Market Impact Costs of Institutional Equity Trades

Jacob A. Bikker[a] Laura Spierdijk[b*] Pieter Jelle van der Sluis[c]

a Supervisory Policy Division, Strategy Department, De Nederlandsche Bank, P.O. Box 98, NL-1000AB Amsterdam, The Netherlands

b Financial Engineering Laboratory and the Department of Applied Mathematics, University of Twente, P.O. Box 217, NL-7500AE Enschede, The Netherlands

c Vrije Universiteit Amsterdam, Department of Finance and Financial Sector Management; GTAA Fund, ABP Investments, P.O. Box 75753, NL-1118ZX Schiphol, The Netherlands

Abstract

This article analyzes market impact costs of equity trading by one of the world's largest pension funds. We find that, on average, these costs are small in terms of market disruption, but substantial in terms of costs for the pension fund. Average market impact costs equal 20 basis points for buys and 30 basis points for sells. Furthermore, we show that momentum and volatility have considerable influence on market impact costs. Other important determinants of these costs are trade type (agency, single, or principal), trade size, trading strategy, trading venue, and industry sector. Additionally, we find that the timing of trades plays a substantial role in explaining trading costs. Moreover, we also establish a cost-risk trade-off: the longer it takes to execute a trade, the lower the expected market impact costs but the higher the volatility of these costs.

JEL-classification: G11, G14, G23, G28

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[*]Corresponding author: Tel.: +31 53 489 3386; fax: +31 53 489 3069. E-mail addresses: j.a.bikker@dnb.nl (J.A. Bikker), l.spierdijk@utwente.nl (L.Spierdijk), pieterjelle.vander.sluis@Abpinvestments.nl (P.J. van der Sluis).

1 Introduction

Institutional investors today account for a large part of international stock holdings and equity trading. For example, in 2001 they owned more than 50% of total US equities[1]. Furthermore, Schwartz and Shapiro (1992) estimated that institutional investors and their member firms accounted for about 70% of total trading volume on the New York Stock Exchange (NYSE) in 1989. Since institutional investors occupy such a predominant position in the equity trading process, the literature has paid much attention to the impact of institutional trading on stock prices. For a survey, see Keim and Madhavan (1998). The upshot of their survey is that institutional trades cause substantial price pressure.

The existence of substantial price effects has important consequences for institutional investors, since they may cause additional trading costs ('market impact costs'). Trading costs occur when price effects cause execution prices to be less favorable than benchmark prices. Usually the decision to buy or sell a particular asset is based on expectations about the future performance of this asset. Buying a stock with high expected returns might result in worse performance than expected if trading costs for this particular stock are high. In such a case a stock with lower expected returns may perform better if its trading costs are lower. Therefore, knowing the trading costs on each stock up front might change the optimal portfolio holdings of an institutional investor. This makes trading costs an important factor to consider when trading decisions have to be taken, since ignoring them reduces the performance of the portfolio substantially.

Trading costs are also of interest from the perspective of regulators such as the U.S. Securities and Exchange Commission. Financial markets must have proper rules to ensure efficient execution of market transactions. Regulators have coined the concept of 'best execution' as a way to provide an assessment of the reasonableness of the prices of market transactions; see Wagner and Edwards (1993) and Macey and O'Hara (1997). Although the distinction between intentional failure and poor performance is hard to make, poor

[1] Source: NYSE Fact Book 2001. See www.nyse.com.

performance can be assessed by means of statistical methods.

Central banks are also interested in the costs of institutional equity trading, since one of their concerns is the existence of a well-functioning financial system in which large institutional investors can find sufficient liquidity to control the risk profile of their portfolios. Institutional trades are not only motivated by investment strategies or sound risk management, but may also stem from regulatory rules. Therefore, it is important for a central bank − in charge of financial stability and possibly also of pension fund supervision − to assess that the eventual procyclical effects of regulation are very limited.

This article analyzes the market impact of the equity trades of the largest Dutch pension fund. The 'Algemeen Burgerlijk Pensioenfonds' (ABP) has 2.6 million clients and an invested capital of about 170 billion Euro.[2] Its assets constitute about one third of total Dutch pension fund assets. Furthermore, ABP is not merely the largest pension fund of the Netherlands, it is also among the five largest pension funds in the world. A unique data set, containing detailed information on all worldwide equity trades of ten different funds at ABP during the first quarter of 2002, is used to identify the trade-, exchange- and stock-specific characteristics that determine the expected price impact of trading. Moreover, in order to gain more insight into the cost-risk relation, this article extends the existing literature by assessing the determinants of the volatility of the price effects as well. Since the data provide a wide set of trade-, exchange-, and stock-specific characteristics including investment style and trade timing, they allow for a comprehensive analysis of the determinants of the price impact of ABP trades. In particular, the detailed information on the timing of each trade is used to address an issue that has not yet been considered in the literature, namely the relation between market impact costs and trade timing.

We find that, on average, market impact and execution costs of the pension fund's trades are small in terms of market disruption, but substantial in terms of costs for the pension fund. Average market impact costs equal 20 basis points for buys and 30 basis points for sells; average execution costs equal 27 basis points and 38 basis points, respec-

[2] This is the invested capital of ABP on March 31, 2005.

tively. Furthermore, we show that volatility and momentum have considerable influence on market impact costs. Other important determinants of these costs are trade type (agency, single or principal), trade size, trading strategy, trading venue, and industry sector. In line with previous literature, we establish considerable differences between buy and sell trades. Additionally, we find that the timing of trades plays a substantial role in explaining trading costs. The time of the day, the day of the week, the period of the month, and the month of the year significantly affect the costs of trading. Moreover, we also establish a cost-risk trade-off: the longer it takes to execute a trade, the lower the expected market impact costs but the higher the volatility of these costs.

We stress that the current paper focuses on a single pension fund in a specific time period. As a consequence, this article merely serves as a case study and its results do not necessarily apply to other pension funds in other countries or under different circumstances.

This paper is organized as follows. Section 2 provides a brief review of the literature on the price effects of institutional trading. In Section 3 the trading process at ABP is explained. Section 4 describes the data set containing information on the equity trades of the pension fund. Some sample statistics on the temporary and persistent price effects of the ABP trades are presented in Section 5. Section 6 assesses the determinants of both the expected price impact and the volatility of the price effects and derives a mean-variance cost relation. Finally, Section 7 summarizes and concludes.

2 Price effects of institutional equity trades: a literature review

Quite a number of articles are devoted to market the impact and execution costs of institutional equity trades.

Chan and Lakonishok (1993) examine the price impact of institutional trades on the basis of transaction data of 37 large institutional money management firms during a two and a half year period (1986−1988). Correcting for market-wide stock price movements, the authors find that the average price change weighted by the dollar size of the trade (called the principal-weighted average) from the open to the close on the trade day equals 34 basis points (bp) for buys and −4 bp for sells.

Using the same data as Chan and Lakonishok (1993), a similar analysis is presented in Chan and Lakonishok (1995). In the latter article the authors do not measure the market impact of individual trades but of trade packages. The authors define a trade package as a series of successive sells or purchases of the same stock, which ends when the money manager stays out of the market for at least five days. After adjustment for market-wide price movements, the principal-weighted average price change from the open on the first trading day of the package to the close on the last day amounts almost 100 bp for buy packages and −35 bp for sell packages.

Keim and Madhavan (1997) investigate the total execution costs (defined as the sum of commission and market impact costs) of institutional trades in relation to investment styles, using data on the equity transactions of 21 institutions during the 1991−1993 period. They distinguish fundamental value managers (who focus on assessment of fundamental value, with a long-term perspective), technical managers (who focus on short-term price movements), and index managers (who focus on mimicking the returns of a certain index). The authors show that total execution costs are significant and that value traders have lower costs than traders using strategies that require more immediacy. Keim and Madhavan (1997) also explain execution costs from trade difficulty. Trade difficulty is measured by variables such as relative trade size, which has a positive impact, and market capitalization, which has a negative effect on the execution costs. Additionally, the authors relate the execution costs to the trading venue by showing that for institutional trades in Nasdaq stocks, costs tend to be higher than for trades in comparable exchange-listed stocks. The authors find that the magnitude of the average total execution costs varies between 49 bp and 123 bp for buys and between 55 bp and 143 bp for sells. On average, commission contributes about 40% to total execution costs.

Chan and Lakonishok (1997) also analyze the effect of the trading venue on execution costs. The authors compare the total execution costs on the NYSE and the Nasdaq for institutional investors, using transaction data from 33 large institutional money management firms during a two and a half year period (1989−1991). Median total execution costs on the Nasdaq are 99 bp versus 54 bp on the NYSE. Moreover, the authors show that − after controlling for firm size, relative trade size, and the money management firm's identity − the execution costs are lower on the Nasdaq for trades in smaller firms and lower on the NYSE for trades in larger firms.

Wagner and Edwards (1993) analyze a sample of institutional trades during the second quarter of 1992 and investigate price effects. They establish average market impact costs of 18 bp.

Domowitz et al. (2001) investigate execution costs across 42 countries in the period September 1996 until December 1998. The authors document wide variation in execution costs, even after correcting for factors affecting costs such as market capitalization and volatility. Average execution costs vary from 30 bp in France up to 138 bp in Korea.

Chiyachantana et al. (2004) investigate the price effects of institutional trading in international stocks from 37 countries in the period from 1997-1998 and 2001. They find that price impact varies across international stocks based on firm-specific determinants, country-specific factors, and order submission strategies. On an overall basis, average price effects vary between 31 and 45 bp.

Several studies analyze the market impact of trades using more general transactions data on block trades that are typically initiated by institutional investors, and often on the upstairs market. On the upstairs market, large institutional block trades are processed through a search-brokerage mechanism. That is, an intermediary or broker first identifies counter parties to trade, after which the order is sent to the downstairs market for final execution. By contrast, smaller trades are routed directly to the downstairs market, where market makers, floor traders, and limit orders provide liquidity on demand.

