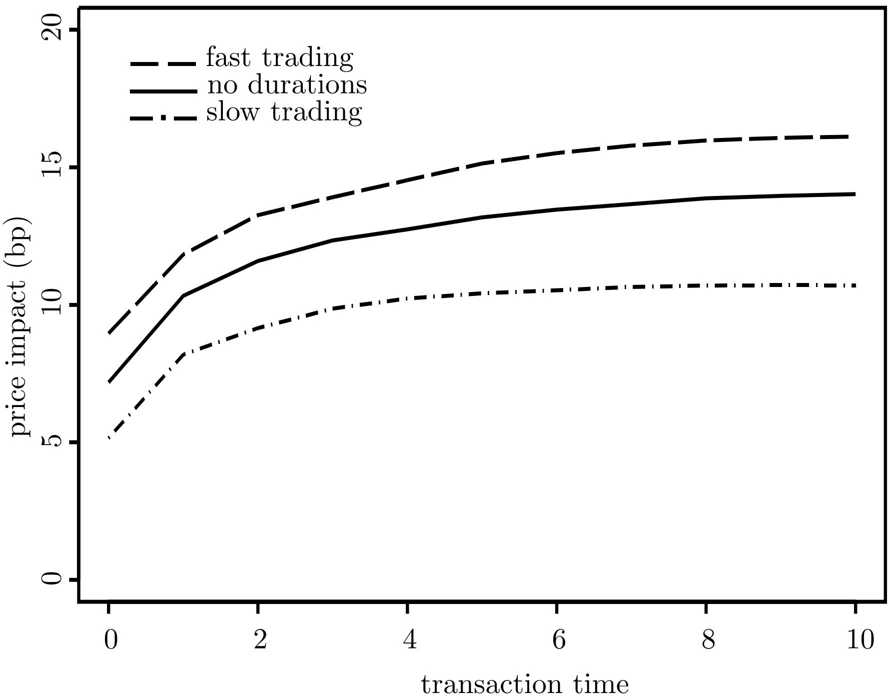

Figure II.4: Impulse response function: slow versus fast trading

This plot shows the 95% quantile of the distribution of the price change caused by a trade of 10,000 shares of the McDonald's stock, based on the VAR-model in equation (II.1) with and without a role for the trading intensity.

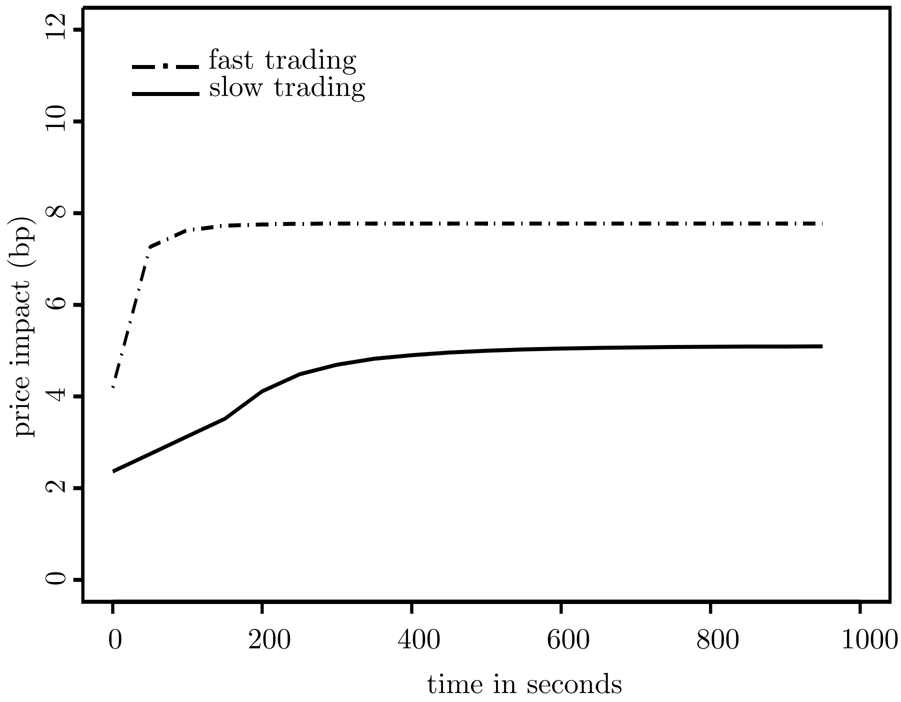

Figure II.5: Impulse response function: convergence time

This plot shows the price-impact function in calendar time following an unexpected trade of 10,000 shares of the McDonald's stock. The impulse response functions are based on the VAR-model in equation (II.1) with duration dependence, in periods of fast and slow trading. The horizontal axis displays the time in seconds starting at the time at which the trade has been initiated.

Furthermore, the trading intensity is significantly positively related to volatility for all five stocks, since the equilibrium multiplier corresponding to the durations is negative in all five cases. The positive impact of the trading intensity on volatility was also found by Manganelli (2002) and implies that, in periods of frequent trading, volatility is higher. This can be explained within the model Easley and O'Hara (1992), in which fast trading is associated to an increased risk of informed trading.

Using Hasbrouck (1991b)'s bootstrap approach as in Section II.4, we find that the 5% quantiles of the expected price change after 20 transactions with slow and fast trading are −0.5 bp and −0.8 bp, respectively. The 95% quantiles of the price change are 10.8 bp and 16.3 bp. Thus, with 90% probability the price change with slow trading is in the interval $[-0.5, 10.8]$ bp. With fast trading the price change is with 90% probability in the interval $[-0.8, 16.3]$ bp. Hence, the entire distribution of the price change is different in periods of fast and slow trading and thus depends upon the trading intensity. The distribution of the absolute price change with fast trading first-order stochastically dominates the distribution of the absolute price change with slow trading. This means that trades have more impact on prices in periods of frequent trading, hence trades convey more information when durations are short. Figure II.3 and II.4 show the 5% and the 95% quantiles of the distribution of the price change without durations and in periods of fast and slow trading. The remaining quantiles of the distribution of the persistent price impact of a trade of 10,000 shares are reported in the columns with the caption 'no feedback' in Table II.6.

Finally, to gain insight into the adjustment process of the price following a large trade, we now consider the expected price-impact function in calendar time. The impulse response functions in calendar time[2] show that it takes approximately 3.5 minutes to reach the new efficient price that follows the unexpected trade in case of frequent trading[3], while this takes about 10 minutes in case of slow trading. See Figure II.5. In the VAR-model without durations we had estimated the time to reach the new efficient price to be approximately 4.5 minutes, which is in between the convergence time for fast and slow trading.

For the other stocks under consideration we obtain similar results.

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

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

II.7 Feedback from trade characteristics to the trading intensity

In Section II.6 we measured the impact of a transitory shock on prices, assuming that there is no feedback from the trade characteristics to the trading intensity. In Section II.2 we made clear that trade characteristics are likely to have impact on the trading intensity. This additional feedback may affect the impulse response functions. In this section we investigate whether or not the trade characteristics affect the trading intensity and to what extent the impulse response functions are influenced by this feedback.
We specify the log ACD(1, 1)-model with feedback as follows. Let again

$$y_t = \psi_t \varepsilon_t, \quad \psi_t = \mathbb{E}_{t-1}(y_t), \tag{II.11}$$

with ε_t iid with unit mean, independent of the information up to time τ_{t-1} and of $\upsilon_{i,s}$ for $i = 1, 2$ and all s. The information known up to time τ_{t-1} now also includes the values of the trade characteristics up to that moment. The log conditional expectation is extended with a vector of trade characteristics:

$$\log \psi_t \quad = \quad \beta_1 + \beta_2 \log \varepsilon_{t-1} + \beta_3 \log \psi_{t-1} + \xi' \nu_{t-1}. \tag{II.12}$$

We include several variables in ν_t that may, according to Section II.2, affect the trading intensity. We take

$$\nu_{t-1} = (r_{t-1}, r_{t-2}, |x_{t-1}|, |x_{t-2}|, Q_{t-1})', \quad Q_{t-1} = \left|\sum_{i=1}^{5} x_{t-i}\right|. \tag{II.13}$$

The variable Q_{t-1} represents the imbalance in signed volume over the five most recent transactions. This variable is included to investigate the effect of order imbalances on the trading intensity. The effect of trade size and absolute returns on durations is probably more related to the magnitude of these variables than their sign, so we take these variables unsigned. The reasons for including absolute returns has been pointed out by Dufour and Engle (2000). Large absolute returns may attract opposite side traders which would increase the trading intensity. Alternatively, they may slow down trading since informed traders interpret large absolute returns as a signal that their private information has already been incorporated into prices. Unsigned trading volume is also included in the conditional expected duration given in expression (II.13). According to Easley and O'Hara (1987), large trading volume indicates an in increased risk of informed trading. This may be a reason for uninformed traders to refrain from trading, which would slow down the trading intensity. However, it may also attract informed traders who want to

benefit from their private information before others do so. This would lead to more trading activity.
Similar to durations, trade characteristics such as absolute returns and trading volume, also exhibit daily periodicities, cf. Engle and Lunde (1998). Therefore, they have to be diurnally corrected in the usual way to account this.

Estimation results
The estimation results for the diurnal components of the trade characteristics are available upon request. Again we use QML to estimate the ACD-model. We use a Wald-test to test for higher-order effects, for which there is no significant evidence. The row with the caption 'with feedback' in Table II.7 displays the estimation results. The estimation results for the diurnal correction factor are available upon request. The null hypothesis of no Granger-causality from the trade characteristics to the trading intensity is rejected at each reasonable confidence level using a Wald-test, making clear that there is significant feedback between the trading intensity and the various trade characteristics. To assess the effect of trade characteristics on the trading intensity, we investigate the sign and significance of the equilibrium multipliers $(\xi_{|r|,1} + \xi_{|r|,2})(1 - \beta_3)^{-1}$ (absolute returns), $(\xi_{|x|,1} + \xi_{|x|,2})(1 - \beta_3)^{-1}$ (unsigned volume), and $\xi_Q(1 - \beta_3)^{-1}$ (imbalance).
For three out of five stocks the long-term impact of absolute returns on durations is significantly positive. For McDonald's the equilibrium multiplier is not significantly different from zero and for Schlumberger the effect is significantly negative. An explanation for the positive impact of absolute returns on durations is given in Dufour and Engle (2000), who note that a large change in the market maker's midprice may be a signal to the informed traders that their information has been revealed to the market maker. This means that their information is no longer superior. Therefore, their incentive to trade disappears, which decreases the trading intensity.
For all stocks the long-term impact of trading volume on durations is significantly negative. The negative relation suggests that informed traders increase their trading intensity when they observe large trades. Since large trades are associated to an increased risk of informed trading, see e.g. Easley and O'Hara (1987), informed traders increase their speed of trading to quickly benefit from the private information they possess.
Finally, the coefficient of the imbalance in trading volume is significantly negative for all five stocks. The negative sign of the volume imbalance over the five most recent transactions suggests some effect of asymmetric information: when there is imbalance between the buy and the ask side of the market this may indicate the presence of news in one direction; either good or bad news.

This may force informed traders to increase their trading intensity to quickly benefit from the private information they possess.

The price impact of trades with feedback
As in the model without feedback, we focus on the price change of a large trade. To estimate the expected price impact of a large trade and the corresponding distribution of the price impact, we proceed as before and use the bootstrap approach of Hasbrouck (1991b).
We consider the McDonald's stock one more time. We estimate impulse response functions for a trade of 10,000 shares and compute the corresponding confidence and prediction intervals. With slow trading the expected price change after 20 transactions equals 5.2 bp with the 5% and 95% quantiles equal to −0.2 bp and 11.2 bp, respectively. In case of fast trading the expected price impact after 20 trades equals 7.5 bp with 5% and 95% quantiles equal to −0.3 bp and 16.2 bp. The estimates of the expected persistent price impact and of the quantiles of the persistent price impact are very close to the corresponding results in the model without feedback. See also Table II.6.
We obtain similar results for the price-impact function for other trading volumes, as well as for impulse response functions in calendar time. For the other stocks in our sample we get comparable results.
Statistically speaking, the feedback from the trade characteristics is significant. Moreover, the effects are economically interpretable, using market microstructure theory. However, the impulse response functions show that economic importance of the feedback from the trade characteristics to the trading intensity is small, since it hardly affects the distribution of the price impact of a large trade.

II.8 Conclusions

In this chapter we investigated the price impact of trades and the relation to the trading intensity, using high-frequency data on five frequently traded stocks listed on the NYSE.
We showed that large trades lead to persistent price changes and for some stocks increase price volatility. Instead of focusing on the expected price change only, we modeled the entire distribution of the price change. In line with Dufour and Engle (2000) and Zebedee (2001), we showed that the price impact of an unexpected buy is larger in periods of frequent trading. The distribution of the absolute price change with fast trading first-order stochastically dominates the distribution of the absolute price change with slow trading. Furthermore, volatility is also higher when durations between trades are

short. Hence, trades are more informative in periods of frequent trading.
We established significant causality from absolute returns, trade size, and trade imbalance to the trading intensity. Ceteris paribus, large trades and large order imbalances increase the trading intensity, but large returns slow down trading. We investigated the economic relevance of this feedback by comparing the distribution of the price change following a trade in the models with and without feedback. We show that there is hardly any difference, which suggests that the economic impact of the feedback from the trade characteristics to the trading intensity is small for the stocks considered in this chapter.

CHAPTER III

Temporary and Persistent Price Effects of Trades in Infrequently Traded Stocks

III.1 Introduction

An extensive literature is available on the price impact of trades in frequently traded stocks. Hasbrouck (1991a) reports that the price impact of a trade is larger when the bid-ask 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), Zebedee (2001), and Spierdijk (2002) show that, for frequently traded stocks, the price impact of a trade is larger and converges 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 frequently traded stocks is clearly of interest, a very substantial part of actual trading is related to less frequently traded stocks. For these stocks the price impact of trades is likely to be substantially larger and temporary effects such as inventory imbalances will probably play an important role and affect prices in short run, cf. Easley et al. (1996). Furthermore, since infrequently traded 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.

Little attention seems to have been paid in the literature to modeling the microstructure properties of infrequently traded stocks. Manganelli (2002) jointly models trading intensity, trading volume, and volatility and concludes that the less frequently traded the stock the more time it takes before the new efficient price has been attained. 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. As a consequence, low volume stocks generally have wider spreads than high volume stocks to compensate for this risk. Hasbrouck (1991a, 1991b) 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 content of trades, Hasbrouck (1991a, 1991b)'s result that the price impact of trades is larger for firms with smaller market value is in line with 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. 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 frequently traded stocks, intuition suggests that the impact will be much more important for the infrequently traded stocks that are analyzed in this chapter. Moreover, inventory effects and other transitory effect may play a more important role than for frequently traded stocks, cf. Easley et al. (1996). Finally, since infrequently traded 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 chapter examines the temporary and persistent price impact of trades in infrequently traded stocks traded on the New York Stock Exchange (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, taking overnight behavior of durations and returns into account. We show that the price of infrequently traded stocks 'overshoots'; that is, prices temporarily exceed the full information price before they mean revert to this level. We provide several explanations for this temporary price effect that is generally not found for more frequently traded stocks, such as inventory effects, imbalances in the limit-order book, asymmetric information, and market power. We show that the degree of overshooting crucially depends upon the bid-ask spread and the trading intensity.

Moreover, the results show that both the temporary and the persistent price impact of a trade are larger for infrequently traded stocks than for frequently traded stocks, which is in line with Easley et al. (1996). Additionally we show that the difference in both temporary and persistent price impact between periods of slow and fast trading is much larger for infrequently traded stocks than for frequently traded stocks. Furthermore, adjustment to the full information price can easily take several days and the speed of adjustment is shown to depend crucially on the current trading intensity and the bid-ask spread. Finally, we show that for infrequently traded stocks, durations persist overnight.

The organization of this chapter is as follows. Section III.2 provides a brief review of relevant market microstructure issues. The data are presented in Section III.3. Section III.4 describes the VAR-model for returns, trade sign 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 III.5. Section III.6 is devoted to the estimation of a joint model for the trade characteristics and the trading intensity, while Section III.7 focuses on the price impact of a trade in this framework. Finally, Section III.8 summarizes and concludes.

III.2 Trading intensity, information, and infrequently traded stocks

An important component of market microstructure theory 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 for infrequently traded stocks. Subsequently, we discuss some existing models that relate the existence of information to the trading intensity.

Easley et al. (1996) show empirically that the risk of information based trading is higher for infrequently traded stocks than for frequently traded stocks. They explain this by noticing that there are too few uninformed traders to sufficiently 'hide' the informed traders. They use this finding to explain why infrequently traded stocks generally have wider spreads than frequently traded securities. Since the persistent price impact of trades is considered the most accurate measure of the risk of informed trading (cf. Hasbrouck (1991a, 1991b)), the price impact of a trade will be higher for infrequently traded stocks according to Easley et al. (1996). Apart from the higher risk of information based trading, Easley et al. (1996) provide two other explanations for the wider spreads of infrequently traded securities. First, market makers of infrequently traded stocks have to deal with inventory effects. Since infrequently traded stocks are traded only occasionally, the market makers want to be compensated for the inventory imbalances which are inherently large. This may lead to wider spreads as well. Secondly, since the market maker of an infrequently traded stock often 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.

Several market microstructure studies relate the trading intensity to the underlying value of the asset. In the model of Easley and O'Hara (1992) an information signal is released at the beginning of the day with a certain probability. The market maker is uncertain about the existence of an information signal. He does not know whether or not an information event has taken place and he does not know the direction of the possible news event (good or bad news). The market maker acts as a Bayesian and adjusts his prices by watching the order flow. Informed traders, who have knowledge on the signal that is possibly released at the beginning of the day, buy or sell their stock in case of good and bad news, respectively. Uninformed traders are allowed to refrain from trading. When a news event has been released, a trade is more likely than a no trade outcome due to the presence of informed traders who want to trade to benefit from the private information they possess. Therefore, Easley and O'Hara (1992) associate fast trading to the existence of news and slow trading to the absence of news.

In a different framework Diamond and Verrecchia (1987) also relate the trading intensity to the presence of news. Traders are either informed or uninformed and, moreover, 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. 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 but every agent knows all relevant probabilities. When they observe a no trade outcome, they know that there are several possibilities. Either a trader did not want to trade, or he could not trade due to short-sell restrictions or prohibitions. The probability of a no trade outcome is higher in case of bad news, because of the informed traders who are constrained from selling short. Therefore, Diamond and Verrecchia (1987) associate slow trading 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 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. Hence, according to Admati and Pfliederer (1988) frequent trading is associated to the existence of news.

In Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002) the predictions made by Easley and O'Hara (1992) have been confirmed empirically for frequently traded stocks by showing that the price impact of trades is higher in periods of fast trading, and vice versa. In this chapter we will investigate the price impact of trades and the relation to the trading intensity for infrequently traded stocks.

III.3 The data

We analyze a sample of infrequently traded stocks traded on the NYSE in the year 1999, taken from the *Trade and Quote* (TAQ) database. 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 10). We report results for a random subsample of the stocks in those deciles only. For ease of comparison, we include 'representative' stocks in the analysis (cf. Engle and Patton (2001)). For decile 2 the representative stock is Greenbrier Companies and for decile 4 this is Commercial Intertech. To allow for some comparison with frequently traded stocks, we moreover consider the IBM stock taken from liquidity decile 10. IBM was the seventh most frequently traded stock in the year 1999 and has been extensively analyzed in the literature. The list of stocks considered in this chapter is given in Tables III.1 and III.2.

On the NYSE 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 trades that take place before the first quotes of the day are posted.
For each trade in a specific stock the following associated characteristics are recorded: trade moment τ_t in seconds after midnight, transaction 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 an overnight 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 of no trading to the overnight duration (the number of hours during which the market is open). We deal with trading halts by removing from the sample the duration between the last trade before and the first trade after the halt.
To each trade we also associate a prevailing bid and ask quote, denoted by q_t^b and q_t^a. To obtain these quotes we use the 'five-seconds rule' by Lee and Ready (1991), 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 quotes the bid-ask spread $s_t = q_t^a - q_t^b$ is constructed. The prevailing midprice m_t is the average of the prevailing bid and ask quotes; i.e. $m_t = (q_t^b + q_t^a)/2$. The log return over the prevailing and subsequent midprice is expressed in basis points (bp) and denoted by r_t. Overnight returns are included in sample. We deal with dividend payments by deleting from the sample 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) 'midquote rule' to classify a trade. With this rule, the prevailing midprice corresponding to a trade is used to decide whether a trade is a buy, a sell, or undecided. If the transaction price is lower (higher) than the midprice, it is viewed as a sell (buy). If the transaction price is exactly at the midprice, 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.

ticker symbol	GBX	HTD	IAL	JAX	PIC
company name	Greenbrier Companies Inc.	Huntingdon Life Science	Int. Aluminium Corp.	J.Alexander Corp.	Pichin Corp.
#transactions	2,618	726	538	961	2,116
# trading days	230	154	155	189	247
mean # trades a day	11	5	4	5	9
durations (hh:mm:ss)					
mean	00:25:47	02:15:36	03:03:25	01:51:10	00:46:31
median	00:11:07	00:37:47	00:55:53	00:32:04	00:20:17
0.5%	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
90%	01:03:19	06:51:11	02:51:39	05:01:35	02:10:07
95%	01:32:38	10:59:14	09:24:49	07:37:31	03:05:02
99.5%	04:50:43	26:05:31	13:51:07	21:03:43	07:22:32
spread ($)					
mean	0.1444	0.0889	0.2734	0.1340	0.1861
median	0.1250	0.0625	0.2500	0.1250	0.1875
5%	0.0625	0.0625	0.0625	0.0625	0.0625
95%	0.2500	0.1250	0.5000	0.2500	0.3750
returns (bp)					
mean	−1.1566	−4.3027	−4.3698	−2.5989	−4.6689
median	0.0000	0.0000	0.0000	0.0000	0.0000
trade sign					
mean	0.1876	−0.0399	0.2770	−0.0749	0.0047
median	0.0000	0.0000	0.0000	0.0000	0.0000

Table III.1: Ticker symbols, company names, and some sample statistics (decile 2)

ticker symbol	CHP	FC	FMN	TEC	XTR	IBM
company name	C&D Techn. Inc.	Franklin Covey Corp.	F&M National Corp.	Commercial Intertech Corp.	Xtra Corp.	Int. Business Machines
#transactions	7,802	6,898	6,122	5,105	5,632	522,580
# trading days	252	252	252	252	252	252
mean # trades a day	31	27	24	20	22	2,071
durations (hh:mm:ss)						
mean	00:12:34	00:14:13	00:16:01	00:19:13	00:17:15	00:00:11
median	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
5%	00:00:04	00:00:07	00:00:06	00:00:06	00:00:06	00:00:02
90%	00:33:10	00:36:04	00:41:41	00:49:43	00:44:53	00:00:24
95%	00:49:10	00:53:23	01:00:24	01:01:19	01:06:14	00:00:33
99.5%	02:03:35	02:02:14	02:16:27	02:46:47	02:52:40	00:01:11
spread ($)						
mean	0.1940	0.1253	0.1631	0.1681	0.1896	0.1681
median	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
95%	0.3750	0.2500	0.3125	0.3125	0.4375	0.3125
returns (bp)						
mean	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
trade sign						
mean	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

Table III.2: Ticker symbols, company names, and some sample statistics (decile 4 and decile 10)

To get an idea of the sample properties of the data, we present an explorative data analysis. Table III.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 2 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 frequently traded stocks like IBM. The means of the overnight durations − which measure the time elapsed between the last trade on the previous trading day and the first trade on the next trading day − are somewhat higher than the means 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 4) or even several days (decile 2) can elapse before a trade takes place in a stock of the lower liquidity deciles. Although infrequently traded stocks usually trade only several times a day (decile 4) and may not be traded for several days (decile 2), all infrequently traded stocks have periods in which they are traded relatively often.

III.4 The price impact of trades in infrequently traded stocks

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 trade sign only. The model that we analyze is the standard VAR-specification proposed by Hasbrouck (1991a, 1991b).
We specify the VAR-model (in transaction time) for $z_t = (r_t, s_t x_t^0, x_t^0)'$ as

$$A(L)z_t = c + \upsilon_t, \tag{III.1}$$

where $A(L)$ is an m-th order (3×3) matrix polynomial in the lag operator L of the form $I - A_0 - A_1 L - \ldots - A_m L^m$. The (k,ℓ)-th element of the matrix A_j is denoted by $a_{j,(k,\ell)}$. The matrix A_0 can be normalized in various ways which do not affect the properties of the model. We choose the formulation of Hasbrouck (1991a, 1991b), such that trade sign and the product of trade sign and bid-ask spread contemporaneously influence returns[1]. In expression (III.1) the variables $\upsilon_t = (\upsilon_{t,1}, \upsilon_{t,2}, \upsilon_{t,3})'$ are (3×1) vectors of mean-zero disturbances that are jointly and serially uncorrelated; i.e.

$$\begin{aligned} &\mathbb{E}\upsilon_{t,i} = \mathbb{E}\upsilon_{t,i}\upsilon_{s,i} = \mathbb{E}\upsilon_{t,2}\upsilon_{s,3} = 0 \qquad [t \neq s; i = 1, 2, 3]; \\ &\mathbb{E}\upsilon_{t,1}\upsilon_{s,2} = \mathbb{E}\upsilon_{t,1}\upsilon_{s,3} = 0. \end{aligned}$$

We will measure the price impact of trades by means of the cumulative impulse response function. Given a certain history up to time τ_t, the cumulative impulse response function at time τ_{t+k} corresponding to an unexpected buy at time τ_t is defined as

$$\mathbb{E}_{t-1}(r_t + \ldots + r_{t+k} \mid \upsilon_{t,3} = 1) - \mathbb{E}_{t-1}(r_t + \ldots + r_{t+k}). \tag{III.2}$$

Hence, the cumulative impulse response function represents the expected price impact of an unexpected trade, relative to the expected price impact conditional on the history only. See e.g. Koop, Pesaran, and Potter (1996). Kraus and Stoll (1972) and Hasbrouck (1991a, 1991b) point out that the persistent price impact of an unexpected trade is naturally interpreted as the information content of the trade. The persistent impact is obtained for $k \to \infty$ in expression (III.2).

Estimation results

Following 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 infrequently traded stocks (Greenbrier Companies and Commercial Intertech) as well as for IBM are reported in Tables III.3, III.4 and III.5. Estimation results for the other stocks under consideration are available upon request.

To investigate the specification of the model, 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 serial correlation in the residuals of a regression model and computationally 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 III.6.

