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Abstract

This paper analyzes the inter-temporal relationship between currency price changes and their expectations on intra-day frequencies. We examine how price expectations are transmitted into prices by means of order flow and how order flow is affected by past prices (feedback effects). Based on a trading activity dataset from a foreign exchange electronic trading platform, OANDA FXTrade, currency price change expectations are approximated by aggregating very detailed individual order information aiming to present an accurate picture of currency price expectations. We investigate on different intra-day sampling frequencies, whether price expectations and trading patterns of the OANDA FXTrade investors are helpful for predicting future currency prices. Moreover, considering the literature on market microstructure and behaviorial finance, we formulate several hypotheses about the relationship between price changes and order flow as well as the trading behavior and the preference structure of our investors, which we investigate with the help of forecasting studies and out-of-sample prediction criteria.

JEL classification: $G10, F31, C32$

Keywords: Trading Activity Dataset, Price Expectations, Order Flow, Foreign Exchange Market

1 Introduction

This paper analyzes the inter-temporal relationship between currency price changes and their expectations on intra-day frequencies. Currency price change expectations are approximated through detailed order flow measures reflecting the trading behavior of market participants. On the one hand, the information content of different order flows is evaluated for the prediction of future currency price changes and on the other hand the influence of historical prices changes on trading decisions is investigated (feedback effects).
The way expectations are aggregated by order flow is central to the understanding of the microstructure of the highly decentralized foreign exchange (FX) market. Information on the interpretation of specific news events, risk preferences, hedging demands, central bank interventions, and most important, private information are widely dispersed and disaggregated among agents. Traditionally, order flow measures have been used to aggregate this dispersed information into one single figure, meant to help explaining and predicting future price changes.

Most of the existing studies (e.g., Evans & Lyons (2002a,b, 2005, 2006), Rime (2003) and Daníelsson, Payne & Luo (2002)) focus on agents in the interbank market and consider the relationship between prices and order flow obtained either from direct (e.g., Reuters Dealing 2000-1) or brokeraged (e.g. Reuters Dealing 2000-2, EBS) interdealer trading. The studies of Osler (2005) and Marsh & O'Rourke (2005) use a dataset of customer trades collected by the Royal Bank of Scotland. They investigate how customer-trading-order-flow, which is the primary source of private information for a player in the interbank market, is related to currency prices. In these studies order flow is usually measured by the standard net order flow measure of Lyons (1995), who suggests aggregating all the dispersed information into one single measure: the difference between the number of buyer- and seller-initiated trades for a given sampling frequency. The studies by Daníelsson et al. (2002), Evans & Lyons (2005, 2006) and Daníelsson & Love (2006) underpin the central role of order flow in explaining exchange rate dynamics. Daníelsson et al. (2002) provide evidence that on intra-day aggregation levels, exchange rates are indeed predictable. They propose simple models which outperform random walk forecasts using additional information on order flow and refute the findings of Meese & Rogoff (1983a,b). Similar results are presented in Evans & Lyons (2005, 2006) for forecasting horizons ranging between 1 day and 1 month. Using standard instrumental variable techniques to estimate a vector autoregressive model that allows for contemporaneous feedback trading Daníelsson & Love (2006) show that when data are sampled at the one and five minute frequencies, the price impact of order flow is underestimated when feedback trading is not incorporated into the model, implying that trades carry more information than previous estimates suggest. Evans & Lyons (2008) examine the impact of macro news on currency prices at intradaily and daily frequencies. Their analysis shows that even if order flow contributes to currency price dynamics at all times, it has more impact on price changes immediately after news arrivals. Furthermore, Evans & Lyons (2007) also show that order flow has some forecasting power for economic fundamentals such as money growth, output growth and inflation in the US and Germany. These results suggest that order flow provide a link between fundamentals and exchange rate movements. Sager & Taylor (2008) provide an overview of the literature on order flow and exchange rate movements, and investigate the forecasting properties of interdealer order flow. Using inter-dealer and commercially available customer order flow data, they find, however, little evidence that inter-dealer or commercially available customer order flow can forecast exchanges rates.

In this paper, our analysis is, in contrast, based on a customer dataset from a FX internet trading platform, OANDA FXTrade, which contains highly detailed information on traders' characteristics, currency positions and detailed information on order flows in different order types (e.g. market, limit and special limit orders). Most of these traders are retail investors without access to private information in form of observing own customer order flow, and therefore, we investigate first whether their price expectations and their trading behavior revealed through their detailed order flow patterns are useful for predicting future currency prices. This approach can be justified by recognizing that for OANDA FXTrade itself, the aggregated actions of their customers (traders) create valuable private information, which can be incorporated into OANDA FXTrades' hedging and trading strategies on the primary market. Furthermore, even if the OANDA FXTrade traders have no access to private information (customer order flow), they do form expectations based on different information sources (e.g., technical analysis, public news) and individual trading experience, which might in its aggregate and/or appropriately extracted form be helpful in explaining future currency price changes. In this context we can take advantage of the structure of the very detailed order flows in the different transaction categories. Second, we analyze in which form feedback effects do exist for the OANDA FXTrade

investors. Considering the literature on market microstructure and behavioral finance, we derive several hypotheses about the relationship between price changes and order flow. Among others, we investigate i) whether stop-loss orders contribute to self-reinforcing price movements and whether take-profit orders impede them (Osler (2005)); and, ii) whether investors watch the price process more closely for de-investment than for investment decisions (monitoring effect).
The validity of our hypotheses is investigated with forecasting studies and out-of-sample prediction criteria. Applying modified Diebold-Mariano tests of Harvey, Leybourne & Newbold (1997), we test whether forecasting models for intra-day price changes (order flow) incorporating additional information on order flow (price changes) provide better forecasts than corresponding benchmark models, which contain information on historical prices changes (order flow) only. We use in addition to Daníelsson et al. (2002), who apply random walk models as benchmark specifications, also AR(p) models as benchmark specifications, since on intra-day frequencies price change processes, as well as order flow processes, are subject to specific intra-day clustering schemes, such as bid-ask bounce (Roll (1984)) and feedback trading effects (e.g., Madhavan (2000), Daníelsson & Love (2006)).
A further reason for concentrating on the analysis and the development of models for the investigation of customer trading activity datasets, such as that from OANDA FXTrade, is that customers essentially have two possibilities for trading: either by trading with a dealer-bank or by trading via an electronic (internet) platform. As pointed out by Lyons (2002), there has been a shift recently in the interdealer market from direct trading towards electronic brokerage trading. One argument explaining this shift is that there is more transparency on electronic brokerage systems. In the customer market segment, one can expect the same shift from dealer-bank trading towards internet platform trading, since these platforms are also more transparent and try to offer small (interbank) spreads to all of their customers independently of their transaction volume.

The paper is organized as follows: In Section 2, we briefly describe the foreign exchange market. Section 3 explains in detail the trading mechanism and the different order types on the OANDA FXTrade platform. Section 4 describes the dataset. We motivate our empirical study and we formulate the economic hypotheses in Section 5. Section 6 presents the empirical results and verification of the hypotheses, while Section 7 concludes.

2 A Brief Description of the Foreign Exchange Market

The FX-market is generally characterized by a high degree of decentralization, low-transparency, and 24h trading. According to the Triennial Bank for International Settlements' (BIS) Report (2007), the nine most active trading centers during 2007 in the FX spot market were London (34.1%), New York (16.6%), Zürich (6.1%), Tokyo (6.0%), Singapore (5.8%), Hong Kong (4.4%), Sydney (4.3%), Paris (3.0%) and Frankfurt (2.5%) accounting for a total turnover of 82.6%. The three most actively traded currency pairs are *USD/EUR* (27%), *USD/JPY* (13%), and *USD/GBP* (12%). In 2007, the total average daily turnover amounted to $3.2 trillion, which was divided into spot (32%), forward (12%), and swap (56%) markets. In the FX market one can distinguish between four groups of agents: first, dealer-banks (accounting for 43% of FX spot market trading); second, financial institutions without access to the interbank market (40%); third, non-financial customers (17%); and fourth, retail investors for which no reliable share of the total turnover in the FX market is available. The trading between these four groups has traditionally been divided into two categories: customer-to-dealerbank trading, where members of the last three groups trade with dealer banks, that offer bid-ask spreads, which are mainly driven by order handling costs (the smaller and the more unconventional the order, the higher the bid-ask spread); and dealer-to-dealer trading, where members of the first group trade with each other in the so-called interbank market. Trading between the members of the last three groups (direct trading) is very rare or nonexisting. However, due to a shift from traditional bi-lateral to electronic trading and to a growing number of internet trading platforms offering small (close or equal to interbank) bid-ask spreads independently of the trade size to attract customers, trading for members of the last three groups on internet trading platforms has become more and more attractive. The market of internet trading platforms is divided into two groups: a) platforms which are established by banks or consortiums of banks, such as FXConnect or Currenex, and b) non-bank trading platforms such as Deal4Free or OANDA FXTrade, the latter being the source of our dataset. Usually, these internet trading platforms are at least partially organized as so called crossing networks, since there is too little trading for an arbitrage free price discovery to be maintained. Bid and ask quotes of crossing networks are either based completely or in addition to own limit order book information on other trading channels, e.g., electronic brokers like Reuters Dealing 3000 or EBS. The quoted prices are then either a simple put through of the external data-feed or forecasted prices based on the recent history of the data-feed. Besides offering interbank spreads, internet trading platforms have the advantage that, depending on the platform, customers may have (limited) access to the limit order book and the recent history of the trades and quotes. Therefore, there is more transparency than in direct bi-lateral customer-to-dealerbank trading.[1]

3 OANDA FXTrade in Detail

OANDA FXTrade is a fully virtual marketplace for trading currencies via internet, without limits on the trade size, and with 24 hours trading time 7 days per week. This platform is a market making system that executes orders using the exchange rate prevalent in the market determined either by their own limit order book or by predicted prices relying on a proprietary forecasting algorithm based on an external data-feed. OANDA FXTrade offers immediate settlement of trades and tight spreads as low as 2 to 3 pips on all transaction sizes.
Given various boundary conditions, as for example sufficient margin requirements, orders are always executed. The OANDA FXTrade platform is based on the concept of margin trading. This means that a trader can enter into positions larger than his available funds. The platform requires a minimum initial margin of 2% on positions in the major currency pairs and 4% in all other currency pairs, which correspond to a leverage[2] of 50:1 and 25:1 respectively. In other words, for each dollar margin available the trader can make a 50 (25) dollar trade. The trader receives a margin call when the net asset value (i.e., the current value of all open positions plus the value of the remaining deposited funds) becomes half the margin requirement. Thus, if the trader does not have sufficient margin to cover twice the losses on an open position, a margin call order is used to close automatically all open positions using the prevalent market rates at the current time.

Market orders (buy or sell) are executed immediately and affect existing open positions. Limit orders are maintained in the system for up to one month. The server manages the limit order book, the current exchange rates, and the current market orders to match existing limit orders. A limit order can therefore be matched either

[1] For a more detailed description of the FX market we refer the reader to Lyons (2001) and Rime (2003).
[2] A leverage of 50:1 is the maximum offered by OANDA FXTrade.

against a market order, or against a bid or an ask price obtained from the external data-feed. The legal counterparty of a trade, however, is always OANDA FXTrade. Stop-loss (SL) orders and take-profit (TP) orders are special limit orders in the sense that they can be set for existing open positions. They can be specified directly while entering a market or a limit order, but they can also be specified later for existing open positions. Stop-loss and take-profit orders are automatically erased from the system whenever a position is closed as a result of further trading activity. Take-profit orders are typically set to close an existing position after a certain profit has been realized. Stop-loss orders, in contrast, specify that the position should be closed after the realization of a certain loss to avoid further losses. Table 1 provides an overview of the transactions and further activities of traders on OANDA FXTrade, which are recorded in an activity record file.