By analyzing data on upstairs block trades traded on the NYSE, the NASDAQ, and the AMEX from July 1985 until December 1992, Keim and Madhavan (1996) show that the average price effect of NYSE-traded stocks belonging to the bottom half of market capitalization equals 145−451 bp for buys and 434−1,024 bp for sells.

Madhavan and Cheng (1997) examine data on block transactions in Dow Jones stocks executed on both the upstairs and downstairs NYSE market. They show that the upstairs market provides significantly better execution of transactions than the NYSE floor market, although economically speaking, the differences are small. The authors establish average market impact costs of 18 bp (upstairs) and 19 bp (downstairs) for buys. For sells they find average price effects between 15 bp (upstairs) and 16 bp (downstairs).

Using transaction data on upstairs and downstairs trades on the Toronto Stock Exchange in June 1997, Smith et al. (2001) show that the adverse selection costs of trades on the upstairs market are significantly lower than on the downstairs market. Furthermore, they show that the price impact of trades depends on the trade type (agency or principal). The authors establish an average implementation price effect of 22 bp (downstairs), 25 bp (upstairs), 27 bp (upstairs, agency), and 22 bp (upstairs, principal).

Price impact asymmetry

Many empirical studies document asymmetries in the market impact costs of buys and sells. Kraus and Stoll (1972), Holthausen et al. (1987, 1990), Chan and Lakonishok (1993, 1995), and Keim and Madhavan (1996, 1997) find that buys have larger price impact than sells. Several explanations appear in the literature to account for this phenomenon. Keim and Madhavan (1996) argue that buys are more often than sells information-based instead of liquidity-motivated, because buys create new long-term positions. Chan and Lakonishok (1993) maintain that buying a stock conveys favorable firm-specific news, since it reflects the choice of one specific security out of many. They argue that, by contrast, there are many liquidity-motivated reasons to dispose of a stock.

A different explanation for the price impact asymmetry is provided by Saar (2001). In his theoretical model the expected permanent price effect of a block trade is determined by the change in the market expectation on the stock's true value as induced by the transaction. The main implication of the model of Saar (2001) is that the history of price performance of a stock affects the degree of asymmetry: the longer the run of price appreciations, the less positive the difference in permanent price impact between buys and sells. When the price run-up is long enough, sells may even have higher price impact than buys.

Another explanation for the price impact asymmetry is given by Chiyachtantana et al. (2004). They find that the asymmetry depends on particular market conditions. Price effects of buyer-initiated trades are greater in bull markets (as in 1997-1998), whereas those of seller-initiated trades are larger in bear markets (as in 2001). The authors explain their findings by arguing that sells have relatively little impact on prices in a bull market, since it is easy to find a buyer under such market conditions. On the other hand, in a bear market many investors are willing to sell, which makes it relatively easy to buy a stock.

Boscuk and Lasfer (2004) take a different view and show that the type of investor and the combination of the size of the trade and the trader's resulting level of ownership are the major determinants of price impact asymmetry at the London Stock Exchange.

3 Trading at ABP

This article analyzes equity trading at ABP during the first quarter of 2002. In this period there were ten internal funds in ABP's equity group, apart from the externally managed funds.

Quantitative approach

Three funds followed a systematic quantitative approach for Japan, the US and Europe. The approach was to make bets on individual stocks, while keeping the overall portfolio sector neutral. The horizon of the fund varied from one to six months. Trading was usually done on the basis of information available up to the previous day. Variables in the model-based process were company specific characteristics such as book to price ratios and analysts' forecasts, but also short-term and longer-term technical indicators, capturing short term mean reversion and long term momentum. New signals were usually generated at the beginning of every month. For all three funds the portfolio managers felt an urgency to trade quickly in response to the new signals, although a careful analysis of the forecasting signals of these models revealed a deterioration of its forecasting power only after six months.

Fundamental approach

There were seven fundamental funds. Three groups of portfolio managers each ran a European fund and a US fund. One group ran a similar Canadian fund. These funds had a fundamental macroeconomic approach to sector rotation. Here the approach was to make bets on sectors, while being neutral on stocks. These funds typically held this view for a longer term horizon, from six months or more. The portfolio managers did not have the urge to trade immediately, although most of the trades were executed within one day. There were no views on individual companies, so the trades only comprised sector bets. Usually groups of companies were bought and sold tracking a certain sector very closely. Obviously the groups crossed trades with each other before going to the market, but these trades are not included in the data set.

All funds had a mandate with a maximum tracking error of 2% per annum with respect to a certain benchmark and a certain outperformance target. All funds were essentially enhanced index funds. Each of them also had a long-only constraint. The benchmarks of these mandates were the S&P500 for the US, the MSCI Europe for Europe, the MSCI Japan for Japan, and the TSE300 for Canada.[3] Most of the trades that took place were for rebalancing purposes to keep portfolios in line with the original allocation. There were also moderate shifts due to changing tilts towards individual stocks for the quantitative portfolio and sectors for the fundamental approach.

Before turning to the trading process at ABP, we make notice of three types of trades.

[3] This is currently the S&P/TSX Composite.

A principal trade is a transaction between the pension fund and the broker, in which case the broker buys or sells stocks from or to the pension fund at a predetermined price. Hence, the risk is transferred to the broker. The broker takes on the other side of the trade and tries to execute the trade in the open market. An agency trade is a trade between the pension fund and a counter party, where the broker acts solely as an intermediate party. Thus, an agency trade involves two clients of the brokerage firm, one of them being the pension fund. Single trades apply to difficult trades that are traded separately, not necessarily with packages of other stocks. In case of single and agency trades the risk resides with ABP. The broker represents the client (ABP) and acts in the client's best interest.

For all the trades the trading process during the first quarter 2002 was as follows. A portfolio manager forms his or her portfolio. Subsequently, he or she approaches a trader at ABP. Together they discuss the proposed trade. In most cases the trader will leave out some parts of the trades (say 10%) for reasons of perceived cost reduction and execute these as an agency or single trade elsewhere in the market. Next, the trader approaches at most two of the large brokerage firms for the remaining trades and reveals some of the characteristics of the trade (volume, US or Europe, quantitative or fundamental, sector decomposition and a judgment on the complexity of the trade). The choice of brokerage firms is based on experience of the trader. Only the largest brokers can make competitive offers in case of principal trades, although sometimes a smaller one has an edge in some market segments, for example Japan. Based on the characteristics of the trade the broker makes an offer for a principal trade. The offer of the broker is compared over brokers and with the trader's own systems and experience. If the offer is acceptable a principal trade is executed. Otherwise the trade is executed as an agency trade.

4 Data and definitions

The data sample consists of all 3,728 worldwide equity trades at ABP, executed during the first three months of the year 2002 and with a total transaction value of 5.7 billion Euro. Of these trades, 1,963 are buys and 1,765 are sells. The total market value of buys and sells is about the same: 2.9 billion Euro for buys and 2.8 billion Euro for sells. In the first quarter of 2002, ABP holds about 50 billion Euro in equity. The internally managed portfolios in our sample have a value of 20 billion Euro.

Unfortunately, the database only provides the direction of the trade as seen from the perspective of the pension fund and does not tell whether a buy by the pension fund is also classified as a buy on the stock market. A buy by ABP is not necessarily a buy on the stock market, since the sign of a trade is determined by the direction of the order that removes volume from the order book. Moreover, since the data do not provide information on the prevailing bid and ask quotes either, we can not use the Lee and Ready (1991) rule to assess the trade sign. However, the primary goal of this article is to assess the market impact of a trade when the pension fund sells (or buys) a large amount of stocks. Therefore, it is natural to condition on the direction of the trade as seen from the perspective of the pension fund. Clearly, the true sign of the trade could have additional explanatory power, but we are able to do our analysis without this information.

For each transaction the data provide the execution price and a benchmark price in Euro. The benchmark price is the price of the stock just before the trade was passed to the broker. Moreover, the data also tell when the trade was submitted to the broker and when it was executed. The data also provide the amount of commission that was paid, which is used to compute the fee rate. Additionally, the data include detailed information on several trade-, exchange-, and stock-specific characteristics including the investment style of the fund and the timing of trades, which will be discussed below.[4]

[4]Trades that were split up into several sub trades are considered as one single trade, if a trader at ABP decided to split up the trade. The data contain about 0.5% of such ‘trade packages’. Orders split up by portfolio managers will be treated as individual trades, since it is not known whether the trader eventually split up the trade in the same way as the portfolio managers did.

The data set has been constructed on the basis of the post-trade analysis, provided by ABP Investments. The remaining data were taken from Factset and Reuters. The information on the characteristics of the exchanges under consideration were obtained from the World Federation of Exchanges and the various exchanges themselves.

Possible determinants of price impact

With respect to the trade-specific characteristics, the data set contains information on trading volume, the exchange on which the stock was executed, and the type of trade (agency/single or principal). Two relative measures of trading volume are considered: trade size as percentage of total shares outstanding ('tradesizertso') and as percentage of average daily trading volume measured over a period of thirty days ('tradesizertdv'). Moreover, three different trade types exist: agency/single and principal trades ('agencysingledum'). The largest part of the data consists of agency trades (2,178 observations). The remaining trades are either principal (1,439 observations) or single (111 observations).

