STOCK MARKET RETURN, ORDER FLOW AND FINANCIAL MARKET LINKAGES*

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Abstract

We study the relation between stock market return, order flow and foreign financial markets in an open and small economy, which means our estimates are likely to be less affected by possible feedback effects from the small economy back to the foreign financial markets. We find that order flow and foreign markets jointly explain a substantial part of stock market return variation—about 30% and 60% in terms of R^2 in the intradaily and daily cases, respectively, and that order flow is an important determinant during the main trading session. However, developments in the geographically closest foreign market prior to the main trading session account for the biggest single portion of total daily stock market return variation. Since foreign markets explain relatively little of the variation in order flow, this suggests there are two relatively distinct effects operating: One inventory-determined or "domestic" effect, and one lead-lag effect from major to minor stock markets.

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1 Introduction

The hypothesis that there is an information impact from stock trades on stock prices dates at least back to Bagehot (1971) in the academic literature, and a substantial number of subsequent empirical studies support the presence of such an effect. In one branch of the literature transaction volume plays centre stage as a measure of the number of information events, and thus as a possible determinant of return volatility.[1] Early contributions are, amongst others, Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), and Gallant et al. (1992).[2] A subsequent branch of the literature makes use of measures of the discrepancy between buy-initiated volume and sell-initiated volume, that is, order flow (or order imbalance), see amongst others Blume et al. (1989), Hasbrouck (1988), Lee and Ready (1991), Hasbrouck (1991), Wermers (1999), Stoll (2000), Engle and Patton (2004), Chordia and Subrahmanyam (2004), Li et al. (2005) and Escribano and Pascual (2006). An important reason for the interest in order flow is that it alone has proved capable of accounting for a notable portion of the variation in daily stock returns, and—exceptionally—it has proved capable of explaining (before controlling for other variables) about 70% of the intrady variation during the turbulence of 19-20 October 1987, see Blume et al. 1989.[3] Recently, there has been a renewed interest in the relation between aggregate stock return and aggregate order flow, see Chordia et al. (2002) and Dunne et al. (2005). The former study an index-weighted sample of stocks traded at the New York Stock Exchange (NYSE), and find that daily aggregate order flow has an impact on daily index returns even after controlling for volume and liquidity. The latter also study a daily index made up of stock traded at NYSE and the associated order flow, but in addition they study the impact of foreign (French) order flow and EUR/USD exchange rate returns. They find that almost 60 percent of daily S&P returns are explained jointly by EUR/USD exchange rate returns and local and foreign order flows. The study of stock market returns can be motivated in part as being of interest by itself, but also in part because studies suggest there are commonalities and/or cross-effects between the stock returns and order flows that make up the aggregate (typically an index), see Cushing and Madhavan (2000), Hasbrouck and Seppi (2001), and Brockman et al. (2006).[4]

Our study contributes to the literature on the relation between stock market return and order flow in at least three ways. First, we study the relation in a small and open economy whose stock market returns are unlikely to have a feedback effect on the major financial centres abroad. Specifically, we study the joint impact of local order flow and foreign markets returns on the return of an index made up of liquid stocks at the Oslo

[1]These ideas provided an important motivation for socalled stochastic volatility models, see Shephard (2005) for a selection of readings.

[2]An early survey is provided by Karpoff (1987).

[3]The sample correlations between their index of S&P stocks and order flow measure are 0.81 for 19 October and 0.86 for 20 October (1989, p. 837). This is equivalent to R^2s of 66% and 74%, respectively, in OLS regressions of the index on a constant and order flow.

[4]A further motivation for studying a stock market index can be given from a portfolio management perspective, since an index can be seen as akin to a portfolio.

Stock Exchange (OSE). Contrary to the study by Dunne et al. (2005), which uses US and French data (the S&P 100 and CAC40 indices, respectively), our coefficient estimates are thus likely to be less affected by possible feedback issues.

A second contribution of our study is that it is more detailed than previous studies because we distinguish between different trading sessions (opening session, main trading session and closing session) within a regime-switching setup, at both intradaily and daily frequencies. This is of great importance because the type and size of effects may depend on trading session, and because temporal aggregation is important in the economic theory behind order flow. Our results confirm previous findings that order flow accounts for a notable portion of the variation in market return even after controlling for developments abroad, and that the information conveyed by order flow cumulate over time. Indeed, we find that the temporally aggregated effect of normalised order flow is almost proportional to the number of intra-period time intervals. However, local order flow is relatively autonomous and unrelated to developments abroad, since foreign markets and lagged local stock market returns jointly explain relatively little of the variation in local order flow.

A third contribution of our study relates to the relation between financial markets. It is widely documented that stock markets are linked to different extent—both geographically and over time—in both the first and second moments of returns, see amongst others Roll (1989), King and Wadhwani (1990), King et al. (1994), Karolyi and Stulz (1996), Beckers et al. (1996), Karolyi and Stulz (2003), Forbes and Rigobon (2002), and Berben and Jansen (2005). Unsurprisingly we find that both US stock market returns and European returns have an influence, and that the main influence comes from the geographically closest market (Europe). In particular, overnight European returns dominate the impact of US returns in the opening session, which suggests that any possible US information of relevance is absorbed by and works through the European market. Surprisingly, however, the economic impact of foreign financial markets is greater than the impact of local order flow. Indeed, over the day the single most important impact on local stock market returns comes from prior developments in the major financial centre abroad that is geographically closest. This strongly supports the hypothesis of a lead-lag effect between major and small stock markets, and provides additional support in favour of the hypothesis that there are two relatively distinct and substantial effects operating in the determination of local stock market return, one inventory-determined or "domestic" effect and one "foreign" effect.

The remainder of the paper is structured as follows. In section 2 we give a brief description of the OSE and the economic context of our study, describe the data, and establish notation. Section 3 explores the intradaily relations between local stock market return, local order flow and foreign financial markets, paying particular attention to the statistical significance of the effects. Section 4 builds upon these results in order to study the economic significance of the effects within a daily parsimonious two-equation model of local stock market return and local order flow. The final section concludes.

2 Economic context and data

The raw data of our study consists of intraday data from 10:00 Central European Time (CET) on 22 January 2004 to 16:10 on 30 December 2004 CET (all hours are in CET unless otherwise stated).[5] The purpose of this section is to give the institutional characteristics and economic context of the OSE over this period, to present the various data and how they are transformed, and to establish notation.

2.1 The Oslo stock exchange

Norway is a small and open economy with only four and a half million inhabitants. In 2005, the country had a gross domestic product (GDP) of $295 billion and a per-capita GDP of $64,000, which is one of the highest in the world. The oil and natural gas sector plays a major role in the Norwegian economy and the vast majority of its oil production is exported. Indeed, in 2005 Norway was the third-largest net oil exporter in the world, only behind Saudi Arabia and Russia,[6] and in 2004 the two biggest companies (Statoil and Norsk Hydro) registered at the OSE were petroleum companies. The OSE is the only regulated marketplace for securities trading in Norway and part of the NOREX-alliance, which is a strategic alliance made up of OSE, the exchanges in Stockholm, Copenhagen, Helsinki, Tallinn, Riga and Vilnius, and the Iceland Stock Exchange. The market value of all companies listed at the OSE totaled 996 billion Norwegian kroner (NOK) by the end of 2004, see table 1. The three largest companies measured in market value, Norsk Hydro, Statoil and Telenor attracted a turnover of a total of NOK 410 billions, representing 45% of the year's total turnover. Telenor is a telecoms company that was formerly owned by the Norwegian Government.[7]

Companies listed at OSE represent a variety of industries and sectors, such as finance, industry, offshore, energy, shipping, technology and telecom. In terms of size, listed companies range from a market capitalization of NOK 25 million to NOK 200 billion. A total of 208 companies were listed at the OSE at the end of 2004, of which 20 were foreign. Indeed, foreign interest has been increasing, as witnessed by an increase in the market share of foreign firms over the two last years from under 10 percent to 25 percent. It does not seem that this increase has been achieved at the expense of Norwegian investment firms, and it is rather the case that it reflects greater trading activity and better liquidity for Norwegian stocks in general. Foreign investors account for between 60 and 70 percent of

[5] In our intraday analyses in section 3 we only use the sample until 29 October 2004, because one of the foreign markets—the International Petroleum Exchange (IPE)—changed opening hours at that point.