Buy/Sell* market open (close)	Immediately executed to open or close a position in a specific currency pair.
Buy/Sell limit order	The trader posted a buy or sell limit order to the system, which is then pending.
Buy/Sell limit order executed open (close)	Pending limit order is executed to open or close a certain position.
Buy/Sell take-profit close	Closes an open position by buying or selling the currency pair when the exchange rate reaches a predetermined level, in order to make a profit.
Buy/Sell stop-loss close	Closes an open position by buying or selling the currency pair when the exchange rate reaches a predetermined level in order to avoid further losses.
Buy/Sell margin call close	Closes automatically all open positions using the current market rates. This happens if the trader does not have sufficient margin to cover two times the losses of all open positions.
Change order	Change of a pending limit order (limits for take-profit or stop-loss, the value of the upper or lower bounds, the quote as well as the number of units).
Change stop-loss or take profit on open trade	Change stop-loss or take-profit limit on an open position.
Cancel order by hand	Cancel a pending limit order by hand.
Cancel order: insufficient funds	Automatically recorded when the trader does not have enough funds to open a new position.
Cancel order: bound violation	Market order or limit order is cancelled because the applied exchange rate is not located inside the specified bounds.
Order expired	A pending limit order is expired.

Table 1: Activity record entries of OANDA FXTrade.
*On the OANDA FXTrade platform, buying EUR/USD means that one buys the base currency (EUR) and sells the quote currency (USD), whereas selling EUR/USD means that one sells the base currency (EUR) and buys the quote currency (USD). Recorded units always refer to the base currency.

4 Description of the Dataset

The dataset that is used in our analysis is constructed from the trading activity record of OANDA FXTrade from 1^{st} October 2003 to 14^{th} May 2004 (227 days). This record contains the complete trading activities for 30 currency pairs on a second by second basis and allows us to distinguish between the transaction types listed in Table 1. In addition, depending on the order type, we receive information on transaction prices (market orders, limit orders executed, stop-loss, take profit, margin call), bid and ask quotes (limit orders pending), adjoint transaction units, and the limits of stop-loss and take-profit orders.

In our analysis we focus on the most actively traded currency pair *EUR/USD*, which accounts for nearly 39 % of all records with an average interrecord-duration of 8.5 seconds. Table 2 contains the descriptive statistics for the dataset and the transaction volumes for the single order categories. All figures are daily averages computed over the whole dataset containing 227 days. The average number of different traders per day amounts to 744 for the *EUR/USD* currency pair.
Using only price determining orders (market orders, limit orders, limit orders executed, stop-loss, take profit, margin call), we construct from this dataset equidistant *EUR/USD* price series for 12 frequencies (1 min, 2 min, 5 min, 10 min, 15 min, 20 min, 25 min, 30 min, 45 min, 1 hour, 2 hours, 4 hours). Throughout the paper, we refer to these price series as the OANDA prices series. In addition from a series of mid-quotes from the interbank market (available on an 1 minute aggregation level), we construct the corresponding price series for the remaining 11 frequencies. The mid-quotes from the interbank market are provided by Olsen Financial Technologies and represent tradeable quotes stemming from different electronic brokerage systems including Reuters Dealing 3000 and EBS. These mid-quote series do not coincide with the bid and ask quotes on OANDA FXTrade. The bid and ask quotes on OANDA FXTrade are generated by an proprietary forecasting algorithm based on an external data-feed which also includes tradeable quotes from Reuters Dealing 3000 and EBS.

5 Motivation and Economic Hypotheses

In the economic literature, an everlasting, extensively studied topic is the relationship between expectations and price formations. The literature can be traced back

Transaction Record	%	Obs	Trading Volume in *EUR* per Day								
			Total	Mean	Min	5% Quan.	25% Quan.	50% Quan.	75% Quan.	95% Quan.	Max
Buy market (open)	13.10	1322	37930860	25854	82	113	515	2065	9240	85854	2220414
Sell market (open)	10.61	1072	30816226	27218	44	89	592	2138	9861	96214	1759412
Buy market (close)	8.27	835	25074760	27468	163	201	672	2326	9553	95940	1630034
Sell market (close)	10.27	1037	31839764	29534	29	66	564	2164	10063	97248	1930846
Limit order: Buy	5.41	546	14041270	28876	24	63	549	2053	9469	95436	1934417
Limit order: Sell	4.76	482	11080825	34283	237	267	515	1662	7509	117914	1511133
Buy limit order executed (open)	3.22	325	5416146	17484	41	79	422	1410	6267	67127	735479
Sell limit order executed (open)	2.92	295	3231307	10554	58	84	242	824	3652	34607	584303
Buy limit order executed (close)	0.46	46	1382690	32718	4800	4824	5313	7020	17994	80426	506182
Sell limit order executed (close)	0.46	46	1470630	32287	407	436	927	3440	16816	93447	452512
Buy take-profit (close)	3.14	317	2918779	9779	144	170	310	704	2724	30314	583296
Sell take-profit (close)	3.49	352	4404025	12857	61	75	256	796	3960	43028	820876
Buy stop-loss (close)	2.18	220	4488496	16433	126	175	667	2535	9837	70968	513989
Sell stop-loss (close)	2.55	258	5309807	16667	23	59	503	2255	9424	66743	650061
Buy margin call (close)	0.12	12	166375	7263	1006	1010	1185	1817	3718	14211	71133
Sell margin call (close)	0.17	17	275282	6381	1369	1372	1440	2351	4409	17266	77231
Change order	3.01	305	13898910	49771	105	203	1295	4888	18181	162927	1622712
Change stop-loss or take-profit	22.36	2260	60965013	26748	10	79	867	3694	14163	95983	1703030
Cancel by hand	2.41	243	10043949	42295	211	272	1031	4186	16003	148571	1662224
Cancel: insufficient funds	0.28	28	2439586	67905	4938	4953	5431	7354	66280	186280	622650
Cancel bound violation	0.20	20	195118	14803	571	571	627	2650	6860	29909	98308
Order expired	0.65	66	1063061	19942	44	54	443	1682	7204	68648	355982

Table 2: Descriptive statistics of the OANDA FXTrade trading activity dataset for the *EUR/USD* currency pair. All numbers are daily averages and all transaction volume statistics are denominated in *EUR*.

to the seminal works of Muth (1961), Mills (1962), and Nerlove (1958), where theories of rational, implicit, and adaptive expectations are introduced. Empirical verification of these hypotheses faces the significant challenge of reliably measuring expectations. For example, in the analyses of firm and expert surveys (e.g., Carlson & Parkin (1975), Nerlove (1983) and Pesaran (1987)), survey responses serve as a proxy for participants' expectations for the future development of macroeconomic or financial price series. In addition to the information contained in the history of the underlying series itself, the responses, usually in aggregated form, are used to predict the underlying series for a medium term time horizon (few months). The information obtained from the survey is treated, in that sense, as private or insider information which should yield an improved forecastability of the underlying series. For the short term prediction (up to one day) of asset price series (e.g., stocks, exchange rates and commodities), a different methodology can be applied to measure the expectations of the market participants, which can then be regarded as insider information as well. The only assumption which is required is that market participants reveal their expectations through their trading behavior. Hence, market participants' order flow can be regarded as information on their conditional expectations of future asset price developments. One theoretical foundation is given in the portfolio allocation model of Evans & Lyons (2002a,b), where exchange rate movements are explained by changes of previous customer order flow, which in turn represent changes in an underlying portfolio. In their model, there are two different markets: the customer-dealer market and the dealer-dealer (interbank) market. Dealers trading in the interbank market learn about order flow in the customer-dealer market and this customer order flow aids in predicting currency price changes and order flow in the interbank market. Another theoretical foundation can be based on the argument of Sarno & Taylor (2001), who consider order flow as a proxy for macroeconomic fundamentals. Thus, changes in currency prices are driven by changes in macroeconomic variables, which are revealed to market participants in the form, for example, of news announcements. Both models require that the market participants interpret information, either on portfolio changes or on changes of macroeconomic fundamentals, in the correct way, that they adjust their expectations for future prices in light of this information, and they therefore place their orders accordingly. The forecasting studies of Daníelsson et al. (2002), Evans & Lyons (2005, 2006) and Daníelsson & Love (2006) show that exchange rates are, contrary to Meese & Rogoff (1983a,b), out-of-sample predictable and outperform random walk forecasts using additional information on order flow. The multi-facetted literature on inventory and/or asymmetric information based models for security markets (Demsetz (1968), Ho & Stoll (1981), Kyle (1985), Foster & Viswanathan (1990), Easley & O'Hara (1992), Biais, Hillion & Spatt (1995), Hansch, Naik & Viswanathan (1998)) provides further theoretical support for the proposition that (bid and ask) prices can be explained by previous order flow. The common idea in virtually all market microstructure models, including those mentioned above, is that market participants react to previous actions (order flow) of other market participants resulting in impacts on current or future prices. In a pure inventory model based market, market makers adjust bid and ask prices according to their current inventory, which is naturally a consequence of orders executed previously. In a fully electronic order book market without market makers, traders react to actions of other traders, which are usually displayed to them (partially) through the limit order book. At the end of the day, in all of these models, the key determinant, which finally decides about the success or failure of the model is that expectations are interpreted, measured, and modelled correctly.

Our analysis is concentrated on data from the FX market. Therein we further focus on a very special segment, namely an internet trading platform, OANDA FXTrade, where most of the traders are retail investors or members of the group of non-financial customers. Most of the research on order flow and currencies focuses on the interbank market (e.g., Bjønnes & Rime (2005), Evans & Lyons (2002a,b, 2005, 2006), Payne (2003), Berger et al. (2008)) and the papers by Marsh & O'Rourke (2005) and Osler (2005) deal with customer orders observed by the Royal Bank of Scotland (dealer bank). To our knowledge there has been no analysis of customer data obtained from an internet trading platform, as of yet.

In the FX market customer order flow (trading between a dealer bank and their non-interbank market customers) is the most fruitful source of private information for a dealer bank. Their customers are usually large companies, commercial banks, security houses, mutual funds, hedge funds, and insurance companies, who want to settle transactions of sizes which are often several times higher than the standardized order sizes in the interbank market. In line with the portfolio allocation model of Evans & Lyons (2002a,b), these customer orders are the primary source of identifying dispersed information and they consequently induce interdealer orders (e.g., "hot potato" trading, inventory control) that affect the currency price.

On the one hand, one can therefore argue that order flow from our internet trading platform **does not** contain any helpful information for predicting future prices, since our traders submit only orders of small size, which do not affect the interdealer market. Stated differently, traders on our internet trading platform are noise traders. On the other hand, also the OANDA FXTrade investors form expectations on the future development of currency prices which they reveal through their trading activity and which represents private information for OANDA FXTrade itself. Based on this private information OANDA FXTrade can trade on his own account in the interdealer market and transfer information from the OANDA FXTrade investors to that market. It is, however, more important that OANDA FXTrade collects its customer orders, which expose OANDA FXTrade to inventory risks, which are hedged with associated orders in the interbank market. Through this channel, the aggregated information on the OANDA FXTrade investors' price expectations is also transmitted to the interdealer market and its price process. For these reasons, one can assume that order flow from our internet trading platform **does** contain information that is helpful for predicting future prices. Therefore we can derive our first hypothesis:

Hypothesis H1:
Information from the order flow on OANDA FXTrade is helpful in predicting future currency prices.

In the empirical verification of this hypothesis an important question arises: how should order flow be measured exactly? Lyons (1995) introduces the standard definition of an aggregated net order flow measure as the difference between buyer initiated and seller initiated trades (within a given period), or stated differently, as the cumulative sum of signed orders where buyer initiated and seller initiated orders receive positive and negative signs, respectively. Focusing on the initiating party of a trade, this definition aims to capture very recent changes in the expectations of future prices that may arise due to new (private) information. For example, an executed buy limit order is treated as a seller initiated trade since it has to be merged with a sell market order. Therefore the expectation of the seller is treated as being more important than the expectation of the buyer, who might not have the latest information. This standard order flow measure is very well suited to predicting future prices when the interbank market is considered, as demonstrated by Daníelsson et al. (2002).

