Price Impact and Profit of Xetra-Traders: Does Profitability increase with Trade Size?

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First draft: March 1999
Current draft: December 2000

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We are grateful to Dr. A. Schäfer and C. Zitzmann, head and staff member, respectively, of the Trading Surveillance Unit of the Frankfurt Security Exchange for providing the data. Moreover, we gratefully acknowledge the financial support from the Deutsche Forschungsgemeinschaft (Grant Tr 255/3 for project 'Manipulation and Regulation' within the program 'Efficient Design of Financial Markets and Financial Institutions').

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Abstract

We use data uniquely available from the Trading Surveillance Unit of the Frankfurt Securities Exchange (*Handelsüberwachungsstelle der Frankfurter Wertpapierbörse*) to analyse the price impact and profit of *all* stock traders trading in 11 liquid DAX stocks and 5 less liquid MDAX stocks via Deutsche Börse AG's electronic trading platform Xetra. Although in strategic models a *monopolist* informed trader may camouflage his trading activity by making several small-sized trades rather than one large trade, it might be optimal to choose a large trade size when there are *multiple* informed traders. The same is true for an uninformed stock price manipulator who tries to establish a trend-creating trading strategy. We find that (1) the impact of trade size on prices is slightly nonlinear, (2) the price response to buy and sell orders is for *most* stocks symmetric making it harder to profit from trade-based price manipulation, and (3) less than 2% (4%) of the traders trading in DAX-stocks (MDAX-stocks) induce a price impact which is *not* related to trade size. But these traders do not consistently outperform other traders. Furthermore, our results suggest that (4) there is a negative relationship between the traders risk and benchmark adjusted profit and his mean trade size in DAX-stocks, while (5) for *all* stocks examined a trader's risk and benchmark adjusted profit increases significantly with the number of transactions in a specific stock.

JEL-Classification: G10, G14, C21

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1 Introduction

Little direct *empirical* research has been conducted on the question whether a *non-price-taker* gains any advantage through taking into account his effect on prices. In models where the presence of a non-price-taker is generated *endogenously* by his superior information over the other agents (Kyle (1985), Holden/Subrahmanyam (1992) when there are multiple informed trader), non-price-taker are better off. In models with *symmetric* information where the presence of a non-price-taker is specified *exogenously*, the non-price-taker has either no advantage (Grinblatt/Ross (1985), Kampovsky/Trautmann (2000)) or is at least as well off as if he were a price-taker (Basak(1996,1997)).

Non-price taking behaviour is related to the notion of *trade-based* stock price manipulation. The latter occurs when a trader attempts to influence artificially stock prices simply by buying and then selling, without taking any publicly observable actions to alter the value of the firm or releasing false information to change the price. This kind of manipulation is even more difficult to detect and eradicate than *information-based* manipulation. The latter is based on releasing false information or spreading false rumors.[1] A third kind of manipulation can be described as *action-based manipulation*, that is, manipulation based on actions that change the actual or perceived value of the assets.[2]

On the face of it, it would seem that *trade-based* manipulation cannot be profitable. The argument is simple. When a trader tries to buy a stock, he drives up the price. When he tries to sell it, he drives down the price. To buy high and sell low is the reverse of what is required to make a profit. Jarrow (1992) has formalized this argument, showing that, under certain conditions, that trade-based manipulation is not profitable in an efficient market. However, in extending Hart‘s (1977) analysis to a stochastic setting, Jarrow (1992) shows that profitable price manipulation is possible if there is 'price momentum', so that an increase in price caused by the manipulator‘s trade at one date tends to increase prices at future dates. In other words, the possible existence of profitable trade-based

[1] Releasing false information has been again an important issue since the Internet allows to spread such price influencing information anonymously under the pseudonyms *Dr. Experience, Lucky Luke, Sparschwein* and the likes.

[2] A famous example is the case of the American Steel and Wire Company (the forerunner of USX). In 1901, its managers shorted the firm‘s stock and then closed its steel mills. When the closure was announced, the stock fell from around USD 60 to around USD 40 per share. The managers then covered their short positions and reopened the mills, at which point the stock price rose to its previous level. Nowadays such an action can be easily controlled and is effectively outlawed in most countries.

market manipulation strategies (with the exclusion of market corners and short squeezes, which always exist) is related to the time asymmetry in the sensitivity of price changes to the manipulator's trades. Such a situation might be due to noise traders following positive feedback investment strategies. That is, as the price rises, noise traders buy with a lag, and as the price falls, they sell with a lag. But numerous other market phenomena, like portfolio insurance, could induce similar patterns. While in the articles of Hart (1977) and Jarrow (1992) the investors' demand functions is taken as exogenous, rather than being derived from expected-utility-behavior, Allen and Gale (1992) show that such a trend-creating strategy can, in fact, be the outcome from a rational equilibrium. They present a model with asymmetric information where all agents have rational expectations and maximize expected utility.

For an uninformed manipulator it might therefore be optimal to choose a large trade size in order to establish a trend-creating trading strategy. A large trade size might also be optimal in strategic models with asymmetric information when there are *multiple* informed traders acting noncooperatively (see Holden and Subrahmanyam (1992)). The latter insight is in contrast to strategic models with a single informed trader where the monopolist informed trader may camouflage his trading activity by making several small-sized trades rather than one large trade (see Kyle (1985), Admati and Pfleiderer (1988) and Foster and Vishwanathan (1990)).

Because of the difficulty in obtaining detailed transaction data, most of the work investigating the profit-maximising trading policy of large and informed traders is theoretical. There appears to have been no previous empirical study on any market of the relationship between a trader's trading profit and his trade size policy. Several important empirical issues, therefore, remain unresolved. This purely empirical paper uses data uniquely available from the Trading Surveillance Unit of the Frankfurt Securities Exchange (*Handelsüberwachungsstelle der Frankfurter Wertpapierbörse*) to analyse the relationship between a trader's trade size, price impact and trading profit for all stock traders trading in 11 liquid DAX stocks and 5 less liquid MDAX stocks via Deutsche Börse AG's electronic trading platform Xetra. The main hypotheses to be tested are the following ones:

H1: Price impact hypothesis: Price impact is linear.

H2: Trade size hypothesis: Traders with a large trade size do not outperform traders with a small trade size.

The remainder of the paper is organized as follows. Section 2 describes the institutional framework of the electronic trading system Xetra. Section 3 contains a description of the data and some striking trading activity statistics. Section 4 describes the observed relationship between trade size and price impact. Section 5 presents the Xetra-traders' trading profits and some of its sources. Section 6 contains concluding remarks.

2 The Institutional Framework

Xetra (eXchange Electronic TRAding), Deutsche Börse AG‘s electronic securities trading platform, is a hybrid market place that offers a menu of facilities to its customers. Actually Xetra accounts for as much as 85 percent or more of the turnover in the DAX blue chips and more than 77 percent of the turnover in stocks traded at German Securities Exchanges. Xetra‘s basic trading platform is an electronic limit order book (the continuous order-driven market). Linked in with the book are at least three call auctions (the batched market) a day: at the open, intra-day, and at the close. Additionally, dealers (*Betreuer*) provide quotes to the public upon request. This interlinking of the three generic modalities should strengthen the overall efficiency of the market while giving customers the choices they need for handling their orders.

2.1 Auctions

The Xetra trading day starts with an opening auction (labelled trading phase 'O') and closes with a final auction (labelled trading phase 'F'). Since October 1998 (Release 3), additional auctions are possible during the trading day. Beside the intra-day auction at noon (labelled trading phase 'A') there is a so-called volatility auction (labelled trading phase 'V') when there occurs a volatility interruption in continuous trading to ensure price continuity. The latter is the case whenever the potential execution price lies outside the predefined price range around a reference price. Volatility interruptions initiate an auction with the start of the call phase. The auction is restricted to orders designated for continuous trading. After price determination or, if price determination was not possible, at the end of the auction, continuous trading is continued.

By means of the 'auction only' trade restriction Xetra puts investors in a position to place orders in the order ledger without the other market participants being able to see them. In this way, even in the case of large orders investors also benefit from the prime price afforded by the auctions. Auctions in Xetra serve the purpose of bringing all orders in the order ledger together at one specific point in time. This increases the probability that the orders can be executed at a fair market price. In the course of each auction, the system automatically establishes the price at which the greatest volume can be traded (principle of highest volume transacted). In Xetra, each auction commences with an "outcry" phase. In the case of shares, the order ledger is closed during this phase - whereas it is open during continuous trading. Only the best buy and sell limits are visible. The end of this phase is determined on a random basis. It is followed by automatic price definition.

2.2 Continuous Trading

Continuous trading (labelled trading phase 'C') starts after the opening auction. The order book is open in continuous trading, displaying the limits and accumulated order volumes for each limit. A new market order or limit order is immediately checked for execution against orders on the other side of the order book and will be executed using price/time priority principle. The execution can be carried out fully or partially in one or several steps or not at all so that one or more trades are generated. In Xetra execution of trade against the book occurs in a "*discriminatory*" fashion. That is, if a trade is large enough to execute against several limit orders at different prices, each limit order transacts at its limit price. For example, if there were two offers at 50 for 1,000 shares of each, and two offers at 51, each for 1,000 shares, a 4,000-share purchase would in effect lead to four transactions – two at 50 and two at 51. The marginal price for this 4,000-share trade would be 51, while the average price would be 50.5. Orders which have not been executed or only partially are entered into the order book and sorted according to the price/time priority. The sorting method according to the price/time priority ensures that bid orders with a higher limit take precedence over such orders with lower limits. Vice versa, ask orders with a lower limit take precedence over orders with a higher limit. The secondary criterion 'time' applies in the event of orders having the same limit. Hence, orders that were entered earlier take priority. Market orders enjoy priority over limit orders in the order book. Time priority also applies to market orders.

2.3 Dual Trading

Xetra allows *dual trading*, that is, each trader is allowed to trade for his own account *and* for a customer's account. A controversial issue facing traders, exchanges and regulators is whether dual trading should be allowed. Critics of dual trading argue that dual trading makes it easier for brokers to cheat their customers. One method for doing so is *frontrunning*, where the trader acts for his own account prior to filling a customer order. Therefore, a trader frontrunning a customer forces the customer to trade at a worse price. In subsection 5.1 we present some results on the profitability of a trading strategy which most market participants would declare as frontrunning.

3 The Data

We use transactions data uniquely available from the Trading Surveillance Unit of the Frankfurt Securities Exchange (*Handelsüberwachungsstelle der Frankfurter Wertpapierbörse*) to analyse all matched buy/sell transactions in 16 stocks traded in Xetra during the 253-trading day period from August 31, 1998 through August 31, 1999. Each data record consists of a time-stamped, matched buy/sell transaction at a given price and quantity with (encoded) buyer/seller identification and information on the character of the trade: (1) whether the transactor is acting for his own account (as a principal or proprietary trader labelled with 'P'), acting for a customers account (as an agent or customer trader labelled with 'A'), or whether he is acting as a specialist (Betreuer, labelled with 'M'), (2) whether the buyer or the seller initiated the transaction, and (3) whether the order initiating the transaction is a limit order or a market order.

Since we observed that there are, on average, more than 1.000 daily transactions in actively traded DAX-stocks, we restrict our analysis to 11 liquid DAX-stocks and 5 less liquid MDAX-stocks. The DAX-stocks selected (*Allianz, Bayer, Daimler-Chrysler, Deutsche Bank, Deutsche Telekom, Lufthansa, Mannesmann, Metro, RWE, Siemens and Veba*) represent at the same time the German stocks included in the Dow Jones Eurostoxx 50. The MDAX-stocks selected (*BHF-Bank, Continental, Douglas Holding, Krupp-Hoesch-Krupp, SGL-Carbon*) form those of the 70 middle-sized stocks included in the MDAX index for which the turnover in Xetra is large in comparison to the turnover at the Frankfurt Securities Exchange in 1998.

3.1 Trader and Trading Activity Statistics

Table 1 summarizes the number of member firms and traders who trade in the selected stocks exclusively for their own account, or exclusively for a customers account, or who trade both for their own account and their customers account during the sample period. On average, there are six traders per exchange member in the liquid DAX-stocks and three in the MDAX-stocks. But from the 299 Xetra member firms trading in the selected stocks, 78 member firms trade only via one trader while the five biggest member firms employ together 310 traders (the biggest member firm employs already 81 traders). Furthermore, this table shows that about one half of the traders and member firms, respectively, trades exclusively for their own account.

Table 2 reports the number of transactions in each stock during the 253-trading day sample period. In the most liquid stocks, *Daimler-Chrysler, Deutsche Bank and Deutsche Telekom*, there are more than 200,000 transactions per stock while in the least liquid stock, *Krupp-Hoesch*, there are only 1,995 transactions. It is obvious that the mean time between trades varies a lot for the stocks of our sample. *Daimler-Chrysler* ist the one with the smallest time span between trades, it is less than half a minute. For all other DAX-stocks the mean time between trades is less than 1.5 minutes. For the MDAX-stocks the time span between trades varies between about 5 minutes and half an our. The mean daily trading volume of the sampled DAX-stocks is highest for the *Deutsche Telekom* with more than 3 million stock trades a day on average, and smallest for the Allianz with only about 400,000 stocks. The mean daily trading volume of the sampled MDAX-stocks is only less than a 10 th of that of the DAX-stocks. With less than 7,000 stocks a day *Krupp-Hoesch* is the stock with the smallest mean daily trading volume of the sampled stocks. About 2/3 of the total trading volume in the DAX stocks is due to transactions for own account and only 1/3 due to customers orders. For the MDAX stocks about 45% of the total turnover is due to orders of customers. For the DAX-stocks in our sample, only about 10% of the total trading volume is due to market orders, where the fraction of market orders is a little bit higher for the proprietary trades than the customers trades. For the MDAX-stocks only less than 5% of the total trading volume is due to market orders and the fraction of market orders is smaller for the proprietary trades than the customers trades.

Table 3 presents the trading volume across the different trading phases explained in section 2. More than 90% of the total trading volume is transacted in the continuous trading phase while only about 10% of the turnover is transacted during the four different types of auctions. From the latter, the final auction and the intra-day auction are (in terms of turnover) the most important one. The mean and maximum of the trade size across the different trading phases reflect the importance of the final auction for placing large orders.

Figure 1 shows for *Deutsche Bank*-stocks the distribution of the trade size in shares across different trading phases. For all other stocks in our sample, the shape of the distribution is quite similar. The last bar represents the frequency of all trade sizes larger than the 95%-quantile. Large trade sizes are observed especially in the final auction (F) and in the volatility auction (V).