[6] Source: http://www.eia.doe.gov/emeu/cabs/Norway/pdf.pdf.

[7] In 2004 Statoil was registered at the NYSE in addition to OSE, Telenor was listed at NASDAQ in addition to OSE, whereas Norsk Hydro was registered at NYSE in addition to several exchanges in Europe (London, Euronext, Frankfurt, Düsseldorf and hamburg). However, only a small share of these companies' total turnover takes place outside OSE, so their share of the US index (the NYSE Index) we use is likely to be negligible. None of the companies were part of the index (EuroFirst 100) that we use as a measure of European stock market return.

daily share trading, which presumably reflects the fact that foreigners at the end of 2004 held 33 percent of the total market capitalization of companies listed on the OSE.

The OSE is an order-driven market without any specialists nor market makers, and investors place orders through brokers registered as members at the exchange. An investor can submit limit orders at any price on a pre specified pricing grid, called tick size.[8] Orders can be placed with a limit price (limit order) or without a limit price (only valid for odd lot orders). Limit orders are placed in a limit order book for each security and are given a price-time priority. Market limit orders are executed immediately against the limit price in the order book. At the OSE, unlike for example the Paris stock exchange, market limit orders are allowed to walk up the book until they are fully executed. A large portion of the 208 securities listed at OSE are traded infrequently, some not even every day, and our focus is therefore the socalled OBX. The OBX is an index made up of the 25 most liquid securities in the OSE Benchmark Index (OSEBX), and comprised 80 percent of the total market value at OSE at the end of 2004.[9]

During our study period trading at the OSE takes place from 9:15 to 16:10 and consists of three different sessions. The first session is a pre-trading period that takes the nature of a "Dutch Auction". This means the equilibrium price for each security is set to the price where the maximum volume can be traded, and hence a theoretical equilibrium price is calculated such that the best buy and sell prices are equal to the equilibrium price. At the end of the opening session orderbooks are uncrossed sequentially, where orders that end up in a trade are subsequently deleted from the orderbook. The exact time of the end of the opening session varies from day to day, but usually ends around 10:05. So for convenience we define the opening session to last until 10:00. The log-return of the OBX in the first intraday interval we define as the log-return from 9:15 in day t to 10:00 in the same day, and is denoted $r_{t,1}^{obx}$. The second trading session is a continuous trading period that lasts until 16:00. During the continuous trading period, orders are automatically matched in the orderbook, meaning that sell and buy orders are matched automatically when the price, volume, and other specifications for a given order corresponds with order(s) previously entered in the order book. The period from 10:00 to 16:00 we divide into 24 intervals each of 15 minutes length. The log-return of the OBX in day t over each interval is thus denoted $r_{t,n}^{obx}$ for $n = 2, \ldots, 25$. For example, the log-return from 15:30 to 15:45 is denoted $r_{t,24}^{obx}$. The third trading session, a closing auction, lasts from 16:00 until 16:10 and is denoted $r_{t,26}^{obx}$. The closing price in this session is determined in the same way as during the opening

[8]The tick size varies according to the price level of the security. For prices below NOK 10 the tick size is NOK 0.01, for prices between NOK 10 and NOK 50 the tick size is NOK 0.10, for prices between NOK 50 and NOK 150 the tick size is NOK 0.25, for prices between NOK 150 and NOK 1000 the tick size is NOK 0.50, and for prices above NOK 1000 the tick size is NOK 1.

[9]The constituents of the OBX are selected on the basis of a six months turnover rating. It is a semiannually revised free float adjusted price index (not dividend adjusted) with composition changes implemented on the third Friday in December and June. In the period between the composition review dates the number of shares for each constituent is fixed with exception of continuous adjustments for corporate actions with priority for existing shareholders. The four largest companies, measured in market capitalization at the end of 2004, were partially owned by the government. This government ownership is not accounted for in the free-float index.

auction, that is, by matching purchase and sale orders through a "Dutch auction" after the brokers have registered their orders in the OSE trading system. In our daily investigations we change the subscript to (t, m) with $m = 1, 2, 3$, where $m = 1$ when $n = 1$, where $m = 2$ when $n = 2, \ldots, 25$, and where $m = 3$ when $n = 26$.

2.2 Order flow

Order flow is a measure of net buying pressure, and in its simplest version it is the net of buyer-initiated and seller-initiated turnover. If buyer-initiated turnover is higher than seller-initiated then order flow is positive, and conversely if buyer-iniated turnover is lower than seller-iniated then order flow is negative. If stock trades convey private information about (say) inventory position, then order flow is a temporally aggregated measure of this heterogeneous and dispersed information.

Our raw data consists of all orders placed in the limit order book at OSE as well as all transactions for each stock listed on the exchange. This allows us to build the limit order book at any given time, and we use the state of the order book at the time of a transaction to assign direction of the trade. If a trade occurs at the best buy price in the order book it is initiated by a seller, and if it occurs at the best sell price in the orderbook it is initiated by a buyer. If the transaction price is between the best price at each side of the order book (inside the spread) it is considered to be undetermined and therefore not included in neither the buy-initiated nor in the sell-initiated turnover.[10] As such our algorithm for assigning direction to the trade is more similar to that of Blume et al. (1989) than Lee and Ready (1991). If intraday buy-initiated and sell-initiated turnover for stock s in period n at day t are denoted $v_{s,t,n}^{Buy}$ and $v_{s,t,n}^{Sell}$, respectively, then buy-initiated turnover, sell-initiated turnover and order flow in period n at day t is given by

$$v_{t,n}^{Buy} = \sum_{s=1}^{25} w_{s,t} v_{s,t,n}^{Buy} \tag{1}$$

$$v_{t,n}^{Sell} = \sum_{s=1}^{25} w_{s,t} v_{s,t,n}^{Buy} \tag{2}$$

$$x_{t,n}^{BMT} = v_{t,n}^{Buy} - v_{t,n}^{Sell}, \tag{3}$$

where $w_{s,t}$ is the index-weight associated with stock s in the OBX in trading day t. The index weights are updated every day based on closing market values in the previous trading day, and hence are constant for every n in day t. Equation (3) is the analogue of the order flow measure used by Blume et al. (1989), hence the superscript BMT. The effect of order flow can depend on liquidity (greater effect when liquidity is low, smaller when liquidity is high), so we also consider two additional measures that adjust for liquidity, namely relative and normalised order flow:

[10] About 2.5% of all transactions are undetermined.

$$x_{t,n}^{rel} = \log v_{t,n}^{Buy} - \log v_{t,n}^{Sell} \tag{4}$$

$$x_{t,n}^{norm} = \frac{v_{t,n}^{Buy} - v_{t,n}^{Sell}}{v_{t,n}^{Buy} + v_{t,n}^{Sell}}. \tag{5}$$

Relative order flow (4) is analogous to returns in that it provides a relative measure of order imabalances, and was first used (without applying the log) by Harris (1989). Normalised order flow (5) is standardised in that it varies between 1 and -1, and was proposed by Lakonishok et al. (1992). Our measures of order flow are always zero when $n = 1$ and $n = 26$, since the direction of the trade is undeterminable during the opening and closing auctions. For $n = 2$ our measures only contains the buy-initiated and sell-initiated volumes from the end of the opening auction—typically around 10:05—to 10:15.