Let us now consider trades on OANDA FXTrade where bid and ask prices depend on an external data-feed. A buy limit order (bid) is therefore usually matched against the ask price of OANDA FXTrade, which is a function of the quotes in the interbank market. For the simplicity of argument let us assume that quotes from the primary market are put through one-to-one to OANDA FXTrade, so that the ask price process on OANDA FXTrade is the same as the one on the interbank market. The lower ask price (crossing limit sell order at the best ask) being matched against the OANDA buy limit order is therefore generated by selling pressure in the primary market shortly before, for example by a large sell market order, consuming the previous best bids in the interbank market and causing also an adjustment of the ask quotes to lower prices. Thus, measuring order flow on OANDA FXTrade with the standard net order flow measure yields a mixture of price expectations from traders on OANDA FXTrade (mainly through market orders) and price expectations from the interbank market (mainly through executed limit orders).

An alternative to the standard net order flow measure is to consider a measure that tries to solely aggregate the price expectations on OANDA FXTrade. In Table 3, we summarize definitions of the standard and the alternative order flow measures, which we denote as "OANDA order flow" measure. Therein, we list the different entries of the OANDA FXTrade activity record in column one, the signs for the standard order flow in column two, and the signs for the OANDA order flow measure in column three. Buy market orders, irrespective of whether they are submitted to open or close a position, get positive signs in both order flow measures since the traders on OANDA FXTrade initiate these trades or believe that the price will go up. Correspondingly, the symmetric sell market orders receive negative signs.
In the standard order flow measure, submitted (pending) limit orders are not considered, since they are not yet executed, which means that there is not yet an initiating party. They are, however, taken into account in the OANDA order flow measure since the trader, who submits a limit order, expresses his beliefs that the price will go up (buy, positive sign) or down (sell, negative sign).
Executed buy limit orders are treated as seller initiated in the standard order flow measure (see the discussion above) and are thus assigned negative signs, whereas they receive positive signs in the OANDA order flow measure, since the submitter still believes that the price will increase. Otherwise he would have cancelled the order before execution. Executed sell limit orders are treated analogously. For the OANDA order flow measure limit orders are counted twice, once at their submission time and once at their execution time. Nevertheless, since they are usually counted at two different time points this does not create a problem, because we still measure beliefs of the investors that might have been revised during the corresponding period. Buy take-profit orders (close) are buy limit orders that receive negative signs in the

standard order flow measure. In the OANDA order flow measure, they get positive signs, because the trader believes that the price will further fall. A buy take-profit order (close) can only be executed if the trader has a short position in a currency pair (short position in the base currency). Sell take-profit orders receive the symmetric signs.

Buy stop-loss orders (close) get negative signs in both measures. In the standard order flow measure the explanation is that it is a special buy limit order. In the OANDA order flow measure the explanation is that the trader believes that the price will further fall. Again, sell stop-loss orders are treated analogously. Buy margin call orders (close) are not used in the standard order flow measure. On the one hand, one can argue that they should get positive signs since they are buy market orders. On the other hand, one can argue that they are not motivated by new information and that by the price process of the primary market the traders are proven to have wrong expectations on the price. Therefore they should receive negative signs. At any rate, due to their scarce occurrence[3] (0.12% and 0.17%) they do not play an important role. In the OANDA order flow measure they are counted, since although the traders are proven to have wrong expectations about the price, they still believe that the price will go down (up) in the case of a buy (sell) margin call order. Given these two order flow measures, we can refine Hypothesis H1 with respect to the measuring of the order flow:

Hypothesis H1.1:
Order flow measuring price expectations from the interbank market and OANDA FXTrade (standard order flow measure) is helpful in predicting future currency prices.

Hypothesis H1.2:
Order flow measuring price expectations from OANDA FXTrade solely (OANDA order flow measure) is helpful in predicting future currency prices.

[3]See Table 2.

Transaction Record	Standard Order Flow Signs	OANDA Order Flow Signs
Buy market (open)	+	+
Sell market (open)	-	-
Buy market (close)	+	+
Sell market (close)	-	-
Limit order: Buy	not used	+
Limit order: Sell	not used	-
Buy limit order executed (open)	-	+
Sell limit order executed (open)	+	-
Buy limit order executed (close)	-	+
Sell limit order executed (close)	+	-
Buy take-profit (close)	-	+
Sell take-profit (close)	+	-
Buy stop-loss (close)	-	-
Sell stop-loss (close)	+	+
Buy margin call (close)	not used	-
Sell margin call (close)	not used	+
Change order	not used	not used
Change stop-loss or take-profit	not used	not used
Cancel order by hand	not used	not used
Cancel order: insufficient funds	not used	not used
Cancel order: bound violation	not used	not used
Order expired	not used	not used

Table 3: Col. 1 states the record entries, col. 2 contains the signs for the construction of the standard net order flow measure and col. 3 contains the signs for the construction of the OANDA order flow measure.

We verify these hypotheses by testing the in-sample and the out-of-sample forecasting performance of the following regressions:

$$\Delta y_t^h = c + \beta_{x1} x_{t-1}^k + \beta_{y1} \Delta y_{t-1}^h + \ldots + \beta_{xp} x_{t-p}^k + \beta_{yp} \Delta y_{t-p}^h + \varepsilon_t,$$

where Δy_t^h denotes the currency price change from $t-1$ to t, x_t^k the value of the order flow measure at t, and ε_t the error term. p defines the number of lags used in the regression. $k \in \{\mathrm{SOF}, \mathrm{OOF}\}$ denotes for x_t^k whether the standard order flow measure, using information from the interbank market ($k = \mathrm{SOF}$), or the OANDA order flow measure, using information solely from OANDA FXTrade ($k = \mathrm{OOF}$), is used. For the price change Δy_t^h, h distinguishes whether price changes from the interbank market ($h = \mathrm{IP}$) or price changes from OANDA FXTrade ($h = \mathrm{OP}$) are used.

In order to provide a comparative basis, we also investigate the performance of a purely data driven order flow measure which is not based on any theoretical motivation of how expectations of future prices should be measured. Since in both order flow measures above buy and sell orders are treated symmetrically (opposite signs), we compute the change of the order flow for every transaction category. For example, we compute the order flow of the market order (open) category as the difference between the number of buy market orders (open) and sell market orders (open) over the sampling period. Thus we obtain eight category specific order flow measures which are summarized in Table 4.

Category	Description
1	Limit orders
2	Limit orders executed (open)
3	Limit orders executed (close)
4	Market orders (open)
5	Market orders (close)
6	Stop-loss orders (close)
7	Take-profit orders (close)
8	Margin call orders (close)

Table 4: Col. 1 states the number of the category and col. 2 gives the category description.

The corresponding regression takes the following form:

$$\Delta y_t^h = c + \sum_{k=1}^{8} \beta_{k1} x_{t-1}^k + \beta_{y1} \Delta y_{t-1}^h + \ldots + \sum_{k=1}^{8} \beta_{kp} x_{t-p}^k + \beta_{yp} \Delta y_{t-p}^h + \varepsilon_t,$$

where x_t^k denotes the order flow in the associated category $k = \{1, \ldots, 8\}$ at time t. Again Δy_t^h with $h \in \{\mathrm{IP}, \mathrm{OP}\}$ denotes the interbank or the OANDA FXTrade price change and p the selected number of lags.

With the hypotheses derived above, the causal relationship from order flow to price changes is investigated. The survey study of Taylor & Allen (1992), however, shows that at least 90% of the London based dealers rely, in addition to private and fundamental information, on information from technical analyses to design their trading strategies. This is a typical example of price changes or certain patterns in the price process causing reactions of market participants, and thereby order flow. Another example of causality from prices to order flow is the study by Osler (2005), in which it is analyzed whether executions of special limit orders (stop-loss and take-profit) contribute to self-reinforcing price movements. The idea behind this investigation is that there are local downward or upward trends in the price process, which are accelerated by the execution of stop-loss orders, which generate positive feedback trading, and are decelerated by the execution of take-profit orders, which generate negative feedback trading. For the illustration of the argument, let us assume that the price is decreasing, which in the first case may cause an execution of a sell stop-loss order and induces further selling pressure, which leads to further executions of sell stop-loss orders. Thus, we get an accelerated downward moving price process (price cascades). In the second case, a downward moving price may cause an execution of a buy take-profit order, which does not induce further selling pressure and therefore neither execution further stop-loss nor take-profit orders, which yields a decelerated downward movement or even an upward moving price process.

The OANDA FXTrade activity dataset is well suited to be used to investigate how traders react to specific patterns in the price process. In light of the order flow measures introduced above, we can analyze whether information on price changes is helpful in predicting future order flow, which forms the basis of our second hypothesis:

Hypothesis H2:
The price process contains information that is helpful in predicting future order flow.

Again, we verify this hypothesis with respect to the price process obtained from the interbank market and the price process obtained from OANDA FXTrade directly. Since the traders on OANDA FXTrade are usually only affected by the FXTrade price process, we expect that it should have more power in explaining future order flow than the interbank price process. Moreover, we use the standard and the OANDA order flow measures, as well as the category based order flows (Table 4), to investigate this hypothesis. Considering the influence of the price processes on the category based order flows more precisely, we can investigate whether we observe self-reinforcing price movements as reported by Osler (2005) on OANDA FXTrade as well:

Hypothesis H3:
Executed stop-loss orders contribute to self-reinforcing price movements and executed take-profit orders impede self-reinforcing price movements.

In investigating this hypothesis, two analyses are conducted with the help of category based order flow: i) provided that hypothesis H3 is correct, then based on their own histories, order flow in the stop-loss order category should lend itself more readily to prediction than order flow in the take-profit order category, ii) if stop-loss orders induce self-reinforcing price movements and take-profit orders not, then (in addition to their own histories) information on the price process itself should be more valuable,

for predicting order flow of take-profit orders than for predicting order flow of stop-loss orders.
Furthermore, the category specific order flow measures allow insight into several aspects of traders' preference structure. Thereby, we are able to exploit the information of whether trades are executed to open or close a certain position, which allows us to analyze the existence of a monitoring effect. We claim that there is a monitoring effect in the sense that traders react to information more quickly when they fear to lose something – which is certainly true when they already hold a position – than when they plan to take a position and thus we formulate our last hypothesis:

Hypothesis H4:
Traders tend to monitor the price process closer when they already hold a position.

Provided that hypothesis H4 is true we should observe that the order flow in the **(close)** categories is better predictable (based on the information contained in the price process) than order flow in the **(open)** categories. Moreover, this effect should then be even more pronounced for market orders than for limit orders since market orders are usually submitted by active and impatient investors who trade for liquidity reasons and watch the market more closely, whereas limit orders are submitted by passive traders who might not monitor the market continuously (c.f. Glosten (1994) and Seppi (1997)).

6 Empirical Findings

6.1 Descriptive Analysis

In Figure 1 we show the diurnal seasonality function of the standard and the OANDA order flow measures, computed using a Nadaraya-Watson kernel regression with a Gaussian kernel and optimal bandwidth selection according to Silverman's (1986) rule on a 10 minute aggregation level, where the time scale is measured in Eastern Standard Time (EST). The first observation that should be made is that there is a kind of diurnal seasonality pattern, which is much more pronounced for the OANDA order flow measure than for the standard one. Both seasonality patterns, however, correspond to standard market activity[4]: we observe a positive peak at 3 o'clock, when European traders enter the market, and a negative peak around 5 o'clock

[4]See Andersen & Bollerslev (1997) and Dacorogna, Gençay, Müller, Olsen & Pictet (2001).

which lunch time in Europe. We see a strong upward recovery between 6-9 o'clock, which corresponds to afternoon trading in Europe and the start of trading in the US. The decline after 9 o'clock can be explained by European traders leaving the market successively and the positive peak around 11 o'clock corresponds to the market phase in which the US traders are most active. The declining trading activity of the US traders from 12 o'clock onwards results in a negative peak at around 17 o'clock. The recovery of the trading activity thereafter, with a peak at 19 o'clock, is due to Asian investors entering the market. Keep in mind that we postulate the same seasonality pattern for every weekday, because on a daily frequency we can only analyze 163 observations.