In the first quarter of 2002, ABP traded on the following stock exchanges: AMEX, Athens, Copenhagen, Dusseldorf, Euronext, Frankfurt, Helsinki, Irish, Italy, London, Madrid, Nagoya, Nasdaq, NYSE, Osaka, Oslo, Stockholm, Stuttgart, SWX, Tokyo, Toronto, Vienna, Virt-x, and XETRA.[5] Dummy variables indicate on which exchange a trade has taken place ('NYSEdum', 'Nasdaqdum' etc.). The data enable us to distinguish several variables that apply to the institutional features of the exchanges where ABP executed its trades. We distinguish (1) pure order-driven markets with a public electronic limit order book, such as the Helsinki Stock Exchange, (2) markets with a public limit order book and designated dealers providing liquidity, such as the Euronext, (3) markets with a traditional floor trading system (Frankfurt and the NYSE) and (4) hybrid markets with continuous dealer presence and an optional order book (Nasdaq).[6] Dummy variables indicate which

[5] We consider Euronext Amsterdam, Brussels, Paris, and Lisbon as one single exchange, because of the similarities in trading systems and the strong integration between these markets. By contrast, the German exchanges are treated separately, because of their substantial differences.

[6] At this point we use the same classification as Swan and Westerholm (2004) and we refer to this paper for more details.

type of trading takes place on the various exchanges (‘LOBdum’, ‘dealerdum’, ‘floordum’, ‘hybriddum’). Moreover, a dummy variable indicates whether a limit order market has an upstairs facility where brokers and dealers can negotiate (‘upstairsdum’). Finally, we consider the market capitalization of all domestic stocks in each country (in billion Euro) and interpret this variable as a proxy for stock market liquidity. (‘mcapdom’).

Regarding stock-specific characteristics we distinguish average daily trading volume (‘adv’), execution price (‘exprice’), market capitalization (‘marketcap’), volatility (‘volatility’), individual momentum (‘momentumperc’), value and growth stocks (‘growthdum’, ‘valuedum’), and sector dummies (‘consumdiscrdum’, ‘consumstdum’, etc.). Market capitalization is computed as the value of all shares outstanding (in billion Euro), using the amount of shares outstanding three months prior to the trade to avoid the look-ahead bias. Volatility is computed over the last thirty trading days prior to the trade and expressed in %. The period of thirty days is chosen to ensure that recent price fluctuations are incorporated in the measure of volatility. Individual momentum is computed as the volume weighted average daily return on a stock over the last five trading days prior to the trade and is expressed in %. Roughly speaking, momentum indicates whether there is a buying or a selling trend for a particular stock. A binary variable distinguishes between value and growth stocks on the basis of its membership of the MSCI Value and Growth Index.[7] Value stocks have a relatively low book-to-price ratio, while this ratio is relatively high for growth stocks. The sector dummies classify each stock into one of the following sectors: consumer discretionary, consumer staples, energy, financials, health, industry, information technology, materials, telecommunications, and utilities. These sectors correspond to the Global Industry Classification Standard (GICS).[8]

[7] Some stocks do not belong to either of these two categories.

[8] The GICS contains the following sectors, with the constituent industry groups in parentheses: Consumer Discretionary Sector (Automobiles and Components, Consumer Durables and Apparel, Hotels, Restaurants and Leisure, Media, Retail), Consumer Staples Sector (Food & Drug Retailing, Food, Beverage, Tobacco, Household & Personal Products), Energy Sector (Energy), Financials Sector (Banks, Diversified Financials, Insurance, Real Estate), Information Technology Sector (Software & Services, Technology Hardware), Industrials Sector (Capital Goods, Commercial Services & Supplies, Transportation), Health Sector (Health Care Equipment & Services, Pharmaceuticals & Biotechnology), Materials Sector (Materials), Telecommunications Services Sector (Telecommunications Services), Utilities Sector (Utilities).

The data also contain information on the investment style of each of the funds under consideration. A dummy variable indicates whether a fund is quantitative or fundamental ('quantdum').

Finally, the data set provides information on the timing of trades. In particular, trade duration ('tradedur') is provided and defined as the time (in hours) elapsed between the moment that the trade was passed to the broker and the moment that it was truly executed. Trade duration can be interpreted as a proxy for the degree of immediacy of a trade, where immediacy refers to the urgency of a trade as determined by the broker. Trades that are executed quickly are generally more urgent than trades that take longer to fulfill. Moreover, dummy variables indicate whether a trade was passed to the broker before or at the opening of the market ('preopendum'), in the morning but after the opening of the market ('morningdum'), or in the afternoon ('middaydum'). Another set of dummies distinguishes trades executed on the different days of the week ('Mondaydum', 'Tuesday' etc.). The data also contain dummy variables that indicate whether a trade took place at the beginning of the month, in the middle of the month, or at the end of the month ('earlymonthdum', 'middlemonthdum', 'endmonthdum') and in which month of the year ('Januarydum', 'Februarydum', 'Marchdum').

Sample properties of ABP trades

Average trade size for buys (sells) is more than 70,000 (84,000) shares and the average value of a trade equals almost 1.5 (1.6) million Euro. Expressed as a percentage of daily trading volume and shares outstanding, average trade size of buys equals 4.29% and 0.02%, respectively. For sells these percentages are 3.41% and 0.02%. Commission equals about 12 bp on average, for both buy and sell transactions. Average commissions documented by Wagner and Edwards (1993), Keim and Madhavan (1997), Domowitz et al. (2001), and Chiyachtantana et al. (2004) are somewhat higher (17−20 bp). Regarding the timing of trades, it takes, on average, almost 4 (4.5) hours for a buy (sell) to be executed.

For both buys and sells, a majority of the trades consists of value stocks (47.1% for buys and 50.1% for sells). The main part of both buys and sells is traded by quantitative funds. The three largest industry sectors for buys are consumer discretionary, financials, and information technology. For sells the three largest sectors are consumer discretionary, industrials, and information technology. Furthermore, the majority of both buy and sell transactions consists of agency and single trades.[9] Most trades are submitted before or at the opening of the market or in the morning period after the opening.[10] The bulk of trades is submitted on Tuesday or Wednesday. Virtually no trades are submitted on Monday and about 12% (16%) of the buy (sell) transactions is submitted on Friday. Furthermore, approximately 86% (80%) of the buys (sells) is submitted at the beginning of the month. Relatively few trades are submitted in the middle of the month. About 43% of all ABP trades takes place in January, 34% in February and the remaining 23% in March. Most trades are executed on the NYSE (about 30% of all buys and sells). Other important market places are the Nasdaq (7%), Tokyo (20%), London (11%), and Toronto (6%). About 80% of all trades is executed on an exchange with an upstairs market where brokers and dealers can negotiate on prices of block trades.

5 Measuring the market impact of ABP trades

This section presents a further exploration of the data described in Section 4 in order to assess the impact of the ABP trades on prices. We start with a definition of market impact.

Market impact

To measure the market impact of trading, a benchmark price has to be chosen. We emphasize that there are several ways to do this; see Collins and Fabozzi (1991) and Chan and Lakonishok (1995) for a discussion. With a same-day benchmark, the benchmark is the

[9] Agency and single trades have been aggregated, since there are too few single trades to treat them as a distinct class. It is natural to aggregate agency and single trades, since these are the trades that the broker acts as an agency for.

[10] Regarding the timing of trades over the day, we always refer to *local* time.

volume-weighted average price calculated over all transactions in the stock on the trade day. With a pre-execution benchmark the opening price on the same day or the closing price on the previous day is used. Finally, with a post-execution benchmark the closing price of the trading day or the opening price on the next day is taken as reference price, ensuring that the temporary price impact has disappeared form the benchmark. This paper opts for the pre-execution benchmark, which is in line with e.g. Wagner and Edwards (1993). More precisely, we take as the benchmark the price at the moment that the order was passed to the broker. For each trade our data set provides this price.

Moreover, we proceed as in Chan and Lakonishok (1995, 1997) and correct the price effects for market-wide price movements during the trade. We use the MSCI World industry group indices as a proxy for these market movements. This means that we approximate the market movement during a trade of, for instance, ABN Amro stocks by the movement of the MSCI World Banks index.

Thus, for a buy transaction in stock i at time t we measure market impact costs (MIC) as follows:

$$MIC_{it}^{B} = \log(P_{it}^{exe}/P_{it}^{pt}) - \log(M_{it}^{exe}/M_{it}^{pt}), \tag{1}$$

where P_{it}^{exe} and P_{it}^{pt} denote the execution and pre-trade price of stock i at time t, respectively. M_{it}^{exe} and M_{it}^{pt} denote the value of the MSCI industry group index corresponding to stock i at the time of the execution of the trade and at the pre-trade time, respectively. In a similar way, market impact costs of sells are defined as

$$MIC_{it}^{S} = \log(P_{it}^{pt}/P_{it}^{exe}) - \log(M_{it}^{pt}/M_{it}^{exe}). \tag{2}$$

For both buys and sells, positive market impact implies that a trade has been executed against a worse price than at the moment of trade initiation.

Sample properties of price effects

The first and second column of Table 1 report sample means, standard deviations, medians and quantiles of market impact for buys and sells with and without correction for market-wide price movements.[11] The sample statistics in Table 1 are calculated on a principal-weighted basis (cf. Chan and Lakonishok (1993)). The principal-weighted statistics are obtained by weighting each observation by the Euro value of the trade, so that smaller trades contribute less to, for instance, the average market impact than larger ones.

[INSERT TABLE 1 ABOUT HERE]

Table 1 shows that the average market impact costs of buys (corrected for market-wide price movements) equal 19.6 bp. Average market impact of sells is even larger at 29.7 bp. The higher average price impact of sells is not in line with the findings of Chan and Lakonishok (1993, 1995) and other studies that establish higher price effects for buys than for sells. Our results coincide with those of Chiyachantana et al. (2004), who show that price effects of sells (buys) tend to be larger than those of buys (sells) in bear (bull) markets. Since the majority of the trades in the sample took place in a bear market (66%), this theory explains our findings.[12]

To give a more complete picture of total trading costs, the first four columns of Table 1 also report execution costs, which are defined as the sum of market impact costs and commission. Execution costs equal 27.4 bp for buys and 37.5 bp for sells, on average. Generally speaking, trading costs consist of explicit and implicit costs. The explicit part consists of fixed costs, such as commissions, taxes, and fees. Implicit costs are more variable and consist of market impact costs, bid-ask spread, delay costs and opportunity

[11]Since we only have closing prices of the MSCI industry group indices, we approximate the market-wide price movements in expressions (1) as

$$\frac{\mathrm{dur}_{it}}{8} \log \left(M_{it}^{pdc} / M_{it}^{close} \right),$$

where M_{it}^{pdc} and M_{it}^{close} denote the previous day closing price and the closing price of the MSCI industry group index of stock i at time t and dur_{it} represents the number of hours it took to complete the trade in stock i at time t. Hence, we assume that there are eight hours in a trading day. Under this assumption we can say that, given the fact that an index rose by 100 bp on a certain day, the expected price change of that index during a one-hour period is 12.5 bp. If, for example, it took four hours to complete a trade, we will correct the price effect for market movements by subtracting fifty percent of the price change in the index during the day of the trade. A further assumption we will have to make is that overnight price movements, which are also included in the index return over the one-day period, are negligible. For the market-wide price movements of sells in expression (2) we use the same approximation.