2.3 Foreign financial markets

As a measure of European stock market value we use the EuroFirst100 (EURF100) Index, as a measure of US stock market value we use the NYSE Composite Index, and in the construction of a measure of the oilprice we use futures transaction prices at the International Petroleum Exchange (IPE) in London.[11] The EURF100 Index is made up of stocks of the 60 largest companies in the Eurozone and UK, and of 40 companies chosen from the most underweight economic groups relative to the index universe. None of these companies were listed at the OSE in 2004, but several were listed at the NYSE. Some or all of the stocks of EURF100 are traded from 9:00 until 17:30, and we denote the intraday log-return of EURF100 over interval n in day t for $r_{t,n}^{eurf}$. In particular, we define opening session return $r_{t,1}^{eurf}$ as overnight return from 16:10 in day $t-1$ to 10:00 in day t. The reason we do this is that stocks in the EURF100 index are traded after the closing hours at OSE, and that the price evolution during this period is likely to have an impact on opening session return at OSE.

The NYSE Composite Index is designed to measure the performance of all common stocks listed on the NYSE. As of year-end 2004, the NYSE Composite consists of more than 2000 stocks and is adjusted to eliminate the effects of capitalization changes, new listings and delistings. The index is weighted using free-float market capitalization and calculated on both price and total return basis. The NYSE is open from 15:30 to 22.00, and we denote the intraday log-returns for period n in day t for $r_{t,n}^{nyse}$. This means the intraday returns $r_{t,n}^{nyse}$ are equal to zero when $n \in \{2, \ldots, 23\}$, and the value of $r_{t,1}^{nyse}$ is in effect calculated from the close of OSE at 16:10 in day $t-1$ to the close of NYSE at 22:00 in day $t-1$.

We use the price per oil barrell implied by transacted crude brent blend futures for the earliest delivery month at the IPE in London as a proxy for the spot oil price of European

[11]The source of our data for each of the three measures is Olsen Financial Technologies (OFT).

oil.[12] The IPE Brent Crude futures contract is a deliverable contract based on Exchange of Futures for Physical (EFP) delivery with an option to cash settle. A continuous price series for the price per barrell of Brent Crude oil is constructed by means of a back-adjusted splicing algorithm using 5-minutes log-returns of the associated futures traded at the IPE. The splicing occurs at the end of the trading day on the trading day prior to the last day the future is traded at the IPE, which typically is around the 15th of each month. The intraday log-return of the oilprice over period n in day t we denote as $r_{t,n}^{oil}$, and note that the intraday log-returns $r_{t,n}^{oil}$ are equal to zero when $n \in \{2, 3, 4, 5\}$, that is, between 10:00 and 11:00. The reason for this is that the IPE opens at 11:00 and closes around 20:30. So in effect $r_{t,1}^{oil}$ is calculated as the log-return from 16:10 in day $t-1$ to the close in day $t-1$.[13]

3 Intraday stock market return, order flow and financial market linkages

Our intraday investigation is made up of three parts. In the first subsection we study the impact of different measures of local order flow without controlling for the impact of other variables. The motivation for this is to compare the three measures of order flow, and to shed light on the explanatory power of our order flow data compared with those of other studies. The second subsection studies local intraday stock market return determination, whereas the third subsection studies local intraday order flow determination.

3.1 Order flow measures compared

The purpose of this subsection is twofold. First, to compare the explanatory power of our order flow measures. For example, Dunne et al. (2005) opts for a normalised version in measuring order flow, presumably because the normalised version has greater explanatory power. The second purpose of this subsection is to shed additional light on how well contemporaneous local stock order flow alone accounts for stock market returns compared with that of other empirical studies. For example, during the turbulence of 19-20 October 1987, intradaily order flow alone (without controlling for other variables) accounted for 66% and 74% on each day, respectively, of the intraday variation in an index of S&P stocks Blume et al. (1989).[14]

[12] The IPE changed name to ICE Futures on the 7th. of April 2005, when it changed from open outcry to electronic trading, see http://en.wikipedia.org/wiki/International_Petroleum_Exchange.

[13] Throughout 2004 the IPE closed at 20:30 or later.

[14] The sample correlations between their intraday index of S&P stocks and intraday order flow measure are 0.81 for 19 October and 0.86 for 20 October (1989, p. 837). This is equivalent to R^2s of 66% and 74%, respectively, in OLS regressions of the index on a constant and order flow. It should also be noted that Blume et al. do not use the official index but a—possibly—less variable index, since the stock prices that make up their index are computed as averages over the 15-minute intervals rather than as end-of-interval prices.

Table 2 contains the estimation results of three intraday models, each with a GARCH(1,1) structure on the residuals, equal to

$$\begin{aligned} r_{t,n}^{obx} &= b_0 + b_1 x_{t,n}^{(\cdot)} + e_{t,n}, \quad n = 1, \ldots, 26 \text{ for each } t \\ e_{t,n} &= \sigma_{t,n} z_{t,n}, \quad z_{t,n} \sim iid(0,1), \\ \sigma_{t,n}^2 &= \omega + \alpha e_{t,n-1}^2 + \beta \sigma_{t,n-1} + \gamma_1 g_{t,n}^a + \gamma_3 g_{t,n}^c. \end{aligned} \tag{6}$$

The three specifications differ only in which measure of order flow $x_{t,n}^{(\cdot)}$ that is included in the conditional mean. In order to study the effect of the different trading sessions on the explanatory power of order flow, two impulse dummies, $g_{t,n}^a$ and $g_{t,n}^c$, are included as explanatory variables in the conditional variance equation. The variable $g_{t,n}^a$ is equal to 1 when $n = 1$ and zero elsewhere, whereas $g_{t,n}^c$ is equal to 1 when $n = 26$ and zero elsewhere. The explanatory power in terms of R^2 differs notably across the three specifications, from 2% in the BMT specification, to 5% and 11% in the relative and normalised specifications, respectively. This suggests that liquidity matters for the impact of order flow, since the liquidity adjusted measures account for a greater proportion of intraday stock return variation than the BMT measure. Compared with other studies on intraday data the proportion of return variation explained by normalised order flow is reasonable. For example, in an intradaily analysis of a "representative" stock, Hasbrouck (1991) explains 10% to 20% of stock return variation when including 10 to 23 regressors, whereas in Engle and Patton's (2004) study the explained proportion of error-correction models of intradaily bid and ask returns, respectively, vary from 15% to 54%. Due to the sign-determination issues explained above we are unable to construct order flow in the opening and closing sessions, and the positive (and significanct at the 2% level) coefficient estimates of both $g_{t,n}^a$ and $g_{t,n}^c$ suggest indeed that the explanatory power drops when in opening and closing sessions. Finally, time-varying autoregressive heteroscedasticity (ARCH), as measured by the sum of the α and β estimates, are very similar across specifications and relatively low as the estimates lie in the 0.37 to 0.43 interval. A sum close to 1 means persistence is high, since a sum equal to or higher than 1 implies explosive conditional variance and thus non-stationarity in the variance, whereas positive values substantially lower than 1 means persistence is low: The impact of a large residual in absolute value has a small effect on the size—in absolute value—of the error term in the subsequent period.