[1] With this normalization A_0 has two nonzero elements, namely $a_{0,(1,2)}$ and $a_{0,(1,3)}$.

		GBX		TEC		IBM	
coeff.	lag	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
R^2		0.2559		0.2606		0.1616	

Table III.3: Estimation results for the return equation without duration dependence

The return equation of the VAR-model defined in equation (III.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.

		GBX		TEC		IBM	
coeff.	lag	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
R^2		0.1119		0.1028		0.2271	

Table III.4: Estimation results for the bid-ask spread/trade sign equation

The equation for the product of the bid-ask spread and the trade sign of the VAR-model defined in equation (III.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.

		GBX		TEC		IBM	
coeff.	lag	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
R^2		0.1252		0.1256		0.1738	

Table III.5: Estimation results for the trade sign equation

The trade sign equation of the VAR-model defined in equation (III.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 × durations
VAR-model (trans. 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 III.6: 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 (III.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 with the caption 'trade sign').

For IBM, for which the results are not included in Table III.6, 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 III.6 also shows that the differences between the results for decile 2 and decile 4 are small.

The price impact of trades

As discussed above, the cumulative impulse response function reflects the expected price impact of an unexpected trade and is fully determined by the VAR-model. Past values of the trade characteristics are set at their sample average. The initial bid-ask spread is set at either the 5% or the 95% sample quantile of the spreads for that stock as reported in Table III.1. These two cases will be referred to as 'low' and 'high' bid-ask spread, respectively. The two conditional expectations in expression (III.2) are obtained by iterating the VAR-model in equation (III.1) k periods ahead. The estimates of the long-run price impact of an unexpected buy for the stocks under consideration are reported in the first column of Tables III.7, III.8, and III.9. For example, for Commercial Intertech the long-run price impact with small spreads equals 27.8 bp and 50.6 bp with wide spreads.

We observe several differences between the cumulative impulse response functions corresponding to the infrequently and frequently traded stocks. We see that the usual monotonically increasing shape that is found for IBM and other frequently traded stocks (see Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002)) is replaced by a price-impact function that first 'overshoots' and subsequently returns to the full information price level. Stated differently, there is mean reversion in the stock prices. More precisely, we define the overshooting effect (for a buy transaction) as the maximum over the adjustment path of the midprice minus its long-run equilibrium level. Overshooting is the phenomenon that the overshooting effect is positive. The overshooting effect is illustrated in Figure III.1. With wide bid-ask spreads, a significant[2] overshooting effect is established for seven out of ten infrequently traded stocks; see again the first column of Tables III.7, III.8, and III.9.

[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 cumulative impulse response functions. We repeat this 1,000 times and compute the number of draws for which the cumulative impulse response function overshoots. Whenever the price-impact function overshoots $(1-\alpha) \times 10$ or more times, the effect is significant at (approximately) an $\alpha\%$ significance level.

	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 slow: 19:10:00, 08:36:40	03:20:00, 01:06:40	36:06:40, 10:50:00
HTD			
price impact	93.2, 238.4	111.6, 246.8	72.6, 212.3
overshooting	**46.0**, **33.0**	**44.9**, **29.7**	**55.0**, **41.6**
convergence time	fast: 12:30:00, 08:20:00 slow: 161:40:00, 118:03:20	13:36:40, 07:46:40	172:46:40, 130:00:00
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 slow: 83:20:00, 69:26:40	23:03:20, 06:23:40	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 slow: 27:46:40, 27:26:40	08:03:20, 16:06:40	33:20:00, 33:20:00
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 slow: 22:46:40, 23:33:00	01:56:40, 01:23:20	25:00:00, 27:46:40

Table III.7: Cumulative impulse responses, overshooting effect and convergence time

	transaction time small, wide spreads	fast trading small, wide spreads	slow trading small, wide spreads
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 slow: 08:36:40, 07:13:20	01:56:40, 01:40:00	07:13:30, 06:56:40
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 slow: 07:30:00, 04:26:40	00:50:00, 00:33:20	07:46:40, 04:43:20
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 slow: 09:43:20, 07:13:20	01:06:40, 00:33:20	02:13:20, 04:43:20
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 slow: 05:50:00, 05:50:00	01:23:20, 01:23:20	05:33:20, 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 slow: 08:03:20, 08:20:00	01:56:40, 01:23:20	07:13:30, 07:30:00

Table III.8: Cumulative impulse responses, overshooting effect and convergence time (continued)

	transaction time small, wide spreads	fast trading small, wide spreads	slow trading small, wide spreads
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 slow: 00:03:30, 00:04:00	00:01:50, 00:01:30	00:04:20,00:04:30

Table III.9: Cumulative impulse responses, overshooting effect and convergence time (continued)

Tables III.7, III.8, and III.9 report the long-run cumulative impulse response in bp (after 20 transactions), the overshooting effect in bp and the convergence time in the VAR-model defined in equation (III.1) as well as 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 extended VAR-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 impulse response after 20 transactions.

With low spreads three out of ten stocks significantly overshoot. For example, for Commercial Intertech the overshooting effect with small spreads equals 3.4 bp, but with wide spreads it mounts up to 4.0 bp. Later we will discuss the convergence time to the full information price that is also reported in Tables III.7, III.8, and III.9.

Explanations for the overshooting effect

There are several possible explanations for the observed overshooting effect. According to Domowitz and Wang (1994), the limit-order book is the result of event arrival processes such as bids and offers at certain prices and sizes. For quotes and transaction prices there exists a limiting distribution. When a buy order enters the limit-order book, it takes time for the ask side to refill. This would lead quotes to deviate temporarily from the limiting distribution and would cause mean reversion in the midprices.

The time-scale is important for explaining the relation between the overshooting effect and the degree of liquidity of the stock. We can think in terms of calendar time (seconds), transaction time (trades only) or event time (all events: trades, quotes, limit orders etc). With respect to calendar time, when we assume that the arrival intensities of all events are higher for frequently traded stocks than for infrequently traded stocks, perturbations from the limiting distribution would disappear more quickly and may not be visible in the impulse response functions of the more frequently traded stocks. Hence, the Domowitz and Wang (1994) paper provides an explanation for the overshooting effect that is observed in calendar time, which we will discuss in more detail in Sections III.5 and III.7. The overshooting effect is also observed in transaction time, but it is more difficult to use the same argument in this case.

The existence of asymmetric information can provide a second explanation of the overshooting effect. According to Easley and O'Hara (1992), informed agents will always trade but uninformed traders have the possibility to refrain from trading. Subsequent to a no trade outcome, the agents update their perception on the probability of an information event and this results in a revision of the bid-ask quotes. The question is whether or not this leads to overshooting. In the model of Easley and O'Hara (1992), transaction prices are a martingale with respect to their own history. Therefore, there should generally be no overshooting or lagged adjustment, except for some incidental cases. However, the mean reversion may be caused by information asymmetries that are ignored in relatively simple models such as Easley and O'Hara (1992).

A third explanation of the overshooting effect is based upon inventory imbalances. Quotes are used as a control mechanism to elicit imbalances in the incoming order flow. Mean reversion in the midprices would then reflect the correction of any inventory imbalances. As pointed out in Easley et al. (1996) the imbalances in the order flow will be larger for infrequently traded stocks than for frequently traded stocks. This could explain why the overshooting effect is larger the lower the trading intensity of the stock. Moreover, the positive relation between bid-ask spread and overshooting that was found in our empirical analysis is consistent in this context.

Note that overshooting caused by imbalances in the limit-order book (see Domowitz and Wang (1994)) and inventory effects would lead to immediate overshooting and monotonic price reversion thereafter. However, our empirical results show that it takes a few transactions before the overshooting effect has been attained. A possible explanation for this phenomenon would be the existence of market imperfections, in particular price-smoothing restrictions (see e.g. Hasbrouck (1991a)). Price smoothing forces the market maker to adjust prices only gradually to information and could lead to a delay in the overshooting effect.

Finally, for infrequently traded stocks, the order book is usually small. Therefore, the market maker has sort of a monopoly position. This monopoly position will allow him to set prices that exceed the efficient price level. Therefore, the overshooting effect may also be caused by market power. Given the virtually empty limit-order book for stocks that are traded only occasionally, the explanation for the overshooting effect based on Domowitz and Wang (1994) may not hold for these stocks. However, for the very infrequently traded stocks the market maker plays a more important role in the trading process (since the order book is so small), making the argument of market power more convincing in this case.

A detailed analysis of the relative importance of each of the possible explanations for the observed overshooting effect is left as important topic for further research.

There are several other differences in impulse response function between frequently and infrequently traded stocks. The cumulative impulse response function shows that both the expected price impact of trades in infrequently traded stocks is very large in comparison to trades in frequently traded stocks such as IBM. For example, for Greenbrier Companies the expected persistent 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 in line with 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 2 is generally higher than for stocks in decile 4, which is also in line with Easley et al. (1996).

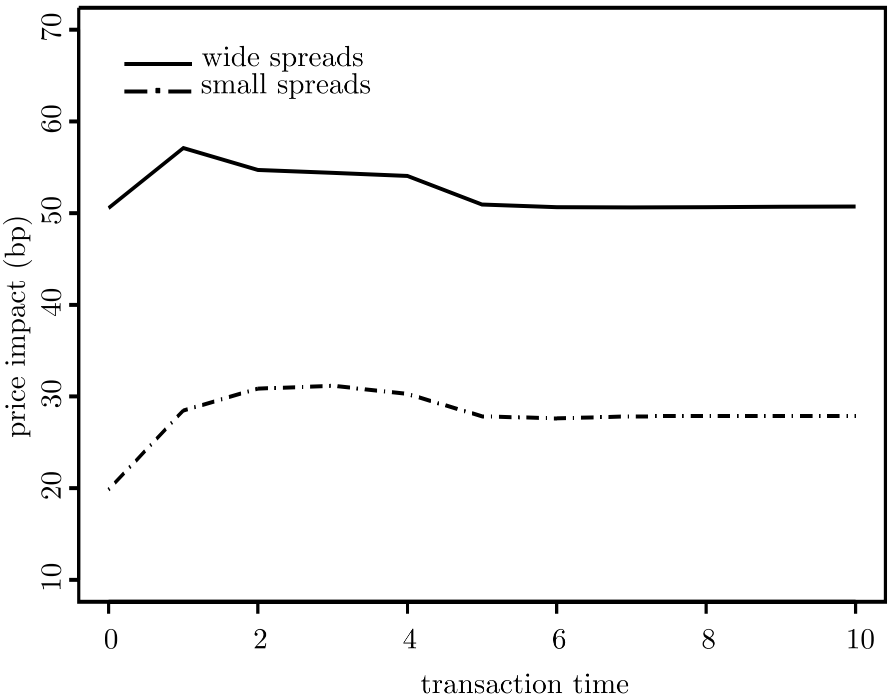

Figure III.1: Expected price impact of a trade: small versus wide spreads

This figure shows the impulse response functions corresponding to an unexpected trade in Commercial Intertech measured in the VAR-model defined in equation (III.1) in periods of small and wide spreads.

Moreover, the long-term expected price impact is larger the wider the initial bid-ask spread. 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 III.1. The long-term cumulative impulse response with wide spreads is significantly larger than with low small spreads for all stocks including IBM. Hasbrouck (1991a, 1991b) 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 than for frequently traded stocks.

III.5 A model for the trading intensity of infrequently traded stocks

In the previous section we measured the price impact of trades in a VAR-model in transaction time for returns, trade sign, and bid-ask spread. However, as discussed in Section III.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 III.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 will then allow 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 Russell (1998)) to model the diurnally corrected duration process $(y_t)_t$. We obtain the diurnally adjusted durations by approximating the expected duration given the time of the day by a piecewise linear and continuous spline with nodes set on $9.30-10.00, 10.00-11.00, \ldots, 14.00-15.00$, and $15.30-16.00$ hours. We compute the diurnally corrected durations by dividing each duration by its corresponding diurnal correction. We assume that the duration process is strongly exogenous, cf. Engle, Hendry, and Richard (1983)[3]. The

[3] In Spierdijk (2002) it is shown that there is significant feedback from trade charac-

ACD$(1,1)$ specification assumes that the marginal process for the durations $(y_t)_t$ satisfies

$$y_t = \psi_t \varepsilon_t, \quad \psi_t = \mathbb{E}_{t-1}(y_t), \tag{III.3}$$

with $(\varepsilon_t)_t$ identically distributed with unit mean and ε_t independent of the information known up to time τ_{t-1}. The conditional expected duration is specified recursively as

$$\psi_t = \omega + \alpha y_{t-1} + \beta \psi_{t-1}. \tag{III.4}$$

The modeling of the duration process of an infrequently traded stock leads to several problems. Most importantly, we need to deal with the overnight durations. The usual approach to modeling the trading intensity ignores overnight durations and initializes the first duration on a new day with the unconditional expected duration. This assumes that information contained in the trading 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[4] $\alpha + \beta < 1$. The standard specification of the conditional expected duration can be rewritten as

$$\psi_t = \mu + \alpha(y_{t-1} - \mu) + \beta(\psi_{t-1} - \mu), \tag{III.5}$$

where $\mu = \omega/(1 - \alpha - \beta)$ is the unconditional expected duration (see Engle and Russell (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.

$$\psi_t = \mu + (1 - \gamma d_{t-1})[\alpha(y_{t-1} - \mu) + \beta(\psi_{t-1} - \mu)], \tag{III.6}$$

where d_t is a binary variable indicating whether or not the t-th duration contains an overnight period and $0 \leq \gamma \leq 1$. 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 is weighted and used for the initialization of the new day together with the unconditional expected duration μ.

teristics (returns, spreads, trade volume) to the trading intensity of five frequently traded stocks traded at the NYSE. It is shown that this feedback affects the cumulative 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.

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

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 apart from the usual regularity conditions. To obtain consistent estimates of the standard errors, 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 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 in such a way 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 III.10 (the results for the linear spline are available upon request). The persistence $\alpha + \beta$ is high as usual and varies between 0.991 and 0.999. 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[5].

The overnight durations will have different impact for frequently and infrequently traded stocks. The intuition is as follows. In case of frequently traded

[5]The significance of the overnight dummies shows that durations persist overnight. Note that this could possibly explain why some empirical studies find that daily trading volume exhibits daily autocorrelation. The autocorrelations in the durations die out at a rate of β^k. For infrequently traded stocks, this means that a positive amount of correlation is transferred to the next day. For example, for Commercial Intertech that is traded about 20 times a day it holds that $\beta = 0.9524$. We thus find $\beta^{20} \approx 0.3770$. For low activity stocks, this may explain the volume correlation at the daily level. For high activity stocks, this does not work, since the number of trades a day is so large that there is no autocorrelation in the durations which is transferred to the next day ($\beta^k \approx 0$).

	TEC		GBX		IBM	
coeff.	estimate	std.error				
ω	0.0036	0.0024	0.0026	0.0004	0.0090	0.0005
α	0.0446	0.0088	0.0795	0.0009	0.0281	0.0006
β	0.9524	0.0074	0.9191	0.0008	0.9629	0.0009
γ	0.1878	0.1115	0.0814	0.0418	0.9100	0.0361

Table III.10: Estimation results for the ACD-model

The coefficients of the ACD$(1,1)$-model as specified in equation (III.6) are estimated using QML. The standard errors are computed from the Bollerslev and Wooldridge (1992) robust covariance matrix.

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 2 the overnight coefficient γ is not significant, meaning that we cannot reject the null hypothesis that the overnight duration is taken into account entirely. For four out of five stocks from decile 4 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 less frequently traded 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 cumulative 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 $N = 10,000$ 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 cumulative impulse response. The results are displayed in the first column of Tables III.7, III.8, and III.9. 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 example, 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 2 has died out.

III.6 A model for the price impact of trades with calendar-time effects

In Section III.4 we estimated the original Hasbrouck (1991a, 1991b) model in which the trading intensity does not play a role. In Section III.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 III.4, we specify the VAR-model for $z_t = (r_t, s_t x_t^0, x_t^0)'$ according to equation (III.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.

$$A(L) = A(y_t)(L). \tag{III.7}$$

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

$$a_{j,(1,3)} = \gamma_j + \delta_j \cdot \frac{1}{1 + y_{t-j}} \qquad [j = 0, \ldots, 5]. \tag{III.8}$$

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 since 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 (III.8) with a dummy d_t indicating whether or not the t-th transaction is the first trade of the day; i.e.

$$a_{j,(1,3)} = \gamma_j + \delta_j \cdot \frac{1}{1 + y_{t-j}} + \xi \cdot 1_{\{j=0\}} \cdot d_{t-j} \qquad [j = 0, \ldots, 5]. \tag{III.9}$$

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 III.11 we see that the durations have negative contemporaneous impact on returns. This also holds for the stocks for which the results are not reported.

[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.

		GBX		TEC		IBM	
coeff.	lag	estimate	st.error				
const	j	−3.7775	1.1768	−0.3949	0.7895	−0.2385	0.0077
ξ		7.5003	4.3659	4.6650	3.9800	31.9244	6.4514
$a_{j,(1,1)}$	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
R^2		0.2656		0.2765		0.1869	

Table III.11: Estimation results for the return equation with duration dependence

The return equation of the VAR-model defined in equation (III.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.

These results coincide with the results obtained by Easley and O'Hara (1987, 1992) and the empirical results of Dufour and Engle (2000), Zedebee (2001), and Spierdijk (2002).
For all stocks in decile 4 apart from Commercial Intertech the impact of the first trade of the day is significantly higher than the impact of the 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 2 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 relatively 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 III.6. For IBM (not included in Table III.6) 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.

III.7 The price impact of trades and calendar-time effects

In this section we focus on the price impact of trades in the setting of Section III.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 cumulative impulse response function are no longer available. Therefore, we simulate $N = 10,000$ paths of durations in the same way as we did for the impulse response function in calendar time in Section III.5. For each path of durations we obtain a value of the price impact, which we average out over all simulations to obtain the final impulse response functions.
We present cumulative 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 Tables III.7, III.8, and III.9.
As in the model without durations, we find price-impact functions for infre-

quently traded stocks that first overshoot and subsequently decrease towards the full information level, see Tables III.7, III.8, and III.9. The overshooting effect is established more often for wide spreads than for small spreads. Both in periods of fast and slow trading the overshooting effect occurs, as shown again in Tables III.7, III.8, and III.9. With small spreads, three out of ten stocks overshoot (with both fast and slow trading), while eight (seven) out of ten stocks overshoot with wide spreads and fast (slow) trading. Figure III.2 displays the cumulative impulse response function for Commercial Intertech with slow and fast trading. Note that the overshooting effect does not only depend upon the bid-ask spread, it is also related to the trading intensity. Given the relation between the trading intensity and the risk of informed trading as put forward in Easley and O'Hara (1992), this result suggests some relation to the existence of information asymmetries.
We observe large differences in the price impact between fast and slow trading for infrequently traded stocks, see also Figure III.2 for the impulse response function corresponding to Commercial Intertech. This figure 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 bp 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.
To get insight in the adjustment process of the price after a large trade, we now turn to the cumulative impulse response functions in calendar time. From the second and third column of Tables III.7, III.8, and III.9 it follows that for the least frequently traded 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 that is executed around 12.30 PM. 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 III.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.
We have analyzed ten infrequently traded stocks, taking five randomly selected stocks from the second and fourth liquidity decile.

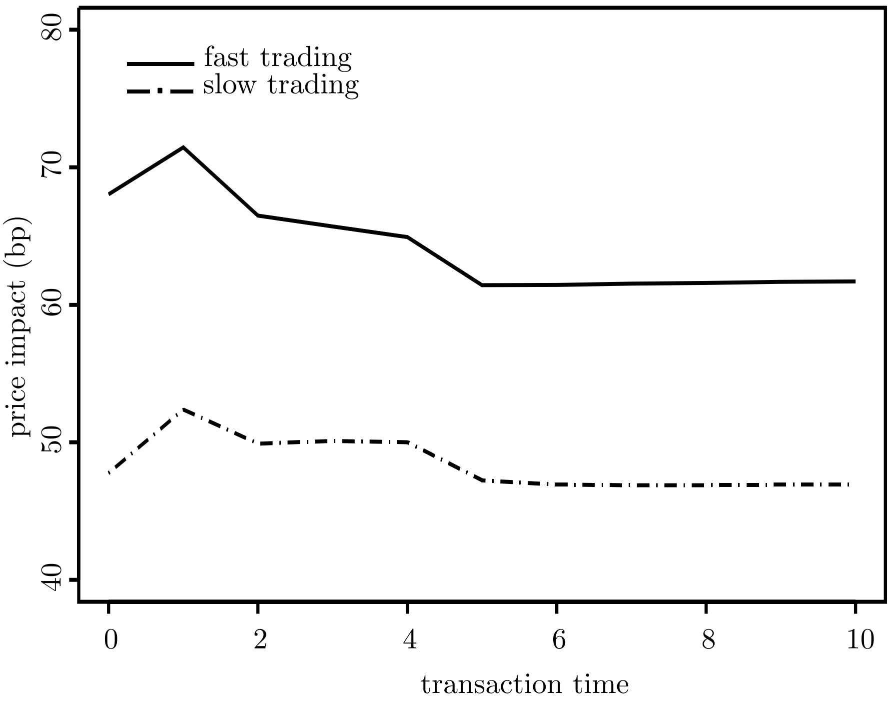

Figure III.2: Expected price impact of a trade: slow versus fast trading

This figure shows the impulse response functions corresponding to an unexpected trade in Commercial Intertech measured in the VAR-model defined in equation (III.1) with duration dependence. Both periods of slow and fast trading are considered.

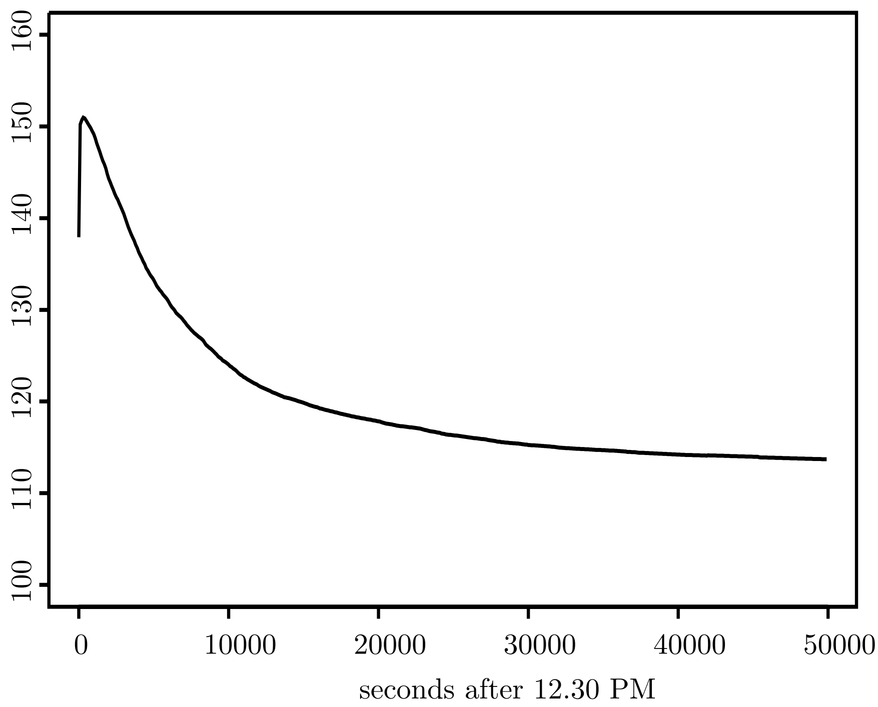

Figure III.3: Convergence time to the new efficient price

This figure shows the impulse response function in calendar time, corresponding to an unexpected trade in Huntingdon Life Science measured in the VAR-model defined in equation (III.1) with duration dependence in a period of fast trading and small spreads.

While stocks in the decile 4 are traded every day, stocks in decile 2 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: virtually all stocks have a price-impact function that overshoots, in particular when spreads are wide and trading takes place either fast or slowly. For stocks in decile 2 and four, it may take several days before the new efficient price is attained. For stocks in decile 2 this holds even in periods of relatively high market activity.

III.8 Conclusions

In this chapter we investigated the temporary and permanent price impact of trades in infrequently traded stocks. We applied a VAR-model based upon Hasbrouck (1991a, 1991b) to ten infrequently traded stocks and one very frequently traded stock (IBM) traded on the NYSE in the year 1999.
For infrequently traded stocks we established the phenomenon of 'overshooting' or mean reversion. After a trade has taken place, prices converge towards the new efficient price. Before the price reaches the new level, it temporarily exceeds the new efficient price. Subsequently prices mean revert to the full information level. Furthermore, we found that the degree of overshooting crucially depends upon the bid-ask spread and the trading intensity. The price of frequently traded stocks such as IBM monotonically increases to the new efficient price after a buy and does not overshoot, as is shown in our analysis and in Dufour and Engle (2000), Zebedee (2001), and Spierdijk (2002). Possible explanations for the temporary price effect are based upon imbalances in the limit-order book, inventory imbalances, asymmetric information, and market power.
We also showed that trades in infrequently traded securities have higher permanent price impact than trades in frequently traded stocks, which can be explained by the higher risk of informed trading that is associated with infrequently traded stocks (see Easley, Kiefer, O'Hara, and Paperman (1996)). Moreover, we found that both the temporary and the persistent price impact of 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.
Although overnight durations are significant for both frequently and infrequently traded stocks in explaining the trading intensity, we showed that its impact on the convergence to the full information price is economically neg-

ligible for IBM both in transaction and in calendar time, while the economic effect is large for the infrequently traded stocks. The convergence to the new efficient price that follows a trade in an infrequently traded stock may take several days.

Further research could 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 chapter we have shown that the answers to these questions are likely to be very different for frequently and infrequently traded stocks.

CHAPTER IV

Price Dynamics and Trading Volume: A Semiparametric Approach

IV.1 Introduction

An important issue for institutional investors and other traders who have to deal with block trades is how large trades affect market prices. Since, in efficient markets, security prices move in response to the release of new information, transactions cause traders and market makers to update their beliefs and prices to be revised. Market impact reflects the change in the security price that is caused by a trade. The relation between trading volume and prices determines to what extent particular trading strategies such as order splitting affect the costs of trading.