[12]We used the monthly return on the corresponding benchmark index (S&P500, TSE300, MSCI Europe, or MSCI Japan) to determine whether a trade took place in a bear or bull market.

costs. Opportunity costs basically represent the cost of not transacting and measure the theoretical performance of the buys and sells that were not executed. If the risk of non-execution is significant, these costs may be considerable. There are two important reasons for unexecuted orders. Either the trader cannot locate the shares to complete the order, or the price has moved out of the range of prices the portfolio manager is willing to pay. Delay costs reflect the risk of adverse price movements that can occur when trading is postponed. These costs are the counterpart to market impact costs. As time increases, impact should decrease. However, as time increases, so does price variability. Waiting too long with trading can therefore increase delay costs considerably. Hence, total trading costs would not only consist of market impact costs, but also of commission, opportunity costs, and delay costs.[13] However, in our data sample opportunity costs are negligible, since all trades on the 'trading list' where truly executed. This is in line with Keim and Madhavan (1997), who found high rates of completion in institutional trades (about 95%). Moreover, notice that the correction for market-wide price movements can be interpreted as a proxy for the delay costs. Since we subtract delay costs, we do not take these costs into account. At this point we follow Bodurtha and Quinn (1990), who argue that losses or gains that could arise from market movements can be neutralized through effective hedging practices. Concluding, this article ignores opportunity costs, but corrects for delay costs and calculates execution costs as the sum of market impact costs (corrected for market-wide price movements) and commission.

The literature distinguishes temporary and persistent price effects. As explained by Kraus and Stoll (1972), temporary price movements are caused by short-term liquidity effects (i.e. price concessions to stimulate buyers or sellers to provide liquidity), inventory effects (temporary price effects due to inventory imbalances), or imperfect substitution (price concessions to induce buyers and sellers to absorb the additional shares). The permanent impact of a trade on prices reflects the change in the perception of the market due to the information contained in a trade. Roughly speaking, a buy transaction tells

[13]We note that our definition of market impact costs already contains part of the bid-ask spread.

the market that the stock may be underpriced, and a sell reveals that a stock may be overvalued. Market participants observe the information contained in trades and adjust their perceptions accordingly, leading to price revisions.

To illustrate temporary and persistent price effects, consider a buy trade. After the buy has been passed to the broker, the price will generally increase. After trade execution, there is a partial price reversion: the price recovers from the liquidity effect of the buy. The temporary price effect is measured as the decline in the price after the buy has been executed. The persistent price effect is defined as the price increase from trade submission to a post-trade moment. The total price effect is calculated as the return from trade submission to trade execution.

Technically speaking, the temporary price impact is defined as the logarithmic return from the moment of trade execution to a post-trade moment (i.e. $\log(P_{post}/P_{exe})$), whereas the persistent price impact is measured as the logarithmic return from a pre-trade moment to the post-trade moment ($\log(P_{post}/P_{pre})$). In this way, the temporary price impact measures the price movement that is needed to provide enough liquidity to absorb the trade and the permanent price impact represents the price change due to the information contained in the trade. Temporary and persistent price effects are corrected for market-wide price movements, cf. Eqs. (1) and (2).

Temporary and persistent price effects (corrected for market-wide price movements) are obtained by taking the moment the trade was passed to the broker as the pre-trade moment and the closure of the market at the day after trade execution as the post-trade moment. The last two columns of Table 1 show that, on a principal-weighted average basis, the temporary and persistent price effects of buys equal −7.2 bp and 12.4 bp, respectively. For sells, these price effects equal 14.5 bp and −16.5 bp. Note that we report signed price effects to emphasize the direction of the price change. The negative temporary price effects of both buys and sells reflect the price reversal that takes place after trade execution and illustrate that stock prices partially recover from the liquidity effect of a trade.[14] Figures 1

[14]For some trades, we did not have enough data on the prices around the time of the trade. We have

and 2 show the average temporary, persistent, and total price effects for buys and sells, respectively.

[INSERT FIGURES 1 AND 2 ABOUT HERE]

To provide an indication of the significance of the estimates of average total, temporary, and persistent price effects Table 1 reports the standard deviations of the average price effects. However, note that these are obtained under the assumption that observations are mutually uncorrelated. Therefore, true standard errors may be different.

Summarizing, average market impact costs are small in terms of market disruption, but substantial in terms of costs for the pension fund. For an average stock with a market value of 56 Euro (the volume-weighted average price of buys in our sample), market impact costs of 20 bp for buys result in a total price increase per share of approximately 11 Euro cents in excess of the market index (of which about 7 cents is persistent). For sells the price decrease per share in excess of the market index is equal to 16 cents, of which 9 cents is persistent. Clearly, the economic significance of these price effects is limited in terms of market disruption. However, market impact costs of this magnitude might already have serious consequences for the pension fund, since they strongly affect the profitability of certain trading strategies. See Korajczyk and Sadka (2004), Mitchell and Pulvino (2001), Knez and Ready (1996) and Chen et al. (2003). Moreover, it is needless to say that, for an enhanced index manager whose target is to outperform his or her benchmark by say 50 bp, every basis point counts.

6 Determinants of market impact

The impact of trades on prices will generally depend on various trade-, exchange-, and stock-specific characteristics, including investment style and the timing of trades. This

therefore computed the sample statistics of the temporary and persistent price effects for a slightly smaller sample than we used to obtain the sample statistics for the market impact costs. We have computed the average temporary and persistent price effects on the basis of 1,933 buy trades and 1,738 sell trades. As a consequence, the total price effect is not exactly equal to the previously computed market impact costs.

section will assess the determinants of the expected market impact costs. Moreover, to get an idea of the market impact *risk* associated with the trades under consideration, we will also analyze the *volatility* of market impact costs. The volatility of market impact costs is directly related to the probability that the price effect is large. Furthermore, the joint analysis of expected market impact costs and the volatility of these costs provides a mean-variance relation that provides insight into the trade-off between costs and risk.

Although it is common practice in the existing literature to analyze buys and sells separately, we do a joint analysis and allow for asymmetries between buys and sells. Statistical testing for differences between buys and sells is easier in a joint framework, justifying our approach.

We assume that the market impact costs of a trade (corrected for market-wide price movements) in stock i at time t have the form

$$MIC_{it} = (\alpha_s' + \alpha_b' d_{it})X_{it} + \nu_{it}, \tag{3}$$

where the ν_{it}'s are jointly and serially uncorrelated disturbances, orthogonal to the regressors in Eq. (3) and satisfying

$$\mathbb{E}(\nu_{it}) = 0, \mathbb{V}\mathrm{ar}\,(\nu_{it}) = \exp((\gamma_s' + \gamma_b' d_{it})Z_{it}). \tag{4}$$

Here X contains the regressors that affect the conditional mean of the market impact costs and Z the regressors that influence the conditional volatility of these costs. Moreover, $\alpha_s, \alpha_b, \gamma_s, \gamma_b$ are unknown vectors of coefficients to be estimated. Finally, d_{it} is a binary variable that is 0 when stock i at time t is a sell transaction and 1 when this trade is a buy.

Note that the regression model in Eq. (3) is formulated in such a way that $\alpha_s' X_{it}$ represents the conditional expected market impact costs of a sell transaction, while $(\alpha_s' + \alpha_b')X_{it}$ denotes the conditional expected market impact of a buy trade. Similarly, $\exp(\gamma_s' Z_{it})^{1/2}$ and $\exp((\gamma_s' + \gamma_b')Z_{it})^{1/2}$ denote the conditional volatility of the market impact of sell and buy transactions, respectively. The pairs $(MIC_{it}, \exp(\gamma_s' Z_{it})^{1/2})$ and $(MIC_{it}, \exp((\gamma_s' + \gamma_b')Z_{it})^{1/2})$ determine the mean-variance relation for sells and buys, respectively. The null hypothesis that the determinants of the conditional expected market impact costs are the same for buys and sells is formulated as $\alpha_b = 0$. For the conditional volatility the same hypothesis is given by $\gamma_b = 0$.

Conditional expectation of market impact costs

The regression model given in Eq. (3) is estimated in two steps.[15] We start with the estimation of the conditional expected market impact costs. Subsequently, we turn to the estimation of the conditional variance.

We estimate conditional mean regression in Eq. (3) by means of OLS, using White (1980)'s heteroskedasticity consistent covariance matrix. The regressors[16] X used in the initial estimation of Eq. (3) are given in Tables 2 and 3. These tables also reports the individual (unconditional) correlations between the various variables and the market impact costs, together with asymptotic standard errors. By including exchange-specific variables into the model specification, we aim to explain country-specific differences in market impact costs. We also include a dummy variable for each exchange in the initial specification to account for differences in market impact costs that cannot be explained by the exchange-specific characteristics. However, some words of caution apply. The Nasdaq is the only hybrid market where ABP trades are executed. Hence, we cannot identify whether differences in market impact are caused by the fact that the Nasdaq is a hybrid market or by other specific properties of the Nasdaq market. A similar difficulty arises with NYSE trades. Although the Frankfurt Stock Exchange is also characterized by floor trading, the sample contains only very few trades at this exchange. Hence, we cannot distinguish between differences in market impact costs caused by floor-trading and by other NYSE-specific characteristics.