Although 11% is reasonably high compared with the studies cited above it is nevertheless far from (say) the 60% achieved by Evans and Lyons (2002) in explaining daily DEM/USD return variation over a three month period. Apart from the fact that order flow possibly explains a greater proportion of exchange rate returns—or at least in normal market conditions, another probable reason is that their data are daily. The economic theory behind order flow implies that information cumulate temporally, and that therefore explanatory power thus is likely to increase as the frequency decreases. To shed light on this possibility table 3 contains the estimation results of three daily models each equal to

$$r_{t,m}^{obx} = b_0 + b_1 x_{t,m}^{(\cdot)} + e_{t,m}, \quad m = 1, 2, 3 \text{ for each } t \tag{7}$$

where $m = 1$ when $n = 1$, where $m = 2$ when $n = 2, \ldots, 25$, and where $m = 3$ when $n = 26$.[15] In other words, m equal to 1,2 and 3 correspond to the opening, continuous and closing sessions, respectively. The underlying economic motivation for order flow is that its informativeness aggregates over time, and the results suggest indeed that this is the case. For all three order flow measures the R^2 is substantially higher than in the intradaily regressions. In particular, the R^2 of 31% achieved by the normalised measure is notably high in a stock market return context, although care should of course be taken in interpreting these numbers since we do not control for the impact of other variables. As a comparison, Chordia et al. (2002) explain up to 33% of market return variation using additional information from the local stock market (contemporaneous and lagged buy and sell volumes, etc.), whereas Dunne et al. (2005) explain about 59% and 40%, respectively, of US and French stock market return using both local and foreign information in addition to order flow.

3.2 What determines local intraday stock market return?

The purpose here is to shed a detailed light on the joint intraday effects of local order flow and foreign financial markets on local stock market return. To this end we estimate a regime-switching model with three regimes. The first regime corresponds to the opening session ($n = 1$), the second regime corresponds to the continuous trading session ($n \in 2, \ldots, 25$), and the third regime corresponds to the closing session ($n = 26$). Specifically, we estimate the model

$$r^{obx}_{t,n} = \begin{cases} f^a \text{ when } n = 1 \text{ in day } t \\ f^b \text{ when } n \in \{2, 3, \ldots, 25\} \text{ in day } t \\ f^c \text{ when } n = 26 \text{ in day } t \end{cases} \tag{8}$$

where

$$\begin{aligned}
f^a &= b_0 + a_1 r^{obx}_{t,n-1} + a_5 r^{eurf}_{t,n} + a_6 r^{eurf}_{t,n-1} + a_9 r^{oil}_{t,n} + a_{13} r^{nyse}_{t,n} + e_{t,n}, \\
f^b &= b_0 + b_1 r^{obx}_{t,n-1} + b_2 r^{obx}_{t,n-2} + b_3 x^{norm}_{t,n} + b_4 x^{norm}_{t,n-1} + b_5 r^{eurf}_{t,n} + b_6 r^{eurf}_{t,n-1} + b_7 r^{eurf}_{t,n-2} \\
&\quad + b_8 r^{eurf}_{t,n-3} + b_9 r^{oil}_{t,n} + b_{10} r^{oil}_{t,n-1} + b_{11} r^{oil}_{t,n-2} + b_{12} r^{oil}_{t,n-3} + b_{13} r^{nyse}_{t,n} + b_{14} r^{nyse}_{t,n-1} + e_{t,n}, \\
f^c &= b_0 + c_1 r^{obx}_{t,n-1} + c_2 r^{obx}_{t,n-2} + c_6 r^{eurf}_{t,n} + c_7 r^{eurf}_{t,n-1} + c_9 r^{oil}_{t,n} + c_{13} r^{nyse}_{t,n} + e_{t,n}, \\
e_{t,n} &= \sigma_{t,n} z_{t,n}, \quad z_{t,n} \sim iid(0,1), \\
\sigma^2_{t,n} &= \omega + \alpha e^2_{t,n-1} + \beta \sigma^2_{t,n-1} + \gamma_1 g^a_{t,n} + \gamma_3 g^c_{t,n} + \gamma_4 id_{t,n}.
\end{aligned}$$

We restrict the constant b_0 in the conditional mean to be equal across regimes, and that for computational convenience we impose the same GARCH(1,1) structure on the errors $\{e_{t,n}\}$ in each regime. The conditional variance equation $\sigma^2_{t,n}$ is the same as in the previous

[15] We do not report estimates with a GARCH-structure on residuals, since the standardised residuals are serially correlated.

subsection, except for the addition of an impulse dummy $id_{t,n}$ which is equal to 1 when $n = 2$ on 19 February 2004 and 0 elsewhere.[16] Finally, recall that the subindex $n-1$ means the variable denotes the value in the previous interval. For example, for $n = 2$ the value of the variable $r^{obx}_{t,n-1}$ in f^a is equal to the opening session OBX-return $r^{obx}_{t,1}$, and for $n = 26$ the variable $r^{nyse}_{t,n-1}$ in f^c denotes NYSE-return in the last interval of the continuous trading session, that is, $r^{nyse}_{t,25}$.

Table 4 contains the estimates of the model, and it should be noted that the significance results—using a significance level of 10%—are robust to small changes in specification (adding insignificant lags or removing insignificant regressors). Also, additional lags of the variables in each regime are insignificant. The explanatory power in terms of R^2 is 32%, which is almost three times higher than in the intraday normalised order flow regression above.[17] This is reasonably well for intraday data—in particular since standardised residuals are very fat-tailed (the high Jarque-Bera statistic is mainly due to excess kurtosis rather than skewness). In the opening session only one variable is signficant at the 10% level, namely contemporaneous EURF-returns. The significant positive impact of EURF-returns is as expected due to the earlier opening hours of European markets, but the insignificance of the other variables—in particular the US and oilprice variables—may come as a surprise. One possible and likely reason is that EURF-returns already have incorporated overnight events and information, and that therefore US and oil-related events and information are already processed by European markets. Indeed, several of the companies of the EURF index are traded in the US.

In the continuous trading session both order flow and all the return categories are significant at some lag. To begin with, the significant negative impact of lagged OBX-returns suggests the presence of stock market return reversals, that is, that positive OBX-returns tend to be followed by negative. The impact of contemporaneous normalised order flow $x^{norm}_{t,n}$ is positive and significant, but the coefficient estimate has dropped to 0.11 compared with 0.14 in the normalised order regression above where we did not control for the effect of other variables. Lagged order flow is not significant, which suggests there is an immediate impact—within 15 minutes—of order flow imbalances. This is not necessarily incompatible with the hypothesis that information regarding trade-imbalances cumulate over time. As in the opening session, contemporaneous EURF-returns $r^{eurf}_{t,n}$ is significant also in the continuous trading session, and endures in a declining manner for two additional periods. In other words, changes in the European stock market tends to have a more enduring effect than local order flow imbalances. The only external financial market which does not seem to have an immediate impact is the oilprice. It does have a significant impact at 5% at lag one and two, however. The oilprice is of great importance for several of the main companies that make up the OBX, so this finding supports that the oilprice matters. However, developments in European stock market seems to have a more immediate and lasting impact than changes in the oilprice. Finally, contemporaneous—not lagged—NYSE-return

[16] The log-return over this interval on this day reached an exceptional high of 2.75%, and the impulse dummy is needed for the standardised residuals to be serially uncorrelated and free from ARCH.

[17] Removing insignificant regressors reduces this to about 30%

$r_{t,n}^{nyse}$ has a positive and significant impact during the main session. This suggests there is a distinct and notable impact from US markets which does not act via the European markets. Economically this is a curious finding because NYSE and OSE opening hours overlap only during 30 minutes in the continuous trading session, namely from 15:30 to 16:00.

During the closing auction there are two significant variables at the 5% significance level, lagged OBX-returns and contemporaneous EURF-returns. The impact of the former is positive, the converse of its impact in the continuous trading session. This suggest the presence of momentums, that is, that returns at the end of the continuous trading sessions tends to be followed by returns with the same sign in the closing auction. The significant impact of contemporaneous EURF-returns is positive, just as in the opening and continuing trading sessions.