3.2 Striking Trading Activity: Self-Crossing

A transaction is called self-crossing if buyer and seller are identical and the trader acts for his own account. Self-crossings are appropriate for manipulation since a trader can move the stock price without changing his stock position. Although self-crossings are not allowed in Xetra they occur across all stocks in our sample. Table 4 reports the observed frequency of self-crossings as well as the mean and the maximum of the EUR-trading volume behind a self-crossing transaction where we distinguishing between the trader level and the member level. On the trader level, transactions are only considered as self-crossings if buyer and seller are identical. On the member level buyer and seller need not be identical but must belong to the same member firm.

In *Mannesmann* the maximal self-crossing transaction at trader level had a value of more than 1.5 Million EUR, and in *Siemens* the largest self-crossing transaction had a value of more than 700.000 EUR. For the member level, the maximal self-crossing transaction in *Deutsche Bank* had a value of more than 5 Million EUR, in *Deutsche Telekom* and in *Mannesmann* they had a value of more than 3 Million EUR.

4 Price Impact and Trade Size

Asymmetric price responses to buy and sell orders might create opportunities for profitable price manipulation as already mentioned in the introduction. Therefore we analyse in this section, first of all, the relation of trade size and price impact separately for sales und purchases to check whether there is a asymmetric price response. Secondly, we are interested in whether the price impact of a trade is linear in its trade size and whether this price impact is temporary or permanent.

4.1 Marginal price impact versus average price impact

The magnitude of the price impact of a large trade in a market is related to the market's liquidity. Four dimensions of liquidity have been mentioned in the literature: tightness, depth, resiliency and immediacy. A market is *tight* if there are enough limit orders or quotes close to the last trading price such that new buy and sell orders can be executed without big price changes. Tightness is directly measured by the bid-ask spread corresponding to the difference between the lowest ask and the highest bid prices. A market is *deep* if large orders can be executed without much effect on prices.

As already mentioned in subsection 2.2, Xetra executes a trade against the book in a "*discriminatory*" fashion. That is, if a trade is large enough to execute against several limit orders at different prices, each limit order transacts at its limit price. We therefore have to distinguish between *marginal price impact* and the *average price impact*. The latter is defined as the logarithm of the actual *average* price of trade minus the logarithm of the last marginal transaction price. These definitions imply that the average price impact is always smaller than the marginal price impact. To demonstrate the difference between these two definitions we consider a buyer initiated transaction consisting of six matches:

No. of match	price	Traded quantity	Buyer	Seller
1	52,25	1.000	B	S1
2	52,27	1.000	B	S2
3	52,28	10.000	B	S3
4	52,28	1.000	B	S4
5	52,30	1.000	B	S5
6	52,30	1.000	B	S6

The variable S_t denotes the marginal price of the transaction at time t. If we assume that the marginal price at time $t-1$ was $S_{t-1} = 52,24$ Euro we get a price impact of $\ln(S_t/S_{t-1}) = \ln(52,30/52,24) = 0,1147\%$. The average price paid for one share is $\bar{S}_t = 52,28$, so that the cost of trade size is $\ln(\bar{S}_t/S_{t-1}) = \ln(52,28/52,24) = 0,0765\%$.

To reduce the noise in the observed marginal and average price impact of individual transactions, we form for each stock up to 40 trade size classes and pool the observations accordingly. Then we calculate the mean price impact for each class. Figures 3 and 4 illustrate for the pooled observations the relationship between trade size and (relative and marginal) price impact and trade size for *Deutsche Bank*, *Mannesmann* and *Lufthansa* stocks. It should be noticed that these plots have different scales. This hint is especially useful when comparing the relative price impact of *Deutsche Bank* stocks during normal trading days (panel A of figure 3) and turbulent trading days (panel B of figure 3). The relation between trade size and price impact is nearly linear for all stocks. The first and last stars in each plot represent the classes of transactions whose absolute trade size is greater than the 99.5%- quantile of the trade size distributions for buy and sell transactions in the corresponding stock, respectively.

The relative price impact considers the *bid-ask bounce* effect connected with reversals. This bounce effect is estimated by the regression

$$\begin{aligned}\ln(S_t/S_{t-1}) &= \alpha_1 \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t>0\}} + \alpha_2 \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t<0\}} \\ &\quad + \alpha_3 \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t>0 \text{ and } \mathrm{TrSize}_{t-1}<0\}} \\ &\quad + \alpha_4 \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t<0 \text{ and } \mathrm{TrSize}_{t-1}>0\}} + \varepsilon_t.\end{aligned}$$

Then the relative price impact (corrected for the bounce effect) is defined as

$$\begin{aligned}\ln(S_t/S_{t-1})^C &= \ln(S_t/S_{t-1}) - \alpha_3 \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t>0 \text{ and } \mathrm{TrSize}_{t-1}<0\}} \\ &\quad - \alpha_4 \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t<0 \text{ and } \mathrm{TrSize}_{t-1}>0\}}.\end{aligned}$$

Table 5 reports the results of the nonlinear regression model

$$\ln(p_t/p_{t-1}) = \alpha\ \mathrm{TrSize}_t + \beta\ \mathrm{TrSize}_t \cdot\ \mathrm{abs}(\mathrm{TrSize}_t) + \varepsilon_t, \quad t = 1, 2, \ldots$$

to test for linearity of the price impact. For all stocks except *Krupp-Hoesch*, the hypothesis of a linear relation between trade size and price impact has to be rejected since the regression coefficient β is signifianctly different from zero.

Table 6 summarizes the results of the regression model

$$\ln(p_t/p_{t-1}) = \alpha\ \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t>0\}} + \beta\ \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t<0\}} + \varepsilon_t, \quad t = 1, 2, \ldots$$

to test for symmetry. The last column gives the p-value, that is the probability that the null-hypothesis ($\alpha = \beta$) is rejected erroneously. Therefore we have an asymmetric relation between trade size and price impact for *Bayer* and *Siemens*. For all the other 14 stocks there is a symmetric relationship cannot be rejected. The same result holds if we include two quadratic terms, one for buy-transactions and one for sell-transactions.

4.2 Spectral analysis of the relative price impact

A standard approach to differentiating effects in time series over different horizons is spectral analysis or frequency domain analysis. Although spectral estimates of a time series contain no more and no less information than the standard time domain techniques, they offer a more direct characterization of horizon effects. A realization of a time series may be expressed as a weighted sum of sinusoidal functions and therefore it is possible to decompose a time series according to the contributions of different frequencies. Since there is a unique relation between frequencies and periods a time series can be expressed as the sum of effects belonging to different horizons. By applying spectral analysis to the time series of price changes it is possible to determine the permanent or long-run price impact of each transaction. This gives us the possibility to compare the traders price impact. We decompose the price impact as follows:

$$\begin{aligned} ln(p_t/p_{t-1}) &= \sum_{j=0}^{T-1} f(\omega_j)e^{i\omega_j t} \\ &= \sum_{j=253}^{T-1} f(\omega_j)e^{i\omega_j t} + \sum_{j=52}^{253} f(\omega_j)e^{i\omega_j t} + \sum_{j=12}^{52} f(\omega_j)e^{i\omega_j t} + \sum_{j=0}^{11} f(\omega_j)e^{i\omega_j t} \\ &=: ln(p_t/p_{t-1})^{Day} + ln(p_t/p_{t-1})^{Week} + ln(p_t/p_{t-1})^{Month} + ln(p_t/p_{t-1})^{Year}, \end{aligned}$$

where f denotes the Fourier transform of the time series of the log-returns. For each component as well as for the total price impact we identify each traders price impact β^H using the regression model

$$\begin{aligned} \ln(p_t/p_{t-1})^H &= \alpha_1^H \text{ TrSize}_t + \alpha_2^H \text{ TrSize}_t|\text{TrSize}_t| + \sum_{i=1}^{N} \beta_i^H \text{sign}(\text{TrSize}_t) \cdot 1_{\{Trader=i\}} \\ & t = 1, 2, \ldots, \end{aligned}$$

where H gives the maximal cycle length (period) and is equal to Day, Week, Month, Year or Total.

Table 7 presents for each component the number of traders with economically significant price impact, that is the number of traders for which the regression coefficient β is positive, significantly different from zero and large enough the induce a price impact of a tick. There are only a few traders with a significant price impact for a maximal period of less than one day or with a significant price impact for the total price impact. Apart form *Allianz*, there is no trader with a price impact in a DAX-stock for a maximal period length longer than one day. Except *Krupp-Hoesch*, there are in all MDAX-stocks traders having a price impact for the component of period length of more than one day.

4.3 Price impact and resiliency

Both *tightness* and *depth* are essentially static concepts of liquidity describing a market at a given point in time. This is in contrast with the concept of *resiliency* which refers to the speed with which the bid and the ask schedules move back to their initial positions after an order has been executed. This is important because large orders are often split into several small orders which are executed sequentially. In a resilient market, an investor doing this would nonetheless obtain a price which, in the absence of any news, would on average be close to the current market price.

To examine the resiliency of the Xetra market, an event-study procedure similar to that of Holthausen, Leftwich and Mayers (1990) and Gemmill (1996) is used. The 40 largest purchases and 40 largest sales (so called *block trades*) are identified for each share and each month. Hence a total of 2560 blocks for each of purchases and sales is selected. With an average of 20 trading days per month, we consider on an average basis about two purchases and two sales per stock and day. To identify the price impact of block trades, we calculate 40 logarithmic returns from the prices for 41 trades centered on each block.

We measure total, temporary and permanent price effects. The temporary price effect is the price rebound of a security following a block transaction, and the permanent price effect is the change from the price level before the block trade to the price level afterwards. The *total* price impact is the change of the (marginal) price before the block trade to the (marginal) price *at* the block trade, that is the sum of temporary and permanent price change.

Denoting the block as trade zero in the sequence, the ten returns for trades -19 to -10 are then used to calculate a benchmark return per block. Let R_{kit} denote the return of the kth block for the ith stock measured at transaction t. The benchmark return measured over trades -19 to -10 is

$$\text{BEN}_{ki} = \frac{1}{10} \sum_{t=-19}^{-10} R_{kit}, \quad k = 1, ..., 320 \quad i = 1, ..., 16. \tag{1}$$

The second step is to calculate an benchmark adjusted return series for each of the trades -9 to $+20$, which for transaction t is

$$\text{RX}_{it} = R_{kit} - \text{BEN}_{ki}. \tag{2}$$

Figures 5 and 6 show the mean benchmark adjusted return around a block transaction in the sampled DAX-stocks in the three subperiods September 1998 until December 1998, January 1999 until April 1999 and May 1999 until August 1999. Figure 7 and 8 illustrate the corresponding results for the less liquid MDAX-stocks.

Five trades prior to a block trade, prices begin to rise or to fall, respectively. There is a large impact when a block purchase or sale occurs. Significant adjustment takes only one or two trades, although there may be small effects for a little longer. The mean price impact of block trades is bigger for the less liquid stocks included in the MDAX-sample compared to the DAX-sample. The patterns of impact and speed of adjustment are similar to those found by Gemmill (1996) and Holthausen et. al. (1990).

Even if simple transaction returns before and after a block trade are not significantly different from zero, they may add up to values which are significantly different from zero. Figures 9 and 10 show *cumulative* benchmark adjusted returns for purchases and sales for the 11 DAX-stocks, respectively, while Figures 11 and 12 show *cumulative* benchmark adjusted returns for purchases and sales for the five MDAX-stocks, respectively. A relative clear pattern arises. When a *block purchase* is made, prices begin rising at time -5, show a large jump at time 0 and then show gentle downward drift. When a *block sale* is made, prices begin falling at time -5, show a large jump at time 0 and then show gentle upward drift. To summarize, when a block trade occurs there appears to be a permanent impact. Not surprisingly, this impact disappears faster in (transaction) time for the more liquid DAX-stocks.

5 Trading Profits

This section examines Xetra traders‘ trading profits, here defined as the gains (or losses) from purchases and sales of stock. Due to a lack of relevant data, these profits are not adjusted for the fees paid by the traders to the Deutsche Börse AG, financing charges, other operational expenses, and salary imputations. Traders‘ commission revenues (the fees received for acting as agent for orders) are also ignored. The focus is strictly on gross trading profits.

Trading profits can be measured either on a cash flow basis or a mark-to-market basis. We prefer the latter approach since cash flow profits are subject to the criticism that the profit is entirely attributed to the instant at which the position is liquidated. Let S denote the price per share of a security at time t, and let N denote the number of shares held. It is assumed that the trade at time t takes place at time price S_t and that N_t is net of all trading at time t with $N_0 = 0$ at $t = 0$, the beginning of the sample period. The mark-to-market profit is defined as the appreciation in the value of the holdings:

$$G_t = N_{t-1}(S_t - S_{t-1}) \tag{3}$$

i.e., the capital gains on shares held at the beginning of the period. Investment returns are typically determined in this way. One criticism of this approach is that it assumes that entire positions can be purchased or liquidated at the prevailing market prices. This assumption of infinite elasticity is not plausible for large positions over short intervals. But changes in traders‘ positions tend to be small relative to the total order flow.

5.1 Profits from Frontrunning

First of all, we study the profitability of frontrunning where a trader simply trades for his own account just before filling his customer's order. We deem a trading strategy as frontrunning if the time span between his own trade and a customer's trade in the same direction is less than 5 minutes *and* if within the next 5 minutes after filling the customer's order the trader transacts for his own account in the opposite direction. According to this convention the percentage of dual traders who frontrun their customers is $6,5\%$ in *Deutsche Bank*-stocks, 6% in *Mannesmann*-stocks and 4% in *SGL Carbon*-stocks.

On a member firm level there are much more opportunities for dual traders to frontrun their customers, since all transactions necessary to profit from frontrunning can be done by different traders of the same member firm. Table 8 reports the number of traders and members, respectively, who frontrun according to our convention their customers, as well as the mean and the maximum of the profit of all observed frontrunnings in the sampled stocks. Considering the maximums of the earned frontrunning profits it is obvious that frontrunning profits are negligible. On the trader level the maximal profit was realised in *Allianz* and was less than 11.000 EUR. On the member level the maximal profit earned was realised in metro and was less than 21.000 EUR.

5.2 Benchmark adjusted profits

Let $N_t^{deme} = N_t - \overline{N}$ be the demeaned value of the trading position held at time t, where $\overline{N}$ denotes the average number of stocks held in the sample period. Then the trading profit on the basis of the demeaned trading position is

$$G^b = \sum_{t=2}^{T} N_{t-1}^{deme}(S_t - S_{t-1}) = \sum_{t=2}^{T} N_{t-1}(S_t - S_{t-1}) - \overline{N}(S_T - S_1).$$

The last equation shows that G^b equals the trading profit minus the trading profit of a benchmark strategy (benchmark adjusted profit). The strategy taken as a benchmark is a buy and hold position in $\overline{N}$ stocks. The benchmark adjusted trading profit can be expressed as the sample covariance of the demeaned trading position and the demeaned price change multiplied by $(T-1)$:

$$G^b = \sum_{t=1}^{T-1} N_t \Delta S_t - \bar{N}(S_T - S_1) = \sum_{t=1}^{T-1} (N_t - \bar{N})(\Delta S_t - \overline{\Delta S}),$$

with the convention $\Delta S_t \equiv S_{t+1} - S_t$.