[INSERT TABLES 2 and 3 ABOUT HERE]

[15] Given the large sample size, the loss of efficiency relative to joint estimation will be no problem. Moreover, the two-step approach has the advantage that no assumptions have to be made regarding the distribution of regression disturbances, apart from the usual regularity conditions.

[16] We include the square root of relative trade size instead of the logarithm. We do this to avoid outliers in the logarithmically transformed data when relative trade size is close to zero.

A specification search from general to specific based on the Akaike information criterion leads to the final specification given in the left-hand-side of Table 4.[17] This part of the table also displays the estimation results, including estimated coefficients and standard errors. We notice that the left-hand-side of Table 4 reports the coefficients $\alpha_s + \alpha_b$ of the conditional mean equation (3). Although one single regression model is estimated, we report the adjusted R^2 for both the buy and the sell part of the model. We compute these statistics using the definition of the adjusted R^2.

[INSERT TABLE 4 ABOUT HERE]

In the following, the discussion of the estimation results is confined to significant coefficients only. We start with the estimation results for buy transactions. Intuitively, when the price of a stock has recently moved upwards, it is more likely that buy order will have increased impact while a sell order will have a reduced impact on prices. We would therefore expect the influence of momentum on the market impact of buy transactions to be positive, since high momentum indicates a buying trend. The significantly positive coefficient of momentum confirms this intuition. The coefficient corresponding to relative trade size is significantly positive; i.e. market impact is higher the larger the relative trade size. This can be explained as follows. Since higher trading volume reflects a higher degree of trade difficulty (see Keim and Madhavan (1997)), the liquidity costs of larger trades are also higher. As a consequence, larger trades have higher temporary price impact. Moreover, according to Easley and O'Hara (1987) large trades convey more information. As a consequence, the permanent price impact of a trade depends positively on the size of the trade. Empirical evidence for the positive relation between trading volume and price effects has been established by Spierdijk et al. (2003) and Keim and Madhavan (1997).

The dummy variable for agency/single and principal trades has a significantly positive coefficient and a value of 54.7. This means that, ceteris paribus, the market impact is 54.7 bp higher for agency and single buy trades than for principal buy transactions.

[17]We notice that all regression specification are very robust, in the sense that similar specifications lead to estimated coefficients of about the same size and magnitude.

This outcome is consistent with the empirical results established by Smith et al. (2001). They explain the higher market impact of agency trades by noticing that brokerage firms are interested in maintaining their reputation capital. Therefore, the visibility of their price impacts and the importance of the broker-client relationships prevents them from cream-skimming their clients. This would imply that the price impact of agency and single trades is typically higher than that of principal trades. We notice that part of the difference in market impact costs between agency/single and principal trades disappears when commission is taken into account. When we run the same regression with market impact *including* commission as dependent variable, the dummy variable for agency/single and principal buys remains significant, but its coefficient drops to 37.7. This is due to the fact that commission also depends on the type of trade. For agency trades fee rates equal $2-8$ bp, for single trades 10 bp, while principal trades carry fee rates above 10 bp.

We note that the pension fund itself decides whether it wants to trade on an agency/single or principal basis. Clearly, the pension fund's choice for either an agency/single or principal trade may be affected by the expected market impact of the trade, which, in turn, is one of the determinants of the initial choice for a specific trade type. This may cause a selectivity or selection bias, see Heckman (1976, 1979). For a detailed survey of the selectivity bias literature, we refer to Vella (1998). When the selection effect is ignored, OLS estimators may be inconsistent. To assess the possible selectivity effects regarding the choice of trade type, we conducted a similar analysis as Madhavan and Cheng (1997). Using a two-stage estimation procedure[18] we estimated a probit-model to explain the choice for an agency/single or principal trade and a regression model with a correction factor for selectivity effects depending on the probit-specification.[19] We did not establish significant

[18] Because of the selection, the usual regression approach fails: the regression equation should contain an additional term. Hence, the selection bias can be thought of as an omitted variable bias. The two-stage approach consists of (1) estimation of this term and (2) estimation of the regression equation containing this term as explanatory variable. See Heckman (1976, 1979) for further details.

[19] Since we aggregated agency and single trades, there are only two order types: agency/single and principal trades. Therefore, we use a probit-model to explain the choice between these two order types. A multinomial logit model can be used when there are more than two choices. See Ellul et al. (2003), who estimate a multinomial logit model to explain the choice between order type (market or limit), order side (buy or sell), and order arrival/cancellation.

evidence for a selection bias.

The coefficient of the dummy indicating whether a buy trade comes from a quantitative or a fundamental fund is significantly negative. This means that buys by quantitative funds cause lower market impact costs. This contradicts the findings of Chan and Lakonishok (1993, 1995) and Keim and Madhavan (1997), who find that quantitative funds trade with more urgency than fundamental funds and are willing to pay the price for higher immediacy, resulting in higher market impact costs.

Regarding the timing of trades, the results show that market impact costs are influenced by the day of the week at which the stock is traded. We find that market impact costs of buys are significantly lower on Wednesday, Thursday, and Friday than on Monday and Tuesday. This is consistent with Foster and Vishwanathan (1990, 1993), who have a theory that explains why trading costs are higher at the beginning of the week rather than at the end of it. Also the period of the month affects market impact costs. Many institutional investors rebalance their portfolios at the beginning of the month. Since it is likely that these investors wish to trade the same stocks, it might be more difficult to trade during these periods. Indeed, the results show that buy trades in the middle of the month have significantly lower trading costs than similar buys at the beginning of the month. Also the month of the year affects the costs of trading. Market impact costs of buys were significantly lower in January (bear market) than in March (bull market). This is in line with Chiyachantana et al. (2004), who argue that the market impact costs of buys are lower in a bear market and higher in a bull market.

Sector dummies reflect sector-specific effects on the market impact unrelated to the other regressors. Buys in the energy and telecommunications sector suffer from significantly higher market impact costs than comparable buy trades in other sectors.

The only exchange dummies that turn out significant and that enter the final specification are those for the NYSE and the Nasdaq. We find that the market impact costs of buys on the NYSE and the Nasdaq are significantly lower than comparable buys at the other exchanges. This might be due to the floor-trading and dealer-trading in these markets, but − as mentioned before − we cannot identify this. However, we can conclude that the lower market impact costs are not caused by liquidity differences between the United States and the other countries, since domestic market capitalization (a proxy for country liquidity) does not turn out significant and is not even selected in the final specification. Using similar arguments we can conclude that it is not caused by dealer presence or the existence of an upstairs market either. These results are not in line with e.g. Beneviste et al. (1992), Schmidt et al. (1993), Theissen (2001), and Vekataraman (2001), who find that exchange characteristics do affect trading costs.

Despite the relatively high and significant correlations between the dummy variables for the exchange-specific characteristics and the market impact costs (see Tables 2 and 3), these variables do not enter the final model specification. This means that they lose their relevance in the presence of other, more important variables.

The right-hand-side of Table 4 reports the coefficients α_s of the conditional mean equation (3) corresponding to sell transactions. The significantly negative coefficient of momentum confirms the intuition that the market impact of a sell is higher when there is a selling trend. As for buys, relative trade size has a significantly positive coefficient. Market capitalization has a significantly negative coefficient, which implies that selling large cap stocks causes less market impact than selling small cap stocks. Large cap stocks are more liquid than small cap stocks and are therefore less expensive to trade. See Hasbrouck (1991a, 1991b), Keim and Madhavan (1997), Stoll (2000), and Spierdijk et al.(2003).

The coefficient of the dummy indicating whether a sell comes from a quantitative or a fundamental fund is significantly positive, hence sells by quantitative funds cause higher market impact costs. This is in line with the findings of Chan and Lakonishok (1993, 1995) and Keim and Madhavan (1997).

Regarding the timing of trades, the results show that sells submitted before the opening of the market have significantly higher market impact costs than similar sells submitted during regular opening hours. This is likely to be due to the presence of informed traders who benefit from their private (‘overnight’) information, making these trades more expensive to execute, cf. Foster and Viswanathan (1993). The result that the time of the day affects the costs of trading is in line with Foster and Viswanathan (1993) and McInish and Wood (1992), who establish strong intraday patterns in adverse selection costs and bid-ask spreads, respectively. Furthermore, we see that sell trades submitted on Wednesday, Thursday, and Friday have higher expected market impact costs than similar sells on Monday and Tuesday. This is in contrast to what we found for buys and is not in line with Foster and Vishwanathan (1990, 1993). Hence, we find a 'reverse Monday effect' for the market impact costs of sells.[20] Sells executed at the end of the month have significantly lower market impact costs than comparable sell trades at the beginning of the month when many institutional traders rebalance their portfolios. In contrast to what we found for buys, sell trades have higher expected market impact costs in January (bear market). This is in line with Chiyachantana et al. (2004), who argue that market impact costs of sells are higher in bear markets. Finally, the longer it takes to execute a sell, the lower the market impact cost. Stated differently, lower immediacy results in lower market impact costs.

With respect to the sector dummies, Table 4 shows that sells in the consumer discretionary sector have significantly lower market impact. The market impact of sells in the consumer staples sectors is significantly higher than comparable sells in the other sectors.

The dummies for sells executed on the NYSE and the Nasdaq turn out significant, but we find different effects than for buys. Sell trades executed on the NYSE and the Nasdaq have higher market impact costs than comparable sells executed at the other exchanges. Similar striking differences between buys and sells have been established for the US market. Keim and Madhavan (1997) show that buys on the Nasdaq are more expensive than comparable buys on the NYSE and the AMEX, but they also find that sells have no significant differences in trading costs between the Nasdaq and the other exchanges. Finally, as for buys, the other exchange dummies, the domestic market capitalization

[20]We take this terminology from the 'reverse Monday effect' established for returns on large cap stocks, see Brusa et al. (2000, 2003). We note that most stocks traded by ABP are also large cap stocks.

variable, the dealer dummy, and the upstairs market dummy are not significant and not selected in the final specification.