In the intradaily regression of OBX return $r_{t,n}^{obx}$ on normalised order flow in the previous section, the estimates suggested the presence of ARCH in the residuals. One might have expected that this would disappear with the inclusion of more regressors in the conditional mean. However, the significance of the α and β coefficients suggest there is still some left, and their sum $\alpha + \beta$ even suggests that it has increased from 0.37 to 0.43—albeit this is still substantially below 1. With respect to the heteroscedasticity impacts of the opening and closing sessions, respectively, as measured by the impulse dummies $g_{t,n}^{a}$ and $g_{t,n}^{c}$, the positive coefficient estimates suggests less explanatory power during the opening and closing sessions, and that the imprecision is higher during the closing session.

3.3 What determines local intraday order flow?

Our analysis so far suggests that local order flow and financial markets abroad jointly determine local stock market returns. But what determines local order flow? Because if the same foreign financial markets that move the local stock market also determine its order flow, then the effect of local order flow on local stock market return is not really distinct from developments abroad. This is a real possibility, since foreigners account for a substantial amount of trading at OSE. The purpose of this section is therefore to shed light on this issue.

We estimate the model

$$\begin{aligned}
x_{t,n}^{norm} &= b_0 + b_1 x_{t,n-1}^{norm} + b_2 x_{t,n-2}^{norm} + b_3 x_{t,n-3}^{norm} + b_4 x_{t,n-4}^{norm} + b_5 x_{t,n-5}^{norm} + b_6 r_{t,n-1}^{obx} \\
&\quad + b_7 r_{t,n}^{eurf} + b_8 r_{t,n-1}^{eurf} + b_9 r_{t,n-2}^{eurf} + b_{10} r_{t,n}^{oil} + b_{11} r_{t,n}^{nyse} + b_{12} r_{t,n-1}^{nyse} + e_{t,n} \\
n &= 2, \ldots, 25 \text{ for each } t \qquad (9) \\
e_{t,n} &= \sigma_{t,n} z_{t,n}, \quad z_{t,n} \sim iid(0,1) \\
\sigma_{t,n}^2 &= \omega + \alpha e_{t,n-1}^2 + \beta \sigma_{t,n-1}^2
\end{aligned}$$

where $n \in 2, \ldots, 25$ for each t. In other words, we do not include the opening session nor the closing session in the estimation of the model, since we cannot calculate order flow in these periods. Nevertheless, the lagged variables are correctly adjusted for the opening and closing session values. For example, for $n = 2$ the value of $r^{obx}_{t,n-1}$ is equal to $r^{obx}_{t,1}$ and not $r^{obx}_{t-1,25}$ as the notation suggests, whereas the value of $x^{norm}_{t,n-1}$ for $n = 2$ is equal to $x^{norm}_{t-1,25}$, and so on.

The estimation results are contained in table 5, and also here is it the case that the significance results—using a significance level of 10%—are robust to small changes in specification (adding insignificant lags or removing insignificant regressors). The joint explanatory power as measured by R^2 is relatively low, only 7%. In other words, although European markets have a significant contemporaneous and lagged impact, and although US returns have a significant contemporaneous impact for n equal to 24 and 25, the total explanatory power of foreign markets is low. Moreover, the fact that the JB statistic is relatively low (16.13 compared with 2886.16 in the model of local stock market return in the previous subsection) suggests the low R^2 is not due to heavy tails in the standardised residuals. Nevertheless, removing the foreign financial markets from the regression reduces the R^2 to 1%, so foreign markets do account for a notable share of the explained variation in local order flow. Oilprice returns are not significant, but four lags of local order flow is significant, and it is not clear that the impact is decreasing beyond the first lag. Indeed, a Wald coefficient restriction test of the null that the impact of lags two to four are equal is not rejected (p-value of 83%). One possible and oft-cited explanation is that large investors split their trades and trade gradually in order to reduce the impact on prices, that is, socalled "stealth trading". Finally, the significant α and β parameters in the conditional variance equation suggests there is some presence of ARCH (time-varying autoregressive imprecision of the conditional mean), with the sum of α and β being equal to 0.77.

4 Local order flow vs. foreign markets: What is most important for daily local stock market returns?

The investigation in this section differs from the two previous subsections in two main respects. First, we do not divide the continuous trading session at OSE into intraday intervals. Rather, we treat the continuous trading period as a single period, so that the day is made up of three periods: The opening session, the continuous trading session and the closing session. According to the economic theory behind order flow the private information conveyed by stock trades cumulate when revealed sequentially to the market. An implication of this is that the explanatory power should increase with temporal aggregation. Differently put, daily order flow should exhibit greater explanatory power than intradaily.[18] The second main difference concerns the main goal of the analysis. Whereas the previous section primarily studied whether the different variables are statistically significant or not, the main aim here is to compare their economic importance. To this end we study the impact of a one standard deviation (SD) value in each regressor within a parsimonious two-equation model of local stock market return and local order flow.

[18]Of course, a similar effect is possibly present with respect to the other explanatory variables as well.

The section is divided into two subsections. The first contains the details of the model, whereas the second addresses the question of whether local order flow or foreign financial markets are most important in the determination of local stock market return.

4.1 A daily model of local stock market return and local order flow

The specification of local stock market return is given by

$$r_{t,m}^{obx} = \begin{cases} f^a \text{ when } m = 1 \text{ in day } t \\ f^b \text{ when } m = 2 \text{ in day } t \\ f^c \text{ when } m = 3 \text{ in day } t \end{cases} \tag{10}$$

where

$$\begin{aligned}
f^a &= b_0 + a_1 r_{t,m}^{eurf} + e_{t,m}, \\
f^b &= b_0 + b_1 r_{t,m-1}^{obx} + b_2 x_{t,m}^{norm} + b_3 r_{t,m}^{eurf} + b_4 r_{t,m-1}^{eurf} + b_5 r_{t,m}^{oilp} + b_6 r_{t,m-1}^{oilp} \\
&\quad + b_7 r_{t,m}^{nyse} + e_{t,m}, \\
f^c &= b_0 + c_1 r_{t,m-1}^{obx} + c_2 r_{t,m}^{oilp} + e_{t,m-1}, \\
e_{t,m} &= \sigma_{t,m} z_{t,m}, \quad z_{t,m} \sim iid(0,1), \\
\sigma_{t,m}^2 &= \omega + \alpha e_{t,m-1}^2 + \beta \sigma_{t,m-1}^2 + \gamma_1 g_{t,m}^a + \gamma_3 g_{t,m}^c,
\end{aligned}$$