An extensive literature is available on the price impact of trades. Hasbrouck (1991a, 1991b) shows that the persistent impact of a trade on the midprice 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), Zebedee (2001), and Spierdijk (2002) show that, for liquid stocks, the price impact of a trade is larger and converges to its full information value faster when subsequent trades are close together in time, i.e. when the trading intensity is high. Spierdijk, Nijman, and Van Soest (2002a) show that the latter effect is even stronger for infrequently traded stocks. Additionally, Spierdijk et al. (2002a) establish the phenomenon of 'overshooting': after a trade, prices temporarily exceed the full information price, before they mean revert to this level. Glosten and Harris (1988), Madhavan and Smidt (1991), and De Jong, Nijman, and Röell (1996) allow prices to depend linearly on trading volume and measure the impact of trades on transaction prices.

Although the majority of models for prices are linear in trading volume, several empirical studies investigate the existence of nonlinearities. Hasbrouck (1991a, 1991b) investigates nonlinearities in the impact of trades on mid-prices using a VAR-model. He establishes an increasing and concave relation between price impact and order flow for several stocks traded on the New York Stock Exchange (NYSE). Hausman, Lo, and McKinlay (1992) use a Box-Cox transformation of trading volume as explanatory variable in an ordered probit-analysis of discrete price changes. They apply the model to several stocks listed on the NYSE and show that the impact of trades on mid-prices is increasing in trading volume, in a nonlinear fashion that differs from stock to stock. Kempf and Korn (1999) establish a nonlinear, increasing, and concave relation between trading volume and prices of German futures, using neural networks. De Jong, Nijman, and Röell (1995) use data on French stocks traded on the Paris Bourse and SEAQ International and find that transaction prices are affected by trading volume in a nonlinear way.

This chapter extends the existing literature in several ways. We investigate the relation between price impact and trading volume for a sample of infrequently traded stocks listed on the New York Stock Exchange. We show that the commonly used parametric VAR-models as introduced by Hasbrouck (1991a, 1991b) impose strong proportionality and symmetry restrictions on the price impact of trades, although market microstructure theory provides many reasons why these restrictions would not hold. We analyze the less restrictive semiparametric partially linear model of Engle, Granger, Rice, and Weiss (1986) and Robinson (1988a, 1988b) and establish significant evidence for a nonlinear, asymmetric, increasing, and concave relation between trading volume and both immediate and persistent price impact. Moreover, we compare the relation between price impact and order size obtained in the partially linear model to the price-order flow relation generated by some commonly used parametric VAR-models and show that there are considerable differences. In contrast to the partially linear model, the parametric models do not capture the nonlinearities in the price-order flow relation. We use the approach of Whang and Andrews (1993) to test the model specification and reject the parametric specifications in favor of the partially linear model. We also test the partially linear model against a more flexible fully nonparametric specification and show that this test does not reject the partially linear model.

The setup of this chapter is as follows. Section IV.2 reviews several theoretical models of market microstructure that predict a nonlinear or asymmetric relation between prices and order flow. Section IV.3 introduces the data that are used in this chapter. Section IV.4 discusses some properties of parametric VAR-models. In Section IV.5 a partial linear specification is used to model the relation between trading volume and midprices. Section IV.6 focuses on the immediate and persistent impact of a trade on midprices and the relation to trading volume. Section IV.7 investigates the temporary effects that trades have on prices. Finally, Section IV.8 summarizes and concludes.

IV.2 Explaining the price-order flow relation

Various models predict a nonlinear price-order flow relation; for example models of reputation (Seppi (1990)), stealth trading (Barclay and Warner (1993)), counter party search (Keim and Madhavan (1996)), and bullish-bearish information (Dridi and Germain (2000)).

Seppi (1990) distinguishes market orders and block trades. While market orders are submitted anonymously to the market, dealers know the identity of the institution that initiated a block trade. This allows the dealer and the institution to enter into additional commitments apart from agreeing on the price and the quantity. The particular commitment examined in Seppi (1990) is one of 'no bagging', which prohibits subsequent trading by the institution. When an institution is uninformed, postponing a trade until the previous trade has been completely executed is not much of a concession. However, when an institution does possess private information, they want to benefit from that and will therefore be less willing to wait with trading. Therefore, when the dealer and the institution agree on 'no bagging', the institution releases the signal that it is most likely uninformed. Such a commitment affects the information content of a trade, and, consequently, it influences the price impact of the trade. This implies that block trades and market orders have different impact on prices. Since block trades are usually larger than market orders, this results in a nonlinear price-order flow relation.

A different explanation for a nonlinear price-order flow relation is given by Barclay and Warner (1993). Using a sample of firms listed on the NYSE, the authors show that most of a stock's cumulative price change takes place on medium-size trades, which supports the 'stealth trading' hypothesis that privately informed traders concentrate their trades in medium sizes. Since medium-size trades are associated to informed trading, larger trades add relatively little additional information. This results in a concave price-order flow relation. More evidence for the stealth-trading hypothesis is found in Chakravarty (2001).

Keim and Madhavan (1996) model the phenomenon of an upstairs market, where large (block) trades are processed through a search-brokerage mechanism. That is, first an intermediary or broker identifies counter parties to trade, after which the order is sent to the downstairs market for final execution. By contrast, smaller trades are directly routed to the downstairs market, where market makers, floor traders, and limit orders provide liquidity on demand. The authors show that spreading the order among more traders − this is what happens at the upstairs market − lowers the liquidity costs. Since the number of counter parties found by the block broker increases with trading volume, the temporary price impact of a block trade is a nonlinear function of order size.

Dridi and Germain (2000) proceed in a different way and model a financial market where informed traders receive a signal that perfectly reveals the sign of the difference between the liquidation value of the asset and its true value, but not the exact value of this difference. This type of information is called bullish or bearish. By endowing informed traders with a buy or sell signal only, the authors deviate from the assumptions made in the model of, for instance, Kyle (1985). Dridi and Germain (2000) show that the assumption of bullish and bearish information has a large impact on prices. They find that the optimal trading strategies for the informed traders in equilibrium are not linear and that, consequently, the price impact of trades is a nonlinear function of trading volume.

Another part of the literature is devoted to the explanation of asymmetries in the price-order flow relation. Although the empirical analysis of Kempf and Korn (1999) does not lead to any evidence that buys have more persistent impact on prices than sells, Karpoff (1988), Madhavan and Smidt (1991), and Chan and Lakonishok (1993) find that buy orders are more informative than sell orders and thus have larger persistent impact on prices. Chan and Lakonishok (1993) provide an institutional explanation for this phenomenon. They put forward that there may be several liquidity-motivated reasons why institutional investors decide to sell a stock. Therefore, selling a stock does not necessarily have to convey negative information. However, buying a stock is likely to convey favorable firm-specific news. This institutional explanation has been formalized by Saar (2001).

A very different issue is put forward by Huberman and Stanzl (2001). They show that, when the price impact of trades is time stationary, the 'no quasi-arbitrage' requirement is only satisfied when the permanent price impact of trades depends linearly on trading volume. The intuition is that, when trade size affects prices in a nonlinear way, certain self-financing trading strategies based on buying large amounts of stocks first and selling small amounts later (or vice versa) lead to quasi-arbitrage. That is, these strategies yield infinite profits with infinite Sharpe-ratios because of the nonlinearity.

Using the same arguments, the no-arbitrage condition rules out asymmetric

ticker symbol	CHP	FC	FMN	TEC	XTR
company name	C&D Techn. Inc.	Franklin Covey Corp.	F&M National Corp.	Commercial Intertech Corp.	Xtra Corp.
#transactions	7,802	6,898	6,122	5,105	5,632
mean # trades a day	31	27	24	20	22
returns (bp)					
mean	0.3219	−1.1461	0.0013	0.0200	0.0440
median	0.0000	0.0000	0.0000	0.0000	0.0000
trade size (# shares)					
mean	−25	−134	33	−1	47
median	0	0	0	0	0
5%	−2,000	−3,000	−1,000	−2,000	−2,000
95%	2,000	2,000	1,000	1,800	2,500

Table IV.1: Ticker symbols, company names, and some sample statistics

impact of buys and sells on prices. The empirical evidence for a nonlinear relation between trading volume and price impact found in Hasbrouck (1991a, 1991b), Hausman, Lo, and McKinlay (1992), and Kempf and Korn (1999) would indicate the existence of arbitrage possibilities in the framework of Huberman and Stanzl (2001). If transaction costs would outweigh the gains derived from quasi-arbitrage strategies, this could justify a nonlinear relation between trading volume and price impact. Empirical evidence that the price impact depends nonlinearly on trade size implies that transaction costs are larger than assumed in Huberman and Stanzl (2001) or that other assumptions made in the latter paper do not reflect reality.

IV.3 The data

We analyze a sample of stocks listed on the NYSE, taken from the *Trade and Quote* (TAQ) database. After ordering all NYSE stocks from least actively traded (decile one) to most actively traded (decile ten), we focus on stocks in liquidity decile 4. Since the semiparametric approach that we will follow requires a large number observations to achieve enough accuracy, we restrict the analysis to less frequently traded stocks taken from the fourth liquidity decile and do not consider stocks from the lower deciles. The results in Spierdijk et al. (2002a) suggest that stocks in decile two and four have very similar behavior with respect to the price impact of trades, which further motivates the restriction to the fourth liquidity decile. We report results for a random subsample of the stocks in decile 4 and discuss in detail the results for the 'representative stock' of this decile (cf. Engle and Patton (2001)) which is the stock Commercial Intertech. The names of the five stocks considered in this chapter are given in Table IV.1.

On the NYSE 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 trades that take place before the first quotes of the day are posted.

For each trade in every stock the following associated characteristics are recorded: transaction price p_t and unsigned trading volume $|y_t|$, where t indexes subsequent transactions (i.e. t indexes 'transaction time'). To each trade we also associate a prevailing bid and ask quote, denoted by q_t^b and q_t^a. To obtain the prevailing quotes we use the 'five-seconds rule' by Lee and Ready (1991) 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. On the basis of the prevailing quotes the prevailing midprice is obtained as $m_t = (q_t^b + q_t^a)/2$. The log return over the prevailing and subsequent midprice is expressed in basis points (bp) and denoted by $r_t = \log(m_{t+1}/m_t)$. The overnight returns are included in sample. We deal with dividend payments by deleting 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) 'midquote rule' to classify a trade. With this rule, the prevailing midprice corresponding to a trade is used to decide whether a trade is a buy, a sell, or undecided. If the transaction price is lower (higher) than the midprice, it is viewed as a sell (buy). If the price is exactly at the midprice, its nature (buy or sell) remains undecided. To each trade we associate a trade indicator y_t^0 which indicates the nature of the trade: 1 (buy), -1 (sell), or 0 (undecided). In combination with unsigned trading volume $|y_t|$ that is associated to each trade, we construct signed trading volume y_t and signed log trading volume v_t.

It sometimes occurs that multiple trades take place at the same second. We follow Engle and Russell (1998) and treat multiple transactions at the same time as one single transaction and aggregate their trading volume and average their prices.

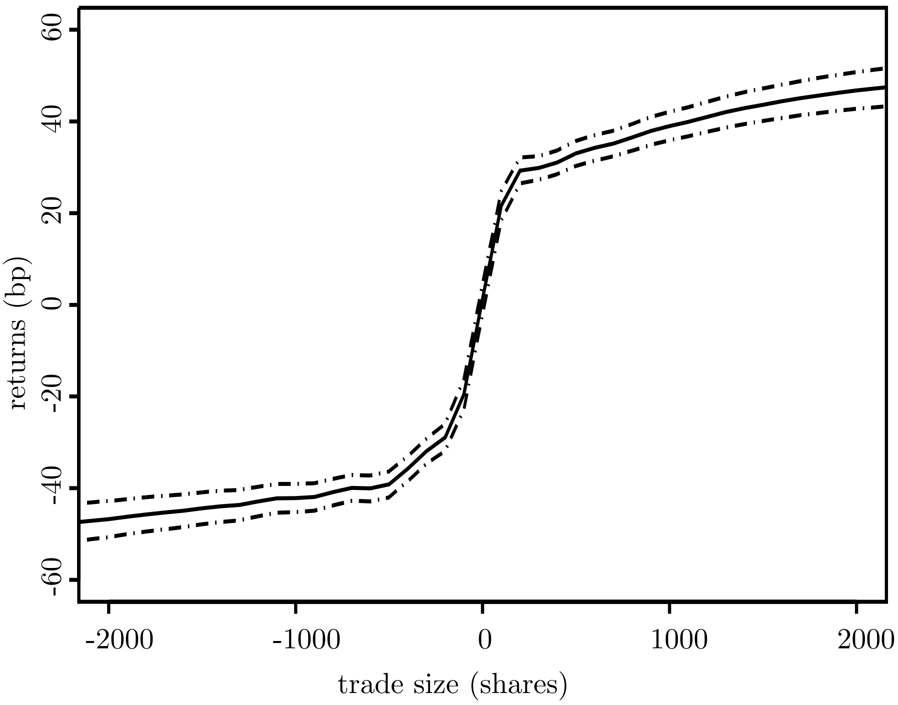

Figure IV.1: Kernel regression: returns versus trading volume

This figure displays the relation between returns and trading volume for Commercial Intertech, based upon a kernel regression. The dashed lines indicate the boundaries of a 95% point-wise confidence interval based on the asymptotic distribution of the kernel estimator as given in expression (B.10) in Appendix B.

To get an idea of the sample properties of the data, we present an explorative data analysis. Table IV.1 shows some sample statistics (sample mean, median, and quantiles) of the trade characteristics of the stocks under consideration. Stocks in liquidity decile 4 are traded every 13-20 minutes (20-31 times a day). Moreover, the 5% sample quantile of trading volume varies from $-3,000$ to $-1,000$ shares and the 95% sample quantile lies between 1,000 and 2,500 shares.
Figure IV.1 displays the result of a simple (univariate) nonparametric kernel regression of midprice returns on trading volume, where we have kept trade size between its 5% and 95% sample quantile. A 95% point-wise confidence interval, based on the asymptotic distribution of the kernel estimator (as given in expression (B.10)), is also included. Figure IV.1 provides preliminary evidence for a nonlinear relation between returns and order flow.

IV.4 Properties of VAR-models for returns and trade size

By far the most popular model that is used in the literature to describe the dynamics between trading volume and prices is the VAR-model proposed by Hasbrouck (1991a, 1991b). Versions of the VAR-model have subsequently been used by Dufour and Engle (2000), Zebedee (2001), Spierdijk (2002), and Spierdijk et al. (2002a), among many others. In this section we will show that the parametric VAR-models impose strong proportionality and symmetry restrictions on the price impact of trades, which are not grounded in theory as we have seen in Section IV.2. In Section IV.5 we will show how the validity of the restrictions can be tested and how they can be avoided.
Consider a simple, bivariate VAR-model for returns $(r_t)_t$ and signed trading volume $(y_t)_t$ defined in terms of the lag-operator as

$$\begin{pmatrix} a(L) & b(L) \\ c(L) & d(L) \end{pmatrix} \begin{pmatrix} r_t \\ y_t \end{pmatrix} = \begin{pmatrix} a_0 \\ b_0 \end{pmatrix} + \begin{pmatrix} \eta_{t,1} \\ \eta_{t,2} \end{pmatrix}, \tag{IV.1}$$

with $(\eta_{t,1})_t$ and $(\eta_{t,2})_t$ mean-zero disturbances that are jointly and serially uncorrelated. We measure the price impact of trades by means of the cumulative impulse response function, cf. Hasbrouck (1991a, 1991b). Given a certain history of returns and trading volume up to time τ_t, the cumulative impulse response function at time τ_{t+k} corresponding to an unexpected buy of M shares at time τ_t is defined as

$$\alpha_{t+k|t}(M) \quad = \quad \mathbb{E}_{t-1}(r_t + \ldots + r_{t+k} \mid \eta_{t,2} = M) - \mathbb{E}_{t-1}(r_t + \ldots + r_{t+k}). \tag{IV.2}$$

Hence, the cumulative impulse response function represents the expected price impact of an unexpected trade, relative to the expected price impact conditional on the history only. See, for instance, Koop, Pesaran, and Potter (1996). Kraus and Stoll (1972) and Hasbrouck (1991a, 1991b) point out that the persistent price impact of an unexpected trade is naturally interpreted as the information content of the trade. The persistent impact is obtained for $k \to \infty$ in expression (IV.2). In Appendix A we show that the price-impact functions corresponding to trades of different volumes are proportional to trading volume; i.e.

$$\frac{\alpha_{t+k|t}(M_1)}{\alpha_{t+k|t}(M_2)} = \frac{M_1}{M_2} \tag{IV.3}$$

for any t, k. This implies that there is a linear relation between volume and prices in the bivariate VAR-model. We also show that the price impact of buys and sells obtained in the bivariate VAR-model is symmetric. This means that the magnitude of the impact of unexpected buys and sells of size is the same; i.e.

$$\alpha_{t+k|t}(M) = -\alpha_{t+k|t}(-M). \tag{IV.4}$$

When we replace signed trading volume y_t by signed log trading volume v_t in the bivariate VAR-model, we get the log-linear VAR-model as proposed by Spierdijk (2002). The impulse response functions generated by the log-linear VAR-model are also symmetric. Moreover, the impulse response functions in the log-linear VAR-model are proportional to log trade size ; i.e. for any t, k

$$\frac{\alpha_{t+k|t}(M_1)}{\alpha_{t+k|t}(M_2)} = \frac{\log M_1}{\log M_2}. \tag{IV.5}$$

Thus, the linear and log-linear VAR-models impose on two strong restrictions on price-impact functions: (log-) proportionality and symmetry. With respect to (log-) proportionality, this property determines the relation between price impact and trading volume and implies a (log) linearity of the price-order flow relation. However, in Section IV.2 we showed that there are various theoretical models predicting a complicated, nonlinear price-order flow relation, suggesting that it may be too restrictive to use a simple parametric specification for this relation. Regarding the symmetric impact of buys and sells, the literature suggests that this assumption may be too restrictive as we explained in Section IV.2.

One way to make the bivariate VAR-model more flexible, is to include additional variables in its specification. The bivariate VAR-model has been extended in several ways. The extended linear VAR-model proposed by Hasbrouck (1991a) is a three-dimensional VAR-model for returns, trade sign, and signed trading volume. Since small trades already have considerable price impact, the inclusion of trade sign in addition to signed trading volume helps to make the estimated price impact of these trades more accurate. The quadratic VAR-model, see Hasbrouck (1991a, 1991b), is a four-dimensional VAR-model for returns, trade sign, signed trading volume, and signed squared trading volume and is used by Hasbrouck (1991a, 1991b) to pick up any nonlinear effects in the price-order flow relation. Although the extended linear and the quadratic VAR-model do not have the proportionality property, the parametric structure of these models determines a priori the relation between price impact and trading volume. Moreover, the impulse response functions generated by the extended linear and the quadratic VAR-models are symmetric in trading volume.

IV.5 A semilinear model for returns and trading volume

In Section IV.2 we provided some explanations for a nonlinear relation between price impact and trading volume. Moreover, we explained in Section IV.4 that some commonly used parametric VAR-models impose strong assumptions on the way volume affects prices, such as proportionality and symmetry. In this section we will use a more flexible semiparametric specification to allow for more complicated price-order flow relations.

The model that we use in this section is based upon the partially linear model introduced by Engle, Granger, Rice, and Weiss (1986) and Robinson (1988a, 1988b). The partially linear model is a semiparametric model, since the conditional mean of the dependent variable consists of both a parametric and a nonparametric part. In our setting, trading volume is allowed to affect returns in a nonlinear way, while lagged returns linearly affect current returns. Moreover, since we are not only be interested in immediate price effects but also in long-term price impact, we have to endogenize trading volume. We will use a partially linear model for trading volume as well, in which past returns and past trading volume affect current trading volume in a possibly nonlinear fashion. Furthermore, we will test the partially linear model against a wide range of alternative specifications, such as fully parametric and fully nonparametric models. For more details on estimation and testing of the partially linear model, we refer to Appendix B.

For notational convenience we write

$$z_{t-1} = (v_{t-1}, \ldots, v_{t-m})' \text{ and } x_{t-1} = (r_{t-1}, \ldots, r_{t-m})'. \tag{IV.6}$$

For returns, the partially linear model is specified as

$$r_t = \beta_1' x_{t-1} + f_1(v_t, z_t) + \varepsilon_{t,1}, \quad \mathbb{E}(\varepsilon_{t,1} \mid x_{t-1}, v_t, z_{t-1}) = 0. \qquad \text{(IV.7)}$$

where β_1 is an $(m \times 1)$ vector of parameters and $f_1(\cdot)$ an unknown function. To model trading volume, we specify

$$v_t = \beta_2' x_{t-1} + f_2(z_{t-1}) + \varepsilon_{t,2}, \quad \mathbb{E}(\varepsilon_{t,2} \mid x_{t-1}, z_{t-1}) = 0. \qquad \text{(IV.8)}$$

where β_2 is an $(m \times 1)$ vector of parameters and $f_2(\cdot)$ an unknown function. Lagged returns appear linearly in the parametric part of equations (IV.7) and (IV.8). Contemporaneous and lagged trading volume, however, are in the nonparametric part of these specifications.

We compare the partially linear model to some commonly used parametric models that where introduced in Section IV.4: the extended linear, the log-linear, and the quadratic VAR-model.

Estimation results

We consider the partially linear model for returns on the midprice as defined in equation (IV.7). Following Hasbrouck (1991a, 1991b), we impose a low order on the recursive structure in the model ($m = 5$) which we estimate as explained in Appendix B. Point estimates and standard errors based on the procedure proposed by White (1980) for all five stocks are given in Table IV.2. To get an idea of the impact of trade size on returns, we consider the function $f_1(\cdot)$ for the representative stock Commercial Intertech. Figure IV.2 shows a plot of the estimate $\hat{f}_{n,1}$ of $f_1(\cdot)$ as a function of its first argument; i.e. of

$$v_t \longrightarrow \hat{f}_{n,1}(v_t, \ldots, v_{t-m}), \qquad \text{(IV.9)}$$

with the values of $v_{t-1}, \ldots, v_{t-m}$ set equal to the sample mean of signed trading volume[1]. Clearly, $\hat{f}_{n,1}(\cdot)$ is an increasing and concave[2] function of its first argument.

We start with equation (IV.7) and do several tests proposed by Whang and Andrews (1993) for which the corresponding p-values are reported in Table IV.3. For an explanation of the testing procedure of Whang and Andrews (1993), see Appendix B. We start with testing the semilinear model against a fully nonparametric specification. For all stocks apart from F&M National, the partially linear model is not rejected at a 5% level. For F&M National the semiparametric model is rejected at a 5% level, but the p-value of 0.0446 indicates that there is only limited evidence against the partially linear model.

[1]We find similar plots for the functions $v_{t-k} \longrightarrow \hat{f}_{n,1}(v_t, \ldots, v_{t-m})$ for $k = 2, \ldots, m$, although the impact of trading volume on $f(\cdot)$ dies out for higher values of m.

[2]With 'concave' we mean concave for buys. Als Figure IV.2 shows, the function is convex for sells. However, for convenience we will simply say that the function is 'concave'.

Furthermore, we test the log-linear, extended linear, and quadratic specifications – which are special cases of equation (IV.7) as pointed out in Section IV.4 – against the partially linear model for all stocks under consideration. We reject at every reasonable significance level the null hypothesis that the parametric models are true. Subsequently, we test for autocorrelation in the disturbances (of the form (B.21)). For all five stocks the null of no autocorrelation in the disturbances of the return equation is not rejected at a 5% level. Finally, we use the test procedure of Whang and Andrews (1993) to detect conditional heteroskedasticity (of the form given in expression (B.24)). The null hypothesis of homoskedastic disturbances in the return equation (IV.7) is rejected at a 5% significance level for Franklin Convey only. For this stock we assume that $\mathbb{V}\mathrm{ar}\,(\varepsilon_{t,1} \mid v_t, \ldots, v_{t-m}) = g(v_t, \ldots, v_{t-m})$, since the Whang and Andrews (1993) test shows that there is no significant evidence for heteroskedasticity with respect to lagged returns. We estimate the function $g(\cdot)$ by means of a kernel regression of $\varepsilon_{t,1}^2$ on $v_t, \ldots, v_{t-m}$.
To get a first impression of the relation between lagged trading volume and contemporaneous trading volume for the representative stocks Commercial Intertech, Figure IV.3 displays the results of a simple univariate kernel regression of lagged log trading volume on contemporaneous log trading volume (where we have kept trading volume between the 5% and 95% sample quantile). A 95% point-wise confidence interval is also given. Figure IV.3 provides preliminary evidence for a nonlinear relation between log trading volume and lagged log trading volume. Subsequently, we consider the model for trading volume as defined in expression (IV.8), which we truncate at lag $m = 5$. The estimation results for the model given in equation (IV.8) are reported in Table IV.2. The function

$$v_{t-1} \longrightarrow \hat{f}_{n,2}(v_{t-1}, \ldots, v_{t-m}), \tag{IV.10}$$

with the values of $v_{t-2}, \ldots, v_{t-m}$ set equal to the sample mean of signed trading volume yields a plot that is very similar to that in Figure IV.3 and is therefore not displayed.
The Whang and Andrews (1993) test results are given in Table IV.3 and show that, for all five stocks under consideration, there is no significant evidence against the partially linear structure assumed in (IV.8). However, the null hypothesis of homoskedastic disturbances $(\varepsilon_{t,2})_t$ in equation (IV.8) is rejected at a 5% level for C&D Technology and Xtra Company. For these stocks, we proceed as before. We assume that $\mathbb{V}\mathrm{ar}\,(\varepsilon_{t,2} \mid v_{t-1}, \ldots, v_{t-m}) = h(v_{t-1}, \ldots, v_{t-m})$ (again the results of the Whang and Andrews (1993) test show that there is no significant evidence for heteroskedasticity with respect to lagged returns) and we estimate $h(\cdot)$ in the usual way.