5.3 Spectral analysis of benchmark adjusted profits

We use again spectral analysis (see appendix) to decompose profits according to cycles with a period less than one day, between one day and one week, between one week and one month or more than one month up to one year:

$$G^b = G^{b,Day} + G^{b,Week} + G^{b,Month} + G^{b,Year},$$

where profits $G^{b,Day}$ correspond to cycles with period less than one day, profits $G^{b,Week}$ correspond to periods between one day and one week, profits $G^{b,Month}$ correspond to periods between one week and one month, profits $G^{b,Year}$ correspond to periods over one month up to one year.

To demonstrate the meaning of the cycle period length as an implied trading horizon we consider two trading strategies in Continental stocks (see figure 12 for the corresponding price movement in the sample period): a profitable strategy and a non-profitable strategy.

Figure 1: Price movements of Continental

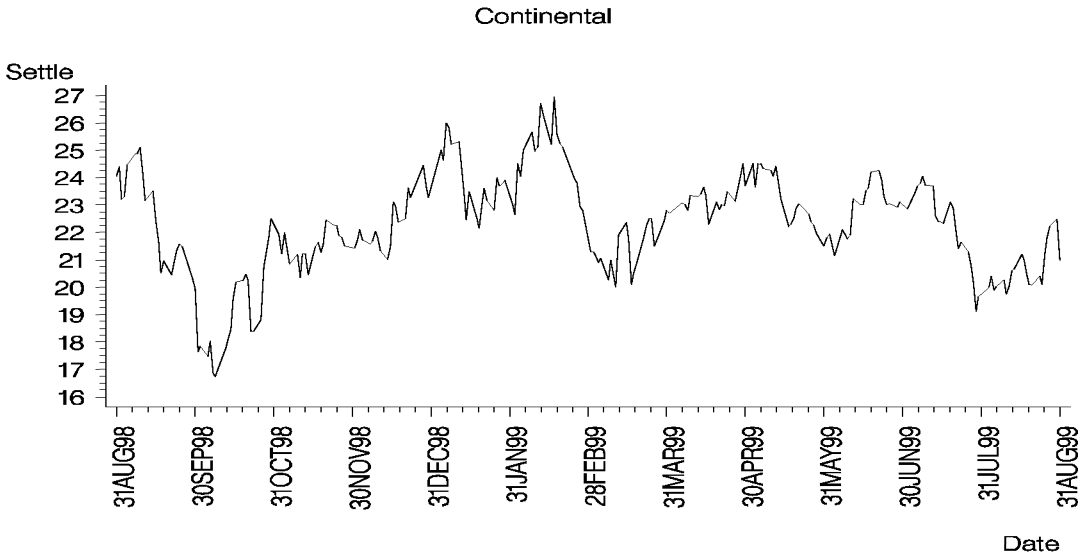


Figure 13 visualizes the non-profitable trading strategy of trader 098FRPRO001; he trades rarely and if he trades then he always trades in the same direction. That is there are only a few transactions that are followed by a transaction in the other direction within a period of less than one day. So he will not realize intraday trading profits. This also holds for trader 679STTMU001 whose profitable trading strategy is plotted in figure 14. In contrast to the former trader he trades frequently. The cospectra of price changes and demeaned trading positions (as plotted in Figure 15) confirm that both traders do not realize intraday profits. For periods less than one day both cospectra equal null. The sum of the needle's length gives the total profit.

5.4 Risk and benchmark adjusted profits

Furthermore, we adjust the benchmark adjusted trading profit for the corresponding inventory risk component. Let $\mathrm{Var}(N^{deme}S) = \mathrm{Var}(N^{deme}S)^{Day} + \mathrm{Var}(N^{deme}S)^{Week} + \mathrm{Var}(N^{deme}S)^{Month} + \mathrm{Var}(N^{deme}S)^{Year}$ be the decomposition of the variance of the value of the demeaned trading position according to the different classes of periods. Then the risk and benchmark adjusted trading profit is defined as

$$G^{br,f} = \frac{G^{b,f}}{InventoryRisk^f / \overline{InventoryRisk^f}}$$

where $InventoryRisk^f = \sqrt{Var(N^{deme}S)^f}$ for the different maximal lengths of period $f =$ Day, Week, Month or Year.

For each of these variables we have in total 3602 observations for the 11 DAX-stocks and 271 observations for the five MDAX-stocks. In other words we have on average 328 observations in each of the DAX-stocks and 54 observations in each of the MDAX-stocks. Table 9 and 10 present summary statistics about benchmark adjusted profits, risk and benchmark adjusted profits, and inventory risk for the different implied holding periods for the DAX-sample and the MDAX-sample, respectively. Furthermore, table 9 and table 10 contain summary statistics for some explanatory variables. The dummy variable DBank is introduced for traders acting for a bank. The dummy variable DDual is equal 1 if a trader is a dual trader. The variable NMStocks gives the number of traders within the same member firm trading the same stock. FrInit indicates the percentage of initiated trades, NTrades give the number of trades in the same stock and TrSizeMean denotes the mean of the trader's trade size in the same stock. For each of these variables table 9 and 10 give the minimum, maximum, mean and standard deviation calculated based on all pooled observations of the DAX-stocks and the MDAX-stocks, respectively.

5.5 Sources of risk and benchmark adjusted profits

We regress the risk and benchmark adjusted profit of trader i in stock j, $G^{br}_{i,j}$, on explanatory variables according to the following linear model:

$$\begin{aligned} G^{br,f}_{i,j} &= \alpha_j + \beta_1 \mathrm{DBank}_{i,j} + \beta_2\ \mathrm{DDual}_{i,j} + \beta_3\ \mathrm{NMstocks}_{i,j} + \beta_4\ \mathrm{FrInit}_{i,j} \\ &\quad + \beta_5\ \mathrm{NTrades}_{i,j} + \beta_6\ \mathrm{PrImpBeta}_{i,j} + \beta_7\ \mathrm{TrSizeMean}_{i,j} + \mu_i + \varepsilon_{i,j}, \\ &\quad f = \text{Day, Week, Month, Year, Total}, \end{aligned}$$

where

$$\begin{aligned} \mathrm{DBank} &\equiv \text{dummy variable for banks} \\ \mathrm{DDual} &\equiv \text{dummy variable for dual traders} \\ \mathrm{NMstocks} &\equiv \text{number of traders of the same member as trader } i \text{ active in stock } j. \\ \mathrm{FrInit} &\equiv \text{percentage of inititated trades} \\ \mathrm{NTrades} &\equiv \text{number of trades} \\ \mathrm{PrImpBeta} &\equiv \text{price impact} \\ \mathrm{TrSizeMean} &\equiv \text{mean trade size} \end{aligned}$$

It should be noticed that we allow for fixed effects for the stocks and random effects for the traders. The three variables NMStocks, NTrades and TrSizeMean are characterized by kurtosis and long right tails. This suggests a logarithmic transformation $\log(\mathrm{NMStocks}_{i,j}/\overline{\mathrm{NMStocks}_j})$, where $\overline{\mathrm{NMStocks}_j}$ is the sample mean over all observations in the stock j to be a more suitable regressor. Analogous transformations are done for the other two variables. Furthermore, we adjust the variables FrInit and PrImpBeta with there sample means, that is we consider $\mathrm{FrInit}_{i,j} - \overline{\mathrm{FrInit}_j}$ and $\mathrm{PrImpBeta}_{i,j} - \overline{\mathrm{PrImpBeta}_j}$. Then the intercept term α_j has the economic interpretation as the average profit in stock j per market transaction of a representative trader belonging to a non-bank not being a dual-trader.

Tables 11 and 12 summarize the regression results. The TrSizeMean variable has a negative coefficient of $-329,996$ when explaining the total risk and benchmark adjuted profit, significant at the 1% level. This suggests that the increasing trade size has led to a reduction in profitability. Therefore hypothesis H2 (Trade size hypothesis) must be rejected.

The positive regression coefficients for NTrades variable, measering the number of trades, statistically significant at least at the 5% level, demonstrate that traders with many transactions outperform traders with few transactions in the same stock. That is, the higher the number of transactions, the higher the trading profit.

Since the regression coefficient for the dummy variable for dual traders (DDual) is negative, dual traders do not outperform non-dual traders. In other words, dual traders are not able to exploit the informational advantage of knowing their clients' order flow.

The regression coefficient for the fraction of initiated transactions (FInit) is also negative, especially for DAX-stocks. That is, traders who often initiate trades (e.g. in trying to exploit private information) are not compensated for paying the bid-ask bounce.

Finally, traders in larger firms do not profit from the fact that they have access to better information sources like databases or in-house research.

6 Conclusion

Deutsche Börse AG's electronic trading system *Xetra*, established in June 1997, accounts for more than 85% of the total turnover for German blue-chips (DAX-stocks) and about 50% of the total turnover for less liquid stocks. Xetra trading takes place in different trading phases, especially in opening and closing auctions and in the form of continuous trading. Trading volume is concentrated in the order-driven continuous trading phase (for most stocks more than 90%). In this paper, we use a comprehensive sample of transaction data to explore the price impact and the profitability of market participants trading for their own account. More precisely, this study examines proprietary trading of 1220 traders in 11 liquid DAX stocks and 5 less liquid MDAX stocks via Xetra from August 31, 1998 until August 31, 1999.

Our main findings are the following ones: (1) the impact of trade size on prices is slightly nonlinear, (2) the price response to buy and sell orders is for *most* stocks symmetric making it harder to profit from trade-based price manipulation, (3) less than 2% of the traders trading in DAX-stocks induce a price impact which is *not* related to trade size, whilethis amount increases to 4 % for MDAX-stocks. But these traders do not consistently outperform other traders. There is (4) a negative relationship between a trader's risk and benchmark adjusted profit and his mean trade size in DAX-stocks, while (5) for *all* stocks examined a trader's risk and benchmark adjusted profit increases significantly with the number of transactions in a specific stock.

7 Appendix A: Details of spectral analysis

The following description follows Hamilton (1994). The most important tool for the analysis of a time series $(x_t)_{t=1,...,T}$ in time domain is the autocovariance function. The autocovariance function $\hat{\gamma}_x$ is defined as$\hat{\gamma}_x(k) = \frac{1}{T}\sum_{t=1}^{T-|k|}(x_t - \bar{x})(x_{t+k} - \bar{x})$. To transfer the information given by the autocovariance function into terms of spectral analysis we define the Fourier transform of x as

$$f(\omega) \;=\; \frac{1}{T}\sum_{t=0}^{T-1} x_t e^{-i\omega t}, \quad \omega \in [0, 2\pi]$$

The data may be recovered using the inverse Fourier transform:

$$x_t \;=\; \sum_{j=0}^{T-1} f(\omega_j) e^{i\omega_j t}, \quad ,t = 1, ...T.$$

where $\omega_j = 2\pi j/T$. The Fourier transform of the autocovariance function $\hat{\gamma}_x$ is called *periodogram* and given by

$$\hat{s}_x(\omega) \;=\; \frac{1}{2\pi}\sum_{k=-T+1}^{T-1} \hat{\gamma}_x(k) e^{-i\omega k} = \frac{\hat{\gamma}(0)}{2\pi} + \frac{1}{\pi}\sum_{k=1}^{T-1}\hat{\gamma}_x(k) cos(\omega k), \quad \omega \in [0, \pi]$$

where the last equation holds because of $\hat{\gamma}_x(k) = \hat{\gamma}_x(-k)$. Since $\hat{\gamma}_x(k) = \int_{-\pi}^{\pi} \hat{s}_x(\omega) e^{i\omega k} d\omega$ and especially

$$Var(x) = \hat{\gamma}(0) = \int_{-\pi}^{\pi} \hat{s}_x(\omega) d\omega,$$

$\hat{s}_x(\omega)$ can be interpreted as the portion of variance of $(x_t)_t$ associated with frequency ω.

In case of two time series x and y the analogue of the autocovariance function is the *cross covariance function* $\hat{\gamma}_{x,y}$ defined by

$$\hat{\gamma}_{xy}(k) = \frac{1}{T}\sum_{t=1}^{T-|k|}(x_t - \overline{x})(y_{t+k} - \overline{y}).$$

Notice that $\hat{\gamma}_{xy}(-k) = \hat{\gamma}_{yx}(k)$ holds for $k = 1, ..., T-1$. The *cross periodogram* is the Fourier transform of the cross covariance function:

$$\hat{s}_{xy}(\omega) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}(\hat{\gamma}_{xy}(k) cos(\omega k) - i\hat{\gamma}_{xy}(k) sin(\omega k)) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\hat{\gamma}_{xy}(k) e^{i\omega k}$$

Analogously to the univariate case we have

$$\hat{\gamma}_{xy}(k) = \int_{-\pi}^{\pi} \hat{s}_{xy}(\omega) e^{i\omega k} d\omega.$$

The real part of the cross periodogram is called *cospectrum* and given by

$$c_{xy}(\omega) = Ref_{xy}(\omega) = \frac{1}{2\pi}\Big(\hat{\gamma}_{xy}(0) + \sum_{k=1}^{T}(\hat{\gamma}_{xy}(k) + \hat{\gamma}_{yx}(k))cos(\omega k)\Big)$$

and the imaginary part is called *quadrature spectrum* and given by

$$q_{xy}(\omega) = Imf_{xy}(\omega) = \frac{1}{2\pi}\sum_{k=1}^{T}(\hat{\gamma}_{xy}(k) - \hat{\gamma}_{yx}(k))sin(\omega k))$$

Furthermore we have for the so called *Fourier frequencies* $\omega_j = 2\pi\frac{1}{T}j, \quad j = 0, \dots, T-1$, the following relation between the covariance of the two time series x and y and their cospectra:

$$E(X_t - \bar{x})(Y_t - \bar{y}) = \frac{4\pi}{T}\sum_{j=1}^{T/2} c_{XY}(\omega_j),$$

which is useful for analysing the trading profits. The average trading profit per transaction can therefore via spectral analysis be expressed as the sum of the cospectra of N^{deme} and ΔS^{deme} :

$$G \quad = \quad \frac{4\pi}{T}\sum_{j=1}^{T/2} c_{N^{deme},\Delta S^{deme}}(\omega_j). \tag{4}$$

where $\omega_j = 2\pi\frac{j}{T}$. Often it is more convenient to think in terms of the period of a cycle rather than its frequency. Recall that if the frequency of a cycle is ω, the period of a cycle is $2\pi/\omega$. Therefore equation (4) can be interpreted as a decomposition of the trading profit into cycles of different period lengths (see e.g. Hasbrouck/Sofianos (1993)).