and is obtained through single-path general-to-specific (GETS) specification search from a more general model. We adopt the convention $(t, m-1) = (t-1, 3)$ when $m = 1$, and recall that $m = 1$ when $n = 1$, $m = 2$ when $n \in \{2, \ldots, 25\}$ and $m = 3$ when $n = 26$. The estimation results are contained in table 6 and the R^2 of 61% suggests indeed that the explanatory power of temporally aggregated variables is substantially higher. In the first regime only European markets as measured by $r_{t,1}^{eurf}$ have an impact, just as in the intraday case. However, the coefficient estimate in this regression is 0.0380, which is about half of 0.0708, the estimate in the intraday specification. In the continuous, main trading session all categories of variables have at least one significant regressor at the 10% level. The positive value of the impact of lagged OBX return $r_{t,m-1}^{obx}$ suggests the presence of a momentum effect, in the sense that positive (negative) returns in the opening session tends to be followed by positive (negative) returns in the main trading session. Normalised order flow $x_{t,m}^{norm}$ is also significant, and interestingly the coefficient estimate is almost proportional to the intradaily estimate of 0.1090 above. Exact proportionality would imply that the daily impact, that is, the total impact over the main trading session $n = 2, \ldots, 25$, would be twenty four times higher: $0.1090 \times 24 = 2.6160$. The daily estimate of 2.3459 is about twenty two times higher than the intradaily estimate. The impact of European markets during the main session comes from developments both prior to and during the main session. Similarly, oilprice returns have an impact both contemporaneously over the main trading session and lagged in that overnight positive (negative) price changes seems to have a positive (negative) effect on local stock market return in the main trading session. Possibly somewhat suprisingly on the other hand US returns have a contemporaneous impact during the main trading session. This is surprising because, in the main trading session, NYSE opening hours overlap with OSE's for only half an hour, from 15:30 to 16:00. In the closing session only lagged OBX returns $r_{t,m-1}^{obx}$ and contemporaneous oilprice returns $r_{t,m}^{oilp}$ have and impact. The estimated impact 0.0260 of lagged OBX returns $r_{t,m}^{obx}$ suggests that also in the closing session there is a local trending or momentum effect of positive/negative returns from the main trading session are repeated in the closing session. The estimated impact 0.0516 of contemporaneous oilprice returns $r_{t,m}^{oilp}$ is similar to the corresponding estimate for the main trading session. Finally, the conditional variance equation suggests there is little time-varying imprecision (heteroscedasticity), since the persistence estimate $\hat{\alpha} + \hat{\beta}$ is equal to only 0.22. Also, the negative and significant impact of the regime dummies $g_{t,m}^{a}$ and $g_{t,m}^{c}$ suggests the model is more precise in the opening and closing session sessions, and the similarity in the estimates suggests the reduced precision is approximately the same in both sessions.

The specification of daily local normalised order flow is

$$\begin{aligned}
x_{t,2}^{norm} &= b_0 + b_1 x_{t-1,2} + b_2 r_{t,1}^{eurf} + b_3 r_{t,2}^{eurf} + b_4 r_{t,1}^{oilp} + b_5 r_{t,2}^{oilp} + b_6 r_{t,2}^{nyse} + e_{t,2} \\
e_2 &= \sigma_{t,2} z_{t,2}, \quad z_{t,2} \sim iid(0,1), \qquad (11) \\
\sigma_{t,2}^2 &= \omega + \alpha e_{t-1,2}^2 + \beta \sigma_{t-1,2}^2 + id_{t,2}^{7/7} + id_{t,2}^{12/7}
\end{aligned}$$

which means m is restricted to 2. In other words, for computational simplicity estimation is over the main trading session only, since normalised order flow $x_{t,m}^{norm}$ is equal to zero whenever $m = 1$ or $m = 3$. However, just as in the intraday specification of normalised order flow, it should be noted that we correctly adjust and transform the variables so that we can study the impact of lagged regressors. Also here it is the case that (11) is obtained through single-path GETS specification search starting from a more general model,[19] and the variables $id_{t,2}^{7/7}$ and $id_{t,2}^{12/7}$ are impulse dummies equal to 1 on 7/7/2004 and 12/7/2004, respectively, and zero elsewhere.[20] The estimation results are contained in table 7. The R^2 of 16% compares with only 7% in the intraday case, which suggests that also here is it the case that the explanatory power increases as the sampling frequency decreases. Nevertheless, 16% is relatively low compared with the 61% achieved for OBX returns above, so in comparison foreign financial markets do not explain a very high proportion of the total variation in local order flow. As for the significant variables, it is interesting that lagged

[19]We did not include contemporaneous local stock market return $r_{t,m}^{obx}$ in the general model, but we did include its lag $r_{t,m-1}^{obx}$.

[20]The impulse dummies neutralise extreme values and are needed for standardised residuals to be serially uncorrelated and free from ARCH. Unfortunately, we have thus far not been able to identify the economic reasons for the extreme values.

normalised order flow $x^{norm}_{t-1,2}$, that is, order flow in the main trading session on the previous trading day, has a positive impact. This is consistent with the presence of stealth trading across trading days, although—of course—alternative explanations can be given as well. Both European market and oilprice returns have pre-opening and contemporaneous effects, whereas US markets only have a contemporaneous effect. Finally, the estimates of the conditional variance equation suggests there is time-varying serially dependent imprecision (ARCH) in the conditional mean, with the persistence estimate being equal to 0.58.

4.2 Daily impulse-response analysis

We explore the economic significance of local order flow and foreign financial markets over the day, by studying the effect of a one standard deviation (SD) value in each regressor given that the intercept, the error and the other regressors in the conditional mean are equal to zero. The impact of a one SD value can be interpreted as the economic or partial impact of a regressor, since the empirical SD is an estimate of how much the regressor "typically" varies. Table 8 contains the empirical SDs of each regressor for each session. OBX return variability over the main session is more than ten times higher than in the opening session, and about eight times higher than in the closing session.[21] For the European market on the other hand, variability is higher for $m = 1$—which for European returns means from 16:10 in day $t - 1$ to 10:00 in day t—than in the main and closing sessions $m = 2$ and $m = 3$, respectively. Higher variability for $m = 1$ compared with $m = 2$ and $m = 3$ is also the case for oilprice and NYSE returns.

Table 9 contains the estimated impacts on local stock market return over each session of a one SD value of each regressor. Only European markets affect local returns prior to the main session, and the impact is estimated to 0.021%. Differently put, a 0.593% (the empirical SD of $r^{eurf}_{t,1}$) increase in the European market prior to the main session at OSE leads to a 0.021% increase in the OBX index during the opening session. The second row contains the impacts during the main session. Possibly somewhat surprisingly the biggest impact comes from European markets prior to the main session. Indeed, whereas the impact from European markets during the main session is 0.18%, the impact from European markets prior to the main session is about 0.34%, almost the double. In other words, since there is no impact from European markets in the closing session, and since OBX variability is ten times higher during the main session compared with the opening session, our estimates as a consequence suggest that the lead-lag effect between small and large stock markets accounts for the biggest single portion of local return variation over the day. The second biggest impact in the main session comes from normalised order flow and is about 0.29%. This suggests indeed that local order flow is an important determinant of local stock market return. The third biggest impact (0.185%) comes from overnight oilprice return $r^{oilp}_{t,1}$. Oilprice returns over the main session also have an impact (0.065%) on local stock market return during the main session, but again is it the case that developments

[21]The main session is longer than the opening and closing sessions, so higher variability over the main session is not surprising.

in the oil market prior to the main session is substantially more important (the impact is almost three times bigger). Indeed, overall our main findings can be summarised in two points. First, most of the impact on main session returns comes from developments prior to the main session, that is, developments in foreign financial markets. As a consequence, since OBX return variation is highest in the main session, this means foreign markets account for the biggest portion of the total variation in local stock market returns. The second point is that, during the main session, the most important determinant is local order flow.

Table 10 contains the estimated impacts on normalised order flow $x_{t,m}^{norm}$ over each session of a one SD value in each regressor. By construction impacts are zero in the first and third rows, which is motivated by the fact that we cannot compute order flow in the opening and closing sessions. The biggest impacts of 0.029% and 0.023% in the main session come from the European markets prior to and during the main session, respectively. Differently put, also here does the single most important influence come from (or via) developments in the European markets. The third biggest impact of 0.021% comes from developments in the oilprice during the main session. This is to some extent in line with the commonplace view among analysts and commentators that the oilprice is of importance for the Norwegian stock market. Indeed, since oilprice return prior to the main session also have an impact (0.010%) on local order flow, effectively this means that the second biggest total partial impact (0.010% + 0.021%) comes from the oil market. The impacts 0.015% and 0.012% of the last two regressors, US returns during the main sessions and local order flow from the previous day, respectively, are only about the half or less of that of the total oilprice impact of 0.031%.