The market impact costs of buy and sell trades show substantially different behavior. Most variables have significantly different impact on the expected market impact costs of buys and sells. Furthermore, a Wald-test shows that the conditional expected market impact costs for buys and sells are significantly different at each reasonable significance level. Interestingly, the constants for buys and sells in the mean regression are *not* significantly different. This means that the differences in sample averages between buys and sells as observed in Section 5 can be *fully* contributed to the different influence of stock-, market-, and trade-specific characteristics.

The above results justify separate estimation of market impact costs for buys and sells, as is often done in the literature. We continue with joint estimation in the sequel, allowing for asymmetric effects.

Conditional variance of market impact costs

The motivation for analyzing the volatility of market impact costs lies in the fact that this provides insight into the risk of facing higher market impact costs.

In Eq. (3) the conditional volatility is given by $\exp(\gamma_s' Z)^{1/2}$ and $\exp((\gamma_s' + \gamma_b')Z)^{1/2}$, for sells and buys, respectively. To estimate γ_s and γ_b, we regress the realized absolute residuals as obtained from the conditional mean regressions in Section 6 (in logarithms) on the variables contained in Z:

$$\log(|e_{it}|) = (\gamma_s' + \gamma_b' d_{it}) Z_{it} + \xi_{it}. \tag{5}$$

The regressors Z used in the initial estimation of Eq. (5) are given in Tables 2 and 3. To arrive at the final specification, we follow the same model selection principle as before. For buys the specification search leads to the model given in the left-hand-side of Table 5. This part of the table reports the coefficients $\gamma_s + \gamma_b$ of the conditional variance equation (5). Again, the discussion of the estimation results is confined to significant coefficients.

[INSERT TABLE 5 ABOUT HERE]

Volatility of market impact costs is likely to be related to the magnitude of momentum rather than to its sign. We therefore use absolute momentum instead of signed momentum in the conditional variance regression. The estimation results show that the market impact costs of buys fluctuate more in periods of high absolute momentum. Since trades cause more extreme price effects in such periods, this results in more volatile market impact costs. Furthermore, stocks with higher price volatility show more fluctuations in market impact costs. More volatile stocks experience higher price fluctuations, resulting in more extreme values of market impact costs. Moreover, the market impact costs of large buys are more volatile than those of smaller buy trades. An explanation for this result is given by models of asymmetric information, in which the size of a trade reflects the extent to which traders disagree about the stock's value (see, for instance, Jones et al. (1994)).

The dummy for the type of trade (agency/single versus principal) is significantly positive, i.e. market impact costs of agency and single buy trades fluctuate more than the trading costs of principal buy trades. Principal trades benefit from the broker's wish to maintain his reputation. The broker will therefore try to avoid excessive price effects of principal trades, leading to less variability in the market impact costs of this type of trades. See Smith et al. (2001). Moreover, buys by quantitative funds show more variability in market impact costs than buy transactions by fundamental funds. Since quantitative funds trade more aggressively and are willing to pay the price for higher immediacy, their trades exhibit more fluctuations in market impact costs.

Regarding the timing of trades, we see that buy trades submitted at the end of the month show significantly more variability in market impact costs than buys submitted at the beginning of the month. Hence, trading costs fluctuate less at the beginning of the month when there is a lot of trading activity. Also the month of the year plays a role. In particular, market impact costs of buys are more volatile in February rather than in March. Hence, we find that the variability of the market impact costs of buys is strongly affected by the timing of these trades. Finally, buys that take longer to execute show more fluctuations in market impact costs. When it takes more time to fulfill a trade, prices have more opportunities to fluctuate, resulting in higher variability of market impact costs.

Furthermore, buys in the consumer staples, IT, and utilities sector have more volatile market impact costs than similar buys in the other sectors, whereas buys in the financial services sector show less fluctuations in market impact costs.

Buys on the Toronto Stock Exchange feature more variability in market impact costs, whereas buy trades on the NYSE show less fluctuations in market impact costs. The exchange-specific characteristics related to the trading system, upstairs trading and domestic market capitalization are not significant and do not enter the final model specification.

The estimation results for sells are displayed in the right-hand-side of Table 5. This part of the table reports the coefficients γ_s in the conditional variance specification (see Eq. (5)).

As for buys, market impact costs of sell transactions show more fluctuations in periods of high absolute momentum and high volatility.

The coefficient of the trade type dummy (agency/single or principal) has a significantly positive value: agency and single sell trades have more fluctuations in market impact than principal sell trades. Moreover, sells by quantitative funds show more variability in market impact costs than buy transactions by fundamental funds. The same results were established for buy trades.

Sells submitted in the morning have more volatile market impact costs than similar sells submitted during other periods of the day. Moreover, market impact costs of sells executed on Wednesday and Thursday are more volatile than on Monday and Tuesday. By contrast, sells executed on Friday show less fluctuations in market impact costs. Similar calendar time effects have been established for return volatility, see Foster and Vishwanathan (1990, 1993). Also the period of the month affects the variability of market impact costs. Sells submitted in the middle of the month and at the end of the month feature more variability in market impact costs than comparable sells at the beginning of the month. A similar result was established for buy trades. Furthermore, the month of the year also affects market impact costs variability. Relative to March, the market impact costs of sells are less volatile in January and more variable in February. Hence, the fluctuations in market impact costs feature strong calendar effects. This conclusion was also reached for buy trades. Finally, sells that take longer to execute show more fluctuations in market impact costs. Also at this point we established the same result for for buys.

Regarding the impact of the industry sector on the fluctuations in market impact costs, we find that sells in the consumer staples, financial services, and utilities sector have less variability in market impact costs than similar sells in the other sectors.

Finally, sells on the Nasdaq, the NYSE, and the Toronto Stock Exchange feature significantly less volatility in market impact costs than similar sells on the other exchange. For buys on the Toronto Stock Exchange we established the opposite effect. By contrast, both buys and sells executed on the NYSE have lower variability in market impact costs than comparable trades on the other exchanges.

Buys and sells show considerable differences in conditional variance. Most variables have a significantly different impact on the variance of buy and sell trades. Moreover, a Wald-test shows that the conditional variances of the market impact costs of buys and sells are significantly different at each reasonable significance level. In particular, the constants for buys and sells in the variance regression are not significantly different. This means that the differences in volatility of market impact costs between buys and sells can be fully contributed to the different influence of stock-, market-, and trade-specific characteristics.

Since we have modelled both expected market impact costs and the volatility of these costs, we can derive mean-variance relations. As noticed before, there is a mean variance trade-off: trades that take long to execute have low expected market impact costs, but high volatility. On the other hand, trades that are quickly executed have high market impact costs and low volatility. The theoretical mean-variance relation is displayed in Figure 3. For a particular sell trade, we use the the estimated conditional mean and variance equations (3) and (5) to assess the empirical mean-variance curve, see Figure 4.

Ceteris paribus, the variance of the market impact costs of this particular sell decreases when the degree of immediacy (as reflected by trade duration) of the sell trade increases. At the same time expected market impact costs increase with higher immediacy.

Finally, we notice that the results obtained in this section do not substantially change when market impact costs are replaced by execution costs.

[**INSERT FIGURES 3 AND 4 ABOUT HERE**]

7 Conclusions

This article has used a unique data set to investigate market impact and execution costs of equity trading by ABP, a major pension fund in the Netherlands and one of the largest pension funds in the world. We have found that, on average, these costs are small in terms of market disruption, but substantial in terms of costs for the pension fund. Average market impact costs equal 20 basis points for buys and 30 basis points for sells, which imply average losses of 11 cents per buy and 16 cents per sell. Furthermore, average execution costs (defined as the sum of commission and market impact) equal 27 basis points and 38 basis points, respectively. The asymmetry in market impact costs between buys and sells is in line with Chiyachantana et al. (2004), who show that price effects of sells (buys) tend to be larger than those of buys (sells) in bear (bull) markets. Since the majority of the trades in the sample took place in a bear market (66%), this theory explains our findings.

The price effects found in this paper seem relatively moderate compared to other studies. We suggest the following explanation. Virtually all transactions in the sample were related to the rebalancing activities of the pension fund. These trades do generally not coincide with news-driven trades and therefore likely to cause less price impact. By contrast, trades motivated by the news of the day cause price movements, which are reinforced by similar trades at the same time.

Although market impact costs seem relatively small, trading costs of this magnitude might already have serious consequences for the pension fund, since they strongly affect the profitability of certain trading strategies. See Korajczyk and Sadka (2004), Mitchell and Pulvino (2001), Knez and Ready (1996) and Chen et al. (2003). Moreover, it is needless to say that, for an enhanced index manager whose target is to outperform his or her benchmark by say 50 bp, every basis point counts.

Previous research has established important roles for trade style and variables related to trade difficulty (such as market capitalization and trade size) in explaining market impact costs. In this article we have found that price volatility and momentum have considerable influence on the market impact costs of buys and sells. Other important determinants of these costs are trade type (agency/single or principal), trading venue, and industry sector. In line with previous literature, we establish considerable differences between buy and sell trades. Additionally, we have found that the *timing* of trades plays a substantial role in explaining trading costs. The time of the day, the day of the week, the period of the month, and the month of the year significantly affect the costs of trading. Moreover, a cost-risk trade-off has been established: the longer it takes to execute a trade, the lower the expected market impact costs, but the higher the volatility of these costs. Trades with more demand for immediacy have higher expected market impact costs, but less uncertainty.