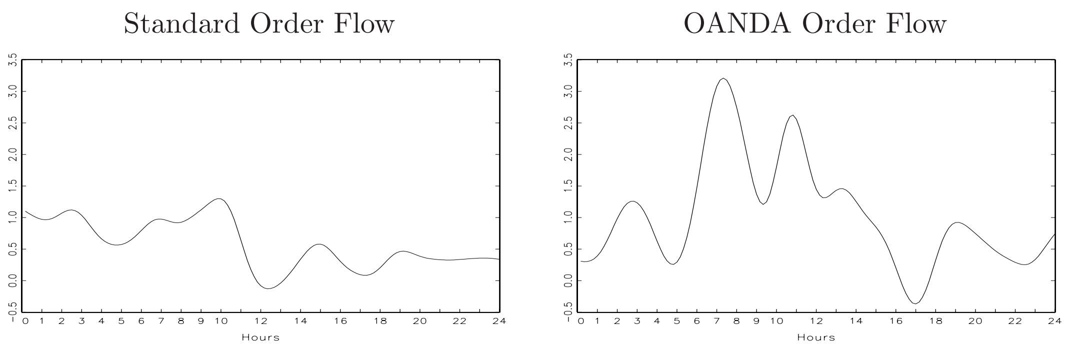

Figure 1: Diurnally seasonality in the standard (1^{st} panel) and the refined (2^{nd} panel) net order flow measures, computed on a 10 minute aggregation level.

Figure 2 depicts the empirical bivariate autocorrelation functions for lags up to 20 periods between price changes and order flow for a frequency of 1 minute.
There are four main panels, each divided into 2 by 2 subordinated panels. The upper left main panel displays the (empirical bivariate) autocorrelation function of OANDA based price changes and standard order flow; the upper right main panel displays the autocorrelation function of OANDA based price changes and the OANDA order flow measure; the lower left main panel displays the autocorrelation function of interbank price changes and standard order flow; and the lower right main panel displays the autocorrelation function of interbank price changes and the OANDA order flow measure. For each main panel, the upper left subordinated panel depicts the autocorrelation function of the particular order flow measure and the lower right panel depicts the autocorrelation function for price changes. For these two, we plot lag 1 through lag 20. The lower left subordinated panel depicts the cross-correlation function of lagged order flow with price changes, and the upper right panel depicts the cross-correlation function of lagged price changes with order flow. For these two,

we plot lag 0 through 19. The value at lag 0 is in both cross-panels the same and represents the contemporaneous correlation between the particular order flow and price changes.

The analysis of the bivariate autocorrelation functions sheds light on the dynamic interaction of the particular order flow and price change series and enables us to verify some of the hypothesis stated in the previous section from a descriptive point of view. The following observations are noteworthly:

For both order flow measures we observe in the lower left subordinated panels significant cross-correlation coefficients, which show that future (OANDA based and interbank) price changes are driven by current order flow supporting hypotheses H1, H1.1 and H1.2 in their statements that order flow is helpful in predicting future currency prices. We observe that only the first order cross-correlation coefficients are significantly positive between current OANDA order flow and future price changes of both price series. In the case of current standard order flow and future interbank price changes only the first order cross-correlation coefficient is significantly positive again, whereas in the case of current standard order flow and future OANDA based prices changes, the first three cross-correlation coefficients are significantly different from zero. The positivity of the first order cross-correlation coefficients, however, is partially compensated by the negativity of the second and the third. Note, in all four cases the first order cross-correlation coefficients are always positive but higher when the interbank instead of the OANDA based prices are involved.

For both order flow measures we observe in the upper right subordinated panels significant cross-correlation coefficients, which show that future order flow is driven by current price changes. This observation supports hypothesis H2 heuristically in stating that investors update their beliefs and place their orders based on the past development of the price process. This effect, however, seems to be a short term effect, since the cross-correlation coefficients between future order flow and current price changes are significant for only up to 3 lags with the OANDA based prices, and up to 5 lags with the interbank prices. Furthermore, the correlation coefficients for the standard order flow measure are larger than those for the OANDA order flow measure. This implies that the standard order flow measure has not only a higher contemporaneous correlation with price changes, but is also influenced more severely by past price changes than the OANDA order flow.

In the upper left subordinated panels, we observe the autocorrelation function of the order flow measures themselves. For the standard order flow measure, we see a very clear slowly declining pattern of the autocorrelation function, whereas for the OANDA order flow measure, only the first, the third, the fourth and the twelfth autocorrelation coefficients are significantly different from zero, generating an unsystematic pattern for the autocorrelation function. Relating order flow to the process of price expectation updates, we observe a persistent updating process when information from the interbank market is incorporated (standard order flow) and a process with an irregular updating pattern in the case where only the information from the OANDA market is used.

In the lower right subordinated panels, we observe the autocorrelation function of the price changes themselves. The price changes are positively first order autocorrelated, which is partially compensated by negative autocorrelation coefficients of order 2 to 5 for the OANDA based price change series. Thus, we observe a kind of short term positive feedback trading pattern for both price processes. Due to the fact that we consider mid-quotes on a 1 minute frequency, we cannot observe the traditional bid-ask bounce effect.

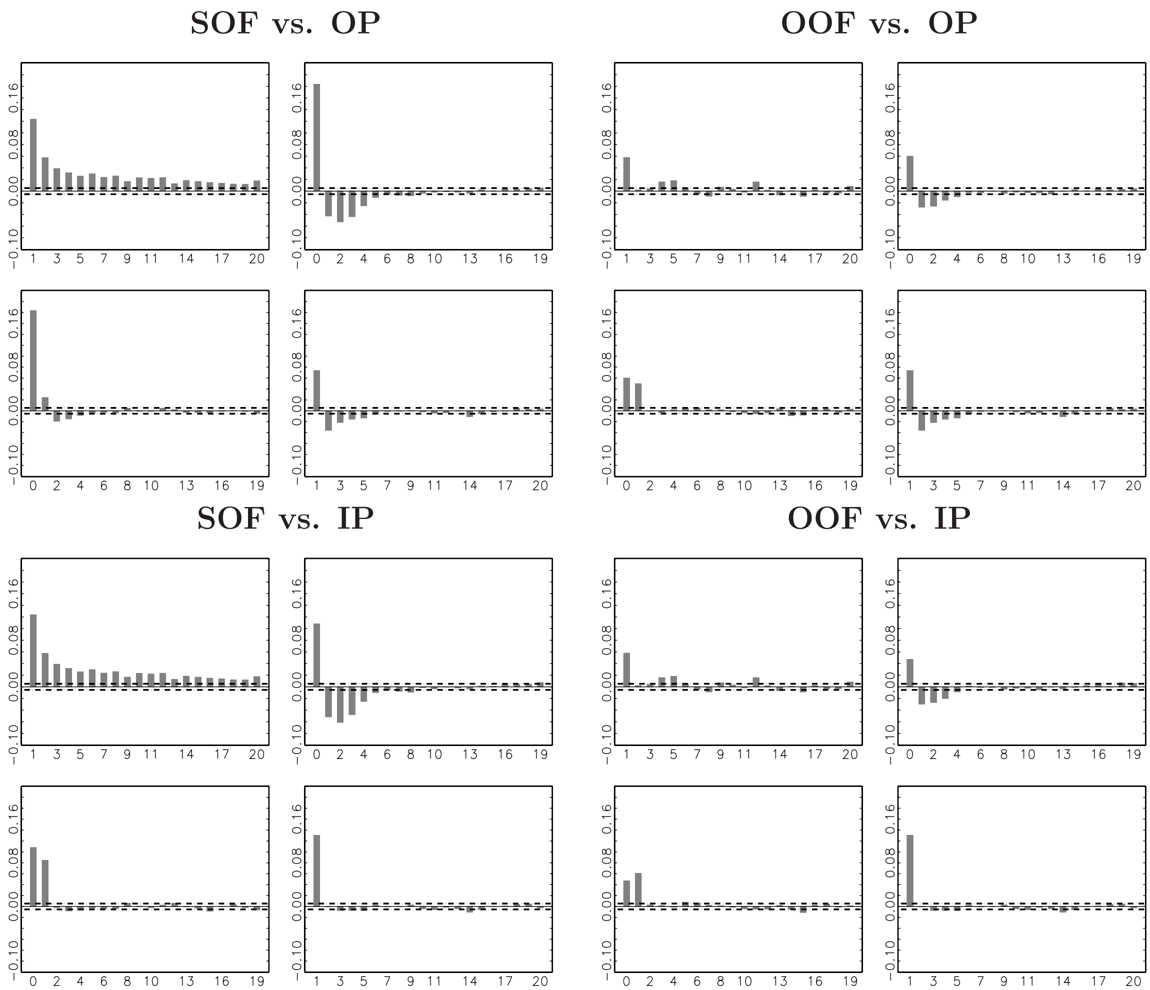

Figure 2: Empirical bivariate autocorrelation function of price changes and order flow for an aggregation level of 1 minute. There are four main panels, each divided into 2 by 2 sub-panels. The upper left main panel displays the (empirical bivariate) autocorrelation function of OANDA based price changes (OP) and standard order flow (SOF), the upper right main panel displays the autocorrelation function of OANDA based price changes and the OANDA order flow measure (OOF), the lower left main panel displays the autocorrelation function of interbank price changes (IP) and standard order flow, and the lower right main panel displays the autocorrelation function of interbank price changes and the OANDA order flow measure. For each group, the upper left panel depicts the autocorrelation function (lag: 1–20) of the particular order flow measure and the lower right panel depicts the autocorrelation function (lag: 1–20) for price changes. The lower left panel depicts the cross-correlation function (lag: 0–19) of lagged order flow with price changes, and the upper right panel depicts the cross-correlation function (lag: 0–19) of lagged price changes with order flow. The dotted lines mark the approximate 99% confidence bounds, computed as $\frac{\pm 2.58}{\sqrt{T}}$, where T denotes the particular number of observations.

The descriptive analysis shows that the dynamic properties of the OANDA based price series differ from those of the interbank price series. To understand these differences, we decide to have a closer look at the relationship between these price series by means of a bivariate vector error correction (VEC) model. This investigation is again based on the price series sampled at a 1 minute frequency. Since the OANDA based price series are transaction prices at quotes derived from an external data-feed from the interbank market, we expect that our interbank price series and the OANDA based price series are co-integrated. This hypothesis is verified with the Johansen (1991) Co-integration test which indicates one co-integrating equation even at the 1% significance level. Since our interbank price series is not the external data-feed interbank price series on which the OANDA prices are based, we cannot expect to determine how the OANDA price series is derived from the interbank price series. The VEC model can be formulated in the following way. Let $y_t = (y_t^{\mathrm{OP}}, y_t^{\mathrm{IP}})'$ denote the vector of OANDA and interbank prices at time t for $t = 1, \ldots, T$. Let $\beta = (\beta_{\mathrm{OP}}, \beta_{\mathrm{IP}})'$ with $\beta_{\mathrm{OP}} = 1$ denote the coefficient vector of the co-integrating equation which is assumed to take the following form:

$$z_t = c + \beta' y_t,$$

where z_t denotes the co-integrating error and the associated VEC model is given by

$$\Delta y_t = \lambda z_{t-1} + \Phi_p(L)\Delta y_{t-1} + \varepsilon_t,$$

with $\lambda = (\lambda_{\mathrm{OP}}, \lambda_{\mathrm{IP}})'$ denoting the adjustment coefficients. $\Phi_p(L)$ denotes the lag-polynomial of order p consisting of matrices $\Phi^{(i)} = \begin{pmatrix} \phi_{11}^{(i)} & \phi_{12}^{(i)} \\ \phi_{21}^{(i)} & \phi_{22}^{(i)} \end{pmatrix}$ where $i = 1, \ldots, p$. ε_t is assumed to be an independent bivariate normally distributed error term process with zero mean. The estimation results are summarized in Table 5, where the number of lags $p = 6$ are chosen according to the Schwarz Information Criterion (SIC). The most important observation that should be made is that both adjustment coefficients $(\lambda_{\mathrm{OP}}, \lambda_{\mathrm{IP}})$ are significantly different from zero and have opposite signs, implying that after a shock in the co-integrating error z_t, both price series respond to this shock aiming to get back to their equilibrium relationship. This means, from an economic point of view, that we do not observe a lead-lag relationship between our two price series on a 1 minute aggregation level, which might have been expected since the interbank data-feed might have caused the price process on OANDA FXTrade. The non-existence of a lead-lag relationship, however, can be explained by the fact that we compare price series on a 1 minute frequency, in which the lead-lag structure might already be aggregated away since we do not know how exactly and on which frequency the OANDA price process relies on the interbank market data-feed.