5 Conclusions

We have studied the interaction between local stock market return, local order flow and foreign financial markets in a small and open economy over different trading sessions, both at the intradaily and daily frequency. We find that local order flow and foreign financial markets jointly explain a large part of local stock market return variation—about 30% in terms of R^2 in the intraday case and about 60% in the daily case, and that local order flow alone accounts for a notable part. Also, our findings are consistent with the underlying theory of order flow which holds that the information conveyed by trades cumulate over time, since our results suggests the effect of temporal aggregation is almost proportional to the number of aggregated time-intervals. Nevertheless, while local order flow is an important determinant of local stock market return, our results suggest that the largest single effect impact comes from abroad prior to the start of the local main trading session. This strongly supports the hypothesis of a lead-lag effect between major and smaller markets. Moreover, although foreign markets are the main determinant of local order flow, jointly they explain relatively little of the variation in local order flow (the R^2s are 7% and 16% in the intradaily and daily specifications, respectively). This suggests there are two relatively distinct effects operating: One “domestic” which can be interpreted as an inventory effect, and one “international” or foreign effect which can be interpreted as a lead-lag relation. Possibly somewhat surprising we find that the effects of the US stock market and, given the role played by petroleum in Norway’s economy, oilprice returns on local stock market returns are comparatively small. One possible explanation is that the European markets have already absorbed and processed the information contained in the US and oil markets, and so that their effects really work via European markets. However, developments in the oil market account nevertheless for the second biggest total impact on local order flow (the biggest impact comes from European markets).

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Table 1: Descriptive statistics of the Oslo Børs Benchmark Index (OSEBX) and the OBX index in 2004

	OSEBX	*OBX*
Index value (end of year)	236.7	821.59
Percentage change 2004	38.4	31.3
Market capitalisation of all companies (billions of NOK)	996	738
Total turnover (billions of NOK)	906	777
Average turnover per day (billions of NOK)	3.6	3.1
Number of transactions	3 407 688	1 992 441
Average value per transaction (NOK)	265 000	390 000
Number of listed companies	188	25
Number of foreign companies	20	5

Table 2: Intradaily regressions of $r^{obx}_{t,n}$ on a constant and different measures of order flow:

$$\begin{aligned} r^{obx}_{t,n} &= b_0 + b_1 x^{(\cdot)}_{t,n} + e_{t,n}, \quad n = 1, \ldots, 26 \text{ for each } t \\ e_{t,n} &= \sigma_{t,n} z_{t,n}, \quad z_{t,n} \sim iid(0,1) \\ \sigma^2_{t,n} &= \omega + \alpha e^2_{t,n-1} + \beta \sigma^2_{t,n-1} + \gamma_1 g^a_{t,n} + \gamma_3 g^c_{t,n} \end{aligned}$$

Regressor	*Est*	*Pval*	*Est*	*Pval*	*Est*	*Pval*
const.	-0.0002	0.90	-0.0018	0.20	-0.0035	0.01
$x^{BMT}_{t,n}$	0.0000	0.25				
$x^{rel}_{t,n}$			0.0368	0.00		
$x^{norm}_{t,n}$					0.1353	0.00
var.const.	0.0057	0.00	0.0046	0.00	0.0046	0.00
$e^2_{t,n-1}$	0.0290	0.11	0.0799	0.01	0.0265	0.17
$\sigma^2_{t,n-1}$	0.3506	0.00	0.3495	0.00	0.3443	0.00
$g^a_{t,n}$	0.3413	0.00	0.3472	0.00	0.3441	0.00
$g^c_{t,n}$	0.0045	0.02	0.0053	0.00	0.0063	0.00
R^2	0.02		0.05		0.11	
LogL	3696.30		3893.90		4181.35	
AR_1	2.21	0.14	1.03	0.31	2.39	0.12
$ARCH_1$	0.01	0.91	0.01	0.92	0.06	0.80
JB	23842.58	0.00	11367.65	0.00	8664.72	0.00
Obs	5096		5096		5096	

The estimation sample is 22 January 2004 (10:30 CET) to 29 October 2004 (16:10 CET) and computations are in EViews 5.1 with robust standard errors of the Bollerslev and Wooldridge (1992) type. *Est* stands for estimate (zero-values are due to rounding), *Pval* stands for *p*-value (the coefficient tests are two-sided with zero as the null hypothesis), *LogL* stands for Gaussian log-likelihood, AR_1 is the Ljung and Box (1979) test for first order serial correlation in the standardised residuals, $ARCH_1$ is the χ^2 version of the Engle (1982) test for first order autoregressive conditional heteroscedasticity in the standardised residuals, *JB* is the Jarque and Bera (1980) test for non-normality in the standardised residuals, and *Obs* is the number of non-missing observations.

Table 3: Daily regressions of $r^{obx}_{t,m}$ on a constant and different measures of order flow:

$$r^{obx}_{t,m} = b_0 + b_1 x^{(\cdot)}_{t,m} + e_{t,m}, \quad m = 1, 2, 3 \text{ for each } t$$

Regressor	*Est*	*Pval*	*Est*	*Pval*	*Est*	*Pval*
const.	0.0142	0.48	-0.0176	0.30	-0.0191	0.25
$x^{BMT}_{t,m}$	0.0000	0.04				
$x^{rel}_{t,m}$			1.9807	0.00		
$x^{norm}_{t,m}$					4.1257	0.00
R^2	0.17		0.30		0.31	
AR_1	1.57	0.21	1.60	0.21	1.58	0.21
$ARCH_1$	3.09	0.08	3.72	0.05	3.76	0.05
JB	3398.02	0.00	2752.39	0.00	2703.89	0.00
Obs	716		716		716	

The estimation sample is 22 January 2004 (10:30 CET) to 30 December 2004 (16:10 CET). Standard errors are heteroscedasticity consistent of the White (1980) type, and AR_1 is the χ^2 version of the Breusch-Godfrey (Godfrey 1988) test for first order residual serial correlation. Otherwise see table 2.

Table 4: Estimates of the intraday regime switching model (8) of OBX returns $r_{t,n}^{obx}$

Regressor	f^a		f^b		f^c	
	Est	*Pval*	*Est*	*Pval*	*Est*	*Pval*
const.	-0.0024	0.05	-0.0024	0.05	-0.0024	0.05
$r_{t,n-1}^{obx}$	-0.0041	0.97	-0.0974	0.00	0.1429	0.03
$r_{t,n-2}^{obx}$			-0.0066	0.60	0.0096	0.90
$x_{t,n}^{norm}$			0.1090	0.00		
$x_{t,n-1}^{norm}$			0.0041	0.28		
$r_{t,n}^{eurf}$	0.0708	0.04	0.3437	0.00	0.2624	0.04
$r_{t,n-1}^{eurf}$	0.0897	0.41	0.2373	0.00	0.0398	0.65
$r_{t,n-2}^{eurf}$			0.0336	0.01		
$r_{t,n-3}^{eurf}$			0.0176	0.32		
$r_{t,n}^{oilp}$	0.0066	0.23	-0.0054	0.32	0.0217	0.40
$r_{t,n-1}^{oilp}$			0.0117	0.04		
$r_{t,n-2}^{oilp}$			0.0085	0.05		
$r_{t,n-3}^{oilp}$			0.0018	0.67		
$r_{t,n}^{nyse}$	-0.0251	0.35	0.0634	0.00	-0.1418	0.34
$r_{t,n-1}^{nyse}$			0.0332	0.17		
var.const.	0.0036	0.00	0.0036	0.00	0.0036	0.00
$e_{t,n-1}^2$	0.0233	0.04	0.0233	0.04	0.0233	0.04
$\sigma_{t,n-1}^2$	0.4095	0.00	0.4095	0.00	0.4095	0.00
$g_{t,n}^a$	0.1669	0.00				
$g_{t,n}^c$					0.0067	0.00
$id_{t,n}$			1.2869	0.39		
R^2	0.32					
LogL	4622.45					
AR_1	1.72	0.19				
$ARCH_1$	0.11	0.74				
JB	2886.61	0.00				
Obs	5092					

The estimation sample is 22 January 2004 (10:30 CET) to 29 October 2004 (16:10 CET). Otherwise see table 2.