	CHP		FC		FMN		TEC		XTR	
returns	estim.	std.error								
$\beta_{1,1}$	0.0068	0.0176	-0.0416	0.0181	0.0224	0.0168	-0.0031	0.0215	0.0103	0.0196
$\beta_{1,2}$	0.0785	0.0122	-0.0092	0.0193	0.0522	0.0142	-0.0161	0.0153	0.0527	0.0145
$\beta_{1,3}$	0.0508	0.0125	0.0299	0.0136	0.0309	0.0126	-0.0009	0.0156	0.0388	0.0142
$\beta_{1,4}$	0.0420	0.0126	0.0161	0.0147	-0.0046	0.0340	0.0143	0.0158	0.0134	0.0143
$\beta_{1,5}$	0.0276	0.0100	0.0098	0.0116	-0.0024	0.0117	-0.0186	0.0129	0.0173	0.0119
volume										
$\beta_{1,1}$	0.0041	0.0024	-0.0037	0.0014	0.0033	0.0030	-0.0057	0.0014	0.0002	0.0039
$\beta_{2,1}$	0.0030	0.0025	-0.0022	0.0015	-0.0005	0.0030	-0.0017	0.0014	0.0013	0.0038
$\beta_{3,1}$	0.0008	0.0024	-0.0048	0.0014	-0.0052	0.0031	-0.0016	0.0014	0.0003	0.0038
$\beta_{4,1}$	0.0042	0.0024	-0.0003	0.0015	-0.0014	0.0030	-0.0013	0.0014	0.0015	0.0039
$\beta_{5,1}$	0.0015	0.0021	0.0005	0.0012	0.0005	0.0026	0.0015	0.0012	0.0086	0.0032

Table IV.2: Estimation results for the partially linear model

This table reports the estimation results for the partially linear model for returns on the midprice and trading volume; cf. equations (IV.7) and (IV.8). The standard errors in the columns on the right-hand-side are computed from White (1980)'s heteroskedasticity-consistent covariance matrix.

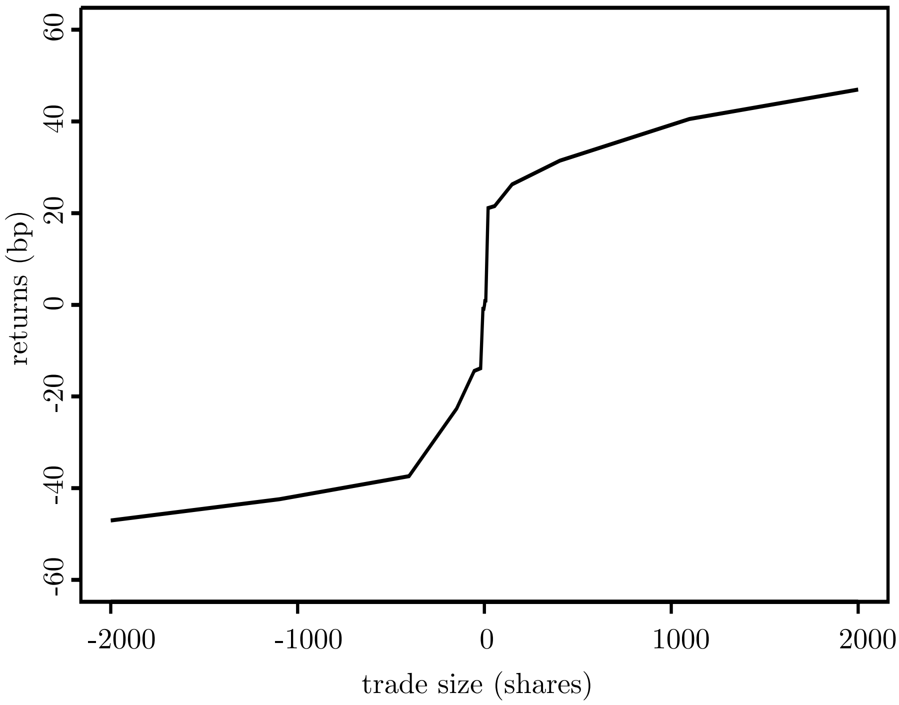

Figure IV.2: Relation between returns and trading volume

This figure shows the function $v_t \longrightarrow \hat{f}_{n,1}(v_t, \ldots, v_{t-5})$ in the model for returns and trading volume given by equations (IV.7) and (IV.8) for Commercial Intertech.

	CHP	FC	FMN	TEC	XTR
returns					
semilinear vs. nonparametric	0.0636	0.3964	0.0446	0.0723	0.5304
linear vs. semilinear	0.0000	0.0000	0.0000	0.0000	0.0000
quadratic vs. semilinear	0.0000	0.0000	0.0000	0.0000	0.0000
log-linear vs. semilinear	0.0000	0.0000	0.0000	0.0000	0.0000
autocorrelation	0.8529	0.8988	0.9255	0.8969	0.9953
heteroskedasticity	0.3872	0.0288	0.3839	0.5191	0.2062
symmetric vs. nonsymmetric	0.0233	0.4108	0.0373	0.0046	0.6463
trading volume					
semilinear vs. nonparametric	0.0611	0.2579	0.0957	0.1703	0.0680
log-linear vs. semilinear	0.0000	0.0000	0.0000	0.0000	0.0000
autocorrelation	0.7072	0.1248	0.1603	0.6646	0.5563
heteroskedasticity	0.0494	0.1828	0.3982	0.1384	0.0122

Table IV.3: The p-values of the Whang and Andrews (1993) tests

The p-values correspond to the Whang and Andrews (1993) tests (see Appendix B) described in the left-hand-side column and apply to the partially linear model for returns on the midprice and trading volume given in equations (IV.7) and (IV.8).

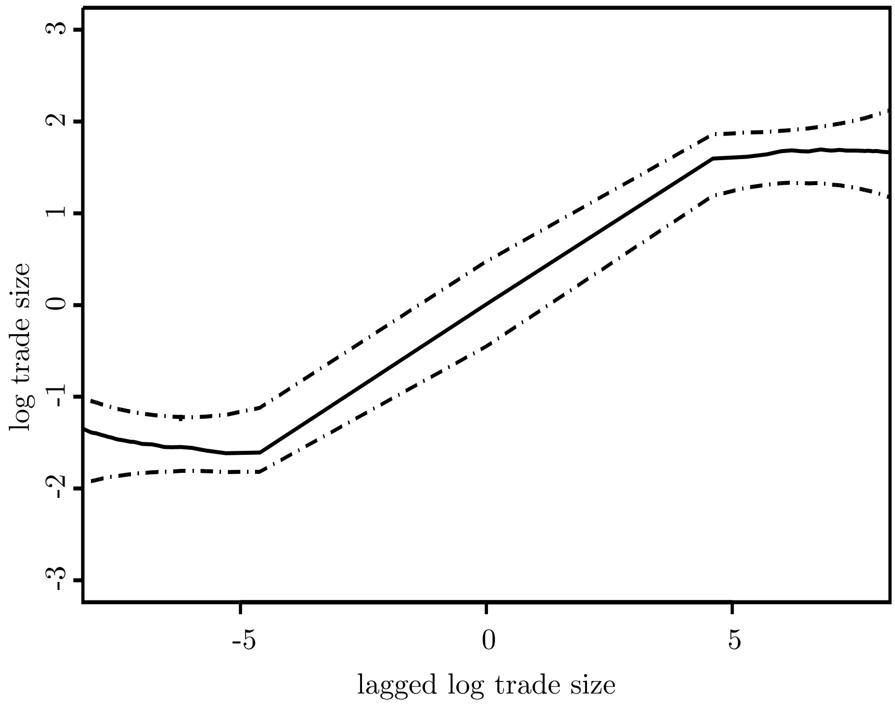

Figure IV.3: Kernel regression: log trading volume versus lagged log trading volume

This figure shows the relation between log trading volume and lagged log trading volume for Commercial Intertech, based upon a kernel regression. The dashed lines indicate the boundaries of a 95% point-wise confidence interval based on the asymptotic distribution of the kernel estimator as given in expression (B.10) of Appendix B.

To estimate the price-impact functions, we need random values of the disturbances $(\varepsilon_{t,1})_t$ and $(\varepsilon_{t,2})_t$ as we will point out in Section IV.6. We assume that the disturbances are independent and identically distributed. We do not impose any parametric assumptions on the distribution of the disturbances and will draw from the empirical distribution of the residuals.

IV.6 Immediate and persistent price impact and trade size

In this section we investigate the expected long-term and short-term price impact and the relation to trading volume.
To estimate the expected price impact of a trade, we use the impulse response function as defined in expression (IV.2). Since the partially linear model is nonlinear in trading volume, we need the distribution of the disturbances $(\varepsilon_t)_t = (\varepsilon_{t,1}, \varepsilon_{t,2})'_t$ in equations (IV.7) and (IV.8) to estimate the impulse response function by means of simulation. We follow the approach of Hasbrouck (1991b) and assume that − given the test results obtained in Section IV.5 − the disturbances are independent and identically distributed. Under this assumption it is possible to estimate the impulse response function by means of simulation. We jointly simulate paths of returns and trading volumes following an unexpected trade of M shares at time τ_0, using the specification given in equations (IV.7) and (IV.8). For each path of returns, say $(r_t)_t$ for $t = 0, \ldots, k$, we compute the corresponding cumulative midprice returns. Finally, we average the midprice changes over all $N = 10,000$ simulations to obtain the expected price impact. Appendix C explains in more detail how we simulate paths of returns and trading volumes and how we estimate impulse response functions in the partially linear model.

The market-impact curve
To gain more insight in the relation between price impact and trading volume, we consider the market-impact curve. This curve is defined as the expected price impact of a trade (at a certain moment in time) as a function of unexpected trading volume, where we keep signed trading volume between the 5% and 95% sample quantiles of trade size. Note the difference between the impulse response function and the market-impact curve. The impulse response function is the expected price impact as a function of time for fixed initial trading volume, while the market-impact curve reflects the expected price impact as a function of the size of the initial trading volume, at a fixed moment in time.
We use the method of Appendix C to derive the market-impact curve from

the impulse response functions at different moments in time: directly after the trade (immediate price impact) and in the long-run when the new efficient price has been reached (persistent price impact). As explained by Kraus and Stoll (1972) and Hasbrouck (1991a, 1991b), the permanent impact of a trade on prices reflects the change in the perception of the market maker due to the information contained in the initial trade. The difference between the persistent and the immediate price impact reflects temporary price movements caused by liquidity effects or lagged adjustment of prices to information. The market-impact curves for Commercial Intertech are shown in Figure IV.4.
The market-impact curves in Figure IV.4, together with the results in Tables IV.4 and IV.5, show that there is an increasing and concave relation between (immediate and persistent) price impact and trading volume. Tables IV.4 and IV.5 are based on the market-impact curves and report the immediate and persistent price impact of buys and sells of different sizes for all five stocks under consideration (see the rows indicated by the abbreviation 'PL' that stands for 'partially linear') and show a similar increasing and concave relation between immediate and persistent price impact and order flow for the other stocks of the sample. This result is in line with the findings of Hasbrouck (1991a, 1991b), Hausman et al. (1992), and Kempf and Korn (1999). Since we establish an increasing and concave relation between the information content of a trade and the size of the trade, this provides evidence for the stealth-trading hypothesis of Barclay and Warner(1993) as discussed in Section IV.2. The concave shape of the market-impact curves shows that trades of medium size contain relatively much information, suggesting that these trades have been initiated by informed traders. This is exactly the stealth-hypothesis as formulated by Barclay and Warner (1993). The concavity of the market-impact curves shows that the immediate and persistent price impact are not proportional to trade size. Moreover, the price impact is not proportional to log trade size either. When we compare the market-impact curves generated by the partially linear model to those obtained in some commonly used parametric models, we find − in line with the test results obtained in Section IV.5 − considerable differences. Figure IV.5 shows the market-impact curve for the representative stock Commercial Intertech in four different models: the partially linear model, the log-linear, the extended linear, and the quadratic VAR-model (see Section IV.4). The quadratic VAR-model is used by Hasbrouck (1991a, 1991b) to pick up any nonlinear effects in the price-order flow relation. However, Figure IV.5 shows that the market-impact curve corresponding to the quadratic model differs considerably from the partially linear model. This suggests that the quadratic terms do not pick up well the nonlinearities that are reflected in the market-impact curve of the semiparametric model.

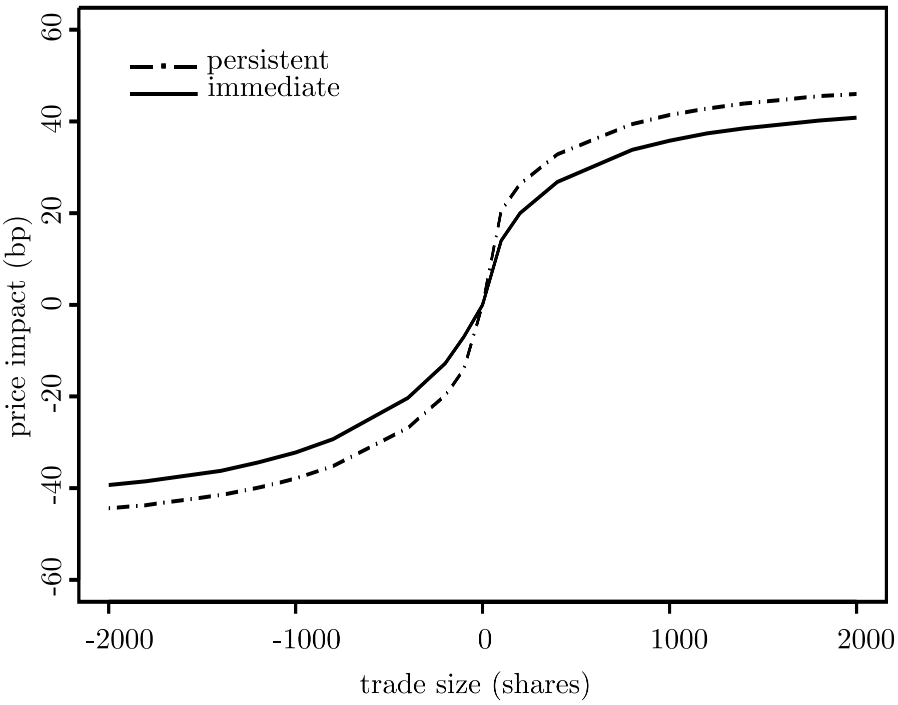

Figure IV.4: market-impact curve: short-term and long-term

The market-impact curve shows the relation between signed trading volume (in shares) and expected price impact (in bp) in the partially linear model given by equations (IV.7) and (IV.8) for Commercial Intertech.

	CHP		FC		FMN		TEC		XTR	
	buy	sell	buy	sell	buy	sell	buy	sell	buy	sell
400 shares										
PL	9.2	−12.4	16.8	−14.2	10.9	−13.9	26.8	−20.3	7.8	−7.7
LL	9.3	−9.3	15.1	−15.1	11.6	−11.6	21.2	−21.7	7.1	−7.1
EL	7.6	−7.6	12.8	−12.8	9.8	−9.8	15.9	−15.9	5.4	−5.4
Q	7.2	−7.2	11.2	−11.2	9.5	−9.5	14.2	−14.2	5.3	−5.3
800 shares										
PL	10.6	−13.6	21.3	−19.3	13.5	−15.7	33.8	−29.3	9.1	−8.6
LL	10.3	−10.3	16.8	−16.8	13.0	−13.0	23.6	−23.6	8.0	−8.0
EL	8.1	−8.1	13.4	−13.4	11.4	−11.4	18.3	−18.3	6.1	−6.1
Q	8.0	−8.0	12.7	−12.7	12.4	−12.4	19.4	−19.4	6.1	−6.1
1,200 shares										
PL	11.4	−14.3	24.0	−22.6	15.1	−16.6	37.4	−34.4	10.2	−9.4
LL	11.0	−11.0	17.9	−17.9	13.7	−13.7	25.0	−25.0	8.4	−8.4
EL	8.6	−8.6	14.1	−14.1	13.0	−13.9	20.7	−20.7	6.8	−6.8
Q	8.8	−8.8	14.2	−14.2	15.2	−15.2	24.4	−24.4	6.9	−6.9
1,600 shares										
PL	11.9	−14.8	25.7	−25.0	16.1	−17.2	39.4	−37.5	11.1	−10.0
LL	11.4	−11.4	18.6	−18.6	14.3	−14.3	26.5	−26.5	8.8	−8.8
EL	9.1	−9.1	14.7	−14.7	14.6	−14.6	23.0	−23.0	7.5	−7.5
Q	9.5	−9.5	16.5	−16.5	17.9	−17.9	29.3	−29.3	7.8	−7.8
2,000 shares										
PL	12.3	−15.2	26.9	−26.8	16.7	−17.6	40.8	−39.3	11.7	−10.5
LL	11.7	−11.7	18.9	−18.9	14.7	−14.7	26.9	−26.9	9.1	−9.1
EL	9.7	−9.7	15.4	−15.4	16.1	−16.1	25.4	−25.4	8.2	−8.2
Q	10.3	−10.3	17.3	−17.3	20.4	−20.4	34.0	−34.0	8.6	−8.6

Table IV.4: Expected immediate price impact of buys and sells of different sizes

This table reports the expected immediate price impact (in bp) of buys and sells of different sizes (in shares) on midprices estimated by the partially linear model given by equations (IV.7) and (IV.8) (abbreviated as 'PL'), the log-linear VAR-model ('LL'), the extended linear VAR-model ('EL'), and the quadratic VAR-model ('Q').

	CHP		FC		FMN		TEC		XTR	
	buy	sell	buy	sell	buy	sell	buy	sell	buy	sell
400 shares										
PL	22.2	−27.0	26.9	−26.6	18.0	−21.6	32.8	−26.9	14.6	−16.2
LL	24.9	−24.9	30.7	−30.7	20.4	−20.4	28.3	−28.3	13.7	−13.7
EL	24.1	−24.1	29.0	−29.0	18.2	−18.2	25.4	−25.4	12.0	−12.0
Q	23.8	−23.8	26.9	−26.9	17.7	−17.7	24.2	−24.2	11.8	−11.8
800 shares										
PL	24.6	−28.8	31.7	−31.2	21.0	−23.9	39.4	−35.2	16.4	−17.4
LL	27.8	−27.8	34.2	−34.2	22.8	−22.8	31.5	−31.5	15.3	−15.3
EL	24.5	−24.5	29.8	−29.8	19.2	−19.2	26.7	−26.7	12.7	−12.7
Q	24.4	−24.4	28.8	−28.8	20.5	−20.5	27.5	−27.5	12.8	−12.8
1,200 shares										
PL	25.8	−29.8	34.5	−34.0	22.7	−24.8	42.8	−39.9	17.8	−18.3
LL	29.5	−29.5	36.3	−36.3	24.2	−24.2	33.4	−33.4	16.2	−16.2
EL	24.9	−24.9	30.6	−30.6	20.2	−20.2	27.9	−27.9	13.3	−13.3
Q	25.0	−25.0	30.7	−30.7	23.1	−23.1	30.7	−30.7	13.8	−13.8
1,600 shares										
PL	26.6	−30.5	36.3	−36.0	23.7	−25.4	44.8	−42.7	18.9	−19.0
LL	30.7	−30.7	37.8	−37.8	25.2	−25.2	34.8	−34.8	16.9	−16.9
EL	25.2	−25.2	31.4	−31.4	21.1	−21.1	29.1	−29.1	14.0	−14.0
Q	25.6	−25.6	33.6	−33.6	25.5	−25.5	33.8	−33.8	14.8	−14.8
2,000 shares										
PL	27.2	−31.0	37.4	−37.4	24.3	−25.7	46.0	−44.4	19.8	−19.6
LL	31.7	−31.7	38.4	−38.4	25.9	−25.9	35.9	−35.9	17.4	−17.4
EL	25.6	−25.6	32.3	−32.3	22.1	−22.1	30.3	−30.3	14.7	−14.7
Q	26.2	−26.2	34.0	−34.0	27.6	−27.6	36.7	−36.7	15.8	−15.8

Table IV.5: Expected persistent price impact of buys and sells of different sizes

This table reports the expected persistent price impact (in bp) of buys and sells of different sizes (in shares) on midprices estimated by the partially linear model given by equations (IV.7) and (IV.8) (abbrevatiated as 'PL'), the log-linear VAR-model ('LL'), the extended linear VAR-model ('EL'), and the quadratic VAR-model ('Q').

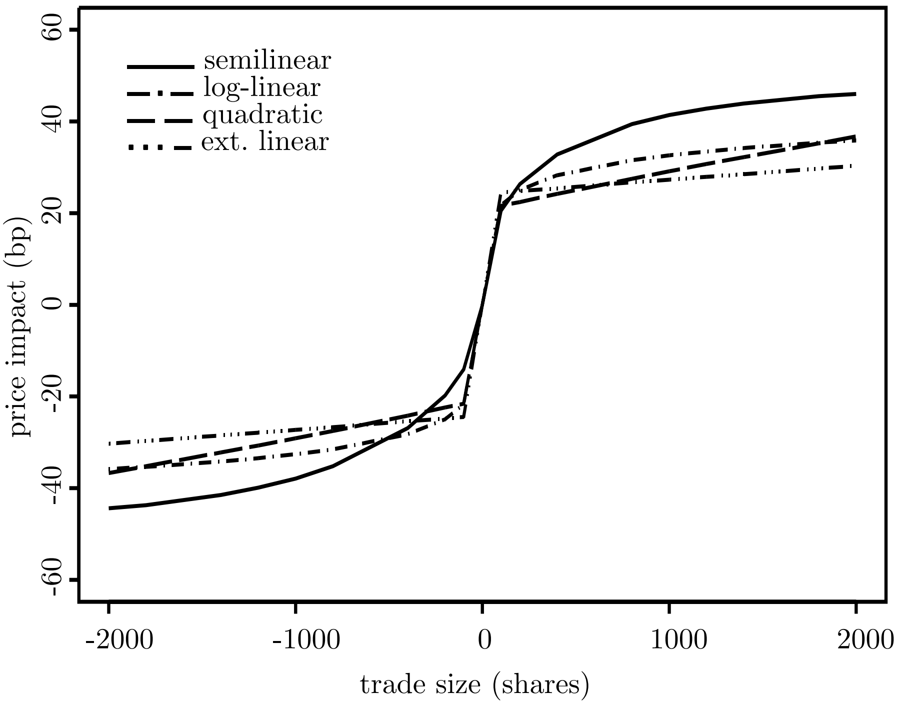

Figure IV.5: Long-term market-impact curve in four different models

The long-term market-impact curve shows the relation between signed trading volume (in shares) and expected persistent price impact (in bp) in the partially linear model, the linear VAR-model, the log-linear VAR-model, the extended linear VAR-model, and the quadratic VAR-model, for Commercial Intertech as defined in Section IV.4.

The market-impact curve of the log-linear model also differs from the partially linear model. Tables IV.4 and IV.5 report the immediate and persistent price impact of trades of different sizes in the log-linear VAR-model (indicated in Tables IV.4 and IV.5 by the abbreviation 'LL'), the extended linear VAR-model (abbreviated as 'EL') and in the quadratic VAR-model (abbreviated as 'Q'). From these tables we see that the fully parametric models suffer from misspecification with respect to the relation between trading volume and returns. The largest differences are found for the representative stock Commercia Intertech. The difference between the partially linear and the log-linear model can amount as much as 34% (2,000 shares) for the immediate impact and 22% for the persistent impact (1,600 shares)[3]. The differences between the partially linear model and the extended linear VAR-model are even larger, 46% (immediate impact, 800 shares) and 35% (persistent impact, 1,600 shares). Finally, the largest differences with respect to the quadratic VAR-model are 43% (immediate impact, 800 shares) and 30% (persistent impact, 800 shares).

Another important issue is the possible difference in persistent price impact between large buy and sell transactions. As explained in Section IV.4, the parametric VAR-models yield symmetric impulse response functions, while the partially linear model allows for asymmetric impact of buys and sells on prices. We test the hypothesis of symmetry (explicitly given in expression (B.19)) using the approach of Whang and Andrews (1993). The null hypothesis of symmetry is not rejected at a 5% level for Franklin Covey and Xtra Company; see Table IV.3 for the test results. We find significant evidence for asymmetric effects of buys and sells on prices for the remaining stocks C&D Technology, F&M National, and Commercial Intertech. However, Table IV.5 does not provide much evidence for the Chan and Lakonishok (1993) hypothesis (see Section IV.2) that buys have larger persistent impact on prices than sells, since this is only the case for Commercial Intertech.

IV.7 Temporary price effects and trade size

To gain more insight in the price adjustment process and the temporary price effects, this section investigates the expected price impact of a trade as a function of time.

Using the method explained in Appendix C we compute impulse response functions corresponding to trades of different volume and focus on the impact

[3]These percentages express the absolute difference between the price impact in the partially linear and the log-linear model, as % of the price impact in the partially linear model.

of trading volume on both immediate and persistent price impact over time. The impulse response functions corresponding to unexpected buys of 2,000, 1,200, 800, and 400 shares of Commercial Intertech are given in Figure IV.6. The impulse response functions for unexpected sells of the same size are shown in Figure IV.7.

In Section IV.6 we established a nonlinear relation between trading volume and both immediate and persistent price impact. The impulse response functions for the representative stock Commercial Intertech shown in Figures IV.6 and IV.7 show once more that there is a complicated, nonlinear price-order flow relation, since they are not (log-) proportional to trading volume.

Moreover, we compare the impulse response functions obtained in the partially linear model to the ones generated by the log-linear, the extended linear, and the quadratic VAR-model discussed in Section IV.4, see Figure IV.8. This plot shows the impulse response functions corresponding to a relatively large trade (1,800 shares; corresponding to the 95% sample quantile of trade size) in each of the four models, for the representative stock Commercial Intertech. We see that not only the market-impact curves in the partially linear model differ from those obtained in the parametric VAR-specifications as we showed in Section IV.6, also the price impact over time is different. For the other stocks we find similar results.

In Section IV.6 we concluded that the partially linear model is flexible enough to capture complicated price-order flow relations and we now see that it can also deal with complicated price movements over time. Clearly, a fully nonparametric model is even more flexible than the semiparametric partially linear model. The fact that the partially linear model is flexible enough for the data at hand is illustrated by the comparison to the fully nonparametric model. The tests of Whang and Andrews (1993) show that the semilinear model cannot be rejected in favor of the fully nonparametric model at a 5% level for all stocks under consideration (see Table IV.3). Furthermore, the impulse response functions generated by a fully nonparametric model are very close to those generated by the partially linear model, which is in line with the test results.