The methodology developed in this paper can contribute to more efficient portfolio management. The predicted cost-risk relation can be used by the pension fund in a pre-trade analysis in order to filter out less favorable trades.

Finally, we emphasize that the present analysis focuses on a single pension fund in a specific time period. As a consequence, this article merely serves as a case study and its results do not necessarily apply to other pension funds in other countries or in different circumstances. We hope that this case study will lead to more research on market impact costs incurred by pension funds to get a more complete picture of the effects of pension fund trading.

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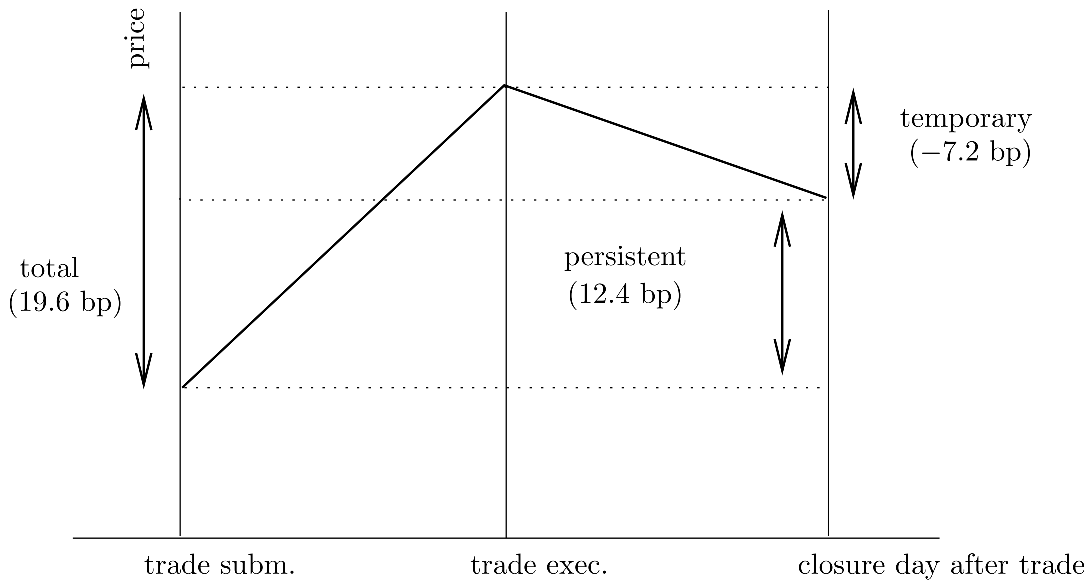
price
temporary
(−7.2 bp)
persistent
(12.4 bp)
total
(19.6 bp)
trade subm.
trade exec.
closure day after trade

Figure 1:

Figure 1: The average temporary, persistent, and total price effects for of buys (in bp)

Notes: This plot shows the average temporary, persistent, and total price effects of buys in bp, corrected for market-wide price movements. After the buy has been passed to the broker, the price increases. After trade execution, there is a partial price reversion: the price partially recovers from the liquidity effect of the buy. The temporary price effect is measured as the decline in the price after the buy has been executed. The persistent price effect is defined as the price increase from trade submission to the closure of the market on the day after trade execution. The total price effect is calculated as the return from trade submission to trade execution.

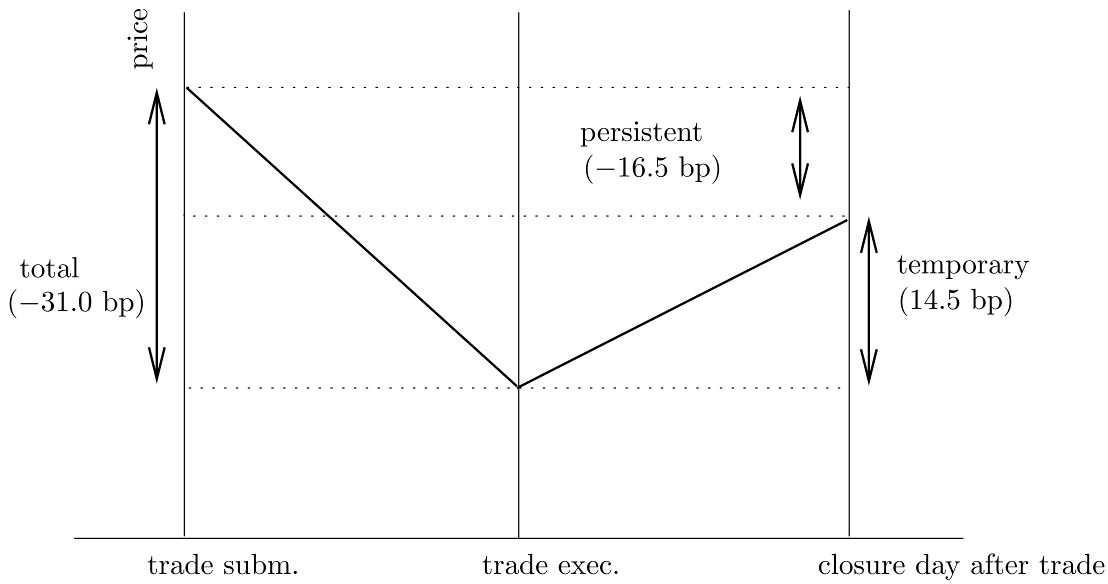
price
persistent
(−16.5 bp)
total
(−31.0 bp)
temporary
(14.5 bp)
trade subm.
trade exec.
closure day after trade

Figure 2:

Figure 2: The average temporary, persistent, and total price effects of sells (in bp)

Notes: This plot shows the average temporary, persistent, and total price effects of sell in bp, corrected for market-wide price movements. After the sell has been passed to the broker, the price decreases. After trade execution, there is a partial price reversion: the price partially recovers from the liquidity effect of the sell. The temporary price effect is measured as the incline in the price after the sell has been executed. The persistent price effect is defined as the price decrease from trade submission to the closure of the market on the day after trade execution. The total price effect is calculated as the return from trade submission to trade execution.

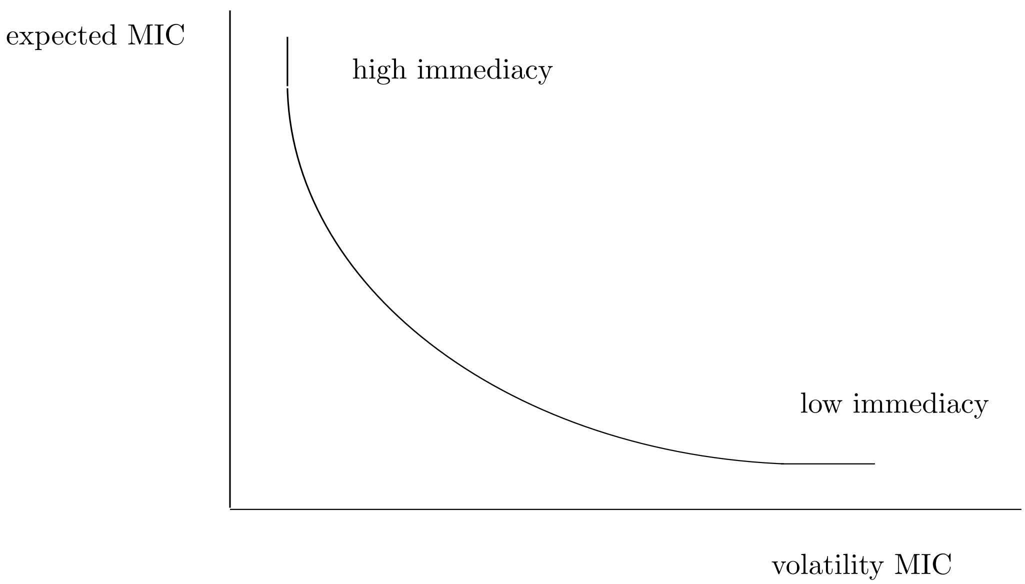

Figure 3:

Figure 3: Theoretical mean-variance relation for market impact costs

Notes: This plot shows the theoretical mean-variance relation for market impact costs, for a given set of trade characteristics. The location of the curve in the isoquant is determined by the trade characteristics.

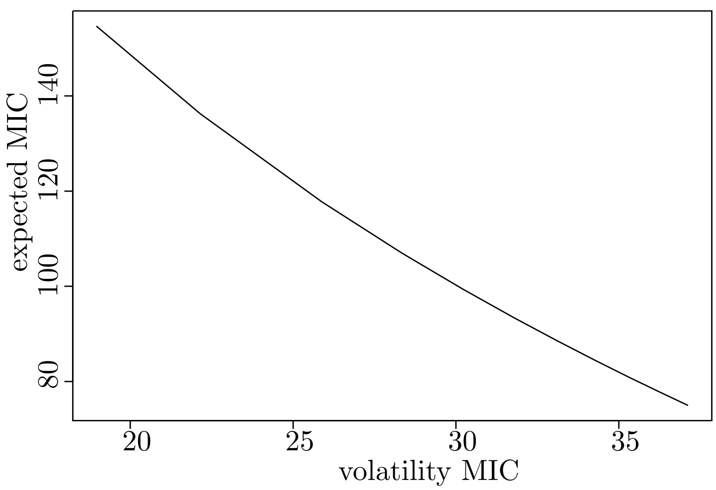

Figure 4:

Figure 4: Empirical mean-variance relation for market impact costs

Notes: This plot shows the empirical mean-variance relation for a particular sell, based on the estimated conditional mean and variance regressions in Eqs. (3) and (5).