8 Appendix B: Tables and Figures

Table 1: Number of Xetra's Member Firms and Traders

P (for proprietary) denotes traders who traded exclusively for their own account during the sample period. A (for agent) denotes traders who traded exclusively for their customers during the sample period. Both denotes traders who traded both for their own account and for their customers at some time during the sample period. The sample period consists of 253 trading days between August 31, 1998 and August 31, 1999.

Name of	Ticker	Member Firms				Traders			
Stock	Symb.	P	A	Both	All	P	A	Both	All
DAX-Stocks:									
Allianz	ALV	114	47	85	246	723	561	181	1465
Bayer	BAY	113	50	86	249	747	589	192	1528
Daimler-Chrysler	DCX	133	51	90	274	821	601	226	1648
Deutsche Bank	DBK	134	48	93	275	825	604	216	1645
Deutsche Telekom	DTE	120	46	89	255	567	546	203	1316
Lufthansa	LHA	108	48	83	239	668	567	173	1408
Mannesmann	MMN	111	47	90	248	723	572	192	1487
Metro	MEO	99	49	85	233	654	532	153	1339
RWE	RWE	106	43	85	234	695	521	157	1373
Siemens	SIE	126	45	91	262	783	585	193	1561
Veba	VEB	113	45	89	247	728	548	174	1450
MDAX-Stocks:									
BHF Bank	BHF	69	44	57	170	304	351	52	707
Continental	CON	82	45	71	198	451	474	90	1015
Douglas	DOU	57	53	41	151	256	325	33	614
Krupp-Hoesch	FKR	50	34	25	109	139	122	9	270
SGL Carbon	SGL	53	47	62	162	294	401	57	752

Table 2: Trading Activity Statistics for Proprietary Trades and Customer Trades

The second column of the table shows the total number of transactions for different stocks. The sample period consists of 80 trading days between August 31, 1998 and August 31, 1999. Column three gives the mean time between transactions and column four gives the mean daily trading volume in shares. The fractions of the total volume due to different accounts are given in columns five and six. For proprietary trades (P) and customer trades (A), respectively, column seven and eight give the percentage of volume due to market orders. 100 minus this percentage gives the percentage of volume due to limit orders.

Stock	Number of Trades	mean time between Trades	mean daily trading volume	Volume in % of total volume		Volume in % due to market orders	
				P	A	P	A
DAX-Stocks:							
ALV	154.391	0:00:50.29	417.528	67,04	32,96	12,54	9,22
BAY	158.506	0:00:49.01	1.712.077	62,81	37,19	11,66	9,89
DBK	238.340	0:00:32.42	2.476.617	68,63	31,37	6,67	9,52
DCX	269.026	0:00:28.83	2.715.646	68,21	31,79	9,68	9,24
DTE	199.990	0:00:38.80	3.259.097	63,62	36,38	11,97	9,25
LHA	114.808	0:01:07.66	1.287.757	56,35	43,65	9,23	7,22
MEO	95.399	0:01:21.39	634.653	63,44	36,56	11,40	7,72
MMN	196.347	0:00:39.51	1.164.724	65,48	34,52	9,03	10,00
RWE	97.761	0:01:19.32	945.239	62,59	37,41	13,02	8,38
SIE	189.621	0:00:40.95	1.725.105	67,00	33,00	8,44	9,67
VEB	134.006	0:00:57.91	1.237.915	61,37	38,63	11,04	9,68
MDAX-Stocks:							
BHF	8.995	0:13:51.91	86.177	51,28	47,97	1,81	4,18
CON	27.160	0:04:45.00	204.045	48,88	47,02	4,25	6,79
DOU	7.847	0:15:44.73	31.237	47,75	46,56	2,78	5,33
FKR	1.995	0:28:44.62	6.698	60,06	39,74	1,15	3,57
SGL	12.249	0:10:22.66	34.132	47,43	46,95	3,35	5,64

Table 3: Percentage trading volume and trade size in different trading phases

Vol denotes the volume, mean and max denote the mean and maximum of the trade size in shares. Trading days start with the opening auction (O), followed by continuous trading (C), interrupted by the amid auction (A) and ended by the final auction (F). The volatility auction is denoted by V. The sample period consists of 253 trading days between August 31, 1998 and August 31, 1999.

	Continuous			Auctions											
Stock	Trading (C)			Opening (O)			Amid (A)			Final (F)			Volatility (V)		
	Vol.	Trading size		Vol.	Trading size		Vol.	Trading size		Vol.	Trading size		Vol.	Trading size	
	in %	Mean	Max	in %	Mean	Max	in %	Mean	Max	in %	Mean	Max	in %	Mean	Max
DAX-Stocks:															
ALV	91,50	545	32.900	0,49	448	25.000	5,00	2.301	1.548.736	2,95	790	139.998	0,06	986	6.400
BAY	91,47	2.192	100.000	0,52	1.870	151.000	4,98	12.553	5.969.601	2,94	4.013	540.575	0,09	4.628	130.000
DCX	92,46	2.042	146.100	0,73	2.102	151.000	3,66	7.871	6.273.842	3,07	4.018	756.869	0,08	2.808	50.000
DBK	94,39	2.159	200.000	0,66	2.228	70.000	2,45	7.030	3.389.804	2,36	3.564	150.000	0,14	3.871	69.500
DTE	89,13	3.170	182.300	0,66	3.606	600.000	3,44	14.123	6.329.144	6,56	13.332	9.363.900	0,21	4.865	64.000
LHA	93,80	2.335	128.200	0,47	1.580	25.000	3,00	8.156	2.415.150	2,61	4.008	292.752	0,11	3.701	39.000
MMN	93,67	1.205	64.400	0,51	944	20.071	2,97	3.358	2.467.602	2,70	1.783	234.674	0,15	2.050	30.000
MEO	92,15	1.384	68.300	0,34	880	25.000	4,48	5.873	2.182.217	2,95	2.264	186.799	0,08	2.018	20.000
RWE	91,36	1.982	74.400	0,37	1.335	30.000	4,96	10.601	3.514.548	3,07	3.493	317.423	0,23	2.986	25.000
SIE	93,85	1.881	140.400	0,46	1.432	30.000	3,01	6.585	3.753.245	2,52	2.986	334.756	0,15	3.388	80.000
VEB	91,78	1.899	99.500	0,61	1.997	150.500	4,46	8.581	3.182.229	3,00	3.210	351.655	0,15	2.818	50.000
MDAX-Stocks:															
BHF	94,87	2.266	100.000	0,44	711	10.000	0,55	540	20.000	3,76	2.212	50.000	0,38	1.200	6.000
CON	95,64	1.667	98.900	0,58	791	10.000	0,38	492	13.600	3,21	2.021	34.900	0,19	2.630	15.000
DOU	94,74	939	17.100	0,58	373	2.800	0,47	184	3.500	3,69	798	20.000	0,53	880	3.400
FKR	95,43	467	6.500	0,28	193	500	0,63	88	843	2,25	178	1.851	1,41	498	3.000
SGL	94,88	643	16.400	0,60	245	2.805	0,50	156	5.000	3,24	604	11.200	0,78	683	8.100

Figure 2: Distribution of trade size for Deutsche Bank (DBK)

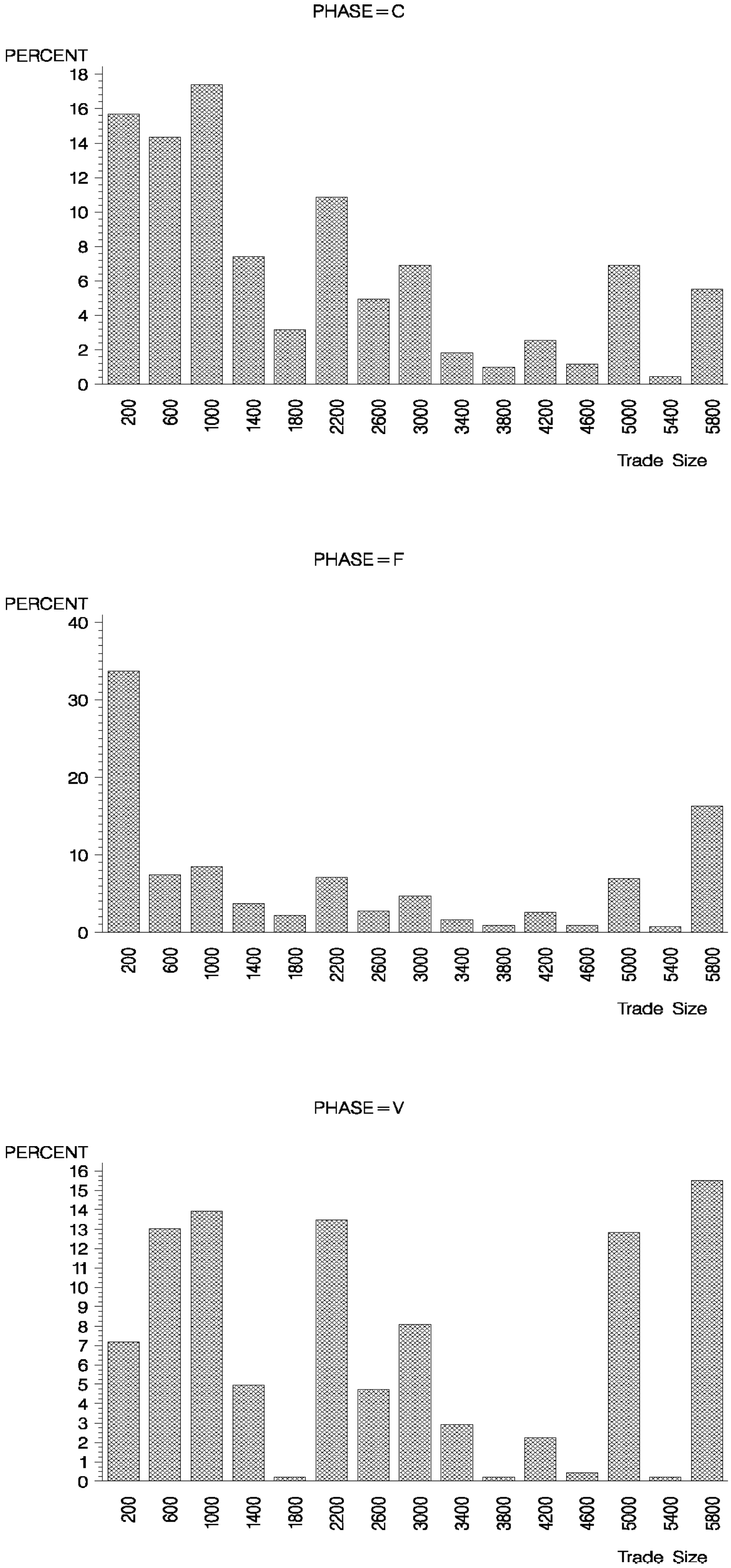


Table 4: Self-Crossing

The table summarizes, for Trader level as well as for Member level, the total number of Self-Crossings, the mean and the maximum EUR-Volume of Self-Crossing transactions. For the Trader level, Self-Crossings are transactions where buyer and seller are idendical and the trader acts for own account. For the Member level, Self-Crossings are transactions where buyer and seller belong to the same member firm and both act for own account. The sample period consists of 253 trading days between August 31, 1998 and August 31, 1999.

	Self-Crossings at Member level			Self-Crossings at Trader level		
		EUR-Volume of Trade			EUR-Volume of Trade	
Stock	Number	Mean	Max	Number	Mean	Max
DAX-Stocks						
ALV	697	181.762	1.463.317	45	114.030	328.761
BAY	577	80.763	638.010	34	86.422	232.080
DBK	729	140.186	5.276.532	75	84.428	356.820
DCX	842	195.811	1.917.345	53	163.712	466.750
DTE	782	119.815	3.259.550	49	105.085	391.400
LHA	376	36.111	884.739	21	36.778	130.845
MEO	624	79.450	708.225	35	78.374	354.606
MMN	822	163.978	3.717.500	73	211.402	1.579.000
RWE	550	76.887	957.624	21	76.912	245.000
SIE	508	116.706	1.163.189	67	133.698	728.091
VEB	571	93.673	1.192.250	43	93.409	465.764
MDAX-Stocks						
BHF	47	90.114	1.017.000	11	39.553	90.008
CON	55	44.968	227.000	10	41.640	84.700
DOU	10	33.074	95.918	8	24.127	49.368
FKR	3	18.589	32.851	1	12.000	12.000
SGL	21	53.017	316.110	10	35.801	114.529

Table 5: Test of Linearity

The table reports the regression coefficients and adjusted R^2 of a nonlinear model regressing price change on trade size:

$$\ln(p_t/p_{t-1}) = \alpha \text{ TrSize}_t + \beta \text{ TrSize}_t \cdot \text{ abs}(\text{TrSize}_t) + \varepsilon_t, \quad t = 1, 2, \ldots$$

Stock	α $\times 10^6$	β $\times 10^{11}$	Adj. R^2 in %
DAX-Stocks:			
ALV	0,50**	-7,16**	97,71
BAY	0,10**	-0,19**	97,49
DBK	0,08**	-0,14**	97,84
DCX	0,05**	-0,03**	98,54
DTE	0,06**	-0,07**	96,06
LHA	0,11**	-0,14**	95,64
MEO	0,15**	-0,35**	97,95
MMN	0,16**	-0,53**	99,31
RWE	0,14**	-0,35**	97,07
SIE	0,08**	-0,10**	98,27
VEB	0,09**	-0,08**	97,27
MDAX-Stocks:			
BHF	0,02**	-0,18**	12,27
CON	0,33**	-1,40**	87,19
DOU	1,02**	-7,61**	87,91
FKR	2,81*	-67,99	90,39
SGL	1,29**	-19,67**	86,27

* (**) significant at level 5%(1%)

Table 6: Test of Symmetry

The table reports the regression coefficients and adjusted R^2 of a linear model regressing price change on trade size:

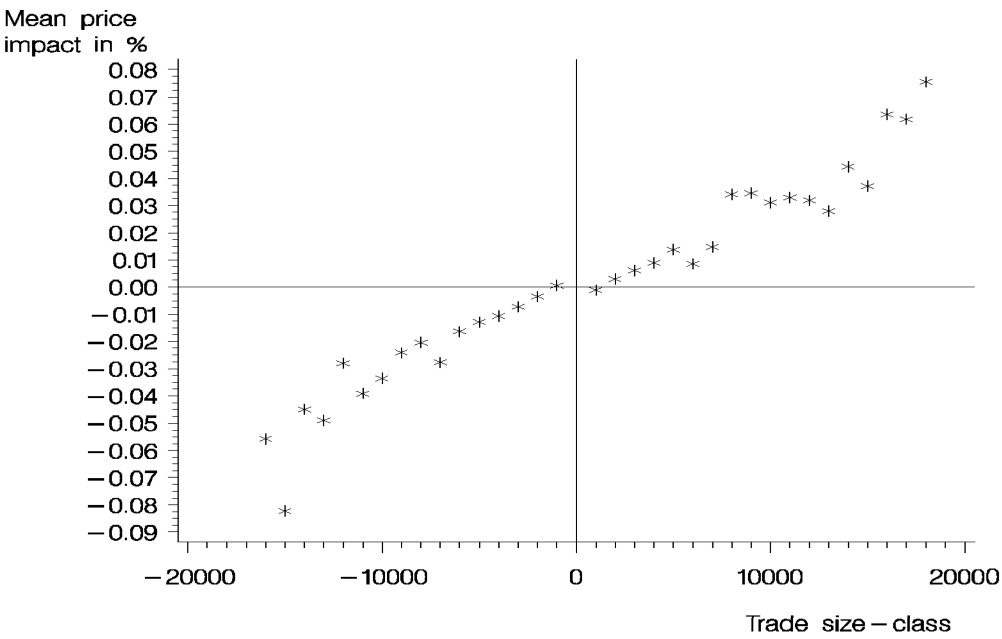
$$\ln(p_t/p_{t-1}) = \alpha\ \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t>0\}} + \beta\ \mathrm{TrSize}_t 1_{\{\mathrm{TrSize}_t<0\}} + \varepsilon_t, \quad t = 1, 2, \ldots$$

Stock	α $\times 10^5$	β $\times 10^5$	Adj. R^2 in %	p-value in %
DAX-Stocks:				
ALV	3,03**	3,47**	94,38	53,99
BAY	0,68**	0,90**	97,74	1,83
DBK	0,55**	0,69**	98,63	5,14
DCX	0,47**	0,48**	98,10	79,94
DTE	0,46**	0,55**	94,80	22,19
LHA	0,87**	1,05**	97,31	12,73
MEO	1,13**	1,34**	97,51	31,25
MMN	1,25**	1,39**	98,92	38,11
RWE	1,05**	1,09**	94,87	84,15
SIE	0,61**	0,86**	96,93	4,31
VEB	0,75**	0,87**	95,17	47,37
MDAX-Stocks:				
BHF	0,65*	0,41	19,46	5,14
CON	2,27**	1,94**	93,26	57,29
DOU	7,71**	5,65**	83,57	51,51
FKR	9,11*	24,56	51,26	22,66
SGL	5,72**	7,37**	74,81	74,33

* (**) significant at level 5%(1%)

Figure 3: Relative price impact versus trade size in Deutsche Bank stocks

Panel A: 20 normal trading days in August 1999



Panel B: 17 turbulent trading days in the period September to December 1998

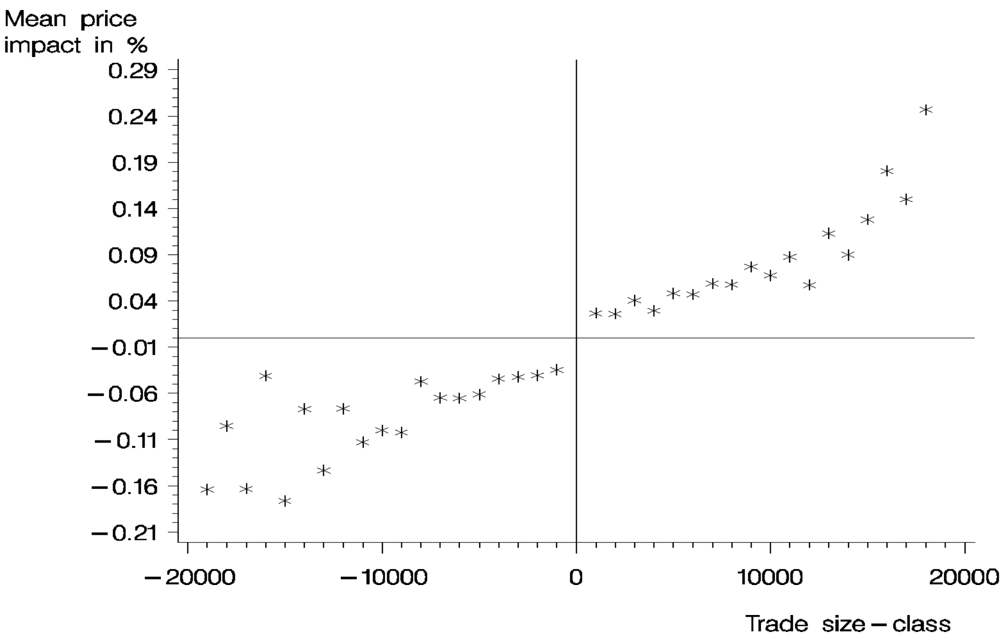
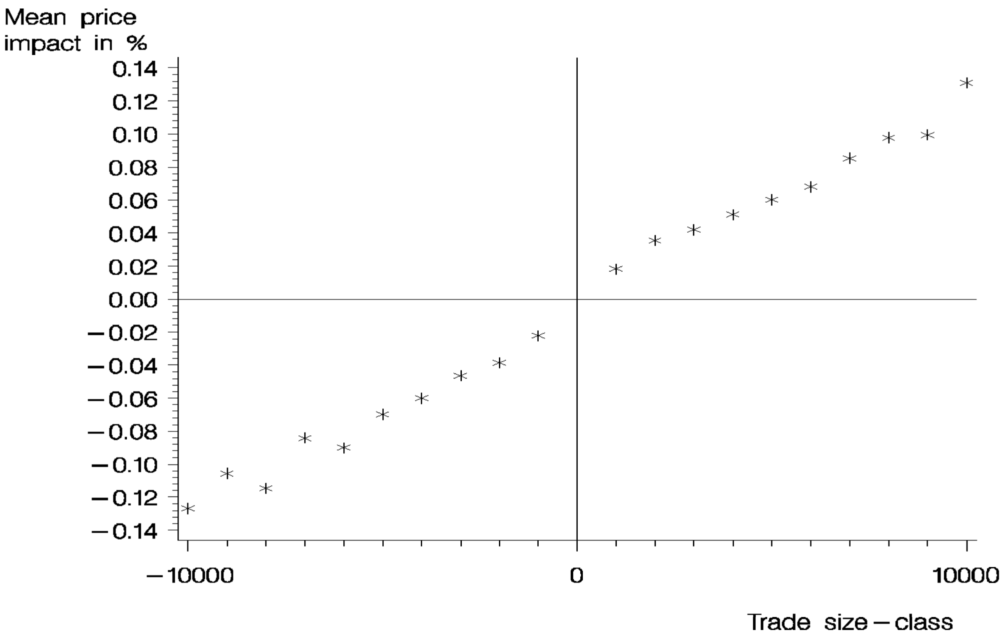


Figure 4: Price impact versus trade size during the period August 1998 - August 1999