The overshooting effect

From the impulse response functions of the representative stock Commercial Intertech in Figures IV.6 and IV.7 we see that the price-impact function 'overshoots' or 'mean reverts'. This means that, after the buy, prices temporarily exceed the full information level, before they mean revert to this level. For sells we find a similar effect. The overshooting effect has also been established for infrequently traded stocks in the parametric VAR-model for returns, bid-ask spread, and trade sign in Spierdijk et al. (2002a). In the

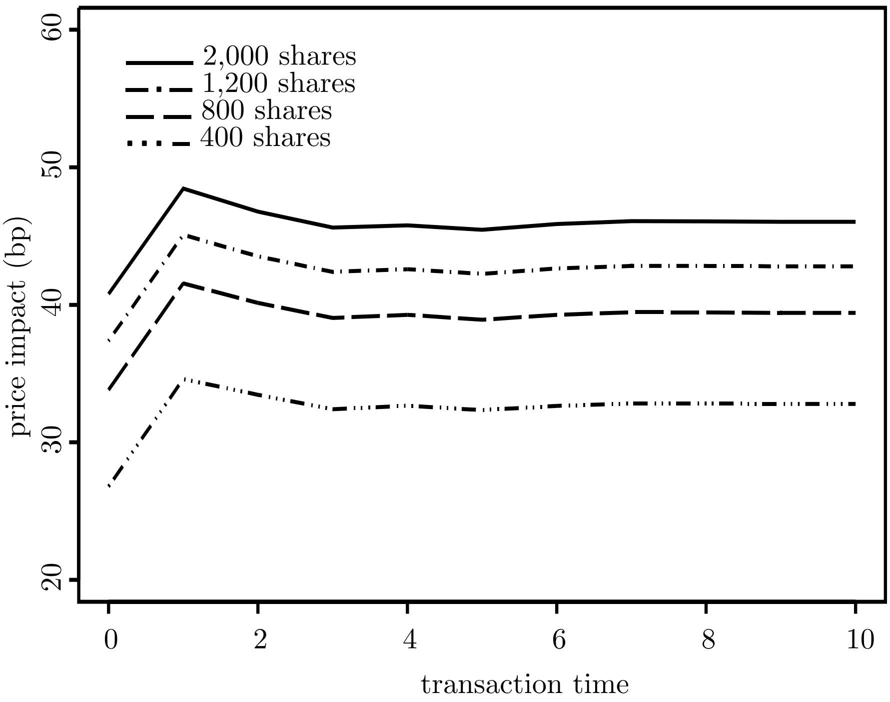

Figure IV.6: Impulse response function for buys of different sizes

The expected price impact (in bp) of unexpected buys of 2,000, 1,200, 800, and 400 shares of Commercial Intertech in the partially linear model given by equations (IV.7) and (IV.8).

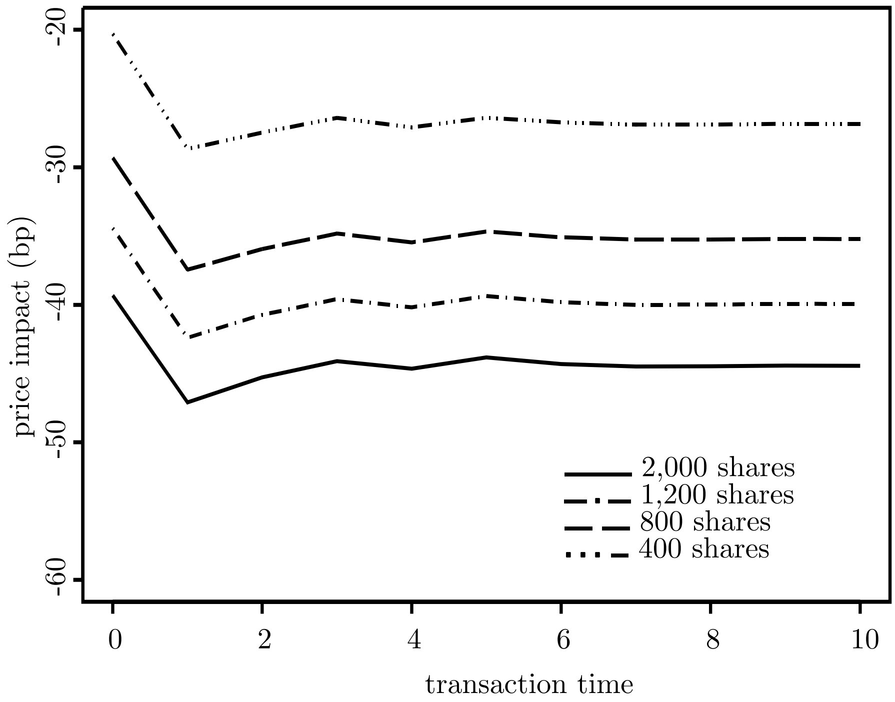

Figure IV.7: Impulse response function for sells of different sizes

The expected price impact (in bp) of unexpected sells of 2,000, 1,200, 800, and 400 shares of Commercial Intertech in the partially linear model given by equations (IV.7) and (IV.8).

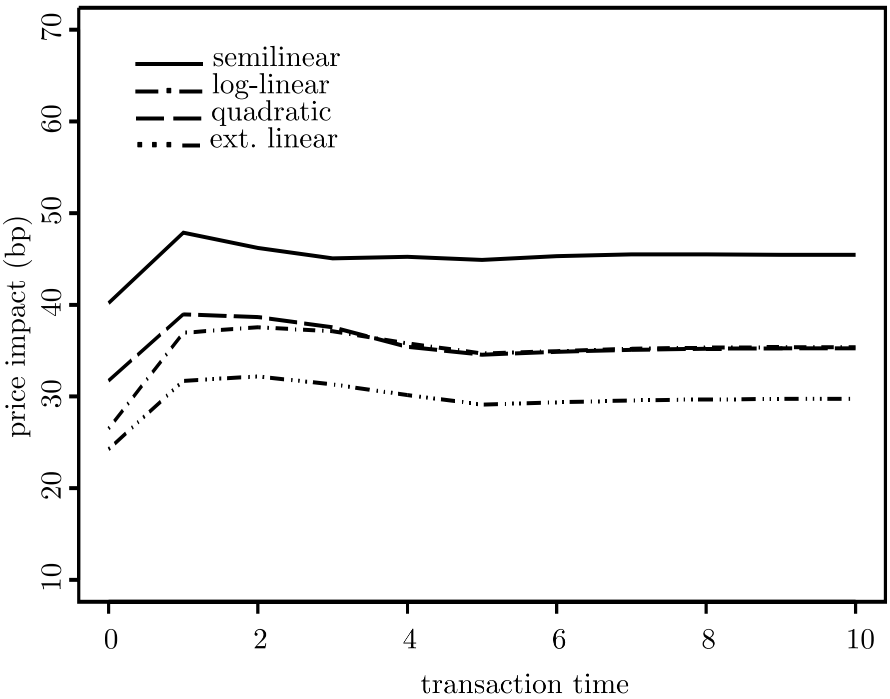

Figure IV.8: Impulse response functions in four different models

This figure shows the impulse response function corresponding to a buy of 1,800 shares of Commercial Intertech in the partially linear model, the log-linear VAR-model, the extended linear VAR-model, and the quadratic VAR-model as defined in Section IV.4.

parametric VAR-model used in latter paper, the overshooting effect − as the maximum over the adjustment path of the midprice minus its long-run equilibrium level − is generally larger than in the partially linear model. This can be explained by the fact that the model in Spierdijk et al. (2002a) also condition on the bid-ask spread and the trading intensity to which the overshooting effect is strongly related. Spierdijk et al. (2002a) provide several explanations for the phenomenon of overshooting, such as order imbalances in the limit-order book, inventory effects, asymmetric information and the monopoly position of the market maker. However, since Spierdijk et al. (2002a) model trade sign and not trading volume, they do not determine the relation between the size of the trade and the degree of overshooting. When we related the degree of overshooting to trade size, we find that there is a positive, approximately concave relation between overshooting and trade size. The positive relation between the overshooting effect and the size of the trade is consistent with the possible explanations of the overshooting effect as given in Spierdijk et al. (2002a). Large trades will lead to larger imbalances in the limit-order book, which are likely to cause more overshooting. Similarly, large trades are associated with larger inventory imbalances which are also likely cause more mean reversion in prices. The positive relation between trading volume and overshooting allows us to gain more insight in the role of asymmetric information − another possible explanation for the overshooting effect as pointed out in Spierdijk et al. (2002a). In Easley and O'Hara (1987) it is put forward that the risk of informed trading is higher for large trades. Consequently, they demonstrate that information affects the price-quantity relationship in a complicated way, since both the size and the sequence of trades determine this relation in a situation of asymmetric information and event uncertainty. For example, when a large block buy takes place, the market maker increases his price for the next small trade. He does this because the large buy changes his perception of the risk of informed trading, which he considers to be higher. When more small trades follow, the market maker adjusts his perception on the risk of informed trading downwards, which leads to a partial recovery of prices. In this case, informational effects lead to overshooting and the overshooting effect increases with the volume of the block trade. See also Kraus and Stoll (1972) and Dann, Mayers, and Raab (1977) who find overshooting caused by block trades in their empirical analysis. Although the above argument of asymmetric information would equally well be applicable for frequently traded stocks, our empirical results show that prices of these stocks do not overshoot after a large trade. The risk of informed trading is larger for infrequently traded stocks than for frequently traded stocks (cf. Easley et al. (1996)), hence large trades in infrequently traded stocks will generally have more impact on the perception of the market maker than large trades in frequently traded stocks. This suggests that for frequently traded stocks the adjustments in perception are too small to lead to visible overshooting.

IV.8 Conclusions

In this chapter we investigated the relation between price impact and trading volume. The parametric VAR-models that have been used in the literature starting with Hasbrouck (1991a, 1991b) impose strong proportionality and symmetry restrictions on the price impact of trades, although market microstructure theory provides many reasons why these restrictions would not hold. We analyzed a more flexible semiparametric partially linear model of Engle, Granger, Rice, and Weiss (1986) and applied the model to a sample of infrequently traded stocks listed on the NYSE in the year 1999. We established significant evidence for a nonlinear, asymmetric, increasing, and concave relation between trading volume and both immediate and persistent price impact. Moreover, we compared the relation between price impact and order size obtained in the partially linear model to the price-order flow relation generated by some commonly used parametric VAR-models and showed that there are considerable differences. In contrast to the partially linear model, the parametric models do not capture the nonlinearities in the price-order flow relation. We used the approach of Whang and Andrews (1993) to test the semiparametric specification and showed that the parametric models are rejected in favor of the partially linear model. We also tested the partially linear model against a more flexible fully nonparametric specification, but this test did not reject the partially linear model for the stocks under consideration.

The nonlinear, increasing, and concave price-order flow relation for order splitting can be explained in several ways (see for instance Seppi (1990), Barclay and Warner (1993), Keim and Madhavan (1996), and Dridi and Germain (2000)), but it implies that order splitting on the basis of price impact leads to an increase in the costs of trading. This suggests that, for order splitting, other costs such as temporary market impact and opportunity costs should be taken into account as well. This is left as an important topic for further research.

Appendices to Chapter IV

Appendix IV.A

Properties of parametric VAR-models for returns and trading volume

In this appendix we focus on some important properties of parametric VAR-models.
Consider a bivariate VAR-model for returns $(r_t)_t$ and signed trading volume $(y_t)_t$, which we specify in terms of the lag-polynomial L as

$$\begin{pmatrix} a(L) & b(L) \\ c(L) & d(L) \end{pmatrix} \begin{pmatrix} r_t \\ y_t \end{pmatrix} = \begin{pmatrix} a_0 \\ b_0 \end{pmatrix} + \begin{pmatrix} \eta_{t,1} \\ \eta_{t,2} \end{pmatrix}, \tag{A.1}$$

where

$$\begin{aligned} &\mathbb{E}\eta_{t,i} = \mathbb{E}\eta_{t,i}\eta_{s,i} = 0 \qquad [t \neq s; i = 1,2]; \\ &\mathbb{E}\eta_{t,1}\eta_{s,2} = 0. \end{aligned}$$

We are interested in the properties of the linear VAR-model defined in equation (A.1) regarding the price impact of trades. We will measure the price impact of trades by means of the cumulative impulse response function, cf. Hasbrouck (1991a, 1991b). Given a certain history of returns and trading volume up to time τ_t, the cumulative impulse response function at time τ_{t+k} corresponding to an unexpected buy of M shares at time τ_t is defined as

$$\alpha_{t+k|t}(M) \;=\; \mathbb{E}_{t-1}(r_t + \ldots + r_{t+k} \mid \eta_{t,2} = M) - \mathbb{E}_{t-1}(r_t + \ldots + r_{t+k}). \tag{A.2}$$

Hence, the cumulative impulse response function represents the expected price impact of an unexpected trade, relative to the expected price impact conditional on the history only. See, for instance, Koop, Pesaran, and Potter (1996). Kraus and Stoll (1972) and Hasbrouck (1991a, 1991b) point out that the persistent price impact of an unexpected trade is naturally interpreted as the information content of the trade. The persistent impact is obtained for $k \to \infty$ in expression (A.2). When we rewrite the VAR-model in expression (A.1) as a vector moving average, we obtain

$$\begin{pmatrix} r_t \\ y_t \end{pmatrix} = \begin{pmatrix} a^*(L) & b^*(L) \\ c^*(L) & d^*(L) \end{pmatrix} \left[\begin{pmatrix} a_0 \\ b_0 \end{pmatrix} + \begin{pmatrix} \eta_{t,1} \\ \eta_{t,2} \end{pmatrix} \right]. \tag{A.3}$$

Let β_j denote the coefficient of L^j in the polynomial $b^*(L)$. Equation (A.3) shows that, at time τ_{t+k}, the impulse response function corresponding to an unexpected trade of size M initiated at time τ_t equals

$$\alpha_{t+k|t}(M) = M \sum_{j=0}^{k} \beta_j. \tag{A.4}$$

The persistent price impact, obtained for $k \to \infty$, yields $\alpha(M) = b^*(1)M$ as long-term impulse response.
From expression (A.4) we can derive some important properties of the impulse response function. Firstly, the price-impact functions corresponding to trades of different volumes are proportional; i.e.

$$\frac{\alpha_{t+k|t}(M_1)}{\alpha_{t+k|t}(M_2)} = \frac{M_1}{M_2} \tag{A.5}$$

for any t, k. This implies that there is a linear relation between volume and prices in the VAR-model of equation (A.1). Secondly, the price impact of buys and sells is symmetric. This means that the magnitude of the impact of unexpected buys and sells of size is the same; i.e.

$$\alpha_{t+k|t}(M) = -\alpha_{t+k|t}(-M). \tag{A.6}$$

Appendix IV.B

The partially linear model

The model that is used to specify the possibly nonlinear relation between prices and trading volume is the partially linear or semilinear model, introduced by Engle, Granger, Rice, and Weiss (1986) and Robinson (1988a, 1988b) and will be discussed in this appendix.
The partially linear model is a semiparametric model, since the conditional mean of the dependent variable y consists of both a parametric and a nonparametric part. The parametric part is a linear transformation of a vector of explanatory variables x of dimension k. The nonparametric part is formed by a transformation of another vector of explanatory variables, say z, that has dimension ℓ. Thus,

$$y_t = \beta' x_t + f(z_t) + \varepsilon_t, \quad \mathbb{E}(\varepsilon_t \mid x_t, z_t) = 0 \qquad [t = 1, \dots, n], \tag{B.1}$$

where β denotes a $(k \times 1)$ vector of parameters and $f(\cdot)$ an unknown function. Note that, to ensure identification, β should not contain an intercept. For the same reason x_t and z_t should not have any variables in common. In Chapter IV the variable z_t is a vector (lagged) trading volumes, which may nonlinearly affect returns.
The coefficient β in the partially linear model is estimated by means of two kernel regressions. A kernel regression of y_t on z_t is used to estimate $\mathbb{E}(y_t \mid z_t)$ and a kernel regression of x_t on z_t is used to estimate $\mathbb{E}(x_t \mid z_t)$. Finally, β is estimated from the model

$$y_t - \mathbb{E}(y_t \mid z_t) = \beta'(x_t - \mathbb{E}(x_t \mid z_t)) + \varepsilon_t, \tag{B.2}$$

which is implied by the initial model given in expression (B.1). To estimate (B.2) by means of OLS, $\mathbb{E}(y_t \mid z_t)$ and $\mathbb{E}(x_t \mid z_t)$ are replaced by the corresponding kernel estimates $\mathbb{E}_n(y_t \mid z_t)$ and $\mathbb{E}_n(x_t \mid z_t)$, respectively. Despite the nonparametric estimation stage that precedes the computation of the OLS-estimator, the estimation errors do not affect the asymptotic distribution of the OLS-estimator $\hat{\beta}_n$ and, under appropriate regularity conditions, the asymptotic distribution of $\hat{\beta}_n$ is

$$\sqrt{n}(\hat{\beta}_n - \beta) \xrightarrow{d} \mathcal{N}(0, A^{-1} B A^{-1}), \tag{B.3}$$

where

$$A = \mathbb{E}[(x_t - \mathbb{E}(x_t \mid z_t))(x_t - \mathbb{E}(x_t \mid z_t))']; \tag{B.4}$$
$$B = \mathbb{E}[(x_t - \mathbb{E}(x_t \mid z_t))(x_t - \mathbb{E}(x_t \mid z_t))' \varepsilon_t^2]. \tag{B.5}$$

See for instance Lee (1996). The function $f(z)$ can be estimated by means of a kernel regression of $y_t - \hat{\beta}_n' x_t$ on z_t. The kernel estimator $f_n(z)$ of $f(z)$ is given by

$$f_n(z) = \frac{g_n(z)}{h_n(z)}, \tag{B.6}$$

where

$$g_n(z) = \frac{1}{n\gamma_n^\ell} \sum_{t=1}^{n} K\Big(\frac{z_t - z}{\gamma_n}\Big)(y_t - \hat{\beta}_n' x_t); \tag{B.7}$$

$$h_n(z) = \frac{1}{n\gamma_n^\ell} \sum_{t=1}^{n} K\Big(\frac{z_t - z}{\gamma_n}\Big). \tag{B.8}$$

Here $h_n(\cdot)$ is an estimate of the density $h(\cdot)$ of z_t. The function $K(\cdot)$ is a kernel function which is bounded, symmetric around zero and which integrates to one; e.g. the Gaussian density function. Moreover, γ_n satisfies $n\gamma_n^\ell \to \infty$ and $\gamma_n \to 0$. As explained in Bierens (1987), the γ_n that minimizes the mean squared error is of the form $cn^{-1/(\ell+4)}$, where the optimal value of c can be determined by means of cross-validation. Instead of using one single bandwidth parameter for all the regressors, we will use the adaptive metric kernel estimation procedure proposed by Goutte and Larsen (2000). This approach allows for different bandwidths for each of the input variables. This is useful in our case, since the regressors in the kernel regression represent different lags of signed trading volume which are likely to be of different importance. We use the BFGS-algorithm of Broyden, Fletcher, Goldfarb, and Shanno (see Shanno (1970)) to carry out the numerical optimization procedure for finding the value of the bandwidth that has the lowest mean-squared error.

The kernel estimator $f_n(z)$ satisfies

$$\sqrt{n\gamma_n^\ell}(f_n(z) - f(z)) \xrightarrow{d} \mathcal{N}\Big(0, h(z)^{-1}\mathbb{V}\mathrm{ar}\,(\varepsilon \mid z) \int K^2(u)\mathrm{d}u\Big). \tag{B.9}$$

This asymptotic result is based on the assumption that the variable z is continuous. In the next sections the regressor z will represent the discrete variable trading volume. In this case a different asymptotic result applies, as proved in Bierens (1987):

$$\sqrt{n}(f_n(z) - f(z)) \xrightarrow{d} \mathcal{N}(0, \mathbb{V}\mathrm{ar}\,(\varepsilon \mid z)h(z)^{-1}). \tag{B.10}$$

For more details on kernel regression with discrete regressors we refer to Bierens (1987) and Delgado and Mora (1995).

Whang and Andrews (1993) have developed several diagnostic tests for the validity of the assumptions underlying the partially linear model. The test statistic that they propose is based upon

$$\overline{r}_n(\beta,\pi) = \frac{1}{n}\sum_{t=1}^{n} r_t(\beta,\pi), \tag{B.11}$$

where π represents a nonparametric regression function and r_t is chosen in such as way that, under the null hypothesis of correct specification, $\mathbb{E}(r_t) = 0$ for $t = 1, \ldots, n$. Hence, we would expect that the sum in expression (B.11), with β and π replaced by $\hat{\beta}_n \xrightarrow{p} \beta$ and $\hat{\pi} \xrightarrow{p} \pi$ respectively, is close to zero when the model is correctly specified. Whang and Andrews (1993) show that, under sufficient conditions,

$$\sqrt{n}\overline{r}_n(\hat{\beta}_n,\hat{\pi}) \xrightarrow{d} \mathcal{N}(0,\Psi), \tag{B.12}$$

under the null hypothesis, for some nonsingular covariance matrix Ψ. Their test statistic has the form

$$T = n\overline{r}_n'\hat{\Psi}^{-1}\overline{r}_n, \tag{B.13}$$

where $\hat{\Psi}$ is a consistent estimator of the matrix Ψ of size $(q \times q)$, with q the dimension of r_t. They also show that the test statistic in (B.13) has, under the null hypothesis of correct specification, a χ^2_q limit distribution. For more details on the precise form of the test statistic and the underlying conditions we refer to Whang and Andrews (1993).
The null hypothesis that the fully parametric model is 'true' is formulated as

$$H_0 : \mathbb{P}(f(z_t) = \gamma' z_t) = 1, \tag{B.14}$$

for some value of γ. The test statistic in (B.13) is based on

$$\begin{aligned} r_t &= [y_t - \mathbb{E}(y_t \mid z_t) - \bar{\beta}'(x_t - \mathbb{E}(x_t \mid z_t))] \\ &\quad \times [x_t - \mathbb{E}(x_t \mid z_t)]/\mathbb{E}(\varepsilon_t^2 \mid z_t). \end{aligned} \tag{B.15}$$

For the computation of (B.11), $\bar{\beta}$ is replaced by the OLS-estimate of β in the fully parametric model. Under the null hypothesis, $\bar{\beta} = \beta_0$ (where β_0 indicates the value of β under the null hypothesis that the fully parametric model is true) and $\mathbb{E}(r_t) = 0$ Whang and Andrews (1993) show that the test statistic in (B.13) is asymptotically χ^2_k distributed under the null hypothesis, with k the dimension of x_t. The test is consistent against alternatives for which $\hat{\beta}_{OLS} \overset{p}{\nrightarrow} \beta_0$.

We also consider testing the partially linear model against the fully nonparametric model given by

$$y_t = f^*(x_t, z_t) + \varepsilon_t^*, \quad \mathbb{E}(\varepsilon_t^* \mid x_t, z_t) = 0 \qquad [t = 1, \ldots, n]. \tag{B.16}$$

The null hypothesis that the semiparametric model is 'true' is formulated as

$$H_0 : \mathbb{P}(f^*(x_t, z_t) = \beta' x_t + f(z_t)) = 1, \tag{B.17}$$

for some β. In this case the test statistic in (B.13) is asymptotically χ_1^2 distributed. In a similar fashion, the fully parametric model can be tested against the fully nonparametric model. To test this hypothesis the sample is split up in two independent subsamples. The sample is split up to avoid degeneracy of the limiting distribution of the test statistic and the subsamples are used to estimate the model under the null hypothesis and the alternative hypothesis. The test statistic (B.13) is based on

$$\begin{aligned} r_t \;=\; & [y_t - \mathbb{E}(y_t \mid z_t) - \beta'(x_t - \mathbb{E}(x_t \mid z_t))]^2 \\ & -[y_t^* - \mathbb{E}(y_t^* \mid x_t^*, z_t^*)]^2, \end{aligned} \tag{B.18}$$

where the variables with a star ('*') refer to the second subsample.
Following the approach of Whang and Andrews (1993), we construct a test for symmetry of the function $f(\cdot)$. The null hypothesis that this function is symmetric in z is stated as

$$H_0 : \mathbb{P}(f(z_t) = -f(-z_t)) = 1. \tag{B.19}$$

The test statistic in (B.13) is based on

$$r_t = [y_t - \hat{\beta}_n' x_t - f_n(z_t)]^2 - [y_t^* - \hat{\beta}_n' x_t^* + f_n(-z_t^*)]^2, \tag{B.20}$$

and is asymptotically χ_1^2 distributed under the null hypothesis. We will later use this to test whether the impact of buys and sells on prices is symmetric. As will be explained later, we are interested in the distribution of the disturbances $(\varepsilon_t)_t$. Therefore, we need some statistical tests for autocorrelation and heteroskedasticity. The test procedure of Whang and Andrews (1993) can also be used for this. To test whether the disturbances $(\varepsilon_t)_t$ are autocorrelated, we consider a simple MA(1) error structure

$$\varepsilon_t = \rho u_{t-1} + u_t \qquad [|\rho| < 1], \tag{B.21}$$

where $(u_t)_t$ is a sequence of iid and zero mean variables such that u_t is independent of (x_t, z_t). The null hypothesis of no autocorrelation is expressed as

$$H_0 : \rho = 0. \tag{B.22}$$

The test statistic is based on

$$\begin{aligned} r_t &= [y_t - \mathbb{E}(y_t \mid z_t) - \beta'(x_t - \mathbb{E}(x_t \mid z_t))] \\ &\quad \times [y_{t-1} - \mathbb{E}(y_{t-1} \mid z_{t-1}) - \beta'(x_{t-1} - \mathbb{E}(x_{t-1} \mid z_{t-1}))] \end{aligned} \tag{B.23}$$

and is asymptotically χ_1^2 distributed under the null hypothesis of no autocorrelation and is similar to the test statistic proposed by Pagan and Hall (1983) for the same null hypothesis in the fully linear model. Note the assumption of MA(1) disturbances is not required. The same test statistic can be used for autocorrelation other than the MA(1)-type; e.g. of the AR(1)-form. The test has power against any alternative for which the first-order autocorrelation is not zero.

Finally, we test for conditional heteroskedasticity in the disturbances $(\varepsilon_t)_t$ in equation (B.1). Under the null hypothesis, the disturbances ε_t are assumed to satisfy

$$\varepsilon_t = \sigma(w_t)\eta_t, \qquad \sigma(w_t) = 1 + k(\gamma' w_t), \tag{B.24}$$

where w_t is a p-dimensional vector of variables related to x_t and z_t, γ a $(p \times 1)$ vector of coefficients, $(\eta_t)_t$ a sequence of homoskedastic variables and $k(\cdot)$ a known function such that $k(0) = 0$. The null hypothesis of homoskedasticity is formulated as

$$H_0 : \gamma = 0. \tag{B.25}$$

This test statistic is based on

$$r_t = w_t[(y_t - \mathbb{E}(y_t \mid z_t) - \beta'(x_t - \mathbb{E}(x_t \mid z_t)))^2 - \sigma^2] \tag{B.26}$$

with $\mathbb{V}\mathrm{ar}\,(\varepsilon_t) = \sigma^2$. Whang and Andrews (1993) show that the test statistic is – under appropriate conditions – asymptotically χ_p^2 distributed under the null hypothesis of homoskedasticity; i.e. its asymptotic distribution is independent of the functional form of $k(\cdot)$. It is noted that this test is the analogue for the partially linear model of the heteroskedasticity tests proposed by Breusch and Pagan (1979) and Koenker (1981) designed for the fully linear model.