Parameter	Estimates	Standard Deviation
c	0.00037	0.00011
β_{OP}	1.0000	
β_{IP}	-1.00031	0.00009
λ	(-0.05284 0.035260)	(0.00201 0.00175)
$\Phi^{(1)}$	$\begin{pmatrix} -0.11204 & 0.30832 \\ 0.33177 & -0.13975 \end{pmatrix}$	$\begin{pmatrix} 0.00345 & 0.00384 \\ 0.00301 & 0.00335 \end{pmatrix}$
$\Phi^{(2)}$	$\begin{pmatrix} -0.18967 & 0.13512 \\ 0.11037 & -0.14589 \end{pmatrix}$	$\begin{pmatrix} 0.00371 & 0.00404 \\ 0.00323 & 0.00352 \end{pmatrix}$
$\Phi^{(3)}$	$\begin{pmatrix} -0.11552 & 0.10699 \\ 0.09116 & -0.08426 \end{pmatrix}$	$\begin{pmatrix} 0.00375 & 0.00407 \\ 0.00327 & 0.00355 \end{pmatrix}$
$\Phi^{(4)}$	$\begin{pmatrix} -0.08784 & 0.07205 \\ 0.05672 & -0.05572 \end{pmatrix}$	$\begin{pmatrix} 0.00370 & 0.00401 \\ 0.00323 & 0.00349 \end{pmatrix}$
$\Phi^{(5)}$	$\begin{pmatrix} -0.06554 & 0.05206 \\ 0.02927 & -0.03138 \end{pmatrix}$	$\begin{pmatrix} 0.00354 & 0.00384 \\ 0.00309 & 0.00335 \end{pmatrix}$
$\Phi^{(6)}$	$\begin{pmatrix} -0.03921 & 0.03255 \\ 0.01740 & -0.00773 \end{pmatrix}$	$\begin{pmatrix} 0.00319 & 0.00337 \\ 0.00278 & 0.00294 \end{pmatrix}$

Table 5: Estimation Results of the VEC Model. The parameters estimates for the co-integrating equation are given in the upper part of the table and the parameters of the associated VEC model in the lower part.

6.2 Testing the Economic Hypotheses

Although the descriptive analysis already provides insight into the dynamic relationship between order flow and price changes, allowing for a first impression on the validity of the hypotheses stated before, we investigate them now in detail with the help of forecasting analyses.

6.2.1 Effect of Order Flow on Price Changes

The hypotheses H1, H1.1 and H1.2, being concerned with the causality direction from order flow to price changes, are tested in the following way. We conduct a forecasting study that investigates whether prices are more predictable when using information from the order flow in addition to the information already contained in the history of the price process itself as opposed to solely using information contained in the history of the price process (benchmark models). Based on these forecasting specifications, we compute their Root-Mean-Squared-Prediction-Errors (RMSPE) and analyze whether the models incorporating information on order flow provide significantly better forecasts than the benchmark models with the help of the modified Diebold-Mariano (mDM) test of Harvey et al. (1997). The forecasting study is performed on 12 intra-day sampling frequencies stated in the first column of Table 7. Since on an intra-day level, there exists a specific autoregressive structure in the price change processes (as shown in the descriptive analysis) we decide to use an AR(p) model, which should capture these effects in addition to a random-walk specification (e.g., Daníelsson et al. (2002)) as benchmark specifications. The random walk specification is given by

$$\Delta y_t^h = \varepsilon_t, \tag{RW-h}$$

and the AR(p) specification takes the following form:

$$\left(1 - B_p^y(L)\right) \Delta y_t^h = c + \varepsilon_t, \tag{AR-h}$$

where $B_p^y(L)$ denotes the associated lag-polynomial specified as

$$B_p^y(L) = \beta_{y1} L + \ldots + \beta_{yp} L^p,$$

where ε_t is a white noise process. The forecasting study is implemented once for the interbank price change process ($h = \text{IP}$) and once for the OANDA based price change process ($h = \text{OP}$). The optimal lag length p is again chosen according to the SIC.

In order to verify whether order flow containing information on price expectations from the interbank market and OANDA FXTrade is helpful in predicting future currency prices (H1.1), we use the following forecasting models:

$$\left(1 - B_p^y(L)\right) \Delta y_t^h = c + B_p^x(L) x_t^{\text{SOF}} + \varepsilon_t, \tag{SOF-h}$$

in which, in addition to the AR(p) benchmark model, the history of the standard order flow measure (x_t^{SOF}) is included. $B_p^x(L)$ denotes the corresponding lag-polynomial.

In order to verify whether order flow that contains information on price expectations solely from OANDA FXTrade is helpful in predicting future currency prices, (H1.2), we use the following forecasting model:

$$\left(1 - B_p^y(L)\right) \Delta y_t^h = c + B_p^x(L) x_t^{\text{OOF}} + \varepsilon_t, \tag{OOF-h}$$

in which, in addition to the AR(p) benchmark model, the history of the OANDA order flow measure (x_t^{OOF}) is included. Furthermore, we use a more flexible forecasting specification in which we include the order flows of the eight trading categories (x_t^k, $k = 1, \ldots, 8$) separately:

$$\left(1 - B_p^y(L)\right) \Delta y_t^h = c + \sum_{k=1}^{8} B_p^{xk}(L) x_t^k + \varepsilon_t. \tag{CAT-h}$$

The forecasting study is executed in the following way: Altogether we consider a period of 32 weeks starting on Monday the 6th of October 2003 and ending on Friday the 14th of May 2004. We divide these 32 weeks into 8 periods of 4 weeks each, where always the first 3 weeks are considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Table 6 summarizes the setup of the in- and out-of-sample periods. We choose this forecasting setup with alternating in-sample and out-of-sample periods in order to guarantee robust forecasting results as compared to studies with only one estimation and one forecasting period.

Period	In-Sample	Out-of-Sample
1	Mo. 6. Oct. 2003 – Fr. 24. Oct. 2003	Mo. 27. Oct. 2003 – Fr. 31. Oct. 2003
2	Mo. 3. Nov. 2003 – Fr. 21. Nov. 2003	Mo. 24. Nov. 2003 – Fr. 28. Nov. 2003
3	Mo. 1. Dec. 2003 – Fr. 19. Dec. 2003	Mo. 22. Dec. 2003 – Fr. 26. Dec. 2003
4	Mo. 29. Dec. 2003 – Fr. 26. Jan. 2004	Mo. 19. Jan. 2004 – Fr. 23. Jan. 2004
5	Mo. 26. Jan. 2004 – Fr. 13. Feb. 2004	Mo. 16. Feb. 2004 – Fr. 20. Feb. 2004
6	Mo. 23. Feb. 2004 – Fr. 12. Mar. 2004	Mo. 15. Mar. 2004 – Fr. 19. Mar. 2004
7	Mo. 22. Mar. 2004 – Fr. 9. Apr. 2004	Mo. 12. Apr. 2004 – Fr. 19. Apr. 2004
8	Mo. 19. Apr. 2004 – Fr. 7. May 2004	Mo. 10. May 2004 – Fr. 14. May 2004

Table 6: In-sample and out-of-sample periods of the forecasting study.

The joint results over all 8 periods of the out-of-sample forecasting analysis are presented in Table 7, whereas the results for the in-sample comparison are stated in the Appendix in Table 11. The first cell entry in Table 7 as well as in Table 11 is the RMSPE of the associated forecasting model. The second and third cell entries in parenthesis are the p-values from the mDM test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).

For the in-sample comparison (Table 11) we observe that on all frequencies all three forecasting models (SOF-h, OOF-h, CAT-h) containing the different order flow measures are able to beat both benchmark specifications (RW-h, AR-h) in terms of smaller RMSPEs (bold cell entries) for both price change series ($h \in \{\text{OP,IP}\}$). It is evident, that in comparison the models which rely on the eight order flow categories separately (CAT-h) provide always the smallest RMSPEs, which is for the in-sample study not surprising since these models are the most flexible and thus provide the best fit. Considering the p-values of the mDM-test reveals that these models outperform both benchmark models for both price change series always on the 5% significance level. Second best is the forecasting specification relying on the OANDA order flow measure (OOF-h) which outperforms the RW benchmark model always on the 5% significance level (for both price change series) and the AR benchmark models, with two exceptions for the interbank price change series, always on the 10% significance level. The specification with the standard order flow measure (SOF-h) takes third place outperforming the RW benchmark model always on the 10% significance level and the AR benchmark models for 6 out of 12 (7 out of 12) frequencies for the OANDA based (interbank) price change series.

The in-sample study shows that expectations of the market participants revealed through the different order flow processes help to explain future currency price changes of up to a frequency of four hours. Thereby, we observe that the data driven specifications which rely on the category specific order flow measures, provide the best forecasts, followed by the specification relying on the OANDA order flow measure and the specification based on the standard order flow measure. Although, these observations suggest that the hypotheses H1, H1.1, and H1.2, concerning the prediction of future price changes may hold, a reliable confirmation of the hypotheses can only be produced by the out-of-sample forecasting study, which is presented in Table 7.

Here, we observe in contrast to the in-sample results, that only the short term price changes (up to 2 minutes) can be better predicted by the models containing (in addition to the price change information) information on the order flow than by the benchmark models containing solely information on the price change process. We observe, that the specifications based on the OANDA order flow measure (OOF-h) outperform both benchmark models (RW, AR) for both price change series (OANDA, interbank) on the 1% significance level on the 1 minute and on the 5% significance level on the 2 minute frequencies, and thus produce the best forecasting performance. The category order flow based specification is able to beat both benchmark models only on the 1% significance level on the 1 minute frequency for both price change series and thus takes the second place. The worst forecasting performance is obtained by the models based on the standard order flow measure which outperforms the RW benchmark specification on the 1 minute frequency for both price change series on the 1% significance level, but the AR benchmark specification only for the interbank price change series on the 5% significance level. In light of these results we conclude that hypotheses H1, H1.1, and H1.2 cannot be rejected, which means that order flow aggregates market participants' expectations, which are useful for predicting future price changes albeit only for short term frequencies up to 2 minutes. The fact that not only the RW specifications but also the AR specifications, which rest on historical price change information, can be outperformed by our forecasting models, which always nest the AR specifications, underpins the idea that information contained in the order flow series constitutes additional (private) information which cannot be inferred from the price process itself. In particular, we observe that the OANDA order flow measure is most beneficial.

The results are qualitatively very robust to the choice of the in-sample estimation and out-of-sample prediction periods and the same conclusions are achieved, when the results are evaluated with respect to the eight separate forecasting setups presented in Table 6. Moreover, the results are robust to the selection of deseasonalized or non-deseasonalized order flow measures and to including or omitting overnight periods. In the analysis above, we always used non-deseasonalized order flow measures.