Panel A: Mannesmann stocks



Panel B: Lufthansa stocks

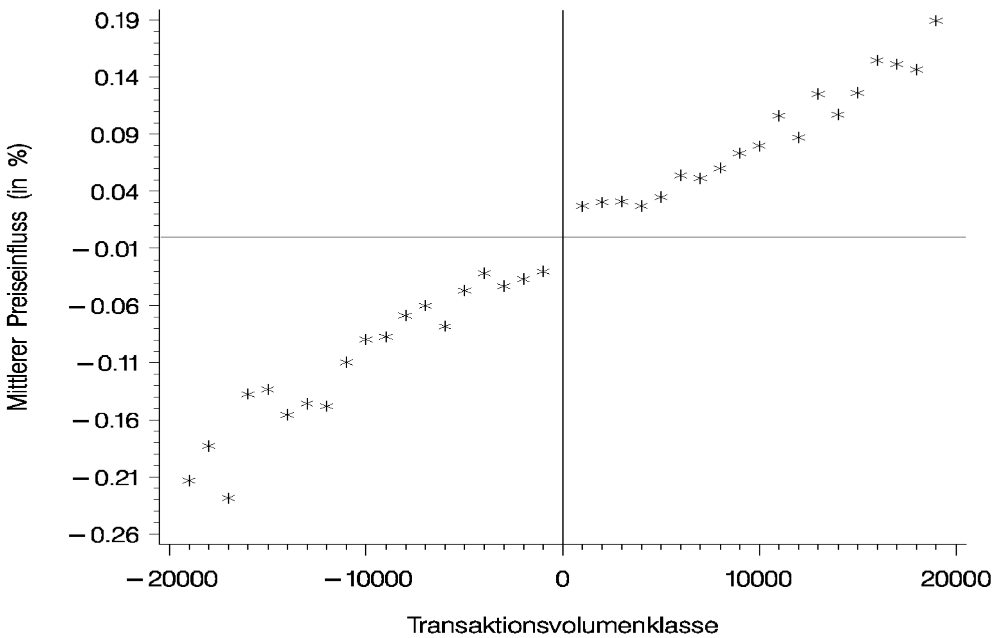


Figure 5: Mean impact of block purchases for DAX stocks

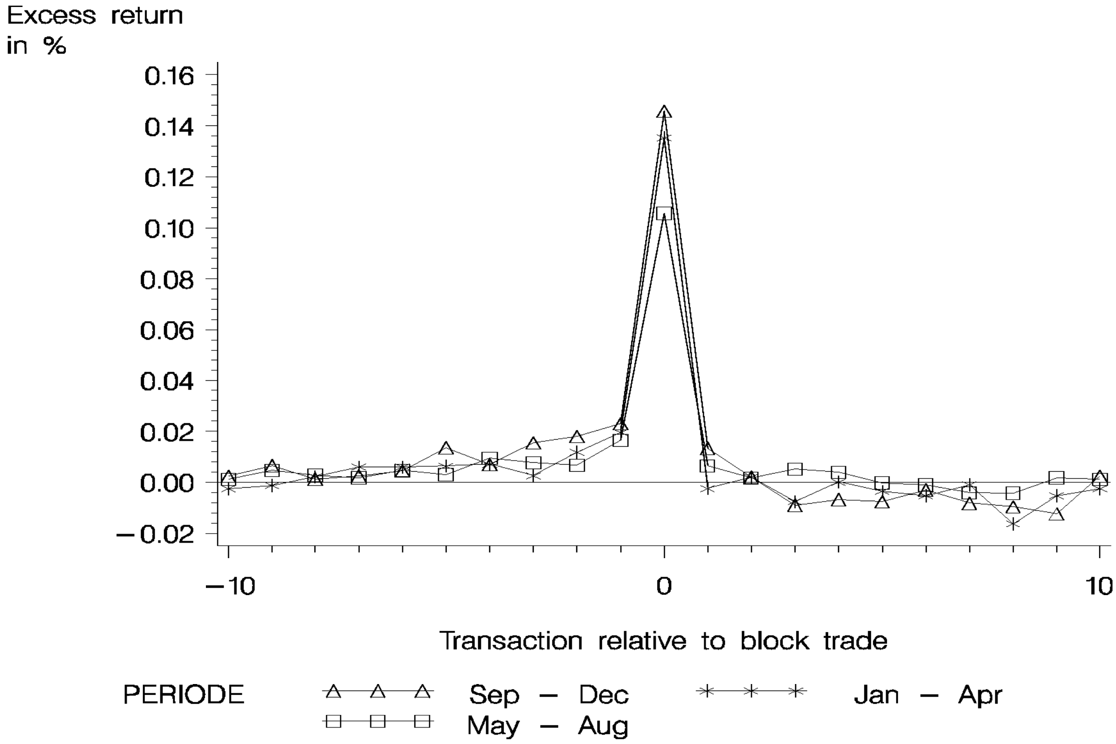


Figure 6: Mean impact of block sales for DAX stocks

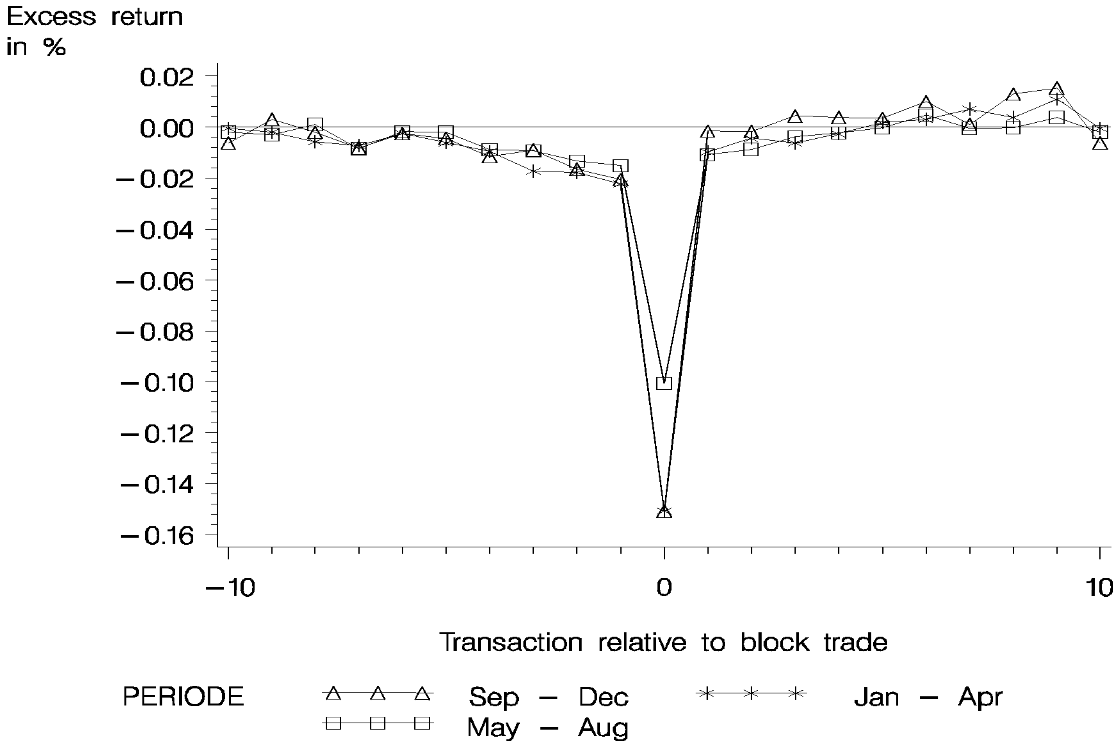


Figure 7: Mean impact of block purchases for MDAX stocks

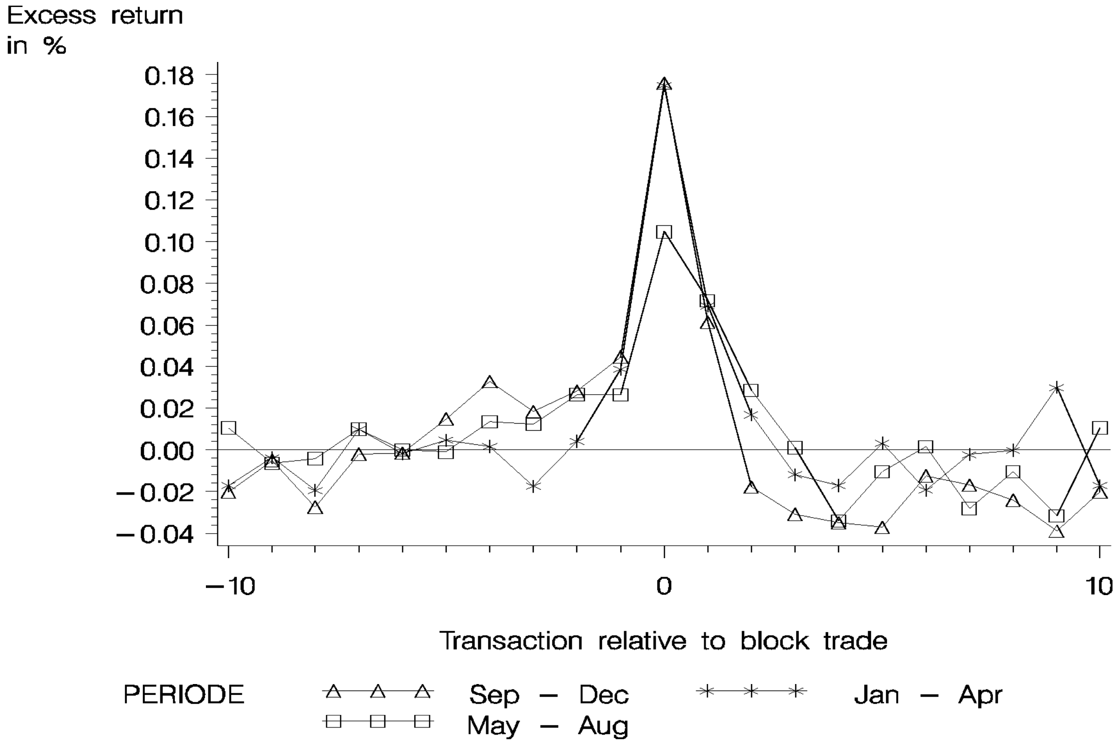


Figure 8: Mean impact of block sales for MDAX stocks

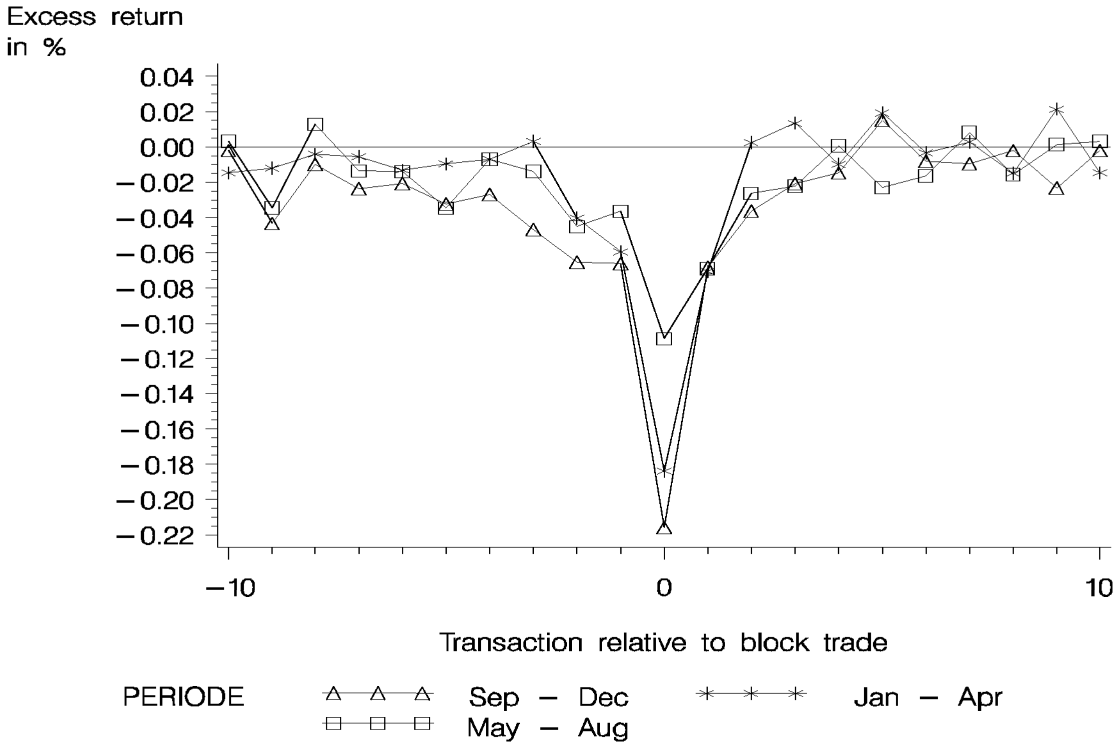


Figure 9: Cumulative impact of block purchases for DAX stocks

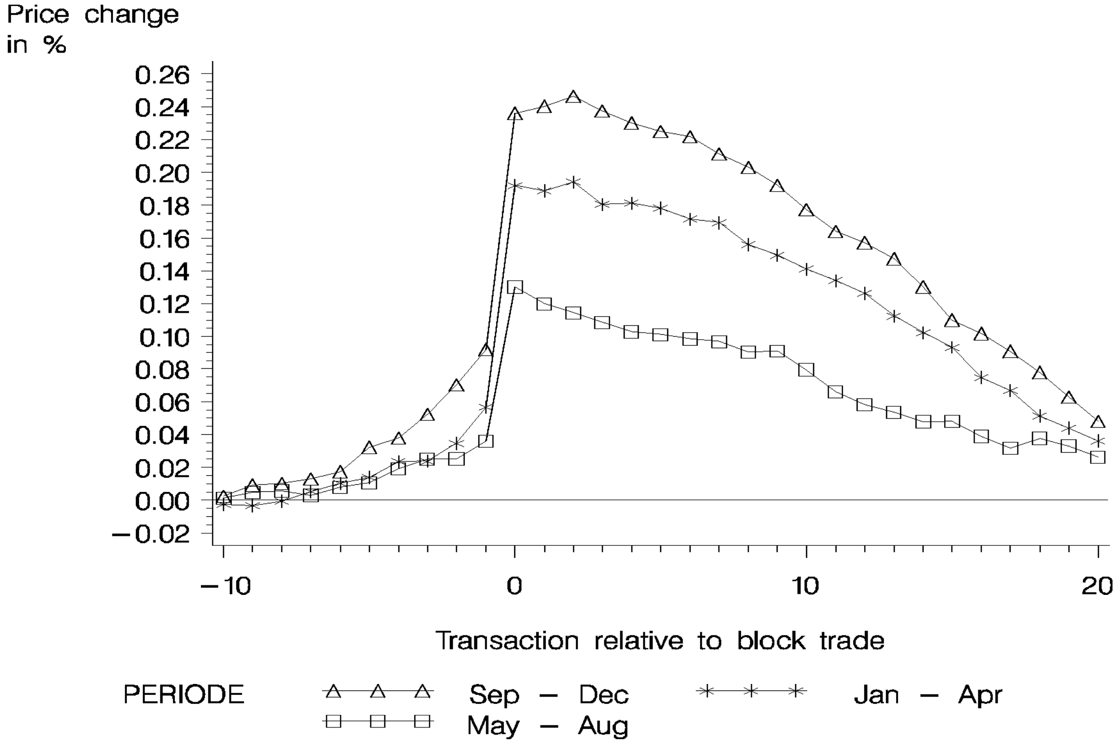


Figure 10: Cumulative impact of block sales for DAX stocks

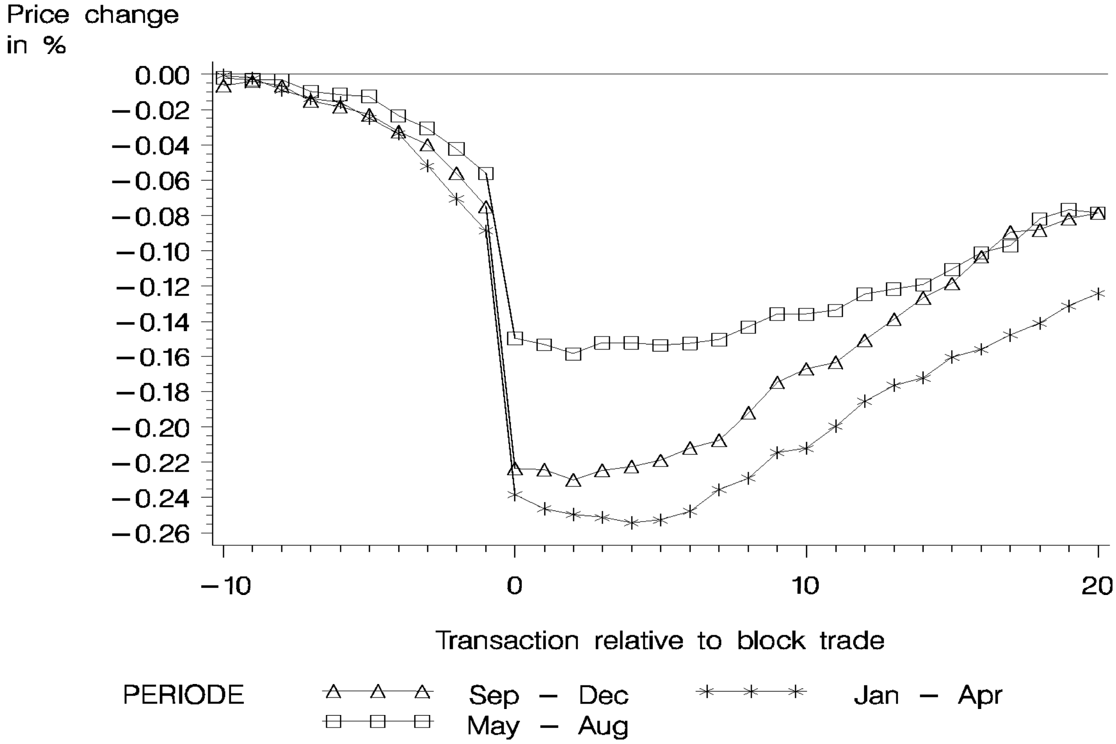


Figure 11: Cumulative impact of block purchases for MDAX stocks

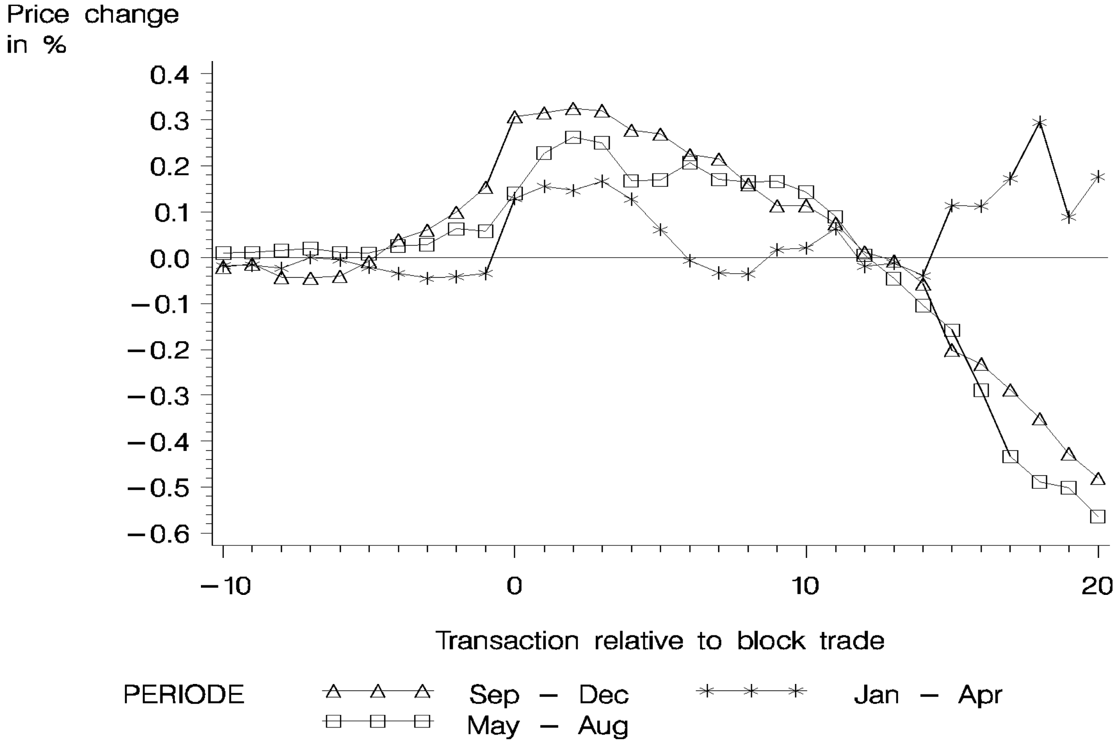


Figure 12: Cumulative impact of block sales for MDAX stocks

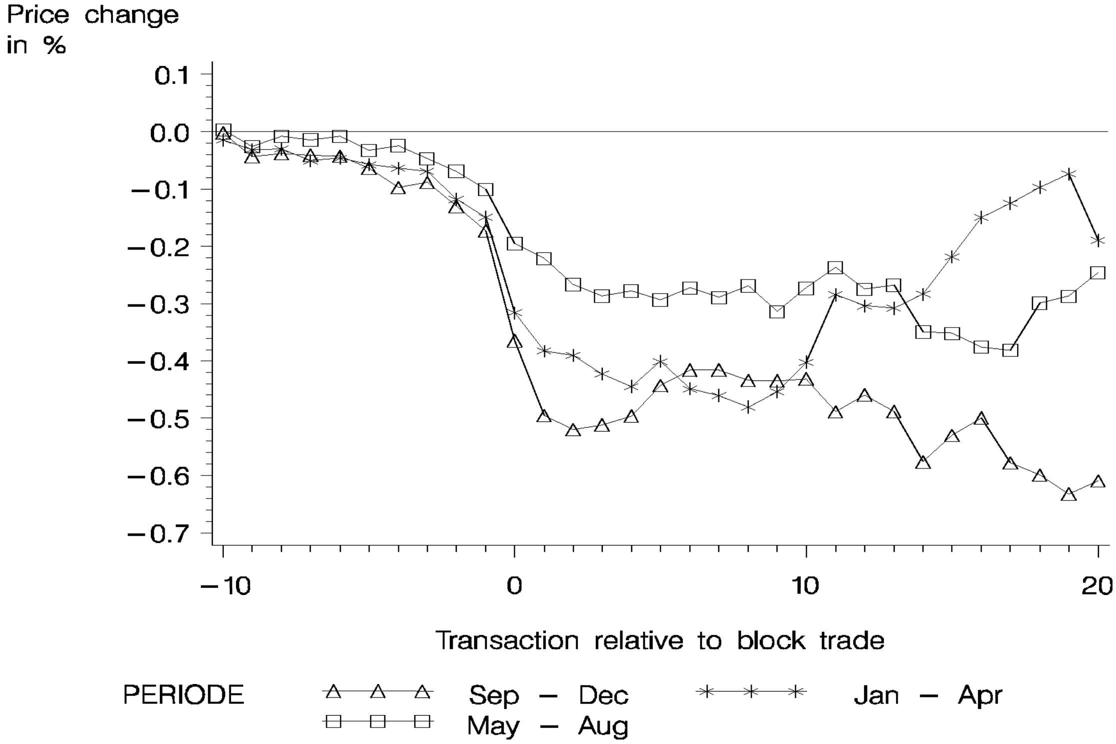


Table 7: Number of traders with price impact not related to trade size

For each band of cycle periods, we determine the number of traders inducing an a economically and statistically significant price impact which is not related to trade size by estimating the model

$$\ln(p_t/p_{t-1})^H = \alpha_1^H \ \mathrm{TrSize}_t + \alpha_2^H \mathrm{sign}(\mathrm{TrSize}_t)\mathrm{TrSize}_t^2 + \sum_{i=1}^{N} \beta_i^H \mathrm{sign}(\mathrm{TrSize}_t) \cdot 1_{\{Trader=i\}} \quad t = 1, 2, \ldots,$$

with H=Day, Week, Month, Year, Total.