Appendix IV.C

Estimation of the impulse response functions

In this appendix we explain how to estimate the impulse response functions in the partially linear model given by equations (IV.7) and (IV.8). Given a certain history of returns and trading volume up to time τ_t, the cumulative impulse response function at time τ_{t+k} corresponding to an unexpected buy of M shares at time τ_t is defined as

$$\begin{aligned} \alpha_{t+k|t}(M) &= \mathbb{E}_{t-1}(r_t + \ldots + r_{t+k} \mid \varepsilon_{t,2} = \log(M)) \\ &\quad -\mathbb{E}_{t-1}(r_t + \ldots + r_{t+k}). \end{aligned} \tag{C.1}$$

The immediate price impact is obtained by taking $k = 0$ in expression (C.1) and the persistent impact is obtained for $k \to \infty$.
We simulate paths of returns and trading volumes in the following way:

- Initialize $v_{t+k} = \overline{v}_n, r_{t+k} = \overline{r}_n$ for $k < 0$;
- For $k = 0, \ldots, K$:
  - For $k = 0$ set $e_{t+k,2} = \log(M)$. Randomly draw a disturbance $e_{t+k,1}$ and for $k > 0$ also a disturbance $e_{t+k,2}$ from the corresponding empirical distribution;
  - Compute, consecutively,

$$\begin{aligned} v_{t+k} &= (r_{t+k-1}, \ldots, r_{t+k-m})\hat{\beta}_{n,2} \\ &\quad +f_{n,2}(v_{t+k-1}, \ldots, v_{t+k-m}) + e_{t+k,2}. \end{aligned} \tag{C.2}$$

  - Calculate

$$\begin{aligned} r_{t+k} &= (r_{t+k-1}, \ldots, r_{t+k-m})\hat{\beta}_{n,1} \\ &\quad +f_{n,1}(v_{t+k}, \ldots, v_{t+k-m}) + e_{t+k,1}. \end{aligned} \tag{C.3}$$

    Subsequently, obtain

$$\alpha^M_{t+k|t} = r_0 + \ldots + r_{t+k}. \tag{C.4}$$

We repeat the above schedule $N = 10,000$ times and average the paths of price changes over the N simulations. This yields a sequence of estimates of expected price changes $\mathbb{E}_N(\alpha^M_{t+k|t})$, for $k = 0, \ldots, K$. In a similar way we estimate the expected price by conditioning on the history only (thus averaging out the initial unexpected trade), yielding $\mathbb{E}_N(\alpha_{t+k|t})$. The difference

$$\hat{\alpha}^N_{t+k|t}(M) = \mathbb{E}_N(\alpha^M_{t+k|t} - \alpha_{t+k|t}) \qquad [k = 0, \ldots, K] \tag{C.5}$$

represents the estimated cumulative impulse response function.

CHAPTER V

Modeling Comovements in Trading Intensities to Distinguish Stock- and Sector-Specific News

V.1 Introduction

There exists a large literature predicting that trading itself conveys information on the underlying value of the asset that is traded. The key ingredient of asymmetric information models is the presence of informed traders. Informed traders possess private information on the value of the asset, which is the very reason why they trade. Uninformed traders, however, do not have this kind of superior information and merely trade from liquidity perspectives. Due to the presence of informed traders, trading itself potentially reveals information on future returns. This suggests that the trading intensity or, equivalently, the durations between consecutive trades, may contain information on the underlying value of the asset. Admati and Pfleiderer (1988) and Easley and O'Hara (1992) predict that frequent trading indicates the presence of news, while Diamond and Verrecchia (1987) predict that slow trading refers to bad news.

It is likely that some information events will refer to idosyncratic stock-specific news, while other events will be sector-specific. Suppose that trader A, who owns a specific stock, observes trader B trading a related stock. Trader A knows that there are several possibilities. Trader B is either informed or uninformed. When he is informed, trader B wants to take advantage of private news, that is either sector-specific or idiosyncratic stock-specific news. Since the probability that trader B possesses private sector-

specific news is positive, his trade reveals information to trader A. Thus, if investors in one stock observe changes in the trade characteristics of related stocks, they know that this may indicate the existence of relevant information and will adapt their own trading behavior accordingly.
Comovements in the trading intensities of stocks are relevant from several points of view. The direction of the comovements in trading intensities provides information on lead-lag relationships; i.e. on ‘driving’ and ‘following’ stocks. Moreover, the relation between trading intensities provides insight in information dissemination and the dynamics of this process. Furthermore, the study of comovements in trading intensities is closely related to the literature addressing the issue of cross-stock commonalities in liquidity. Harris (1990) distinguishes four dimensions of liquidity: width (bid-ask spread), depth (the number of shares that can be traded at given bid and ask quotes), immediacy (how quickly a trade of a given size can be done at a given cost), and resiliency (how quickly prices revert to previous levels after they change in response to large order flow imbalances). Dufour and Engle (2000), Zebedee (2001), Spierdijk (2002), and Spierdijk et al. (2002) show that the trading intensity is closely related to depth and resiliency, since trades have more impact on prices and converge faster to their long-term values when the trading intensity is high. Hence, the trading intensity can be interpreted as a proxy for liquidity. Therefore, comovements in trading intensities are closely related to commonality in liquidity. As put forward by Chordia Roll, and Subrahmanyam (2000b) commonalities in liquidity have important implications, for instance for asset pricing. When liquidity across stocks has common components, shocks in liquidity constitute a source of non-diversifiable risk. When a stock would be very sensitive to this kind of shocks, the market could require a higher average return. Huberman and Halka (1999), Chordia, Roll, and Subrahmanyam (2000a), and Chordia et al. (2000b) find significant evidence for commonalities in the liquidity of stocks listed on the NYSE. Using data on 30 Dow stocks, Hasbrouck and Seppi (2001) find only weak evidence for liquidity commonalities, but do establish significant comovements in stock returns and order flows.
Several models have been proposed to capture comovements among different trading intensities. Engle and Lunde (1999) propose a model that captures the relation between the intensities of the trade and the quote process. Russell (1999), as well as Davis, Rydberg, Shephard, and Street (2001) jointly model the intensities of several types of events such as the arrival of market- and limit-orders. In this chapter we propose a more parsimonious reformulation of Russell (1999), consisting of a duration model for trades corresponding to stocks in the same industry and a probit-specification to model the type of stock in the industry that is traded. We establish significant comovements in

the trading intensities of US department stocks listed on the New York Stock Exchange (NYSE), which we explain by distinguishing idosyncratic stock-specific news that applies to one stock only and sector-specific news that is potentially relevant for stocks in the same type of industry. We provide estimates of the amounts of stock- and sector-specific news contained in the trading intensities and show that all stocks under consideration convey both stock- and sector-specific news.

The setup of this chapter is as follows. Section V.2 briefly discusses the data. Section V.3 provides a review of the literature on multivariate duration models. Section V.4 introduces the specification of a joint model of several trading intensities and applies it to transaction data on stocks of US department-store operators. Section V.5 uses the model estimates to identify stock- and sector-specific news contained in the trading intensities of stocks of US department stores. In Section V.6 the economic effect of the comovements is investigated using simulation. Some extensions of the model are discussed in Section V.7. Finally, Section V.8 concludes.

V.2 The data

This chapter uses high-frequency data taken from the *Trade and Quote* (TAQ) database, distributed by the NYSE. We consider five large US department-store operators (industry code 146) traded on the NYSE. This results in a sample of five stocks including the three largest upscale department-store operators of the US, see Table V.1. The sample covers the period August 1 until October 31, 1999 and consists of 64 trading days.

We remove all trades before 9.30 AM and after 16.00 PM. Moreover, we also delete trades that take place before the first quotes are generated. For all trades in each stock $i = 1, 2, \ldots, 5$ the associated trade moments $\tau_{s,i}$ (expressed in seconds after midnight) are recorded, where s indexes subsequent transactions (i.e. s indexes 'transaction time'), $s = 1, 2, \ldots$. The duration (in 'calendar time') between subsequent trades (in the same type of stock) is defined as $y_{s,i} = \tau_{s,i} - \tau_{s-1,i}$. The total number of trades in stock i up to time τ is denoted by $N_i(\tau)$. To deal with multiple trades at the same second in the same stock, we treat multiple transactions at the same time as one transaction. Hence, we follow Engle and Russell (1998) and interpret multiple trades as a single transaction that is split up into several parts[1]

[1] It also happens that trades in two different stocks take place at the same second. This happens in about 1% of the transactions in our sample. Again we treat these multiple trades as one single transaction and randomly assign the trade to one of the two stocks. We verified that the way of dealing with multiple transactions is not important for the

ticker symbol	DDS	FD	JCP	MAY	SKS
company name	Dillard's Inc.	Federated Departm. Stores	J.C. Penney Corp.	May Departm. Stores	Saks Inc.
# transactions	14,731	24,875	27,133	23,611	14,641
durations (mm:ss)					
mean	01:40	01:00	00:55	01:03	01:40
median	00:52	00:32	00:31	00:35	00:54
0.5% quantile	00:01	00:01	00:01	00:01	00:01
5% quantile	00:03	00:02	00:03	00:03	00:03
95% quantile	06:06	03:31	03:09	03:40	06:05
99.5% quantile	12:33	07:48	07:12	08:03	12:14

Table V.1: Ticker symbols, company names, and some sample statistics

Federated, May and Dillard's are the number one, two and three upscale department-store operators in the US, respectively. Saks and J.C. Penney are other large department-store operators.

For any combination of two stocks, we compute the durations between two subsequent transactions of the 'pooled' process; i.e. the process consisting of all transactions in any of the two stocks. This process is denoted by $(\tau_t)_t$ and the corresponding pooled duration process is denoted by $(y_t)_t$. The total number of trades up to time τ is denoted by $N(\tau)$. To each transaction of the pooled process we associate a variable $(z_t)_t$ that gives the type of stock traded; i.e. $z_t \in \{0, 1\}$.
Table V.1 reports some sample statistics for the five department stores selected for our analysis. J.C. Penney is the most frequently traded stock (average duration 55 seconds), while Saks is most infrequently traded (average duration 1 minute and 40 seconds).
To get a notion of the comovements among trading intensities of the stocks in the sample, we construct pairs of stocks. Given stocks i and j, we determine the first transaction in stock j that follows the $(t-1)$-th transaction in stock

results.

i; i.e., for each t we compute

$$\tilde{\tau}_{t,j} = \inf\{\tau_{s,j} : \tau_{s,j} > \tau_{t-1,i}\}. \tag{V.1}$$

Subsequently, we compute the duration between the $(t-1)$-th transaction in stock i and the first transaction in stock j after that, which is given by

$$w_{t,j} = \tilde{\tau}_{t,j} - \tau_{t-1,i}. \tag{V.2}$$

We compute Spearman's rank correlation between $y_{t-1,i}$ and $w_{t,j}$. For each stock we also report the rank autocorrelation in the durations. The resulting correlations and their standard errors are given in Table V.2. For example, for J.C. Penney and Dillard's the 'cross'-correlation equals 0.103, with standard error 0.006. Thus, the correlation is significantly positive[2]. Doing the same with the roles of the two stocks interchanged, gives a correlation of 0.060 with standard error 0.010. This correlation is also significantly positive. Furthermore, the autocorrelation in the durations of J.C. Penney equals 0.130 (standard error 0.006) and for Dillard's it equals 0.127 (0.003). For the remaining stocks the cross-correlations vary from -0.002 (-0.007) to 0.103 (0.006) and the autocorrelations are between 0.048 (0.007) and 0.149 (0.008). The significant cross-correlations among the stocks suggest that J.C. Penney contains most sector-specific news, since the impact of J.C. Penney on any other stock is larger than the other way around. The stocks Federated and May contain most sector-specific news after J.C. Penney, and, finally, Dillard's and Saks follow.

The correlations reported in Table V.2 can be caused by sector-wide news events, but can equally well be due to other factors such as time of the day periodicities. Another complication with the interpretation of the correlations is the problem of censoring. This phenomenon arises when, after a trade in stock A, another trade in stock A takes place before the subsequent trade in stock B. In order to separate these effects, we will explicitly model the comovements in trading intensities in the next sections. Furthermore, in the next sections we will use this model to estimate the amount of sector-specific information contained in the trading intensity of each stock.

V.3 A review of multivariate duration models

In this section we discuss three models that have been proposed to jointly analyze two or more trading intensities. We start with the model of Engle

[2] Unless stated otherwise, hypotheses will be tested at a 5% significance level.

from stock	to stock DDS	FD	JCP	MAY	SKS
DDS	0.127	0.065	0.060	0.052	0.062
	(0.003)	(0.008)	(0.010)	(0.007)	(0.009)
FD	0.073	0.076	0.082	0.073	0.035
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
JCP	0.103	0.101	0.130	0.100	0.041
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
MAY	0.064	0.077	0.081	0.048	0.023
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
SKS	0.033	−0.002	0.005	0.027	0.149
	(0.008)	(−0.007)	(0.008)	(0.008)	(0.008)

Table V.2: Rank correlations between consecutive durations

The diagonal of this table contains estimates of Spearman's rank autocorrelation in the durations of each individual stock. The corresponding standard errors are between parentheses. The remaining values in this table are estimates of the rank correlation between the $(t-1)$-th duration in stock i and the duration between the $(t-1)$-th transaction in stock i and the next trade in stock j.

and Lunde (1999). Subsequently we discuss Davis et al. (2001) and Russell (1999).

Engle and Lunde (1999) model one marginal ('independent') duration process and the other ('dependent') process conditional on that. They apply the model to the trade (independent) and quote process (dependent). For the current application, the direction of the causality could be motivated, for example by arguing that company A is much larger than company B (or market leader) and will therefore influence B rather than the other way around. In this case information on A would be more relevant for sector-wide information than information on B, since A is market leader. Although the Engle and Lunde (1999) model is appealing, the assumption of a priori determined 'leading' and 'following' stocks seems a drawback for the current application.

The count in bin (Cbin-) model for counts, see Davis et al. (2001), focuses on the number of trades in each stock during equally spaced time intervals of length Δ. These are specified as conditionally Poisson distributed variables. This approach has the advantage that probabilities in terms of the number of events during some time period usually have a closed-form expression, while that would require simulation in the ACD-type model of Engle and Lunde (1999). However, the main drawback is the choice of the time-aggregation level Δ, which is arbitrary.

Engle and Russell (1998) explicitly model the durations between trades in a univariate framework. This is a convenient specification for predicting durations if the purpose is not to model the effect of other events on the duration. In the case of two related stocks, however, we want to allow that transactions of the other process affect the conditional expected duration, since they may contain information relevant for the other process. This is more conveniently modeled by specifying directly the conditional intensity function, following Russell (1999). He focuses on a bivariate transaction process, consisting of two dependent transaction processes, indexed by $i = 1, 2$. Let $\underline{y}_{t-1}$ and $\underline{z}_{t-1}$ denote the history of the pooled durations $(y_t)_t$ and the type of trade variables $(z_t)_t$ up to time τ_{t-1}, respectively. The intensity function of the i-th transaction process, conditional upon the history of the pooled transaction process up to time τ_{t-1}, is defined as

$$\begin{aligned} \lambda_{t-1,i}(s) &= \lambda_i(s \mid \underline{y}_{t-1}, \underline{z}_{t-1}) \\ &= \lim_{\Delta s \to 0} \frac{\mathbb{P}(N_i(\tau_{t-1} + s + \Delta s) > N_i(\tau_{t-1} + s) \mid \underline{y}_{t-1}, \underline{z}_{t-1})}{\Delta s}, \end{aligned} \tag{V.3}$$

for $i = 1, 2$ and $s > 0$. For fixed $s > 0$ and conditional upon the history of the pooled transaction process up to time τ_{t-1}, $\lambda_{t-1,i}(s)\Delta s$ can be interpreted as the (conditional) probability of a transaction of type i during the interval $(\tau_{t-1} + s, \tau_{t-1} + s + \Delta s]$, for $\Delta s \to 0$. Russell (1999) assumes that the conditional intensity function can be specified as a specific time invariant function of past marginal durations of the two processes. In Russell (1999)'s model, the direction of the dependence between the two processes is not determined a priori and all trades in every stock are taken into account. In the bivariate case, for example, the two processes can be the market- and limit-order arrival-processes, which is the framework of Russell (1999). He shows that there is significant Granger-causality between the arrival processes of market orders and limit-orders. The Russell (1999) model can also be used to model the duration dependence among several stocks, which is the context of this chapter. We will show in Section V.4 that the model proposed in this chapter can be interpreted as a more parsimonious reformulation of the Russell (1999) model.

V.4 The probit-pooled ACD-model

In the previous sections we discussed several ways to model the dependence between trading intensities of related stocks. The model of Engle and Lunde (1999) is appealing, but is asymmetric and explains only the dependence between durations of one stock on the consecutive durations in the other stock. The Cbin-model of Davis et al. (2001) requires a choice of a time aggregation interval Δ. The Russell (1999) model seems the most flexible specification to examine the comovements in the trading intensities of stocks in the same industry. However, its specification is less appealing than the univariate ACD-model and estimation and simulation of the model is more demanding. Therefore, we propose a more parsimonious and more appealing specification to model dependent trading intensities.

Russell (1999) specifies the conditional intensity functions corresponding to the marginal transaction processes. Instead of modeling the conditional intensity functions of the marginal processes separately, we directly specify the conditional intensity function of the pooled transaction process, as well as the probability that a trade is in either type of stock. We consider the pooled transaction process $(y_t)_t$ and use a simple univariate duration model of the ACD-type (cf. Engle and Russell (1998)), possibly including explanatory variables. The type of trade variable $(z_t)_t$ is modeled using a probit-specification. We will call the resulting bivariate model the probit-pooled ACD-model.

We first consider the joint conditional density of the pooled durations and the type of trade variables, denoted by

$$f(y_t, z_t \mid \underline{y}_{t-1}, \underline{z}_{t-1}). \tag{V.4}$$

Following Engle (2000), we decompose the joint conditional density in two marginal conditional densities: the conditional density corresponding to the durations $(y_t)_t$ and the conditional density corresponding to the 'marks' $(z_t)_t$ (i.e. the type of trade variables). Thus,

$$f(y_t, z_t \mid \underline{y}_{t-1}, \underline{z}_{t-1}) = g(y_t \mid \underline{y}_{t-1}, \underline{z}_{t-1}) h(z_t \mid \underline{y}_t, \underline{z}_{t-1}). \tag{V.5}$$

Notice that this way of jointly modeling the trading intensities of two stocks is equivalent to the approach of Russell (1999), who specifies the individual conditional intensity functions and their interaction. To see this, we note that the conditional intensity function of the pooled transaction process and the conditional density of the type of trade completely determine the conditional intensity functions of the marginal processes, since

$$\lambda_{t-1,1}(s) = \lambda_{t-1}(s) \mathbb{P}(z_t = 0 \mid \underline{y}_{t-1}, \underline{z}_{t-1}, y_t = s) \tag{V.6}$$

A similar expression is obtained for $\lambda_{t,2}(\cdot)$. Furthermore, specification of the two conditional intensity functions determines the conditional intensity function of the pooled transaction process and the density of the type of trade variable:

$$\lambda_{t-1}(s) = \lambda_{t-1,1}(s) + \lambda_{t-1,2}(s) \tag{V.7}$$

$$\mathbb{P}(z_t = 0 \mid \underline{y}_{t-1}, \underline{z}_{t-1}, y_t = s) = \frac{\lambda_{t-1,1}(s)}{\lambda_{t-1,1}(s) + \lambda_{t-1,2}(s)}.$$

Hence, the probit-pooled ACD-model and the Russell (1999) model are equivalent in a nonparametric sense. Only when assumptions on the functional forms are added, the two models are different and nonnested.
We start with the conditional density corresponding to the marks $(z_t)_t$, the binary variables that indicate whether a transaction is a trade in stock A $(z_t = 0)$ or stock B $(z_t = 1)$. Let $\Phi(\cdot)$ denote the normal distribution function. We assume that

$$p_t = \mathbb{P}(z_t = 0 \mid \underline{y}_t, \underline{z}_{t-1}; \delta) = \Phi(\delta' x_t). \tag{V.8}$$

Here $x_t = x_t(\underline{y}_t, \underline{z}_{t-1})$ represents a vector of regressors − to be specified later − and δ is the corresponding vector of coefficients. We allow p_t to depend upon lagged values of z_t. An issue that we have to consider is the persistence in the type of trade variable z_t. To deal with the persistence effectively, we allow the conditional probability p_t to depend upon lagged values of itself; i.e. we include as potential regressors lagged values of p_t. Furthermore, the type of trade variable z_t may also be affected by how long ago trades in both stocks have taken place. We therefore take

$$\begin{aligned} \delta' x_t &= \delta_1 + \delta_2 z_{t-1} + \delta_3 z_{t-2} + \delta_4 \Phi^{-1}(p_{t-1}) \\ &\quad + (\delta_5 + \delta_6 z_{t-1}) y_t + (\delta_7 + \delta_8 z_{t-2}) y_{t-1}. \end{aligned} \tag{V.9}$$

It will sometimes be convenient to write $p_t = p_t(\underline{z}_{t-1}, \underline{y}_t)$ to emphasize the dependence of p_t upon the past history of the type of trade variable and the durations. The specification given in expression (V.9) is the result of a specification search. We use a Wald-test for omitted variables (more lags) in the probit-model for which there is no significant evidence. Moreover, we use a Lagrange-multiplier (LM) test for heteroskedasticity in the probit-model. We proceed in the line of Harvey (1976) by considering heteroskedasticity of the form $\mathbb{V}\mathrm{ar}\,(\eta_t) = \exp(\xi' \eta_t)$. Here η_t is the disturbance in the unobserved process underlying the probit-model and

$$\eta_t = (z_{t-1}, z_{t-2}, \Phi^{-1}(p_{t-1}), y_t, z_{t-1} y_{t-1}, y_{t-1}, z_{t-2} y_{t-1})'. \tag{V.10}$$

For none of the pairs of stocks the null hypothesis of no heteroskedasticity is rejected.
We now turn to the specification of the conditional density corresponding to the pooled duration process, expressed in terms of the diurnally corrected durations $(y_t)_t$, which are constructed as in Engle and Russell (1998). That is, we obtain the diurnally adjusted durations by approximating the expected duration given the time of the day by a piecewise linear and continuous spline with nodes set on $9.30 - 10.00, 10.00 - 11.00, \ldots, 14.00 - 15.00$, and $15.30 - 16.00$ hours. We compute the diurnally corrected durations by dividing each duration by the diurnal correction factor. We consider a log ACD$(1,1)$-model, see Bauwens and Giot (2000), which is specified as

$$y_t = \psi_t \varepsilon_t, \quad \psi_t = \mathbb{E}(y_t \mid \underline{y}_{t-1}, \underline{z}_{t-1}), \tag{V.11}$$

with $(\varepsilon_t)_t$ identically distributed with unit mean and ε_t independent of $\sigma(\underline{y}_{t-1}, \underline{z}_{t-1})$. The log of the conditional expected duration is given by

$$\log \psi_t = \omega + \alpha \log \varepsilon_{t-1} + \beta \log \psi_{t-1} + \gamma' \nu_{t-1}, \tag{V.12}$$

where ν_{t-1} is a vector of variables related to the past types of trades and γ a vector of parameters. We take

$$\nu_{t-1} = (\Delta z_{t-1}, \log p_{t-1})'. \tag{V.13}$$

The Ljung-Box test for autocorrelation shows that the logarithmic ACD$(1,1)$ specification succeeds in removing most of the autocorrelation out of the ACD-residuals ε_t. The choice of explanatory variables in ν_{t-1} as given in equation (V.12) is the result of a specification search. Initially, we estimated the model with $\nu_{t-1} = (z_{t-1}, z_{t-2}, \log p_{t-1}, \log p_{t-2})'$, allowing for feedback from the two most recent trades (z_{t-1}, z_{t-2}) and the entire history of the type of trade variable captured by $\log p_{t-1}$ and $\log p_{t-2}$. For all pairs of stocks, the null hypothesis that z_{t-1} and z_{t-2} add up to zero could not be rejected. Moreover, $\log p_{t-2}$ turned out insignificant for all pairs of stocks under consideration. In our final specification, we therefore set $\nu_{t-1} = (\Delta z_{t-1}, \log p_{t-1})'$. Since the variable $\Delta z_{t-1} = z_{t-1} - z_{t-2}$ indicates whether or not a change in the type of trade has taken place, it can be interpreted as an indication of 'news' and may therefore affect the pooled trading intensity. The variable $\log p_{t-1}$ represents the log of the conditional probability of a trade in stock A. When, for example, stock A contains much sector-specific news, it may be the 'driving ' process behind the pooled transaction process. In this case, a high conditional probability of a trade in stock A may increase the trading intensity.

Estimation results

For all pairs of stocks, we estimate the probit-model by means of maximum likelihood, using the Berndt, Hall, Hall, and Hausman (1974) algorithm for the numerical optimization. The ACD-part of the model is estimated by means of quasi-maximum likelihood (QML) using the same optimization algorithm, cf. Engle and Russell (1998) and Drost and Werker (2001). The estimation results for the probit-pooled ACD-model are given in Tables V.3, V.4, and V.5.

By analyzing sample correlations we established significant comovements in the trading intensities of the stocks under consideration. We would also like to know whether or not the type of trade variable conveys additional information relative to the history of the pooled transaction process. If this is not the case, then the fact that there has been a trade provides all information that is relevant for both stocks' interarrival times, while the type of trade is 'redundant'. The individual trading intensities of both stocks then only depend upon the history of the pooled transaction process. This is easy to test for in the probit-pooled ACD-model. Note, however, that this hypothesis is inherently difficult to test in the Russell (1999) model. On the other hand, the null hypothesis of independent transaction processes is testable in the Russell (1999) model, but this is not straightforward in the pooled ACD-model.

We start with the ACD-part of the model. The persistence in the ACD-model is high, since the estimated value of β varies between 0.982 and 0.997. We test the hypothesis that the type of trade variable does not affect the conditional expected duration. For all stocks this hypothesis is rejected at any reasonable significance level. For eight out of ten pairs of stocks there is significant impact from Δz_{t-1} to the conditional expected duration. In seven out of ten cases $\log p_{t-1}$ significantly influences ψ_t. We will later turn to the economic significance of the estimated coefficients.