Freq	BM-OP	SOF-OP	OOF-OP	CAT-OP	BM-IP	SOF-IP	OOF-IP	CAT-IP
1 min	.	0.2165	0.2144	0.2145	.	0.1872	0.1857	0.1841
(RW)	0.2172	**(0.0001)**	**(0.0000)**	**(0.0000)**	0.1903	**(0.0000)**	**(0.0000)**	**(0.0000)**
(AR)	0.2166	**(0.2723)**	**(0.0000)**	**(0.0000)**	0.1875	**(0.0386)**	**(0.0000)**	**(0.0000)**
2 min	.	0.3164	0.3158	0.3186	.	0.2888	0.2883	0.2909
(RW)	0.3166	**(0.1347)**	**(0.0003)**	(0.9107)	0.2889	**(0.4292)**	**(0.0125)**	(0.8898)
(AR)	0.3164	(0.5114)	**(0.0020)**	(0.9272)	0.2887	(0.7488)	**(0.0237)**	(0.9034)
5 min	.	0.4827	0.4821	0.4841	.	0.4560	0.4558	0.4576
(RW)	0.4819	(0.8985)	(0.5859)	(0.8913)	0.4555	(0.8900)	(0.7400)	(0.9029)
(AR)	0.4826	(0.6182)	**(0.1284)**	(0.8379)	0.4562	**(0.2589)**	**(0.1910)**	(0.8359)
10 min	.	0.6760	0.6760	0.6788	.	0.6552	0.6548	0.6587
(RW)	0.6746	(0.9566)	(0.9190)	(0.9783)	0.6533	(0.9937)	(0.9752)	(0.9967)
(AR)	0.6759	(0.6286)	(0.5912)	(0.9468)	0.6549	(0.7573)	**(0.3951)**	(0.9839)
15 min	.	0.8344	0.8345	0.8390	.	0.8173	0.8178	0.8225
(RW)	0.8336	(0.8029)	(0.7382)	(0.9765)	0.8158	(0.9367)	(0.9626)	(0.9964)
(AR)	0.8335	(0.8984)	(0.7887)	(0.9827)	0.8149	(0.9975)	(0.9957)	(0.9992)
20 min	.	0.9513	0.9486	0.9558	.	0.9275	0.9273	0.9344
(RW)	0.9449	(0.9996)	(0.9572)	(0.9975)	0.9212	(0.9995)	(0.9967)	(0.9994)
(AR)	0.9472	(0.9869)	(0.7547)	(0.9879)	0.9233	(0.9890)	(0.9684)	(0.9971)
25 min	.	1.0513	1.0461	1.0731	.	1.0301	1.0272	1.0524
(RW)	1.0408	(1.0000)	(0.9725)	(1.0000)	1.0204	(0.9998)	(0.9948)	(1.0000)
(AR)	1.0433	(0.9999)	(0.8763)	(0.9999)	1.0218	(0.9999)	(0.9928)	(1.0000)
30 min	.	1.1425	1.1409	1.1566	.	1.1360	1.1345	1.1552
(RW)	1.1398	(0.7809)	(0.6319)	(0.9920)	1.1338	(0.7401)	(0.5966)	(0.9940)
(AR)	1.1371	(0.9939)	(0.9624)	(0.9981)	1.1305	(0.9948)	(0.9837)	(0.9985)
45 min	.	1.4079	1.4043	1.4601	.	1.3984	1.3968	1.4615
(RW)	1.3940	(0.9951)	(0.9848)	(0.9996)	1.3878	(0.9865)	(0.9707)	(0.9987)
(AR)	1.4003	(0.9872)	(0.8586)	(0.9991)	1.3928	(0.9792)	(0.8651)	(0.9980)
1 hr	.	1.6539	1.6562	1.6970	.	1.6517	1.6552	1.6940
(RW)	1.6457	(0.9453)	(0.9949)	(0.9962)	1.6446	(0.9288)	(0.9962)	(0.9978)
(AR)	1.6532	(0.5629)	(0.7982)	(0.9900)	1.6517	(0.5050)	(0.8488)	(0.9936)
2 hr	.	2.3975	2.3948	2.4376	.	2.4051	2.4047	2.4535
(RW)	2.3406	(0.9958)	(0.9990)	(0.9858)	2.3517	(0.9944)	(0.9990)	(0.9872)
(AR)	2.3603	(0.9629)	(0.9879)	(0.9613)	2.3707	(0.9533)	(0.9899)	(0.9668)
4 hr	.	3.4671	3.4352	4.0073	.	3.4788	3.4263	3.9825
(RW)	3.3472	(0.8878)	(0.8678)	(0.9986)	3.3549	(0.8963)	(0.8300)	(0.9989)
(AR)	3.3467	(0.8924)	(0.8569)	(0.9986)	3.3521	(0.9046)	(0.8257)	(0.9989)

Table 7: Results for the price change **out-of-sample** prediction on different sampling frequencies (Freq). The forecasting study is conducted over a period of 32 weeks starting on Monday the 6^{th} of October 2003 and ending on Friday the 14^{th} of May 2004. These 32 weeks are divided into 8 periods of 4 weeks each, where always the first 3 weeks are considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second and third cell entries in parenthesis are the p-value from the modified Diebold-Mariano (mDM) test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).

6.2.2 Effects of Price Changes on Order Flow

We now investigate the economic hypotheses considering the causal relationships from price changes to order flow by using forecasting setups similar to those applied before. Based on the results of the descriptive analysis, we consider for the standard, the OANDA based and the category specific order flow measures in addition to a RW benchmark model, benchmark models in which, based on AR(p) specifications, only the histories of the order flow measures themselves serve to explain and to predict future order flows. These predictions are then compared, using the mDM-test, to the predictions of those forecasting models in which, in addition to the information contained in the history of the order flows, the information contained in the history of the price change processes is incorporated. This proceeding enables us to identify whether the additional information contained in the past prices is helpful to improve order flow forecasts significantly. The RW benchmark model is given by

$$x_t^k = \varepsilon_t, \tag{RW-k}$$

and the AR(p) benchmark specification is given by

$$\left(1 - B_p^x(L)\right) x_t^k = c + \varepsilon_t, \tag{AR-k}$$

where $B_p^x(L)$ denotes the associated lag-polynomial and ε_t a white noise process. The forecasting study is implemented for the standard order flow measure (k = SOF), for the OANDA order flow measure (k = OOF), and the eight category specific order flow measures ($k = 1, \ldots, 8$) already listed in Table 4. The forecasting models containing additional information on the history of the price change process are given by

$$\left(1 - B_p^x(L)\right) x_t^k = c + B_p^y(L)\Delta y_t^h + \varepsilon_t, \tag{h-k}$$

where $h \in \{\text{IP}, \text{OP}\}$ denotes whether the interbank or the OANDA based price change process is included.

For the interpretation of the hypotheses H2 to H4 we only compare the RMSPEs of the AR(p) benchmark model with those of the corresponding forecasting models. Nevertheless, the RMSPEs of the RW benchmark specifications are presented for comparison reasons and in maintaining the design of the forecasting study above. Due to the findings in the descriptive analysis, however, and in particular to the high persistence of the autocorrelation functions for the order flow measures presented in Figure 2, we do not believe that RW specifications for order flow measures in contrast to the before considered case of price series constitute appropriate benchmark models. The results of the in-sample study are presented in Tables 12 to 14 in the Appendix and the results of the out-of-sample study are given in Tables 8 to 10. Since in contrast to the study above there are practically no qualitative differences between the conclusions drawn from the in-sample and the out-of-sample investigation, we will directly interpret the results of the out-of-sample forecasting comparison in the following.

We observe that the general hypothesis H2, which claims that the information contained in the price process is helpful in predicting future order flow, cannot be rejected, since the information contained in the history of the price process in addition to the information contained in the order flow measures themselves is helpful in predicting both aggregated order flow measures (standard and OANDA) and helpful in predicting the eight category specific order flow measures. This statement is based on the observations that i) for the prediction of the standard order flow measure, the RMSPEs are for the 3 (3) forecasting horizons up to 5 minutes smaller than those of the AR(p) benchmark models, when additional information on the OANDA based (interbank) price change process is incorporated in the forecasting models. Irrespective of the choice of the price series we see that the RMSPEs for 1 and 2 minutes forecasting horizons are significantly smaller using a 1% significance level in the mDM test. ii) for the prediction of the OANDA order flow measure we observe for all frequencies, except for 4 hours, smaller RMSPEs in comparison to those from the AR benchmark model; up to 25 minutes all of them are significantly smaller at the 1% level and the remaining are except for 1 (2) significant on the 10% level. iii) for the prediction of the category specific order flow measures we observe that over all eight categories 59 (59) RMSPEs are smaller than those of the AR(p) benchmark models; 20 (19) of them are significantly smaller at the 1% level, 24 (25) of them are significantly smaller at the 5% level and even 35 (31) at the 10% level.
These figures allow for an interesting interpretation: First, we essentially do not observe any information advantages of the OANDA based price series over the interbank price series since the forecasting models incorporating these series generate very similar RMSPE patterns. Thus, we do not observe that the OANDA based price series influences the traders on OANDA FXTrade more severely than the interbank price series. This can be explained by the fact that both price series are, as shown before, co-integrated and therefore convey closely related dynamic patterns.

Second, since both aggregated as well as the category specific order flow measures can most often be predicted with the help of historical price information being, in particular in the absence of macroeconomic news and private (customer order flow) information, the only source of information for the trader, is an indication that traders update their beliefs and place their orders based on interpretations of technical analysis patterns as pointed out by Taylor & Allen (1992). This observation is supported by the fact that the OANDA order flow measure is more predictable than the standard order flow measure. Thus, we observe that the information contained in the price process has more influence on the price expectation process of the OANDA market, represented by the OANDA order flow measure than on the price expectation process of the OANDA and the interbank market, represented by the standard order flow measure. This is intuitively clear, since information on the price process is more valuable on the OANDA market, where most of the traders do not have own customer order flow, which can serve as private information, than on the interbank market where private information is available.

Let us now consider hypothesis H3, which states that executed stop-loss orders (category 6) contribute whereas executed take-profit orders (category 7) impede, self-reinforcing price movements. Table 10 shows that on all forecasting frequencies, the RMSPEs of the benchmark models BM-6 are smaller than those of benchmark models BM-7. This observation supports hypothesis H3 since stop-loss order flow, based on its own historical order flow, is more predictable (in terms of smaller RMSPEs) than take-profit order flow, which is foreseen if stop-loss orders contribute to self-reinforcing price movements causing a sequence of further stop-loss order executions. However, comparing the RMSPE pattern of the OP-6 (IP-6) forecasting models with those of the OP-7 (IP-7) forecasting models, we observe that there is essentially no difference in the value of the histories of both price processes in predicting take-profit order flow or stop-loss order flow. This observation diminishes the evidence for the validity of hypothesis H3, since we expected that the information on the direction of the price change process should already be included in the historical stop-loss order flow, and therefore should be of less importance in predicting future stop-loss order flow in contrast to the case when take profit order flow is considered, which contains less information on the direction of the price change process. Thus, we find no clear-cut evidence to support or reject hypothesis H3.

Hypothesis H4 postulating the existence of a monitoring effect is clearly supported.

Indeed, we see that the price process contributes more to the prediction of market order (close) order flow (OP-5, IP-5) than to the prediction of market order (open) order flow (OP-4, IP-4). In detail, we observe that only the RMSPEs for the 1 minute and the 2 minute frequencies of the OP-4 (IP-4) forecasting models are significantly smaller (1% level) than those of the AR(p)-benchmark models BM-4, but that the first 5 (5) RMSPEs corresponding to frequencies up to 15 minutes are significantly smaller than those of the benchmark models BM-5 at the 1% level and from the remaining frequencies 2 (1) are significant on the 10% level of the mDM-test for the OP-5 (IP-5) forecasting models. A similar, but not as pronounced, observation can be made for limit order executed (close) order flow (OP-3, IP-3) and limit order executed (open) order flow (OP-2, IP-2) as well. The reason why this effect is not as clear as for market orders is that limit orders are posted to the system before market orders, and their execution is later then simply implied by the price process. Market orders, however, reflect changes in price preferences directly since they are executed immediately.

The results concerning hypotheses H2 to H4 are again very robust to the choice of the in-sample estimation and out-of-sample prediction periods. Moreover, the same conclusions can be made if the hypotheses are evaluated separately with respect to the eight forecasting setups presented in Table 6. Again, the results are robust to the choice of deseasonalized or non-deseasonalized order flow measures and as in the analysis concerning causality from order flow to price changes, we here always used non-deseasonalized order flow measures in the estimations.