		Number of traders with price impact on cycles with a period up to a									
		Day		Week		Month		Year		Total	
Stock	Trader in total	adj. R^2 in %	#	adj. R^2 in %	#	adj. R^2 in %	#	adj. R^2 in %	#	adj. R^2 in %	#
DAX-Stocks:											
ALV	324	12,75	2	2,19	0	3,28	0	7,16	0	13,39	2
BAY	330	11,89	1	1,98	0	2,34	0	6,65	0	12,19	0
DBK	453	10,00	2	1,23	0	2,20	0	7,31	0	10,38	3
DCX	436	9,17	3	1,42	0	2,04	0	11,31	0	9,61	3
DTE	363	9,51	0	1,81	0	3,53	0	1,48	0	9,90	0
LHA	238	10,47	1	2,44	0	2,77	0	10,23	0	10,96	1
MEO	225	10,69	2	2,50	0	3,85	0	8,34	0	11,33	2
MMN	356	12,56	4	1,69	0	2,80	0	2,94	0	13,15	7
RWE	228	10,03	2	2,72	0	3,95	0	4,52	0	10,56	2
SIE	371	12,16	2	1,73	0	2,25	0	9,30	0	12,69	5
VEB	282	9,99	3	2,06	0	3,47	0	6,58	0	10,41	3
MDAX-Stocks:											
BHF	92	8,57	1	3,92	0	8,34	3	15,66	2	9,83	1
CON	233	8,44	2	7,64	2	10,86	0	13,33	0	10,52	3
DOU	87	11,10	0	9,05	0	9,01	0	12,33	0	16,36	0
FKR	30	5,07	1	3,07	0	3,47	1	20,58	4	8,48	1
SGL	100	8,61	1	6,32	4	9,67	3	25,53	3	11,74	3

Table 8: Profits from Frontrunning

Number of Members refers to the number of members frontrunning their customers in the referring stock during the sample period. Frontrunning profit denotes the profit in EUR due to frontrunning activity. We define frontrunning as a trade for own account if the time span between this trade and the next trade for customers and the time span between the customer trade and the next trade for own account are both less than 5 minutes.

	Trader level			Member level		
	Number of	Frontrunning Profit		Number of	Frontrunning Profit	
Stock	Traders	Mean	Max	Members	Mean	Max
DAX-Stocks						
ALV	66	312,95	10.710,96	70	-6.521,66	16.888,93
BAY	69	-121,21	275,00	72	-2.738,11	2.781,43
DBK	80	-3.637,04	-65,90	95	550,83	10.475,00
DCX	78	1.267,71	6.579,07	99	-2.904,46	13.700,00
DTE	69	-2.160,29	-1.004,69	84	-3.129,88	14.579,20
LHA	63	-2.004,05	6.536,58	45	-1.570,54	150,00
MEO	64	-2.228,32	445,95	51	2.131,79	20.898,86
MMN	72	-22.850,00	-22.850,00	74	-12.320,15	10.778,92
RWE	60	2.127,36	7.225,81	48	52,04	16.000,00
SIE	71	-23.768,89	9.120,00	77	91,00	12.511,31
VEB	68	1.137,88	2.364,00	65	-3.317,48	9.879,00
MDAX-Stocks						
BHF	23	145,00	300,00	8	-120,00	-120,00
CON	38	624,09	4.242,73	19	12,78	12,78
DOU	18	497,07	2.200,00	6	-1.439,80	-670,81
FKR	5	-1.815,09	869,20	-	-	-
SGL	27	1.066,82	2.700,00	12	-60,00	1.690,00

Figure 13: Position changes of trader 098FRPRO001

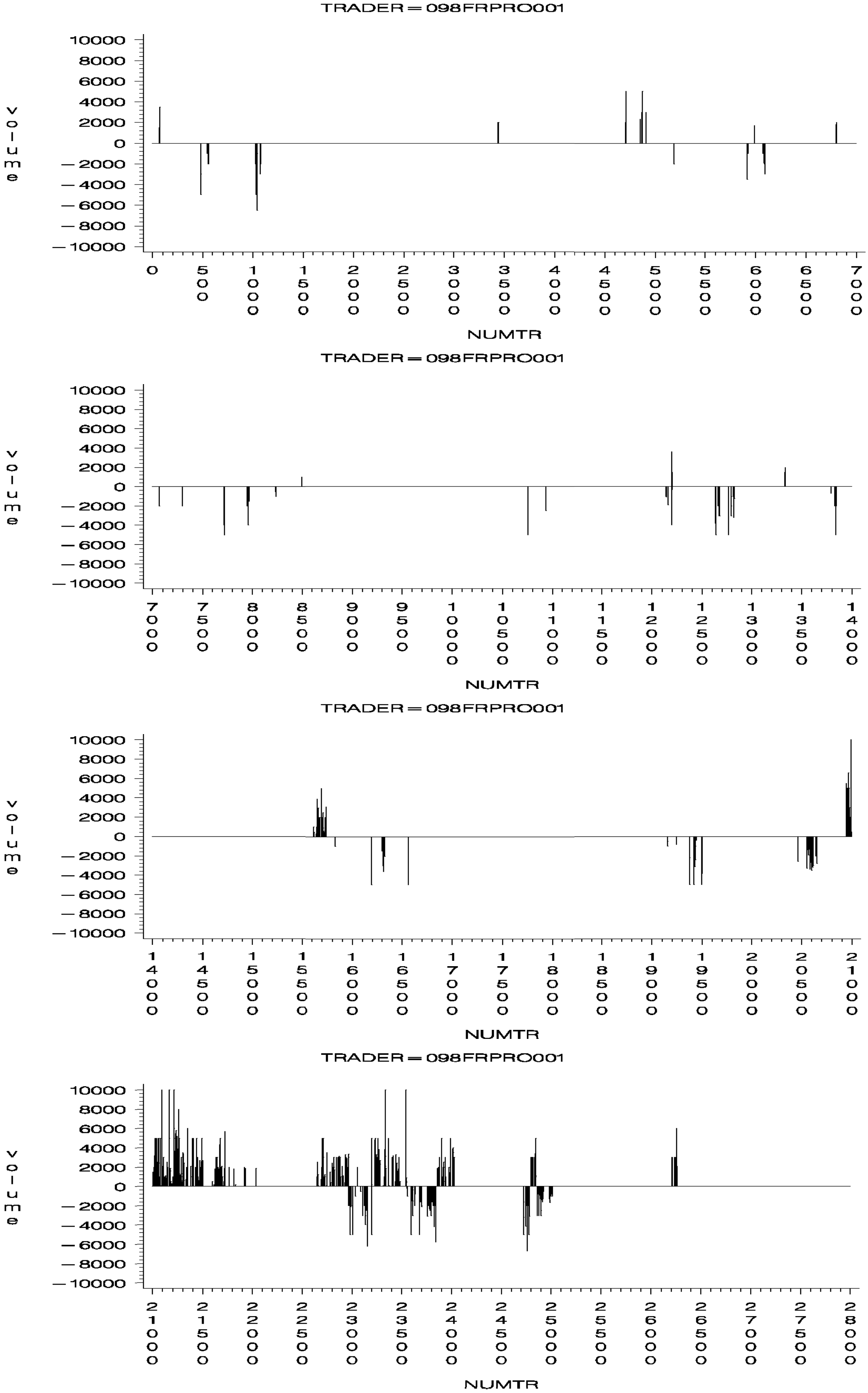


Figure 14: Position changes of trader 679STTMU001

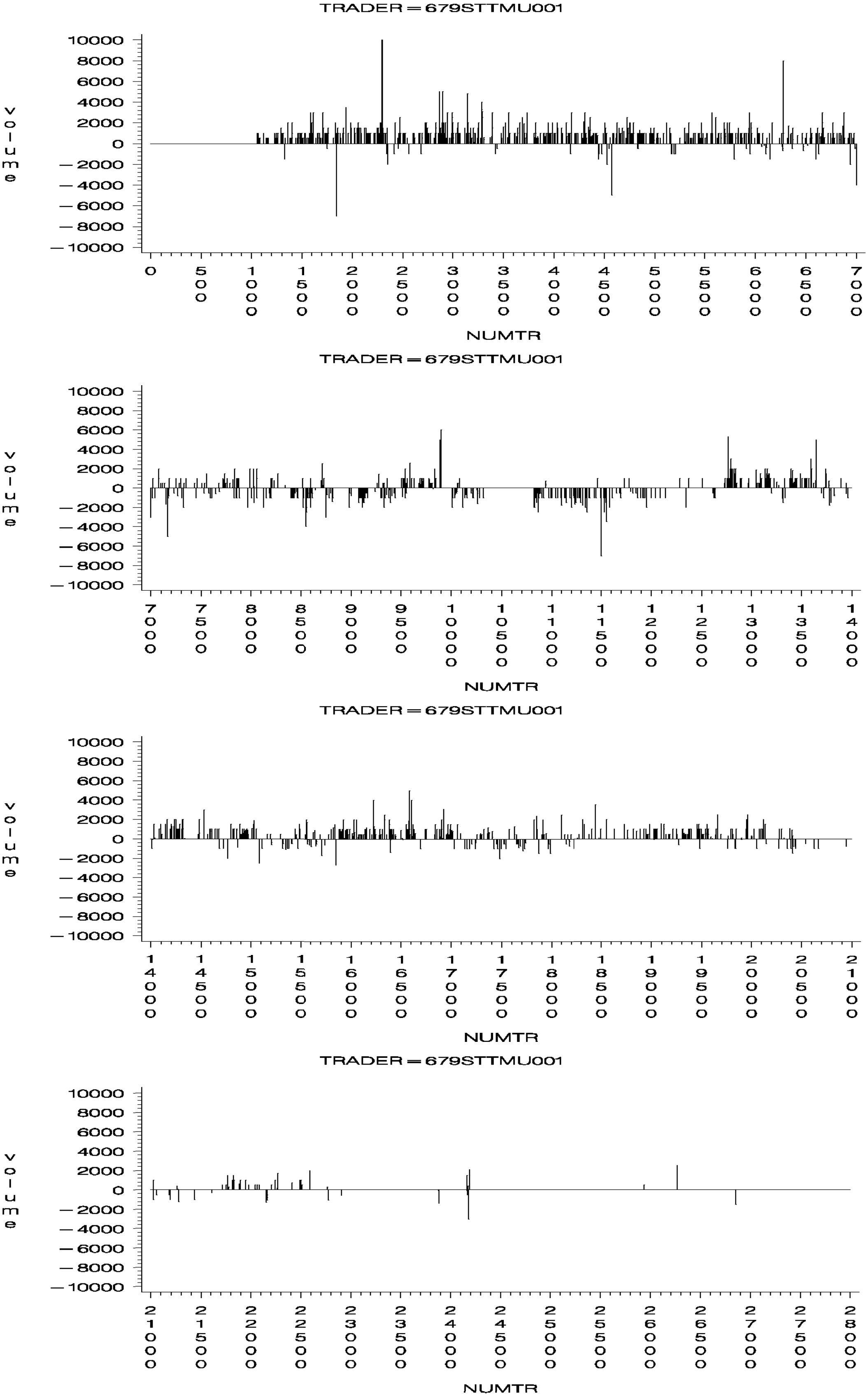
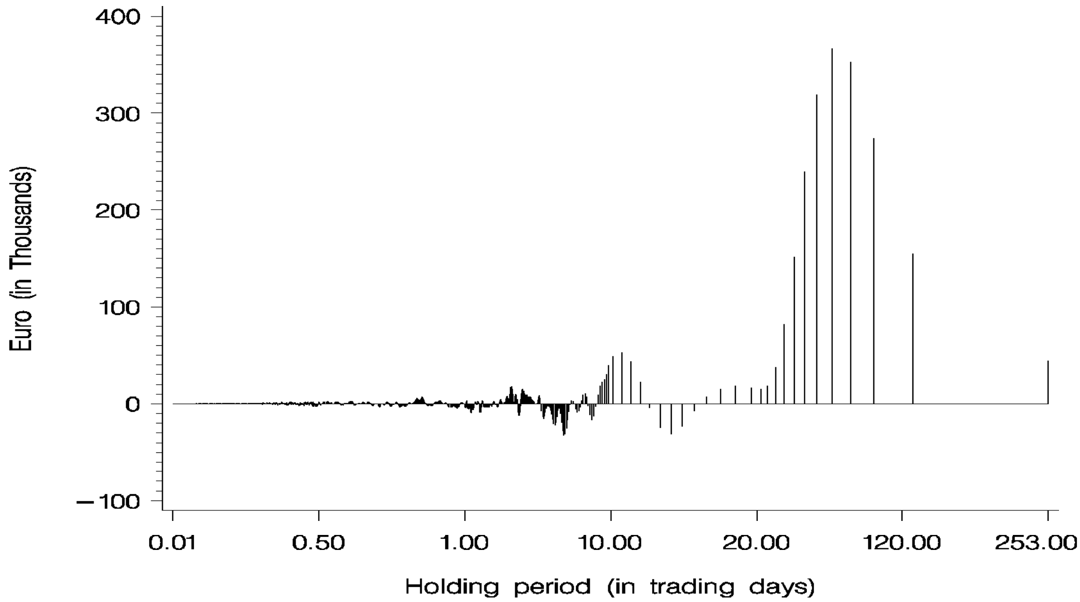