We now turn to the probit-model. The persistence in the type of trade variable z_t is high, since the coefficients of $\Phi^{-1}(p_{t-1})$ are close to one for all stocks; they vary between 0.95 and 0.99. To test whether or not the type of trade variable depends upon the pooled transaction process only, we test the hypothesis

$$H_0 : \delta_i = 0 \quad [i = 2, 3, 6, 8]. \tag{V.14}$$

This null hypothesis is rejected for all stocks at any reasonable significance level, so the type of trade variable depends significantly on both the pooled and the individual transaction processes.

The null hypothesis that the type of trade variable is not informative (for the entire process) is strongly rejected for all pairs of stocks.

		JCP-DDS		MAY-DDS		MAY-JCP		SKS-DDS	
ACD-model									
coefficient	variable	estimate	std. error						
ω	const	−0.0615	0.0029	−0.0440	0.0223	−0.0415	0.0100	−0.0397	0.0008
α	$\log \varepsilon_t$	0.1023	0.0047	0.0831	0.0429	0.0868	0.0147	0.0666	0.0010
β	$\log \psi_{t-1}$	0.9862	0.0006	0.9816	0.0082	0.9856	0.0018	0.9973	0.0001
γ_1	Δz_{t-1}	−0.0386	0.0018	−0.0096	0.0035	0.0378	0.0113	−0.0781	0.0541
γ_2	$\log p_{t-1}$	−0.0049	0.0008	0.0077	0.0053	0.0117	0.0022	−0.0015	0.00031
probit-model									
coefficient	variable	estimate	std. error						
δ_1	const	0.0213	0.0018	0.0210	0.0020	0.0207	0.0020	0.0299	0.0025
δ_2	z_{t-1}	−0.1610	0.0167	−0.2416	0.0172	−0.0564	0.0145	−0.5452	0.0198
δ_3	z_{t-2}	0.1214	0.0169	0.1986	0.0174	0.0048	0.0147	0.4890	0.0200
δ_4	$\Phi^{-1}(p_{t-1})$	0.9839	0.0014	0.9821	0.0017	0.9683	0.0024	0.9797	0.0018
δ_5	y_t	0.0297	0.0065	−0.0097	0.0069	−0.0039	0.0067	−0.0832	0.0086
δ_6	$y_t z_{t-1}$	0.0290	0.0101	0.0671	0.0108	−0.0228	0.0090	0.1842	0.0121
δ_7	y_{t-1}	−0.0319	0.0065	0.0078	0.0069	0.0046	0.0067	0.0746	0.0086
δ_8	$y_{t-1} z_{t-2}$	−0.0258	0.0101	−0.0597	0.0108	0.0284	0.0090	−0.1701	0.0121

Table V.3: Estimation results for the probit-pooled ACD(1, 1)-model

Tables V.3, V.4, and V.5 contain the estimation results for the probit-pooled ACD-model. The pooled ACD-model and the probit-specification are estimated by means of QML and ML-estimation, respectively. The Bollerslev and Wooldridge (1992) robust covariance matrix is used to compute the standard errors in the pooled ACD-model. The pooled ACD-model is specified according to equation (V.12) and the probit-model is defined in expression (V.8).

coefficient	variable	SKS-JCP estimate	std. error	SKS-MAY estimate	std. error	FD-MAY estimate	std. error
ACD-model							
ω	const	−0.0410	0.0013	−0.0349	0.0012	−0.0441	0.0036
α	$\log \varepsilon_t$	0.0700	0.0021	0.0550	0.0018	0.0748	0.0055
β	$\log \psi_{t-1}$	0.9956	0.0002	0.9946	0.0002	0.9878	0.0009
γ_1	Δz_{t-1}	−0.0191	0.0419	−0.0400	0.0121	0.0174	0.0021
γ_2	$\log p_{t-1}$	0.0001	0.0002	−0.0029	0.0003	−0.0016	0.0014
probit-model							
δ_1	const	0.0550	0.0033	0.0297	0.0024	0.0210	0.0021
δ_2	z_{t-1}	−0.3637	0.0178	−0.4121	0.0181	−0.2205	0.0147
δ_3	z_{t-2}	0.2490	0.0184	0.3556	0.0184	0.1816	0.0148
δ_4	$\Phi^{-1}(p_{t-1})$	0.9539	0.0024	0.9785	0.0017	0.9775	0.0026
δ_5	y_t	−0.0584	0.0084	−0.0559	0.0087	−0.0395	0.0065
δ_6	$y_t z_{t-1}$	0.0905	0.0108	0.1109	0.0112	0.0696	0.0090
δ_7	y_{t-1}	0.0469	0.0084	0.0486	0.0087	0.0351	0.0065
δ_8	$y_{t-1} z_{t-2}$	−0.0717	0.0109	−0.1012	0.0112	−0.0630	0.0090

Table V.4: Estimation results for the probit-pooled ACD(1, 1)-model (continued)

		FD-DDS		FD-JCP		FD-SKS	
ACD-model							
coefficient	variable	estimate	std. error				
ω	const	−0.0419	0.0013	−0.0477	0.0016	−0.0348	0.0015
α	$\log x_{t-1}$	0.0776	0.0020	0.0926	0.0029	0.0644	0.0026
β	$\log \psi_{t-1}$	0.9880	0.0002	0.9871	0.0004	0.9920	0.0003
γ_1	Δz_{t-1}	−0.0225	0.0056	0.0535	0.0182	0.0612	0.0176
γ_2	$\log p_{t-1}$	0.0052	0.0004	0.0083	0.0009	0.0054	0.0004
probit-model							
coefficient	variable	estimate	std. error				
δ_1	const	0.0219	0.0020	0.0145	0.0014	0.0316	0.0023
δ_2	z_{t-1}	−0.2942	0.0170	−0.1407	0.0143	−0.4456	0.0181
δ_3	z_{t-2}	0.2507	0.0172	0.1082	0.0144	0.3790	0.0184
δ_4	$\Phi^{-1}(p_{t-1})$	0.9830	0.0017	0.9835	0.0015	0.9767	0.0017
δ_5	y_t	−0.0272	0.0065	−0.0431	0.0064	−0.0686	0.0069
δ_6	$y_t z_{t-1}$	0.0913	0.0104	0.0258	0.0090	0.1246	0.0110
δ_7	y_{t-1}	0.0231	0.0065	0.0435	0.0064	0.0631	0.0069
δ_8	$y_{t-1} z_{t-2}$	−0.0800	0.0104	−0.0237	0.0089	−0.1076	0.0111

Table V.5: Estimation results for the probit-pooled ACD$(1,1)$-model (continued)

Hence, not only the fact that there has been a trade conveys information, also the type of trade is informative.

V.5 Distinguishing stock- and sector-specific news

In this section we analyze to what extent the trading intensity of a stock depends on the past trading activity in the stock itself and the trading activity in the sector as a whole. We first examine the information content of the history of the pooled transaction process in addition to the history of the type of trade. Subsequently, we examine the informativeness of the type of trade in addition to the pooled transaction process.
We estimate the variances

$$\begin{aligned} v_y &= \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1}(\underline{y}_{t-1})), \\ v_z &= \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1}(\underline{z}_{t-1})), \\ v_{yz} &= \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1}(\underline{y}_{t-1}, \underline{z}_{t-1})). \end{aligned} \tag{V.15}$$

The probit-pooled ACD-model is estimated three times to obtain the variances in expression (V.15). The conditional intensity function in v_y is obtained by estimation of the probit-pooled ACD-model with the restriction $\gamma = 0$ imposed on equation (V.12). The conditional intensity function in v_z is obtained by imposing the restrictions $\alpha = \beta = 0$ and $\delta_i = 0$ for $i = 5, \ldots, 8$ on equations (V.8) and (V.12). Finally, the intensity function in v_{yz} is obtained from the unrestricted probit-pooled ACD-model. The variances in expression (V.15) are estimated using the corresponding sample variances of the one-step ahead predictions of the conditional intensity functions. Notice that the ratios $\hat{v}_z/\hat{v}_{yz}$ and $\hat{v}_y/\hat{v}_{yz}$ are R^2-like statistics. Clearly, the explained variance of the conditional intensity function in the probit-pooled ACD-model without any parameter restrictions will in general be larger than the explained variance in the model with restrictions imposed upon the coefficients. However, the ratios $\hat{v}_z/\hat{v}_{yz}$ and $\hat{v}_y/\hat{v}_{yz}$ will indicate to what extent the explained variance increases due to the additional information contained in the durations and type of trade variable, respectively. The values of the ratios are displayed in Table V.6. The lower the ratio, the higher the explained variance and the more informative the newly added information. The results show that the marks add very little new information to the information on the pooled transaction process; i.e. the economic impact of the Granger-causality from the marks to the pooled durations is small. However, the history of the pooled transaction process is very informative in addition to the marks.

pair of stocks	$\hat{v}_y/\hat{v}_{yz}$	$\hat{v}_z/\hat{v}_{yz}$	$\hat{w}_y/\hat{w}_{yz}$	$\hat{w}_z/\hat{w}_{yz}$
DDS-FD	97.0	39.6	0.2	91.1
DDS-JCP	99.1	37.3	7.7	95.2
DDS-MAY	95.6	46.9	6.0	94.4
DDS-SKS	99.2	15.4	0.1	88.9
FD-JCP	98.1	14.8	2.5	93.6
FD-MAY	99.6	48.5	2.5	88.8
FD-SKS	89.8	37.1	25.1	93.7
JCP-MAY	99.3	46.2	51.0	94.6
JCP-SKS	99.3	31.8	1.4	97.6
MAY-SKS	94.5	33.6	27.5	95.5

Table V.6: Variances ratios in the probit-pooled ACD-model

This table reports the variance ratios (in %) as defined in expressions (V.15) and (V.16), which provide an indication of the relevance of the information contained in the pooled duration process (first and third column) and the type of trade variable (second and fourth column).

In a similar way we estimate

$$w_y = \mathbb{V}\text{ar}\left(\hat{p}_t(\underline{y}_t)\right), \;\; w_z = \mathbb{V}\text{ar}\left(\hat{p}_t(\underline{z}_{t-1})\right), \;\; w_{yz} = \mathbb{V}\text{ar}\left(\hat{p}_t(\underline{y}_t, \underline{z}_{t-1})\right), \quad \text{(V.16)}$$

and compute ratios as before. The results in Table V.6 show that the history of the type of trade adds much information to the type of trade process, but that the pooled transaction process hardly contains any additional information.

We explained before that news events may consist of two parts: a stock specific component and a component that applies to sector-specific news. When the trading intensity of stock A has much impact on the intensity of stock B, the trading intensity of stock A contains a lot of sector-specific news that is relevant for stock B.

To estimate the amount of sector- and stock-specific news in the trading intensities of the stocks under consideration, we estimate for each stock the explained variance of the one-step ahead prediction of the conditional intensity function in both the probit-pooled ACD-model and a univariate ACD-model. We obtain the estimated conditional intensity functions in the pooled ACD-model using equation (V.6).

pair of stocks	$\hat{v}_1/\hat{v}_1^p$	$\hat{v}_2/\hat{v}_2^p$
DDS-FD	92.4	90.2
DDS-JCP	85.6	96.9
DDS-MAY	96.4	82.0
DDS-SKS	76.5	87.2
FD-JCP	83.4	95.7
FD-MAY	86.9	83.8
FD-SKS	79.3	86.1
JCP-MAY	92.0	80.7
JCP-SKS	91.1	85.3
MAY-SKS	71.4	87.2

Table V.7: Variance ratios: univariate versus bivariate model

This table reports the ratios of the sample variance (in %) of the conditional intensity functions in the probit-pooled ACD-model and the univariate ACD-model for each pair of stocks, as defined in expression (V.22).

In the probit-pooled ACD-model we get, under the assumption of exponentially distributed disturbances,

$$\lambda_{t-1,1}(s) = \mathbb{P}(z_t = 0 \mid \underline{y}_{t-1}, \underline{z}_{t-1}, y_t = s)/\psi_t, \tag{V.17}$$

and

$$\lambda_{t-1,2}(s) = \lambda_{t-1}(s) - \lambda_{t-1,1}(s). \tag{V.18}$$

Let $\underline{y}_{s-1,i}$ denote the history of the durations of stock i up to time $\tau_{s-1,i}$, $s = 1, 2, \ldots$. In a univariate framework we specify a log ACD$(1,1)$-model, cf. Engle and Russell (1998); i.e.

$$y_{s,i} = \psi_{s,i}\varepsilon_{s,i}, \quad \psi_{s,i} = \mathbb{E}(y_{s,i} \mid \underline{y}_{s-1,i}) \qquad [i = 1, 2]. \tag{V.19}$$

Here $(\varepsilon_{s,i})_s$ is a sequence of identically distributed variables with unit mean, independent of the information known up to time $\tau_{s-1,i}$ and $\varepsilon_{s,1}$ independent of $\varepsilon_{t,2}$ for all s, t. Moreover, $\psi_{s,i}$ is parameterized recursively as

$$\log \psi_{s,i} = \omega^{(i)} + \alpha^{(i)} \log \varepsilon_{s,i} + \beta^{(i)} \log \psi_{s-1,i} \qquad [i = 1, 2]. \tag{V.20}$$

We estimate the univariate ACD-model for each individual stock using QML; the estimation results are available upon request. Note that − assuming exponentially distributed disturbances $(\varepsilon_{s,i})_s$ − the univariate ACD-model yields

$$\lambda_{s-1,i}(s) = \frac{1}{\psi_{s,i}} \qquad [i = 1, 2]. \tag{V.21}$$

We now define

$$v_1 = \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1,1}),\; v_2 = \mathbb{V}\text{ar}\,(\hat{\lambda}_{t-1,2}), \tag{V.22}$$

that is, v_1 and v_1 denote the explained variance of the one-step ahead predictions of the conditional intensity function of respectively stock A and stock B in the univariate ACD-models (where t indexes the pooled transaction process). Similarly, let v_1^p and v_2^p denote these explained variances in the probit-pooled ACD-model. We estimate the variances by means of the sample variances of the one-step ahead predictions of the conditional intensity functions. The ratios $\hat{v}_1/\hat{v}_1^p$ and $\hat{v}_2/\hat{v}_2^p$ are reported in Table V.7. Note again that the ratios $\hat{v}_1/\hat{v}_1^p$ and $\hat{v}_2/\hat{v}_2^p$ are R^2-like statistics. The explained variance of the conditional intensity function in the probit-pooled ACD-model will in general be larger than the explained variance in the univariate ACD-model, since the individual conditional intensity functions obtained the probit-pooled ACD-model are allowed to change when a trade in the other stock occurs. The ratios $\hat{v}_i/\hat{v}_i^p$ will indicate to what extent the explained variance increases due to the additional information contained in the transactions of the other stock. Consider, for example, the results for the pair Federated and Saks. Table V.7 shows that for Federated the explained variance of the conditional intensity function in the pooled ACD-model is 79.3% of the explained variance in the univariate ACD-model. This means that the trading intensity of Saks contains much sector-wide information that is relevant for Federated. Conversely, for Saks the explained variance of the conditional intensity function in the pooled ACD-model is 86.1% of the explained variance in the univariate ACD-model. This means that the trading intensity of Federated contains also quite some sector-wide information that is relevant for Saks.

Furthermore, from Table V.7 it follows J.C. Penney contains more sector-wide information than any other stock, which is in line with the correlations in Table V.2. Therefore, it can be viewed as the most informative stock with respect to sector-wide information. Similarly, Federated contains more sector-wide information than all other stocks except J.C. Penney. When we rank the remaining stocks based upon the number of stocks they outperform with respect to the amount of sector-specific news contained in the trading intensity as given in Table V.7, we obtain the ranking Saks (outperforms three other stocks), Dillard's (two), Federated (one), and finally May (zero)

follow. Hence, the least informative stock is May; i.e. all other stocks have more sector-specific news contained in the trading intensity.
Note that the most informative stocks, J.C. Penney, is also the most frequently traded stock. In fact, the ranking based upon Table V.7 (J.C. Penney, Saks, Dillard's, Federated, and May) assigns J.C. Penney as the stock that contains most sector-specific news, which is in line with the ranking based upon the number of transactions (J.C. Penney, Federated, May, Dillard's, and Saks). Clearly, when a stock is traded more often, there are more opportunities to convey information to other stocks.
We now return to the ranking obtained in Section V.2, based upon the cross-correlations reported in Table V.2. Note that, according to this ranking, the trading intensity of J.C. Penney is most important, followed by Federated and May, and finally by Dillard's and Saks. Hence, this ranking also sets J.C. Penney on top. However, it is not able to distinguish between Federated and May (shared second position) and Dillard's and Saks.
Although we refer to 'sector-specific news' as the source of the comovements found in the trading intensities of the stocks under consideration, these comovements could also be caused by market-wide news. To distinguish sector-specific news from market-wide news, we could model the trading intensities of stocks in different types of industry. When we would still find comovements in the trading intensities, this would indicate the existence of market-wide news. Conversely, when there would be no comovements in the trading intensities of these stocks, only sector-specific news would cause comovements in trading intensities. Further distinction of sector-specific and market-wide news seems an important topic for further research.
Finally, we notice that the established comovements in the trading intensities of US department stock operators shed a new light on the results of Huberman and Halka (1999), Chordia et al. (2000b), and Hasbrouck and Seppi (2001). Since the trading intensity is a proxy for liquidity, our results provide evidence for commonalities in the liquidity of stocks in the same type of industry. This result is in line with the findings of Chordia et al. (2000b) and Huberman and Halka (1999), who find significant cross-stock commonalities in liquidity.

V.6 The economic relevance of comovements in trading intensities

To gain more insight in the dynamics of the duration process, we perform a simulation of the pooled ACD-model discussed in the previous section.

scenario 1: 'few trades in the other stock'	time (mm:ss)
bivariate model	
exp. duration A	00:49
exp. duration B	01:29
exp. duration to 10 trades A	08:25
exp. duration to 10 trades B	14:55
scenario 2: 'many trades in the other stock'	
bivariate model	
exp. duration A	01:09
exp. duration B	03:40
exp. duration to 10 trades A	12:12
exp. duration to 10 trades B	33:37
univariate model	
exp. duration A	01:00
exp. duration B	02:30
exp. duration to 10 trades A	09:54
exp. duration to 10 trades B	24:24

Table V.8: Expected durations: bivariate versus univariate modeling

This table displays the results of a simulation (with $N = 10,000$ runs) and reports the expected duration (mm:ss) to the next trade and the expected time it takes before ten trades in the specific stock have taken place. The stocks under consideration are J.C. Penney (stock A) and Dillard's (stock B).

We compare the simulation results of the bivariate model to the results of the univariate ACD-model. In the univariate model the history of the other process is not taken into account. Therefore, comparison of the results to those of the bivariate model provides another indication of the information content of the trading intensity of the other process.
Given a certain history of two transaction processes, we focus on the expected duration to the first trade in each stock and the expected time it takes until each stock has been traded ten times. We vary the history of the transaction process to assess the effect of different scenarios on the expected durations. The history of the two processes consists of three parts: the durations to the two most recent trades, the nature of the two most recent trades (i.e. stock A or stock B) and the most recent value of the conditional probability of a trade in stock A.
Technically speaking, for each pair of stocks we simulate the binary process $(z_t)_t$ jointly with the durations of the pooled transaction process $(y_t)_t$. For each path of durations and type of trade variables, we compute the time to the first trade in each stock and the time it takes before ten trades in stock A and stock B have taken place. We do this $N = 10,000$ times and estimate the expected durations by taking the corresponding averages of the durations over all simulation runs. We simulate the durations by randomly drawing from the empirical distribution of the ACD-residuals. Moreover, we obtain confidence intervals for the calculated statistics by means of a parametric bootstrap from the joint asymptotic distribution of the model parameters.
We consider a pair of stocks, which we again refer to as stocks A and B. We consider the expected duration to a trade in stock A under two different scenarios: one of only few trades in stock B and one with many trades in stock B. From the path of trades in stock A we compute the variables needed to initialize the univariate ACD-model. From the paths of pooled transactions we compute the variables required for the initialization of the probit-pooled ACD-model. We do the same for stock B, in which case we focus on the scenarios that many or few trades in stock A have taken place. Thus, we are able to assess the effect of trades in one stock on trades in the other stock and, moreover, we are able to see the difference between the bivariate probit-pooled ACD-model and the univariate ACD-model.
We consider the stocks J.C. Penney (stock A) and Dillard's (stock B) for which we concluded in the previous section that the impact of J.C. Penney on Dillard's is quite large and that the trading intensity of Dillard's contains a small amount of sector-specific information that is relevant for J.C. Penney. Table V.8 reports the expected time to the first transaction in each stock as well as the expected time it takes before each stock has been traded ten times, obtained by a simulation of $N = 10,000$ runs. These expected durations are

estimated in both the probit-pooled ACD-model under the above mentioned scenarios and in the univariate ACD-model.
We first consider the simulation results for J.C. Penney. In a period with few trades in Dillard's the expected duration to the first trade in J.C. Penney equals 49 seconds, see the 'expected duration A' in the upper part of Table V.8 that has the caption 'few trades in the other stock'. With many trades in the other stock it equals 1 minute and 9 seconds, which is significantly larger. In the univariate ACD-model the expected duration equals 1 minute. Hence, in the univariate model, which ignores the history of the other stock, the expected duration falls between the expected durations with few trades in Dillard's and many trades in Dillard's as obtained in the bivariate model. With few trades in J.C. Penney the expected duration to a trade in Dillard's equals 1 minute and 29 seconds, while it equals 3 minutes and 40 seconds when J.C. Penney is traded often. For the expected time it takes until each stock is traded ten times, we find similar results. Again the expected duration in the univariate ACD-model falls between the expected durations in the probit-pooled ACD-model with many and few trades in the other stock. The results also show that J.C. Penney is much less affected by Dillard's than the other way around. This asymmetry is consistent with the results in Table V.7. For the other pairs of stock we obtain similar results.

V.7 Extensions

In this section we discuss several extensions of the model presented in this chapter.
The probit-pooled ACD-model can be extended with the inclusion of explanatory variables such as returns on the mid quote, bid-ask spread and trade volume in equation (V.12). The idea is that stock- and sector-specific news is related to several trade characteristics such as trading volume, volatility, trade sign, and bid-ask spread; see for instance Hasbrouck (1991a), Easley, Kiefer, and O'Hara (1997), and Gourieroux, Jasiak, and Le Fol (1999), and Roll (1984). One way to do this is to allow for feedback from the trade characteristics to the trading intensity in which case ν_{t-1} in expression (V.12) would be a vector of explanatory variables, including variables related to the trade characteristics. With a similar motivation explanatory variables can be included in the probit-model. Although several trade characteristics (lagged bid-ask spread and unsigned trade volume) turn out significant in the ACD-part of the model applied to the stocks under consideration, the economic impact of the trade characteristics appears to be small in the sense that the expected durations as simulated in previous section are hardly af-

fected by the additional feedback. This is consistent with the evidence found in Spierdijk (2002). Further research could focus on alternative ways to allow news to depend upon variables such as trading volume, volatility, and bid-ask spreads.
Another extension is the multivariate analogue of the bivariate model considered in this chapter. Instead of considering pairs of stocks, the focus could be on $K > 2$ stocks. This would provide a different way of measuring the amount of sector and stock specific information contained in the trading intensity of each stock. Moreover, in this way it becomes possible to see whether there are any stocks that provide sector-specific information when modeled jointly with a single other stock, but are redundant when other stocks are added. In our case, we could take all five stocks of US department-store operators into account. The model would then consist of a duration model of the ACD-type for the pooled durations and, for example, a multinomial logit-model to model the conditional probability of a trade in each type of stock.
Moreover, in line with Engle and Lunde (1999), Russell (1999), and Davis et al. (2001) the pooled ACD-model can be applied to trade and quote data instead of transactions data on different stocks to investigate how information contained in the quote intensity affects the intensity of trades and vice versa. Similarly, the model can be applied to model possible comovements between the same stocks traded on different markets.

V.8 Conclusions

In this chapter we proposed a probit-pooled ACD-model to capture the comovements in the trading intensities of related stocks, consisting of a duration model for trades in the same industry and a probit-model for the type of stock in the industry that is traded. We applied the probit-pooled ACD-model to a sample of five stocks of large US department-store operators, listed on the NYSE during the months August-October 1999.
We established strong comovements in the trading intensities of all stocks under consideration. We made a distinction between idiosyncratic stock-specific news that applies to one stock only and sector-specific news that is potentially relevant for stocks in the same type of industry. We provided estimates of the amounts of stock- and sector-specific news contained in the trading intensities and showed that all stocks under consideration convey both stock- and sector-specific news.
We compared the outcomes of the probit-pooled ACD-model to those of the univariate ACD-model that is often used in the literature to model durations. We showed that the modeling of the comovements in the trading intensities

helps to make the predictions of the durations more accurate.
Finally, we put forward that the analysis of cross-stock comovements in trading intensities is closely related to the issue of liquidity commonalities across stocks. Since the trading intensity can be seen as a proxy for liquidity, the comovements in the trading intensities of US department-store operators provide new evidence for commonalities in liquidity. As pointed out by Chordia (2000b) et al., commonalities in liquidity may have practical implications for traders and investors; see also Chordia et al. (2000a). For example, transaction costs may be better controlled for by a careful timing of trades. The results of our analysis, in turn, suggest that the time management of trades may be a complicated issues because of the cross-stock comovements in trading intensities.

CHAPTER VI

Summary, Conclusions, and Further Research

VI.1 Summary and conclusions

This thesis contains empirical research on market microstructure theory and covers two closely related topics: the information content of large trades and the information revealed by the trading intensity of stocks listed on the New York Stock Exchange. It builds on the work of Hasbrouck (1991a, 1991b), Engle and Russell (1998), Dufour and Engle (2000), among others.

In Chapter II we investigated the distribution of the persistent price impact of trades and its relation to the trading intensity for a sample of frequently traded stocks listed on the New York Stock Exchange (NYSE). We combined a vector autoregressive (VAR-) model for returns and trading volume with an autoregressive conditional duration (ACD-) model for the trading intensity. We made some assumptions on the distribution of the disturbances in the VAR-model as well as in the ACD-model, which allowed us to derive the entire distribution of the price impact and its relation to the trading intensity. We showed that the distribution of the persistent (absolute) price change with fast trading first-order stochastically dominates the distribution of the persistent (absolute) price change with slow trading, which means that trades are more informative in periods of frequent trading. Furthermore, we established significant feedback from the trade characteristics to the trading intensity. Large returns slow down trading, while large trades increase the speed of trading. However, we showed that this feedback has little impact on the distribution of the price impact of trades.