Table 5: Estimates of the intraday model (9) of normalised order flow $x_{t,n}^{norm}$

Regressor	*Est*	*Pval*
const.	0.0195	0.00
$x_{t,n-1}^{norm}$	0.0789	0.00
$x_{t,n-2}^{norm}$	0.0375	0.01
$x_{t,n-3}^{norm}$	0.0274	0.07
$x_{t,n-4}^{norm}$	0.0398	0.00
$x_{t,n-5}^{norm}$	0.0108	0.45
$r_{t,n-1}^{obx}$	0.0457	0.20
$r_{t,n}^{eurf}$	0.8181	0.00
$r_{t,n-1}^{eurf}$	0.1719	0.00
$r_{t,n-2}^{eurf}$	0.0122	0.71
$r_{t,n}^{oilp}$	0.0052	0.79
$r_{t,n}^{nyse}$	0.0966	0.05
$r_{t,n-1}^{nyse}$	-0.0095	0.75
var.const.	0.0260	0.00
$e_{t,n-1}^2$	0.1001	0.00
$\sigma_{t,n-1}^2$	0.6718	0.00
R^2	0.07	
LogL	-1523.62	
AR_1	1.03	0.31
$ARCH_1$	0.14	0.70
JB	16.13	0.00
Obs	4702	

The estimation sample is 22 January 2004 (10:30 CET) to 29 October 2004 (16:10 CET). Otherwise see table 2.

Table 6: Estimates of the daily regime-switching model (10) of OBX returns $r^{obx}_{t,m}$

$Regressor$	f^a		f^b		f^c	
	Est	$Pval$	Est	$Pval$	Est	$Pval$
$const.$	-0.0054	0.07	-0.0054	0.07	-0.0054	0.07
$r^{obx}_{t,m-1}$			1.0717	0.09	0.0260	0.02
$x^{norm}_{t,m}$			2.3459	0.00		
$r^{eurf}_{t,m}$	0.0360	0.00	0.4681	0.00		
$r^{eurf}_{t,m-1}$			0.5718	0.00		
$r^{oilp}_{t,m}$			0.0547	0.03	0.0449	0.05
$r^{oilp}_{t,m-1}$			0.0990	0.00		
$r^{nyse}_{t,m}$			0.1781	0.08		
$var.const.$	0.2540	0.00	0.2540	0.00	0.2540	0.00
$e^2_{t,m-1}$	0.0355	0.00	0.0355	0.00	0.0355	0.00
$\sigma^2_{t,m-1}$	0.1764	0.01	0.1764	0.01	0.1764	0.01
$g^a_{t,m}$	-0.2543	0.00				
$g^c_{t,m}$					-0.2898	0.00
R^2	0.61					
$LogL$	324.91					
AR_1	0.57	0.45				
$ARCH_1$	0.63	0.43				
JB	232.06	0.00				
Obs	715					

The estimation sample is 22 January 2004 (10:30 CET) to 30 December 2004 (16:10 CET). Otherwise see table 2.

Table 7: Estimates of the daily model (11) of normalised order flow $x_{t,2}^{norm}$

Regressor	*Est*	*Pval*
const.	-0.2053	0.47
$x_{t-1,2}^{norm}$	0.1000	0.09
$r_{t,1}^{eurf}$	0.0497	0.00
$r_{t,2}^{eurf}$	0.0595	0.00
$r_{t,1}^{oilp}$	0.0055	0.06
$r_{t,2}^{oilp}$	0.0179	0.00
$r_{t,2}^{nyse}$	0.0125	0.03
var.const.	0.0037	0.04
$e_{t-1,2}^2$	-0.1112	0.01
$\sigma_{t-1,2}^2$	0.6915	0.00
$id_{t,2}^{7/7}$	0.1275	0.31
$id_{t,2}^{12/7}$	0.0286	0.65
R^2	0.16	
LogL	221.08	
AR_1	0.15	0.70
$ARCH_1$	0.04	0.85
JB	0.57	0.75
Obs	238	

The estimation sample is 22 January 2004 (10:30 CET) to 30 December 2004 (16:10 CET). Otherwise see table 2.

Table 8: Empirical standard deviations

Regime	$\hat{\sigma}_{t,m}^{obx}$	$\hat{\sigma}_{t,m}^{norm}$	$\hat{\sigma}_{t,m}^{eurf}$	$\hat{\sigma}_{t,m}^{oilp}$	$\hat{\sigma}_{t,m}^{nyse}$
$m = 1$	0.069	0.000	0.593	1.866	0.524
$m = 2$	0.882	0.125	0.387	1.191	0.388
$m = 3$	0.118	0.000	0.118	0.307	0.104

The empirical standard deviations are calculated under the assumption of means equal to zero. For example, $\hat{\sigma}_{t,1}^{obx} = \sqrt{\frac{1}{253} \cdot \sum_t (r_{t,1}^{obx})^2}$ and $\hat{\sigma}_{t,2}^{norm} = \sqrt{\frac{1}{253} \cdot \sum_t (x_{t,2}^{norm})^2}$.

Table 9: Impacts on OBX returns $r^{obx}_{t,m}$ of a one standard deviation value in each regressor

	$\hat{\sigma}^{obx}_{t,1}$	$\hat{\sigma}^{obx}_{t,2}$	$\hat{\sigma}^{norm}_{t,2}$	$\hat{\sigma}^{eurf}_{t,1}$	$\hat{\sigma}^{eurf}_{t,2}$	$\hat{\sigma}^{oilp}_{t,1}$	$\hat{\sigma}^{oilp}_{t,2}$	$\hat{\sigma}^{oilp}_{t,3}$	$\hat{\sigma}^{nyse}_{t,2}$
$m = 1$	0.000	0.000	0.000	0.021	0.000	0.000	0.000	0.000	0.000
$m = 2$	0.074	0.000	0.292	0.339	0.181	0.185	0.065	0.000	0.069
$m = 3$	0.000	0.023	0.000	0.000	0.000	0.000	0.000	0.014	0.000
sum	0.074	0.023	0.292	0.360	0.181	0.185	0.065	0.014	0.069

The numbers in the first three rows can be interpreted as the empirical one SD partial impact (intercept, error and other regressors in the conditional mean assumed equal to zero) of the regressor. For example, the coefficient estimate of $x^{norm}_{t,2}$ is 2.3459, so its one SD partial impact is computed as $2.3459 \cdot \hat{\sigma}^{norm}_{t,2} = 0.293$ (the discrepancy of 0.001 compared with the value in the table is because higher numerical accuracy is used in the actual calculations).

Table 10: Impacts on normalised order flow $x^{norm}_{t,m}$ of a one standard deviation value in each regressor

$Regime$	$\hat{\sigma}^{norm}_{t-1,2}$	$\hat{\sigma}^{eurf}_{t,1}$	$\hat{\sigma}^{eurf}_{t,2}$	$\hat{\sigma}^{oilp}_{t,1}$	$\hat{\sigma}^{oilp}_{t,2}$	$\hat{\sigma}^{nyse}_{t,2}$
$m =1$	0.000	0.000	0.000	0.000	0.000	0.000
$m =2$	0.012	0.029	0.023	0.010	0.021	0.015
$m =3$	0.000	0.000	0.000	0.000	0.000	0.000

See table 9.