Figure 15: Cospectrum of price changes and demeaned trading positions

Panel A: A profitable trader (679STTMU001) in Continental stocks



Panel B: A non-profitable trader (098FRPRO001) in Continental stocks

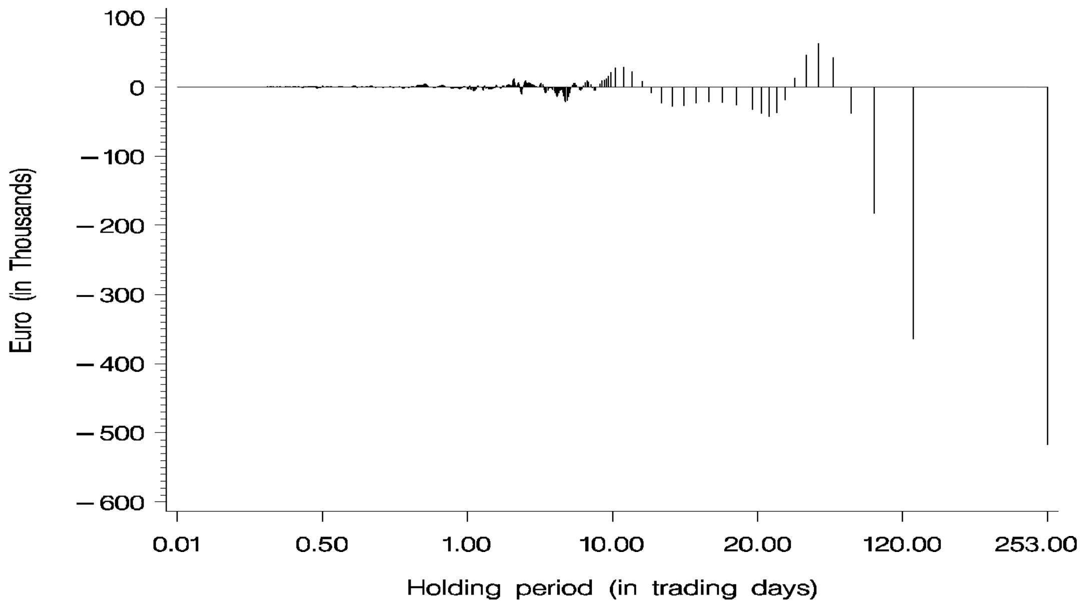


Table 9: Statistics DAX-Stocks

The table reports mean, standard deviation, minimum and maximum of benchmark adjusted profits, risk and benchmark adjusted profits, inventory risk, and explanatory variables. These statistics are calculated based on all pooled observations for the DAX-stocks. The dummy variable DBank is equal 1 for bank traders. DDual is equal 1 if a trader is a dual trader. NMStocks denotes the number of traders within the same member trading the same stock. FrInit indicates the percentage of initiated trades, NTrades denotes the number of trades, and TrSizeMean denotes the mean of the trader's trade size in the same stock.

Variable	Mean	STD	Minimum	Maximum
BM adjusted Profit (Total)	131,426	3,914,412	$-55,871,290$	107,302,017
BM adjusted Profit (Day)	18,255	240,612	$-4,184,099$	4,053,713
BM adjusted Profit (Week)	7,885	353,863	$-4,042,724$	7,056,595
BM adjusted Profit (Month)	9,742	825,725	$-11,516,665$	10,250,123
BM adjusted Profit (Year)	95,543	3,736,859	$-55,471,315$	108,534,429
Risk and BM adj. Profit (Total)	297,388	2,501,894	$-9,983,510$	43,461,479
Risk and BM adj. Profit (Day)	44,830	184,771	$-675,417$	1,654,925
Risk and BM adj. Profit (Week)	33,448	213,442	$-1,075,266$	1,546,240
Risk and BM adj. Profit (Month)	17,901	479,245	$-2,188,835$	2,361,210
Risk and BM adj. Profit (Year)	26,503	1,851,116	$-9,046,271$	10,960,618
Inventory Risk (Total)$\times 10^{-3}$	4,906	9,314	2.4	132,876
Inventory Risk (Day) $\times 10^{-3}$	176	296	1.5	5,829
Inventory Risk (Week) $\times 10^{-3}$	389	653	1.0	11,864
Inventory Risk (Month) $\times 10^{-3}$	900	1,544	0.5	23,543
Inventory Risk (Year) $\times 10^{-3}$	4,786	9,166	0.3	130,104
DBank	0.49	0.50	0	1
DDual	0.13	0.34	0	1
NMStocks	11.14	9.59	1	41
FrInit	0,46	0,17	0,01	0,98
NTrades	633	1,128	100	35,066
TrSizeMean	2,122	1,298	101.30	15,489

Table 10: Statistics MDAX-Stocks

The table reports mean, standard deviation, minimum and maximum of benchmark adjusted profits, risk and benchmark adjusted profits, inventory risk, and explanatory variables. These statistics are calculated based on all pooled observations for the MDAX-stocks. The dummy variable DBank is equal 1 for bank traders. DDual is equal 1 if a trader is a dual trader. NMStocks denotes the number of traders within the same member trading the same stock. FrInit indicates the percentage of initiated trades, NTrades denotes the number of trades, and TrSizeMean denotes the mean of the trader's trade size in the same stock.

Variable	Mean	STD	Minimum	Maximum
BM adjusted Profit (Total)	70,493	797,586	$-5,365,319$	5,556,001
BM adjusted Profit (Day)	7,732	89,697	$-341,641$	1,169,929
BM adjusted Profit (Week)	$-1,666$	95,273	$-1,236,179$	315,545
BM adjusted Profit (Month)	$-23,710$	290,378	$-3,814,345$	939,533
BM adjusted Profit (Year)	88,136	986,536	$-6,049,875$	9,436,596
Risk and BM adj. Profit (Total)	8,680	600,702	$-4,272,202$	1,968,606
Risk and BM adj. Profit (Day)	1,388	43,235	$-174,176$	284,163
Risk and BM adj. Profit (Week)	5,082	53,258	$-153,316$	224,790
Risk and BM adj. Profit (Month)	9,720	134,905	$-389,737$	479,324
Risk and BM adj. Profit (Year)	$-16,520$	607,250	$-4,380,530$	1,772,324
Inventory Risk (Total) $\times 10^{-3}$	1,127	3,087	26.4	4,723
Inventory Risk (Day) $\times 10^{-3}$	48.7	142.4	1.6	2,214
Inventory Risk (Week) $\times 10^{-3}$	101.1	283.9	3.9	4,412
Inventory Risk (Month) $\times 10^{-3}$	221.5	572.2	8.3	8,735
Inventory Risk (Year) $\times 10^{-3}$	1,096	3,018	20.3	46,157
DBank	0.46	0.5	0	1
DDual	0.15	0.36	0	1
NMStocks	7.43	5.58	1	23
FInit	0.51	0.18	0.05	0.98
NTrades	162	202	50	1,715
TrSizeMean	1,495	926	89.39	5,822

Table 11: Regression on trader characteristics for DAX-stocks

The table reports the results of a pooled regression of risk and benchmark adjusted profits on trader characteristics:

$$Gf_{i,j}^{adj} = \alpha_j + \beta_1 \text{DBank}_{i,j} + \beta_2 \text{ DDual}_{i,j} + \beta_3 \text{ NMstocks}_{i,j} + \beta_4 \text{ FrInit}_{i,j} + \beta_5 \text{ NTrades}_{i,j} + \beta_6 \text{ PrImpBeta}_{i,j} + \beta_7 \text{ TrSizeMean}_{i,j} + \mu_i + \varepsilon_{i,j},$$

f=Day, Month, Week, Year, Total.

		Maximal length of cycle period			
	Total	Day	Week	Month	Year
Dummy ALV	374,431*	76,056**	9,418	32,922	−68, 499
Dummy BAY	307,970*	58,901**	−8, 184	36,478	−1, 192
Dummy DBK	410,072**	63,607**	14,210	43,855	11,790
Dummy DCX	257,202	42,755**	47,632**	−97, 204**	−75, 933
Dummy DTE	421,144**	106,451**	1,043	33,691	−36, 847
Dummy LHA	243,769	56,892**	−3, 315	13,225	16,294
Dummy MEO	216,452	55,498**	−7, 624	40,305	−78224
Dummy MMN	733,970**	85,509**	7,153	60,272*	278,804*
Dummy RWE	224,103	57,187**	−15, 043	13484	−44, 429
Dummy SIE	244,493	71,226**	−1, 340	3,083	−66, 333
Dummy VEB	254,088	76,166**	−19, 268	132,454**	−156, 949
DBA	188,542	15,618	48,201**	23,008	100,581
DDUAL	−349, 904*	−9, 775	−35, 102	−95, 647**	−96, 799
NMStocks	−310, 590**	−15, 971**	−17, 257**	−37, 595**	−118, 271**
FInit	−711, 831*	−256, 907**	−73, 543**	−225, 304**	−3, 448
NTrades	324,919**	42,754**	−2, 458	16,825	84,239*
PrImpBeta	206,946	−7, 244	451,050	1,141,796	−893, 805
TrSizeMean	−329, 996**	−32, 734**	−11, 159	20,448	−159, 998
Observations	3602	3602	3602	3602	3602
Adjusted R^2 in %	38.83	57.71	29.00	24.02	13.12

* (**) significant at level 5%(1%)

Table 12: Regression on trader characteristics for MDAX-stocks

The table reports the results of a pooled regression of risk and benchmark adjusted profits on trader characteristics:

$$\begin{aligned} Gf_{i,j}^{adj} = &\ \alpha_j + \beta_1 \text{DBank}_{i,j} + \beta_2\ \text{DDual}_{i,j} + \beta_3\ \text{NMstocks}_{i,j} + \beta_4\ \text{FrInit}_{i,j} \\ &+ \beta_5\ \text{NTrades}_{i,j} + \beta_6\ \text{PrImpBeta}_{i,j} + \beta_7\ \text{TrSizeMean}_{i,j} + \mu_i + \varepsilon_{i,j}, \end{aligned}$$

f=Day, Month, Week, Year, Total.

		Maximal length of cycle period			
	Total	Day	Week	Month	Year
Dummy BHF	104,059	−16,782*	33,118*	57,448*	9,435
Dummy CON	182,895*	8,478	3,510	−23,608	180,073*
Dummy DOU	159,087	3,032	−3,200	−4,763	156,311
Dummy FKR	95,102	−132	−7,883	−16,848	110,149
Dummy SGL	196,932	−2,652	−8,939	2,079	188,383
DBA	−208,792*	9,672	4,641	9,722	−209,419*
DDUAL	38,800	−444	4,982	−9,954	−14,415
NMStocks	18,357	4,777	−2,174	−6,522	14,824
FrInit	−132,973	−42,100**	−20,516	6,473	−109,100
NTrades	162,060**	9,140*	7,873	−20,730	170,970**
PrImpBeta	161,083**	−277	21,945	−45,820	375,884
TrSizeMean	36,539	1,003	−6090	−24,955	33,092
Observations	271	271	271	271	271
Adjusted R^2 in %	25.74	8.43	30.89	1.83	24.88

* (**) significant at level 5%(1%)

References

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

Allen, F. and D. Gale (1992): *Stock-Price Manipulation*, The Review of Financial Studies 5, 503-529.

Allen, F. and G. Gorton (1992): *Stock price manipulation, market microstructure and asymmetric information*, European Economic Review 36, 624-630.

Chang, E. C., J. M. Pinegar and B. Schachter (1997): *Intraday variations in volume, variance and participation of large speculators*, Journal of Banking and Finance 21, 797-810.

De Long, J. B., A. Shleifer, L. H Summers and R. J. Waldmann (1990): *Positive Feedback Trading and Destabalizing Rational Speculation*, Journal of Finance 44, 793-805.

Fishman, M. J. and F.A. Longstaff (1992): *Dual Trading in Futures Markets*, Journal of Finance 47, 643-671.

Foster, F. D. and S. Vishwanathan (1990): *A Theory of Intraday Variations in Volume, Variance and Trading Costs in Securities MArkets*, The Review of Financial Studies 3, 593-624.

Gemmill, G. (1996): *Transparency and Liquidity: A Study of Block Trades on the London Stock Exchange under Different Publication Rules*, Journal of Finance 51, 1765-1790.

Gerke, W. and M. Oerke (1998): *Marktbeeinflussung durch Analyseempfehlungen - eine empirische Studie*, Working Paper, Universität Erlangen-Nürnberg.

Hamilton, J.D. (1994): *Time Series Analysis*, Princeton University Press.

Hansch, O., N. Naik and S. Viswanathan (1998): *Do Inventories matter in dealership markets? Evidence from the London Stock Exchange*, Journal of Finance 53, 1623-1655.

Hart, O. D. and D. M. Kreps (1986): *Price Destabilizing Speculation*, Journal of Political Economy 94, 927 -952.

Hasbrouck, J. and G. Sofianos (1993): *The Trades of Market Makers: An Empirical Analysis of NYSE Specialists*, Journal of Finance 48, 1565-1593.

Holden, M. and A. Subrahmanyam (1992): *Long-lived Private Information and Imperfect Competition*, Journal of Finance 47, 247-270.

Holthausen, R.W., R.W. Leftwich and D. Mayers (1990): *Large-block transactions, the speed of response, and temporary and permanent stock-price effect*, Journal of Financial Economics 26, 71-95.

Jarrow, R. (1992): *Market Manipulation, Bubbles, Corners, and Short Squeezes*, Journal of Financial and Quantitative Analysis 27, 311-336.

Jarrow, R. (1994): *Derivative Security Markets, Market Manipulation and Option Pricing Theory*, Journal of Financial and Quantitative Analysis 29, 241- 261.

Jones, C. M., G. Kaul and M. C. Lipson (1994): *Transactions, Volume, and Volatility*, The Review of Financial Studies 7, 632-651.

Kampovsky, A.-K. and S. Trautmann (1997): *Market Power and Regulation: Feedback Effects from Derivatives Hedging*, Working Paper University Mainz.

Kampovsky, A.-K. and S. Trautmann (1998): *A Large Trader's Impact on Equilibrium Price Processes*, Working Paper University Mainz.

Keim, D. B. and A. Madhavan (1995): *Anatomy of the trading process - Empirical evidence on the behavior of institutional traders*, Journal of Financial Economics 37, 371-398.

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

Kempf, A. and O. Korn (1998): *Market Depth and Order Size*, Working Paper, University of Mannheim.

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