In Chapter III we examined the temporary and permanent price effects of trades in infrequently traded stocks for a sample of ten infrequently traded stocks listed on the NYSE, for which we adopted a similar approach as in

Chapter II. We established the phenomenon of overshooting: after a trade in an infrequently traded stock, the price of the stock temporarily exceeds the full information price before it mean-reverts to this level. We showed that the overshooting effect depends crucially upon the bid-ask spread and the trading intensity. For frequently traded stocks, however, the price converges directly to the full information price and does not exceed this level. We provided several explanations for the overshooting effect, such as imbalances in the limit-order book, inventory effects, asymmetric information, and the monopoly position of the market maker. We also showed that trades in infrequently traded securities have higher permanent price impact than trades in frequently traded stocks, which can be explained by the increased risk of informed trading that is associated with infrequently traded stocks (see Easley, Kiefer, O'Hara, and Paperman (1996)). Moreover, we found that both the transitory and permanent price effects of trades in infrequently traded stocks depend 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. Although the latter result was also established for frequently traded stocks, the dependence on the trading intensity and the bid-ask spread is much stronger for infrequently traded stocks than for infrequently traded stocks. Furthermore, we found that the overnight durations are significant for both frequently and infrequently traded stocks in explaining the trading intensity. We showed that its impact on the convergence to the full information price is economically negligible for frequently traded stocks, while the economic effect is large for the infrequently traded stocks. Finally, we found that the convergence to the new efficient price that follows a trade in an infrequently traded stock may take several days.

In Chapter IV we investigated the relation between price impact and trading volume for a sample of infrequently traded stocks listed on the NYSE. Unlike the analysis in Chapters II and III, we assumed in this chapter that the durations between consecutive trades have no information content. Rather than using a parametric model that imposes strong proportionality and symmetry restrictions on the price-order flow relation, we applied the more flexible semiparametric partially linear model of Engle, Granger, Rice, and Weiss (1986) and Robinson (1988a, 1988b) to derive the exact relation between prices and volume. We established significant evidence for a nonlinear, asymmetric, increasing, and concave relation between trading volume and both temporary and persistent price impact. Moreover, we compared the relation between price impact and order size obtained in the partially linear model to the price-order flow relation generated by some commonly used parametric VAR-models and showed that there are considerable differences. In contrast to the partially linear model, the parametric models do not capture the nonlinearities in the price-order flow relation. We used the approach of Whang and Andrews (1993) to test the semiparametric specification and rejected the parametric models in favor of the partially linear model. We also tested the partially linear model against a more flexible fully nonparametric specification, but this test did not reject the partially linear model for the stocks under consideration.

In Chapter V we investigated the comovements in the trading intensities of stocks in the same industry. We proposed a probit-pooled ACD-model, consisting of a duration model for trades in the same industry and a probit-model for the type of stock in the industry that is traded. We applied the probit-pooled ACD-model pair-wise to the trading intensities of the stocks of five large US department-store operators listed on the NYSE. We established strong comovements in the trading intensities of all stocks under consideration, which we explained by distinguishing stock-specific news that applies to one stock only and sector-specific news that is potentially relevant for stocks in the same type of industry. We provided estimates of the amounts of stock- and sector-specific news contained in the trading intensities and showed that all stocks under consideration convey both stock- and sector-specific news. Moreover, we showed that modeling the comovements in trading intensities helps to make predictions of the durations more accurate.

VI.2 Further research

There are several directions for future research. Besides the high-frequency data used in this thesis, the NYSE distributes additional high-frequency data on the limit-order book. These data provides various opportunities to capture the dynamics of the incoming and outgoing order flow; see e.g. Kavajecz and Odders-White (2001) and Hasbrouck and Saar (2002). With respect to infrequently traded stocks, knowledge on the state of the limit-order book may shed new light on the phenomenon of overshooting. Moreover, the limit-order book can be used to determine the type of each trade − market or limit-order. This adds an additional dimension to the problem of optimal trading, since the type of trade can then be modeled as a decision variable. More opportunities for further research are provided by fully electronic markets, such as electronic communications networks. These virtual markets provide a vast amount of high-frequency data that can be used to compare these new markets to conventional national exchanges and decentralized dealer markets to assess the impact of different trading protocols and market designs on, for instance, the price effects of trades, market liquidity, and market efficiency.

Nederlandse Samenvatting (Summary in Dutch)

De financiële markten hebben de afgelopen jaren grote veranderingen doorgemaakt. Een van de oorzaken van deze veranderingen is de opkomst van computertechnologie en internet, waardoor het mogelijk is om marktpartijen overal ter wereld met elkaar te verbinden en markten te creëren. Dit heeft niet alleen geleid tot ruimere toegankelijkheid van bestaande markten, maar het heeft ook nieuwe markten doen ontstaan zoals bijvoorbeeld virtuele aandelenmarkten. Deze markten staan bekend als elektronische communicatie netwerken. Tegelijkertijd heeft de ontwikkeling van computertechnologie het verzamelen van gedetailleerde financiële data mogelijk gemaakt. Deze data, ook wel 'tick-by-tick' of 'high-frequency' data genoemd, bevatten informatie over alle transacties die in een bepaalde periode hebben plaatsgevonden. Ze zijn derhalve bij uitstek geschikt om te analyseren hoe de marktstructuur het transactieproces beïnvloedt.
Het vakgebied dat zich bezig houdt met onderzoek naar de invloed van de marktstructuur op het transactieproces, wordt aangeduid met de Engelse terminologie 'market microstructure' analyse. Dit vakgebied houdt zich onder andere bezig met het vergelijken van verschillende marktstructuren en transactiemechanismen en hun effect op het transactieproces, alsmede met het vergelijken van het transactieproces van verschillende soorten aandelen (bijvoorbeeld frequent en minder frequent verhandelde aandelen).
Informatie speelt een belangrijk rol in market microstructure analyse. In efficiënte markten wordt nieuwe informatie onmiddellijk in de prijzen van aandelen verwerkt. Bij informatie denken we meestal aan gebeurtenissen van buitenaf, zoals bijvoorbeeld winstwaarschuwingen en renteveranderingen. Echter, (grote) transacties zelf bevatten ook informatie en zijn dus 'news-events'. De gedachte hierachter is dat er tussen de gewone beleggers ook marktdeelnemers actief zijn die over 'inside-informatie' beschikken. Zij kopen en verkopen aandelen op een strategische manier om van hun extra informatie te profiteren. Door de aanwezigheid van beleggers met inside-informatie is er een kleine

kans dat een transactie geïnitieerd is door een geïnformeerde belegger. Als er op een bepaald moment een grote hoeveelheid aandelen gekocht wordt, kan dat dus betekenen dat er een belegger is die over (positieve) inside-informatie beschikt en daarom die aandelen wil kopen. Bij het constateren van een dergelijke transactie, zullen andere marktpartijen hun verwachtingen derhalve naar boven aanpassen. Dit leidt dan tot verandering van de aandelenkoersen. Wat betreft prijsveranderingen kunnen we onderscheid maken tussen tijdelijke en blijvende (persistente) prijseffecten. Tijdelijke prijseffecten worden bijvoorbeeld veroorzaakt door voorraadeffecten en onevenwichtigheden in vraag en aanbod. Blijvende prijsveranderingen worden direct geassocieerd met de informatie die bevat is in een transactie.
Echter, niet alleen prijzen veranderen als gevolg van vrijgekomen informatie. Ook de snelheid waarmee transacties plaatsvinden − de transactie-intensiteit − kan worden beïnvloed door informatie. Als er zojuist een news-event heeft plaatsgevonden, zullen geïnformeerde beleggers daar snel op willen reageren, wat de transactie-intensiteit zal beïnvloeden.
Dit proefschrift gaat dieper in op bovenstaande, nauw gerelateerde onderwerpen: de informatie die bevat is in aandelentransacties en de informatie die vervat is in de transactie-intensiteit. We maken hierbij gebruik van door de New York Stock Exchange (NYSE) verstrekte high-frequency data. Deze data bevatten gedetailleerde informatie over alle transacties die in een bepaalde periode hebben plaatsgevonden, voor alle aan de NYSE genoteerde fondsen.
In Hoofdstuk II modelleren we de relatie tussen prijzen, transactie-omvang en transactie-intensiteit voor frequent verhandelde aandelen genoteerd aan de NYSE. Met behulp van dit model bepalen we de relatie tussen het (blijvend) prijseffect van grote transacties en de transactie-intensiteit. We laten zien dat het effect van transacties op de prijs sterk afhangt van de transactie-intensiteit: als er veel aandelen verhandeld worden − en de transactie-intensiteit dus hoog is − hebben transacties een groter effect op de prijs dan in periodes met weinig transacties. Dit betekent dat transacties meer informatie bevatten in periodes waarin veel gehandeld wordt. Tevens onderzoeken we in dit hoofdstuk of transactiekenmerken significante invloed hebben op de transactie-intensiteit. We vinden we dat dit inderdaad het geval is: grote prijsveranderingen leiden tot een verlaging van de transactie-intensiteit en grote transacties leiden tot een verhoging van de transactie-intensiteit. Echter, we laten zien dat het geschatte prijseffect van transacties in het model met invloed van transactiekenmerken op de transactie-activiteit vrijwel hetzelfde is als in het model waarin deze invloed niet is opgenomen, wat betekent dat het economisch belang van deze feedback gering is.
In Hoofdstuk III volgen we een soortgelijke aanpak ter bepaling van het prijs-

effect van transacties in minder frequent verhandelde aandelen genoteerd aan de NYSE. In dit hoofdstuk bepalen we niet alleen de persistente prijseffecten (die direct zijn gerelateerd aan de informatie die bevat is in een transactie), maar onderzoeken we ook de tijdelijke prijseffecten. We laten zien dat de minder frequent verhandelde aandelen meer tijdelijke prijseffecten vertonen dan frequent verhandelde aandelen. In het bijzonder laten we zien dat de prijs van minder frequent verhandelde aandelen het fenomeen 'overshooting' vertoont: na een (koop-) transactie komt de prijs tijdelijk boven de evenwichtsprijs uit, waarna de prijs uiteindelijk het evenwichtsniveau bereikt. We stellen vast dat de mate van overshooting sterk afhangt van de bid-ask spread and de transactie-intensiteit. Bij frequent verhandelde aandelen bereikt de prijs het evenwichtsniveau zonder deze eerst te overschrijden. We verklaren het optreden van overshooting door te wijzen op voorraadeffecten, aanpassingen in het orderboek (de verzameling van alle transacties die nog moeten worden uitgevoerd), asymmetrische informatie tussen marktpartijen en de monopoliepositie van de market maker. Tevens laten we zien dat het persistente prijseffect van transacties in minder frequent verhandelde aandelen veel groter is dan het prijseffect van transacties in meer liquide aandelen. We verklaren dit door erop te wijzen dat informatie een grotere rol speelt bij minder liquide aandelen dan bij de frequenter verhandelde aandelen. Tevens laten we zien dat zowel het tijdelijke als permanente effect van een transactie op de prijs sterk afhangen van de bid-ask spread en transactie-intensiteit: hoe hoger de bid-ask spread and transactie-intensiteit, hoe groter het prijseffect. Deze afhankelijkheid is veel sterker dan voor frequent verhandelde aandelen.
Hoofdstuk IV is wederom gewijd aan het effect van transacties op de aandelenprijs van minder frequent verhandelde aandelen. In dit hoofdstuk staat de relatie tussen prijseffect en transactie-omvang centraal. In tegenstelling tot de vorige hoofdstukken gebruiken we in dit hoofdstuk geen parametrische modellen die sterke aannames maken over hoe de transactie-omvang de aandelenprijzen beïnvloedt, maar passen we een flexibelere, semi-parametrische benadering toe door gebruik te maken van een semi-lineaire specificatie. We vinden een positieve, niet-lineaire, asymmetrische en concave relatie tussen volume en prijzen. We vergelijken de prijs-volume relatie verkregen in het semi-lineaire model met prijs-volume relatie volgens een aantal vaak gebruikte parametrische modellen en laten zien dat er grote verschillen zijn. In tegenstelling tot het semi-parametrische model, zijn de parametrische modellen niet goed in staat de niet-lineaire prijs-volume relatie weer te geven. We maken dit formeel met een aantal toetsen, waarmee we laten zien dat de parametrische modellen worden verworpen ten gunste van het semi-parametrische, semi-lineaire model. Tevens tonen we aan dat het semi-lineaire model flexibel genoeg is om de relatie tussen volume en prijzen te modelleren, omdat

het semi-parametrische model niet verworpen wordt ten gunste van een nog flexibeler, volledig niet-parametrisch model.
In Hoofdstuk V staat de relatie tussen de transactie-intensiteiten van verschillende aandelen in dezelfde bedrijfssector centraal. We introduceren een nieuw model om deze spill-over effecten te bepalen en laten zien dat er significante spill-over effecten zijn tussen de transactie-intensiteiten van aandelen van Amerikaanse warenhuizen. We verklaren deze effecten door onderscheid te maken tussen aandeel-specifiek nieuws dat alleen relevant is voor één bepaald aandeel en sector-specifiek nieuws dat belangrijk is voor alle aandelen in dezelfde bedrijfssector. We geven schattingen van de hoeveelheden van deze twee soorten nieuws die bevat zijn in de transactie-intensiteiten van de verschillende aandelen. Tot slot laten we zien dat het in acht nemen van spill-over effecten bijdraagt aan de nauwkeurigheid van de voorspelde transactie-intensiteiten.
Het proefschrift sluit af met enkele aanbevelingen voor toekomstig onderzoek. Sinds enige tijd verstrekt de NYSE naast de reguliere high-frequency data (zoals gebruikt in dit proefschrift) ook gegevens over over het orderboek. Deze data bieden de mogelijkheid om meer inzicht te verkrijgen in de binnenkomende en uitgaande stroom van transacties. Kennis omtrent het orderboek geeft daarnaast een extra dimensie aan het probleem van optimale transactiestrategiëen, omdat het type transactie (marktorder of limietorder) dan als beslissingsvariabele kan worden gemodelleerd. Daarnaast kan de stand van het orderboek meer inzicht geven in het in dit proefschrift gevonden fenomeen van overshooting, dat optreedt na transacties in minder frequent verhandelde aandelen. Tevens zou toekomstig onderzoek zich kunnen richten op de mede door de ontwikkelingen binnen de computertechnologie tot stand gekomen elektronische communicatie netwerken. Hierbij zou kunnen worden onderzocht in welk opzicht deze virtuele markten verschillen van conventionele aandelenmarkten, bijvoorbeeld wat betreft het prijseffect van transacties, marktliquiditeit en marktefficiëntie.

Bibliography

Admati, A. R. and Pfleiderer, P., 1988, A Theory of Intraday Patterns: Volume and Price Variability, *The Review of Financial Studies*, 1, pp. 3-40.

Barclay, M.J. and Warner, J.B., 1993, Stealth Trading and Volatility. Which Trades Move Prices?, *Journal of Financial Economics*, 34, pp. 281-305.

Bauwens, L. and Giot, P., 2000, The Logarithmic ACD-Model: An Application to the Bid-Ask Quote Process of three NYSE-Stocks, *Annales d'Economie et de Statistique*, 60, pp. 117-150.

Berndt, E.R., Hall, B.H., Hall, R.E., and Hausman, J.A., 1974, Estimation and Inference in Nonlinear Structural Models, *Annals of Economic and Social Measurement*, 3, pp. 653-665.

Bierens, H.J., 1987, Kernel Estimators of Regression Functions, in T. F. Bewley (ed.), *Advances in Econometrics: Fifth World Congress*, Cambridge University Press.

Bollerslev, T., 1986, Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 31, pp. 307-327.

Bollerslev, T. and Wooldridge, J.M., 1992, Quasi Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances, *Econometric Reviews*, 11, pp. 143-172.

Breusch, T.S. and Pagan, A.R., 1979, A Simple Test for Heteroskedasticity of Residual Security Returns, *Journal of Business and Economic Statistics*, 1, pp. 163-168.

Chakravarty, S., 2001, Stealth Trading: Which Traders' Trades Move Stock

Prices?, *Journal of Financial Economics*, 61, pp. 289-307.

Chan, L.K.C. and Lakonishok, J., 1993, Institutional Trades and Intraday Stock Price Behavior, *Journal of Financial Economics*, 33, pp. 173-199.

Chordia, T., Roll, R., and Subrahmanyam, A., 2000a, Co-Movements in Bid-Ask Spreads and Market Depth, *Financial Analysts Journal*, 56, pp. 23-27.

Chordia, T., Roll, R., and Subrahmanyam, A., 2000b, Commonality in Liquidity, *Journal of Financial Economics*, 56, pp. 3-28.

Dann, L., Mayers, D., and Raab, R.J., 1977, Trading Rules, Large Blocks, and the Speed of Price Adjustment, *Journal of Financial Economics*, 4, pp. 3-22.

Davis, R.A., Rydberg, T.H., Shephard, N., and Street, S.B., 2001, The Cbin Model for Counts: Testing for Common Features in the Speed of Treading, Quote Changes, Limit and Market Order Arrivals, unpublished working paper, Nuffield College.

De Jong, F., Nijman, Th.E., and Röell, A., 1995, A Comparison of the Cost of Trading French Shares on the Paris Bourse and on SEAQ International, *European Economic Review*, 39, pp. 1277-1301.

De Jong, F., Nijman, Th.E., and Röell, A., 1996, Price Effects of Trading and Components of the Bid-Ask Spread on the Paris Bourse, *Journal of Empirical Finance*, 3, pp. 193-213.

Delgado, M.A. and Mora, J., 1995, Nonparametric and Semiparametric Estimation with Discrete Regressors, *Econometrica*, 63, pp. 1477-1484.

Diamond, D.W. and Verrecchia, R.E., 1987, Constraints on Short-Selling and Asset Price Adjustments to Private Information, *Journal of Financial Economics*, 18, pp. 277-311.

Domowitz, I. and Wang, J., 1994, Auctions as Algorithms. Computerized Trade Execution and Price Discovery, *Journal of Economic Dynamics and Control*, 18, pp. 29-60.

Dridi, R. and Germain, L., 2000, Bullish-Bearish Strategies of Trading: A Nonlinear Equilibrium, unpublished working paper, École Supérieure de Toulouse.

Drost, F.C. and Werker, B.J.M., 2001, Semiparametric Duration Models, Discussion Paper Tilburg University and CentER nr. 2001-11, forthcoming *Journal of Business and Economic Statistics*.

Dufour, A. and Engle, R.F., 2000, Time and the Impact of a Trade, *Journal of Finance*, 55, pp. 2467-2498.

Easley, D. and O'Hara, M., 1987, Price, Size and the Information in Security Markets, *Journal of Financial Economics*, 16, pp. 69-90.

Easley D. and O'Hara, M., 1992, Time and the Process of Security Price Adjustment, *Journal of Finance*, 47, pp. 577-605.

Easley D., Kiefer, N.M., and O'Hara, M., 1997, One Day in the Life of a Very Common Stock, *Review of Financial Studies*, 10, pp. 805-836.

Easley, D., Kiefer, N.M., O'Hara, M., and Paperman, J.B., 1996, Liquidity, Information and Infrequently Traded Stocks, *Journal of Finance*, 51, pp. 1405-1437.

Engle, R.F., 1982, Autoregressive Conditional Heteroskedasticity With Estimates of the Variance of U.K. Inflation, *Econometrica*, 50, pp. 987-1008.

Engle, R. F., Granger, C.W.J., Rice, J., and Weiss, A., 1986, Semiparametric Estimates of the Relation between Weather and Electricity Sales, *Journal of the American Statistical Association*, 81, pp. 310-320.

Engle, R.F., Hendry, D.F., and Richard, J.F., 1983, Exogeneity, *Econometrica*, 51, pp. 277-304.

Engle, R.F. and Lunde, 1998, Trades and Quotes: a Bivariate Point Process, unpublished working paper, University of California San Diego.

Engle, R. F. and Patton, A.J., 2001, Impact of Trades in an Error-Correction Model of Quote Prices, forthcoming *Journal of Financial Markets*.

Engle, R.F. and Russell, J., 1998, Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction data, *Econometrica*, 66, pp. 1127-1162.

Foster, F. D. and Viswanathan, S., 1990, A Theory of the Intraday Variations in Volume, Return Volatility and Trading Costs: Evidence in Recent Price Information Models, *Journal of Finance*, 48, pp. 187-211.

Glosten, L. and Harris, L., 1988, Estimating the Components of the Bid-Ask Spread, *Journal of Financial Economics*, 21, pp. 123-142.

Goodhart, C.A.E. and O'Hara, M., 1997, High Frequency Data in Financial Markets: Issues and Applications, *Journal of Empirical Finance*, 4, pp. 73-114.

Gouriéroux, C., Jasiak, J., and Le Fol, G., 1999, Intra-day Market Activity, *Journal of Financial Markets*, 2, pp. 193-226.

Goutte, C. and Larsen J., 2000, Adaptive Metric Kernel Regression, *Journal of VLSI Signal Processing Systems*, 26, pp. 155-167.

Harris, L.E., 1990, *Liquidity, Trading Rules, and Electronic Trading Systems*, Monograph Series in Finance and Economics nr. 1990-4, New York University Salomon Center.

Harvey, A., 1976, Estimating Regression Models with Multiplicative Heteroskedasticity, *Econometrica*, 44, pp. 461-465.

Hasbrouck, J., 1991a, Measuring the Information Content of Stock Trades, *Journal of Finance*, 66, pp. 179-207.

Hasbrouck, J., 1991b, The Summary Informativeness of Stock Trades: an Econometric Analysis, *Review of Financial Studies*, 4, pp. 571-595.

Hasbrouck, J. and Saar, G., 2002, Limit Orders and Volatility in a Hybrid Market: The Island ECN, unpublished working paper, New York University Stern School of Business.

Hasbrouck, J. and Seppi D.J., 2001, Common Factors in Prices, Order Flows and Liquidity, *Journal of Financial Economics*, 59, pp. 383-411.

Hausman, J.A., Lo, A.W., and McKinlay, A.C., 1992, An Ordered Probit Analysis of Transaction Stock Prices, *Journal of Financial Economics*, 31, pp. 319-379.

Ho, T.S.Y. and Stoll, H., 1981, Optimal Dealer Pricing under Transactions and Return Uncertainty, *Journal of Financial Economics*, 9, pp. 47-73.

Huberman, G. and Halka, D., 1999, Systematic Liquidity, Working Paper Columbia Business School nr. PW-99-09.

Huberman, G. and Stanzl, W., 2001, Quasi Arbitrage and Price Manipulation, unpublished working paper, Yale School of Management/Columbia Business School.

Karpoff, J.M., 1988, Costly Short Sales and the Correlation of Returns with Volume, *Journal of Financial Research*, 11, pp. 173-188.

Kavajecz, K.A. and Odders-White, E.R., 2001, An Examination of Changes in Specialists' Posted Price Schedules, *The Review of Financial Studies*, 14, pp. 681-704.

Keim D.B. and Madhavan, A., 1996, The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects, *The Review of Financial Studies*, 9, pp. 1-36.

Kempf, A. and Korn, O., 1999, Market Depth and Order Size, *Journal of Financial Markets*, 2, pp. 29-48.

Koenker, R., 1981, A Note on Studentizing a Test for Heteroskedasticity, *Journal of Econometrics*, 17, pp. 107-112.

Koop, G., Pesaran M.H., and Potter, S.M., 1996, Impulse Response Functions in Nonlinear Multivariate Models, *Journal of Econometrics*, 74, pp. 119-147.

Kraus, A. and Stoll, H., 1972, Price Impacts of Block Trading on the New

York Stock Exchange, *Journal of Finance*, 27, pp. 569-588.

Lamoureux, C. and Lastrapes, W., 1990, Heteroskedasticity in Stock Return Data: Volume versus GARCH-effects, *Journal of Finance*, 45, pp. 221-229.

Lee, M.J., 1996, *Methods of Moments and Semiparametric Econometrics for Limited Dependent Variable Models*, Springer, New York.

Lee, C.M.C. and Ready, M.J., 1991, Inferring Trade Direction from Intraday Data, *Journal of Finance*, 46, pp. 733-746.

Madhavan, A. and Smidt, S., 1991, A Bayesian Model of Intraday Specialist Pricing, *Journal of Financial Economics*, 30, pp. 99-134.

Manganelli, S., 2002, Time, Volume and the Price Impact of Trades, Working Paper European Central Bank nr. 125.

O'Hara, M., *Market Microstructure Theory*, Basil Blackwell, 1995.

Robinson, P.M., 1988a, Root-N Consistent Semiparametric Regression, *Econometrica*, 56, pp. 931-954.

Robinson, P.M., 1988b, Semiparametric Econometrics, *Journal of Applied Econometrics*, 3, pp. 35-51.

Roll, R., 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, *Journal of Finance*, pp. 1127-1140.

Russell, J., 1999, The Econometric Modeling of Multivariate Irregularly-Spaced High-Frequency Data, unpublished working paper, University of Chicago Graduate School of Business.

Seppi, D.J., 1990, Equilibrium Trading and Asymmetric Information, *Journal of Finance*, 45, pp. 73-94.

Shanno, D.F., 1970, Conditioning of Quasi-Newton Methods for Function Minimization, *Mathematics of Computation*, 24, pp. 647-657.

Spierdijk, L., 2002, An Empirical Analysis of the Role of the Trading Intensity in Information Dissemination on the NYSE, Discussion Paper Tilburg University and CentER, nr. 2002-30, forthcoming *Journal of Empirical Finance*.

Spierdijk, L., Nijman, Th. E., and Van Soest, A.H.O., 2002a, The Price Impact of Trades in Illiquid Stocks in Periods of High and Low Market Activity, Discussion Paper Tilburg University and CenteER nr. 2002-29.

Spierdijk, L., Nijman, Th. E., and Van Soest, A.H.O., 2002b, Modeling Comovements in Trading Intensities to Distinguish Stock and Sector Specific News, Discussion Paper Tilburg University and CentER nr. 2002-69.

Spierdijk, L., Nijman, Th. E., and Van Soest, A.H.O., 2003, Price Dynamics and Trading Volume: A Semiparametric Approach, unpublished working paper, Tilburg University and CentER.

Stoll, H.R, 1989, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, *Journal of Finance*, 44, pp. 115-134.

Whang, Y-J. and Andrews, D.W.K, 1993, Tests of Specification for Parametric and Semiparametric Models, *Journal of Econometrics*, 57, pp. 277-318.

White, H., 1980, A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica*, 48, pp. 817-838.

Zebedee, A.A., 2001, The Impact of a Trade on National Best Bid and Offer Quotes: A New Approach to Modeling Irregularly Spaced Data, *Journal of Multinational Management*, 11, pp. 363-383.

Index