Freq	BM-SOF	OP-SOF	IP-SOF	BM-OOF	OP-OOF	IP-OOF
1 min	.	4.2754	4.2726	.	6.1327	6.1281
(RW)	4.3442	**(0.0000)**	**(0.0000)**	6.7559	**(0.0000)**	**(0.0000)**
(AR)	4.2978	**(0.0000)**	**(0.0000)**	6.2202	**(0.0000)**	**(0.0000)**
2 min	.	6.4619	6.4540	.	10.1446	10.1427
(RW)	6.5639	**(0.0000)**	**(0.0000)**	11.1609	**(0.0000)**	**(0.0000)**
(AR)	6.5110	**(0.0000)**	**(0.0000)**	10.2965	**(0.0000)**	**(0.0000)**
5 min	.	11.2111	11.2066	.	20.1572	20.1488
(RW)	11.3480	**(0.0005)**	**(0.0004)**	21.7650	**(0.0000)**	**(0.0000)**
(AR)	11.2270	**(0.2059)**	**(0.1451)**	20.5097	**(0.0000)**	**(0.0000)**
10 min	.	16.9384	16.9430	.	33.5809	33.5789
(RW)	17.1771	**(0.0026)**	**(0.0029)**	35.6428	**(0.0000)**	**(0.0000)**
(AR)	16.8088	(0.9992)	(0.9996)	34.0007	**(0.0000)**	**(0.0000)**
15 min	.	21.6196	21.6271	.	46.0984	46.1100
(RW)	22.0375	**(0.0030)**	**(0.0041)**	48.2420	**(0.0000)**	**(0.0000)**
(AR)	21.5097	(0.9909)	(0.9888)	46.5844	**(0.0000)**	**(0.0000)**
20 min	.	26.0270	26.0218	.	53.9924	53.9966
(RW)	26.6182	**(0.0032)**	**(0.0031)**	57.1482	**(0.0000)**	**(0.0000)**
(AR)	25.8728	(0.9935)	(0.9914)	54.3832	**(0.0008)**	**(0.0006)**
25 min	.	29.9238	29.9160	.	65.6482	65.5908
(RW)	30.8043	**(0.0020)**	**(0.0020)**	67.9482	**(0.0018)**	**(0.0014)**
(AR)	29.8577	(0.7667)	(0.7327)	66.1141	**(0.0027)**	**(0.0009)**
30 min	.	33.5134	33.5240	.	73.6010	73.5952
(RW)	34.4623	**(0.0055)**	**(0.0063)**	76.6212	**(0.0003)**	**(0.0003)**
(AR)	33.4052	(0.8553)	(0.8807)	74.2258	**(0.0394)**	**(0.0410)**
45 min	.	44.9104	44.9230	.	96.5877	97.2642
(RW)	45.8347	**(0.0670)**	**(0.0705)**	99.3191	**(0.0299)**	**(0.0774)**
(AR)	44.6980	(0.7556)	(0.7714)	97.5647	**(0.0260)**	**(0.0912)**
1 hr	.	52.7614	52.8020	.	115.5227	115.5154
(RW)	53.6718	**(0.1599)**	**(0.1689)**	119.6130	**(0.0027)**	**(0.0032)**
(AR)	52.1271	(0.9581)	(0.9685)	115.8363	**(0.2127)**	**(0.2003)**
2 hr	.	86.2782	86.3036	.	199.6192	199.7721
(RW)	89.7007	**(0.0264)**	**(0.0275)**	196.7060	(0.7388)	(0.7459)
(AR)	85.9340	(0.6825)	(0.6968)	200.5890	**(0.0765)**	**(0.1251)**
4 hr	.	144.5557	144.5649	.	319.5417	318.8468
(RW)	148.5538	**(0.1907)**	**(0.1929)**	312.9562	(0.7190)	(0.7002)
(AR)	143.6758	(0.7883)	(0.7909)	309.7606	(0.8830)	(0.8738)

Table 8: Results for the standard and the OANDA order flow measures **out-of-sample** predictions on different sampling frequencies (Freq). The forecasting study is conducted over a period of 32 weeks starting on Monday the 6^{th} of October 2003 and ending on Friday the 14^{th} of May 2004. These 32 weeks are divided into 8 periods of 4 weeks each, wherethe first 3 weeks are always considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second and third cell entries in parenthesis are the p-value from the modified Diebold-Mariano (mDM) test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).

Freq	BM-1	OP-1	IP-1	BM-2	OP-2	IP-2	BM-3	OP-3	IP-3	BM-4	OP-4	IP-4
1 min	.	1.5050	1.5050	.	1.8391	1.8370	.	0.7411	0.7409	.	1.8716	1.8708
(RW)	1.7495	**(0.0000)**	**(0.0000)**	1.8960	**(0.0000)**	**(0.0000)**	0.7486	**(0.1396)**	**(0.1342)**	1.9642	**(0.0000)**	**(0.0000)**
(AR)	1.5059	**(0.0022)**	**(0.0031)**	1.8412	**(0.1558)**	**(0.1212)**	0.7415	**(0.2569)**	**(0.1797)**	1.8765	**(0.0000)**	**(0.0000)**
2 min	.	2.5435	2.5435	.	2.8709	2.8699	.	1.1964	1.1969	.	2.8866	2.8844
(RW)	2.9918	**(0.0000)**	**(0.0000)**	2.9532	**(0.0000)**	**(0.0000)**	1.1963	(0.5454)	(0.6740)	3.0912	**(0.0000)**	**(0.0000)**
(AR)	2.5477	**(0.0002)**	**(0.0002)**	2.8676	(0.7798)	(0.6597)	1.1982	**(0.1656)**	**(0.2627)**	2.8995	**(0.0000)**	**(0.0000)**
5 min	.	5.4922	5.4916	.	5.1609	5.1626	.	1.7625	1.7621	.	5.2944	5.2926
(RW)	6.1810	**(0.0000)**	**(0.0000)**	5.3660	**(0.0004)**	**(0.0004)**	1.7743	**(0.1258)**	**(0.1161)**	5.8405	**(0.0000)**	**(0.0000)**
(AR)	5.5135	**(0.0108)**	**(0.0118)**	5.1697	**(0.0471)**	**(0.0662)**	1.7648	**(0.0639)**	**(0.0305)**	5.2898	(0.7175)	(0.6315)
10 min	.	9.8495	9.8526	.	8.3994	8.4009	.	2.8602	2.8594	.	8.6961	8.7002
(RW)	10.5907	**(0.0031)**	**(0.0032)**	8.6144	**(0.0011)**	**(0.0014)**	2.8601	(0.5153)	**(0.4229)**	9.7280	**(0.0000)**	**(0.0000)**
(AR)	9.8622	**(0.2850)**	**(0.3319)**	8.3812	(0.9029)	(0.9185)	2.8620	**(0.2269)**	**(0.1706)**	8.7090	**(0.1637)**	**(0.2641)**
15 min	.	13.4723	13.4816	.	11.7552	11.7542	.	3.5241	3.5243	.	11.7451	11.7545
(RW)	14.5181	**(0.0030)**	**(0.0033)**	12.0227	**(0.0046)**	**(0.0044)**	3.5251	**(0.4716)**	**(0.4755)**	13.2532	**(0.0000)**	**(0.0000)**
(AR)	13.5125	**(0.3509)**	**(0.3837)**	11.7627	**(0.3310)**	**(0.3281)**	3.5404	**(0.1508)**	**(0.1543)**	11.6636	(0.9741)	(0.9845)
20 min	.	16.4821	16.4909	.	12.8155	12.8136	.	4.1440	4.1438	.	14.1780	14.1836
(RW)	17.7882	**(0.0055)**	**(0.0057)**	13.5116	**(0.0009)**	**(0.0008)**	4.1371	(0.6665)	(0.6631)	16.2804	**(0.0000)**	**(0.0000)**
(AR)	16.5926	**(0.0616)**	**(0.0745)**	12.8240	**(0.4326)**	**(0.4148)**	4.1443	**(0.4658)**	**(0.4413)**	14.1298	(0.7377)	(0.7615)
25 min	.	19.8148	19.8155	.	16.2772	16.2733	.	4.6563	4.6562	.	16.9341	16.9292
(RW)	21.1085	**(0.0140)**	**(0.0139)**	16.5117	**(0.2280)**	**(0.2233)**	4.6409	(0.9789)	(0.9778)	19.4349	**(0.0000)**	**(0.0000)**
(AR)	19.9732	**(0.1585)**	**(0.1639)**	16.1600	(0.9592)	(0.9573)	4.6501	(0.8764)	(0.8752)	16.7700	(0.9143)	(0.9079)
30 min	.	22.1440	22.1888	.	17.6026	17.8720	.	5.3209	5.2601	.	19.7887	19.7348
(RW)	23.7797	**(0.0105)**	**(0.0130)**	18.4779	**(0.0022)**	**(0.0272)**	5.2895	(0.9746)	**(0.2472)**	22.5287	**(0.0000)**	**(0.0000)**
(AR)	22.2530	**(0.0593)**	**(0.2247)**	17.6244	**(0.4224)**	(0.9036)	5.3137	(0.8782)	**(0.1672)**	19.5854	(0.9620)	(0.9072)
45 min	.	30.2322	30.2350	.	23.5191	23.5171	.	6.5703	6.5685	.	25.9643	25.9390
(RW)	31.9925	**(0.0395)**	**(0.0397)**	24.2620	**(0.0901)**	**(0.0899)**	6.4990	(0.9371)	(0.9314)	30.5838	**(0.0000)**	**(0.0000)**
(AR)	30.3289	**(0.2547)**	**(0.2603)**	23.3965	(0.9983)	(0.9981)	6.5633	(0.7641)	(0.7099)	25.6376	(0.9411)	(0.9258)
1 hr	.	36.0894	36.1042	.	27.5473	27.5341	.	7.4613	7.4618	.	31.9533	31.9349
(RW)	38.2671	**(0.0340)**	**(0.0344)**	29.3296	**(0.0166)**	**(0.0162)**	7.4475	(0.7321)	(0.7387)	38.1311	**(0.0001)**	**(0.0001)**
(AR)	36.3297	**(0.1362)**	**(0.1467)**	27.4002	(0.9470)	(0.9314)	7.4748	**(0.2767)**	**(0.2858)**	31.2881	(0.9709)	(0.9688)
2 hr	.	58.5671	58.5918	.	49.8939	49.8873	.	10.8941	10.8932	.	55.7354	55.6411
(RW)	62.2111	**(0.0256)**	**(0.0263)**	50.6499	**(0.3568)**	**(0.3555)**	10.8502	(0.6031)	(0.5991)	67.5312	**(0.0017)**	**(0.0015)**
(AR)	58.4704	(0.6301)	(0.6544)	49.5621	(0.9541)	(0.9539)	10.9815	**(0.0058)**	**(0.0080)**	53.8287	(0.9778)	(0.9771)
4 hr	.	104.9977	105.0585	.	80.5436	80.6359	.	17.0417	17.0386	.	103.8191	103.8547
(RW)	107.3258	**(0.1651)**	**(0.1695)**	79.6642	(0.7276)	(0.7494)	16.5768	(0.8460)	(0.8434)	123.2949	**(0.0024)**	**(0.0024)**
(AR)	107.3412	**(0.0454)**	**(0.0482)**	81.5804	**(0.0628)**	**(0.0775)**	17.0937	**(0.1977)**	**(0.1817)**	101.5470	(0.8728)	(0.8717)

Table 9: Results of the **out-of-sample** predictions of the category specific order flow measures on different sampling frequencies (Freq). The forecasting study is conducted over a period of 32 weeks starting on Monday the 6^{th} of October 2003 and ending on Friday the 14^{th} of May 2004. These 32 weeks are divided into 8 periods of 4 weeks each, where the first 3 weeks are always considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second and third cell entries in parenthesis are the p-value from the modified Diebold-Mariano (mDM) test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).