BUYS

	MIC (incl. MWPM)	EC (incl. MWPM)	MIC (excl. MWPM)	EC (excl. MWPM)	temporary	persistent
mean	3.9	11.6	19.6	27.4	-7.2	12.4
st.dev. mean	5.3	5.4	5.7	5.7	-10.5	12.1
median	0.0	0.8	0.2	1.1	0.0	0.4
0.5% quantile	-1056.5	-1046.8	-942.7	-922.8	-2345.1	-2028.2
5% quantile	-171.7	-155.4	-133.1	-123.1	-418.5	-398.3
95% quantile	174.8	207.0	241.6	265.7	383.0	509.6
99.5% quantile	993.6	1024.8	1329.5	1341.9	2024.0	2463.6

SELLS

	MIC (incl. MWPM)	EC (incl. MWPM)	MIC (excl. MWPM)	EC (excl. MWPM)	temporary	persistent
mean	49.8	57.6	29.7	37.5	14.5	-16.5
st.dev. mean	7.3	7.3	6.5	6.5	9.6	11.2
median	0.1	2.1	0.0	0.4	0.0	-0.1
0.5% quantile	-848.6	-787.7	-950.7	-857.8	-1711.0	-2475.1
5% quantile	-125.0	-97.1	-157.3	-135.2	-359.6	-555.4
95% quantile	432.3	442.3	357.5	374.0	487.1	467.1
99.5% quantile	1904.5	1916.9	1426.2	1440.0	1799.5	1823.3

Table 1:

Table 1: Market impact costs (MIC), execution costs (EC), and temporary and persistent price effects for buys and sells (in bp)

Notes: Execution costs are defined as the sum of commission and market impact costs. Both market impact and execution costs are given with and without correction for market-wide price movements (abbreviated as MWPM). All values are on a principal-weighted basis. Temporary and persistent price effects of buys and sells (in bp) are corrected for market-wide price movements and calculated on a principal-weighted basis.

	BUYS		SELLS	
	corr.	st.dev.	corr.	st.dev.
momentumperc	**0.149**	0.043	**-0.151**	0.042
log(volatility)	-0.039	0.030	0.045	0.033
sqrt(tradesizertdv)	0.029	0.019	**0.152**	0.020
log(marketcap)	**-0.057**	0.026	-0.029	0.027
exprice	-0.036	0.054	**0.045**	0.017
adv	-0.020	0.016	0.025	0.026
agencysingledum	**0.086**	0.021	**0.074**	0.019
growthdum	**0.044**	0.022	**-0.073**	0.024
quantdum	**-0.146**	0.025	**0.274**	0.025
preopendum	**0.080**	0.026	-0.022	0.025
morningdum	**-0.049**	0.023	0.030	0.023
(middaydum)	**-0.046**	0.011	-0.010	0.012
(Mondaydum)	**0.034**	0.017	**0.015**	0.006
(Tuesdaydum)	**0.145**	0.020	**-0.209**	0.022
Wednesdaydum	**-0.136**	0.021	**0.183**	0.024
Thursdaydum	0.005	0.028	-0.024	0.021
Fridaydum	-0.011	0.029	**0.050**	0.025
(earlymonthdum)	-0.018	0.024	**0.221**	0.029
middlemonthdum	**-0.029**	0.014	**-0.088**	0.036
endmonthdum	0.035	0.026	**-0.194**	0.026
Januarydum	0.037	0.022	**-0.047**	0.024
Februarydum	**0.055**	0.026	0.001	0.024
(Marchdum)	-0.017	0.019	**0.051**	0.020
log(tradedur)	**0.059**	0.019	0.009	0.018
consumdiscrdum	**0.045**	0.022	**-0.065**	0.022
consumerstdum	-0.024	0.022	0.010	0.024
financialsdum	-0.029	0.018	**-0.086**	0.022
energydum	**0.072**	0.024	-0.011	0.013
healthdum	-0.002	0.023	0.033	0.019
ITdum	-0.020	0.034	-0.024	0.032
materdum	-0.037	0.020	0.023	0.020
telecomdum	0.031	0.018	0.035	0.031
utilitiesdum	0.010	0.020	**0.048**	0.019
(industrydum)	-0.008	0.020	**0.111**	0.019
log(mcapdom)	**-0.067**	0.019	**0.080**	0.018
upstairsdum	**0.080**	0.019	**-0.111**	0.026
dealerdum	-0.020	0.017	**0.049**	0.017
(LOBdum)	**0.170**	0.025	**-0.160**	0.024
floordum	**-0.086**	0.023	**0.094**	0.022
hybriddum	**-0.136**	0.030	**0.181**	0.032

Table 2:

Table 2: Regression variables and their correlation to market impact costs

Notes: This table lists the regressors that are taken as a starting point in the model selection procedure in Section 6, together with their correlation with market impact costs. Asymptotic standard errors for the (unconditional) correlations are derived using the central limit theorem in combination with the Delta-method. Correlations in boldface are significant at a 5% significance level. The dummy variables in parentheses have not been included in the model to avoid exact collinearity, but are included in the table for completeness.

	BUYS		**SELLS**	
	corr.	st.dev.	corr.	st.dev.
AMEXdum	**0.026**	0.013	**-0.034**	0.017
Athensdum	-0.004	0.007	**0.023**	0.009
Copenhagendum	**-0.022**	0.007	0.002	0.003
Dusseldorfdum	0.001	0.005	-0.001	0.002
Euronextdum	0.003	0.010	**-0.037**	0.014
Frankfurtdum	**-0.004**	0.002		
Helsinkidum	-0.010	0.007	-0.025	0.016
Irishdum	0.007	0.008	0.011	0.017
Italydum	-0.013	0.008	**-0.017**	0.007
Londondum	-0.007	0.013	**-0.030**	0.014
Madriddum	**-0.021**	0.008	**-0.020**	0.009
Nagoyadum			0.006	0.011
Nasdaqdum	**-0.136**	0.030	**0.181**	0.032
NYSEdum	**-0.088**	0.023	**0.096**	0.022
Osakadum	-0.003	0.031	-0.050	0.030
Oslodum	-0.015	0.008	0.013	0.010
Stockholmdum	-0.013	0.008	-0.002	0.013
Stuttgartdum	-0.008	0.007	-0.007	0.008
SWXdum	-0.005	0.004	0.015	0.009
(Tokyodum)	**0.129**	0.030	**-0.149**	0.027
Torontodum	**0.125**	0.032	0.001	0.022
Viennadum			-0.005	0.003
Virtxdum	-0.009	0.006	**-0.019**	0.006
XETRAdum	0.007	0.012	**-0.016**	0.007

Table 3:

Table 3: Regression variables and their correlation to market impact costs (continued)

Notes: A blank indicates that there were not enough observations to estimate the correlation and its standard deviation.

	BUYS		SELLS	
	coeff.	st.dev.	coeff.	st.dev.
const	**61.2**	23.9	-10.3	36.7
momentumperc	**23.4**	4.8	**-20.4**	4.4
sqrt(tradesizertdv)	**4.2**	2.1	**6.0**	2.4
log(marketcap)	2.4	2.1	**-9.6**	3.2
agencysingledum	**54.7**	8.7	-4.6	10.9
quantdum	**-58.1**	15.5	**67.5**	20.1
preopendum	1.2	10.3	**32.2**	14.8
Wednesdaydum	**-46.9**	8.2	**22.8**	11.0
Thursdaydum	**-85.9**	13.5	**78.1**	19.5
Fridaydum	**-110.5**	13.9	**97.2**	13.7
middlemonthdum	**-90.0**	16.4	-41.9	29.1
endmonthdum	2.1	17.7	**-83.0**	25.7
Januarydum	**-24.6**	9.1	**22.9**	10.6
Februarydum	9.7	8.9	-13.3	9.6
log(tradedur)	7.4	6.7	**-26.6**	10.1
consdiscrdum	6.2	6.2	**-15.4**	7.4
consumstdum	-19.5	12.4	**48.1**	13.4
energydum	**35.2**	13.1	-17.9	12.5
telecomdum	**25.3**	12.8	28.6	22.2
NYSEdum	**-54.8**	11.8	**83.2**	16.9
Nasdaqdum	**-101.3**	19.6	**147.4**	20.4
adj. R^2	0.17		0.24	

Table 4:

Table 4: Estimation results for buys and sells (conditional expectation)

Notes: The standard errors are obtained using White (1980)'s heteroskedasticity consistent covariance matrix. Coefficients in boldface are significant at a 5% significance level.

	BUYS		SELLS	
	coeff.	st.dev.	coeff.	st.dev.
const	**1.417**	0.342	**1.768**	0.286
abs(momentumperc)	**0.189**	0.035	**0.086**	0.028
log(volatility)	**0.275**	0.080	**0.269**	0.060
sqrt(tradesizertdv)	**0.054**	0.020	-0.018	0.026
agencysingledum	**0.400**	0.102	**0.738**	0.115
quantdum	**0.492**	0.136	**0.317**	0.139
morningdum	0.022	0.082	**0.233**	0.085
Wednesdaydum	-0.004	0.077	**0.332**	0.080
Thursdaydum	-0.005	0.127	**0.886**	0.189
Fridaydum	0.148	0.110	**-0.389**	0.138
middlemonthdum	-0.288	0.223	**0.488**	0.188
endmonthdum	**0.869**	0.176	**0.954**	0.172
Januarydum	-0.073	0.086	**-0.490**	0.098
Februarydum	**0.439**	0.089	**0.238**	0.085
log(tradedur)	**0.216**	0.051	**0.224**	0.063
consumstdum	**0.271**	0.125	**-0.236**	0.121
financialsdum	**-0.218**	0.086	**-0.216**	0.079
ITdum	**0.208**	0.085	0.061	0.085
utilitiesdum	**0.299**	0.100	**-0.240**	0.119
NYSEdum	**-0.230**	0.101	**-0.352**	0.133
Nasdaqdum	0.221	0.125	**-0.454**	0.163
Torontodum	**0.696**	0.177	**-0.692**	0.276
adj. R^2	0.20		0.20	

Table 5:

Table 5: Estimation results for buys and sells (conditional variance)

Notes: The standard errors are obtained using White (1980)'s heteroskedasticity consistent covariance matrix. Coefficients in boldface are significant at a 5% significance level.