Freq	BM-5	OP-5	IP-5	BM-6	OP-6	IP-6	BM-7	OP-7	IP-7	BM-8	OP-8	IP-8
1 min	.	2.6174	2.6100	.	1.8330	1.8324	.	3.4894	3.4894	.	0.7689	0.7687
(RW)	2.8051	**(0.0000)**	**(0.0000)**	1.8740	**(0.0000)**	**(0.0000)**	3.7077	**(0.0000)**	**(0.0000)**	0.7762	**(0.1000)**	**(0.0961)**
(AR)	2.6810	**(0.0000)**	**(0.0000)**	1.8428	**(0.0000)**	**(0.0000)**	3.5039	**(0.0021)**	**(0.0091)**	0.7707	**(0.0766)**	**(0.0693)**
2 min	.	4.0384	4.0264	.	2.8247	2.8272	.	5.8327	5.8311	.	1.1370	1.1373
(RW)	4.4293	**(0.0000)**	**(0.0000)**	2.8730	**(0.0000)**	**(0.0000)**	6.0838	**(0.0000)**	**(0.0000)**	1.1456	**(0.1349)**	**(0.1480)**
(AR)	4.1646	**(0.0000)**	**(0.0000)**	2.8420	**(0.0000)**	**(0.0000)**	5.8825	**(0.0001)**	**(0.0004)**	1.1404	**(0.0984)**	**(0.1203)**
5 min	.	7.7049	7.6980	.	4.9182	4.9223	.	10.7454	10.7474	.	2.0976	2.0974
(RW)	8.5139	**(0.0000)**	**(0.0000)**	4.9686	**(0.0001)**	**(0.0002)**	11.1705	**(0.0000)**	**(0.0000)**	2.1046	**(0.3324)**	**(0.3277)**
(AR)	7.9576	**(0.0000)**	**(0.0000)**	4.9441	**(0.0000)**	**(0.0000)**	10.8902	**(0.0001)**	**(0.0001)**	2.1087	**(0.2088)**	**(0.2095)**
10 min	.	12.6435	12.6485	.	7.4097	7.4011	.	17.2073	17.2111	.	3.1085	3.1080
(RW)	13.8218	**(0.0000)**	**(0.0000)**	7.4622	**(0.0024)**	**(0.0009)**	17.6507	**(0.0000)**	**(0.0000)**	3.1239	**(0.3050)**	**(0.2952)**
(AR)	12.9142	**(0.0000)**	**(0.0000)**	7.4257	**(0.0529)**	**(0.0002)**	17.3042	**(0.0146)**	**(0.0217)**	3.1301	**(0.1936)**	**(0.1991)**
15 min	.	17.1291	17.1217	.	9.4695	9.4698	.	23.8305	23.8357	.	3.9350	3.9300
(RW)	18.6050	**(0.0000)**	**(0.0000)**	9.5257	**(0.0348)**	**(0.0348)**	24.2981	**(0.0103)**	**(0.0110)**	3.9433	**(0.4105)**	**(0.3551)**
(AR)	17.3679	**(0.0000)**	**(0.0000)**	9.4822	**(0.0998)**	**(0.1016)**	23.7763	(0.6374)	(0.6523)	3.9560	**(0.1889)**	**(0.1594)**
20 min	.	20.9936	21.0014	.	11.0743	11.0712	.	26.6076	26.6077	.	4.6211	4.6193
(RW)	22.6110	**(0.0000)**	**(0.0000)**	11.1374	**(0.0843)**	**(0.0761)**	27.6149	**(0.0000)**	**(0.0000)**	4.5808	(0.8914)	(0.8916)
(AR)	21.1034	**(0.0908)**	**(0.1051)**	11.0635	(0.8416)	(0.7544)	26.5161	(0.7731)	(0.7757)	4.5620	(0.9203)	(0.9044)
25 min	.	25.5134	25.4827	.	12.6992	12.6941	.	32.7414	32.7224	.	5.6090	5.6005
(RW)	27.0583	**(0.0003)**	**(0.0002)**	12.6929	(0.5479)	(0.5096)	33.1749	**(0.1867)**	**(0.1734)**	5.5369	(0.9827)	(0.9807)
(AR)	25.6057	**(0.2265)**	**(0.1614)**	12.7121	**(0.3002)**	**(0.2426)**	32.6157	(0.7309)	(0.7022)	5.6977	**(0.0651)**	**(0.0596)**
30 min	.	28.2222	28.2159	.	14.0291	14.0252	.	36.4649	36.4566	.	5.7558	5.7616
(RW)	30.4332	**(0.0000)**	**(0.0000)**	14.1282	**(0.0718)**	**(0.0660)**	37.6070	**(0.0027)**	**(0.0023)**	5.6966	(0.8067)	(0.8293)
(AR)	28.3720	**(0.0568)**	**(0.0538)**	14.0931	**(0.0074)**	**(0.0062)**	36.6937	**(0.0058)**	**(0.0071)**	5.7202	(0.7538)	(0.7729)
45 min	.	37.8890	37.9234	.	17.6935	17.6993	.	47.8009	47.8084	.	7.2350	7.2341
(RW)	40.4501	**(0.0004)**	**(0.0004)**	17.7127	**(0.4327)**	**(0.4531)**	47.9439	**(0.4166)**	**(0.4211)**	7.1160	(0.9991)	(0.9991)
(AR)	37.7322	(0.8270)	(0.8651)	17.6807	(0.7299)	(0.8152)	47.9815	**(0.0340)**	**(0.0373)**	7.0983	(0.9945)	(0.9954)
1 hr	.	44.3015	44.2877	.	20.4940	20.4799	.	55.7957	55.8053	.	9.1189	9.1169
(RW)	48.3164	**(0.0000)**	**(0.0000)**	20.5012	**(0.4827)**	**(0.4491)**	57.4274	**(0.0374)**	**(0.0403)**	8.9965	(0.9916)	(0.9904)
(AR)	44.0571	(0.8483)	(0.8383)	20.3353	(0.9506)	(0.9346)	55.7560	(0.5788)	(0.5955)	9.0440	(0.8906)	(0.8867)
2 hr	.	77.4399	77.4581	.	30.8722	30.8688	.	98.2016	98.2703	.	13.8723	13.8434
(RW)	82.0107	**(0.0007)**	**(0.0008)**	30.9309	**(0.4531)**	**(0.4507)**	96.7641	(0.7976)	(0.8098)	13.6316	(0.9707)	(0.9435)
(AR)	77.4225	(0.5200)	(0.5472)	30.9472	**(0.2666)**	**(0.2532)**	98.1701	(0.5299)	(0.5990)	13.4674	(0.8690)	(0.8713)
4 hr	.	125.1750	125.0778	.	42.0281	42.0985	.	144.3387	144.3137	.	21.4392	21.4649
(RW)	36.2601	**(0.0062)**	**(0.0057)**	43.5935	**(0.1273)**	**(0.1353)**	143.9142	(0.5651)	(0.5583)	20.5223	(0.9548)	(0.9584)
(AR)	23.6795	(0.7521)	(0.7443)	43.0342	**(0.0079)**	**(0.0150)**	145.2135	**(0.3223)**	**(0.3253)**	20.6128	(0.8172)	(0.8248)

Table 10: Results of the **out-of-sample** predictions of the category specific order flow measures on different sampling frequencies (Freq). The forecasting study is conducted over a period of 32 weeks starting on Monday the 6^{th} of October 2003 and ending on Friday the 14^{th} of May 2004. These 32 weeks are divided into 8 periods of 4 weeks each, where the first 3 weeks are always considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second and third cell entries in parenthesis are the p-value from the modified Diebold-Mariano (mDM) test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).

7 Conclusion

We investigate the relationship between currency price changes and their expectations with the help of a customer dataset from OANDA FXTrade. Price expectations are inferred from the trading behavior of the OANDA FXTrade investors and measured by order flow. We distinguish between price expectations relying on information from the interbank market and OANDA FXTrade, which are measured with the standard order flow measure of Lyons (1995), price expectations derived solely from OANDA FXTrade measured by the OANDA order flow measure and a pure data driven order flow measure, which does not rely on any theoretical reasoning of how specific orders should affect future price changes.

We conduct forecasting studies on 12 intra-day frequencies and find that those forecasting models incorporating information on order flows and price changes provide significantly better forecasts than benchmark models using only information on past price changes through AR(p) specifications, and trivial Random Walk benchmark models. In comparison to the Root-Mean-Squared-Prediction Errors (RMSPE) of the benchmark specifications, forecasting models relying on the different order flow measures provide smaller RMSPEs for short term prediction horizons of 1 and 2 minutes.

In a similar forecasting setup we investigate the influence of past price changes on the two aggregated order flow measures and on eight transaction category specific order flow measures (feedback effect). We find i) that the trading behavior, and thus the price expectations, of our investors are affected by past currency price changes and ii) evidence for the existence of a monitoring effect stating that investors interpret price information different in making opening and closing decisions. This has several consequences for theoretical market microstructure models in which investors are assumed to place market and limit orders irrespectively of their current investment status. Furthermore, we find only slight evidence that stop-loss orders contribute to and take-profit impede self-reinforcing price movements, which would support the hypothesis of Osler (2005) with a different methodology.

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A Appendix

Freq	BM-OP	SOF-OP	OOF-OP	CAT-OP	BM-IP	SOF-IP	OOF-IP	CAT-IP
1 min	.	0.2260	0.2244	0.2233	.	0.1993	0.1985	0.1951
(RW)	0.2273	**(0.0000)**	**(0.0000)**	**(0.0000)**	0.2035	**(0.0000)**	**(0.0000)**	**(0.0000)**
(AR)	0.2261	**(0.0034)**	**(0.0000)**	**(0.0000)**	0.1999	**(0.0000)**	**(0.0000)**	**(0.0000)**
2 min	.	0.3363	0.3359	0.3353	.	0.3091	0.3091	0.3069
(RW)	0.3367	**(0.0005)**	**(0.0000)**	**(0.0001)**	0.3100	**(0.0001)**	**(0.0000)**	**(0.0000)**
(AR)	0.3363	**(0.1939)**	**(0.0001)**	**(0.0010)**	0.3094	**(0.0014)**	**(0.0019)**	**(0.0000)**
5 min	.	0.5261	0.5255	0.5243	.	0.5033	0.5030	0.5015
(RW)	0.5276	**(0.0074)**	**(0.0001)**	**(0.0094)**	0.5043	**(0.0150)**	**(0.0057)**	**(0.0184)**
(AR)	0.5262	**(0.3121)**	**(0.0236)**	**(0.0419)**	0.5035	**(0.1540)**	**(0.0367)**	**(0.0332)**
10 min	.	0.7314	0.7303	0.7273	.	0.7164	0.7162	0.7126
(RW)	0.7331	**(0.0172)**	**(0.0010)**	**(0.0017)**	0.7177	**(0.0532)**	**(0.0266)**	**(0.0050)**
(AR)	0.7316	**(0.2138)**	**(0.0163)**	**(0.0021)**	0.7167	**(0.1552)**	**(0.0771)**	**(0.0029)**
15 min	.	0.8828	0.8813	0.8765	.	0.8705	0.8699	0.8652
(RW)	0.8841	**(0.0344)**	**(0.0059)**	**(0.0003)**	0.8719	**(0.0246)**	**(0.0215)**	**(0.0007)**
(AR)	0.8830	**(0.3621)**	**(0.0298)**	**(0.0004)**	0.8706	**(0.3813)**	**(0.1683)**	**(0.0012)**
20 min	.	1.0103	1.0082	1.0006	.	1.0057	1.0038	0.9961
(RW)	1.0125	**(0.0449)**	**(0.0036)**	**(0.0001)**	1.0078	**(0.0521)**	**(0.0075)**	**(0.0002)**
(AR)	1.0110	**(0.2910)**	**(0.0310)**	**(0.0004)**	1.0063	**(0.3294)**	**(0.0468)**	**(0.0006)**
25 min	.	1.1116	1.1088	1.0999	.	1.1066	1.1044	1.0959
(RW)	1.1146	**(0.0224)**	**(0.0029)**	**(0.0000)**	1.1096	**(0.0277)**	**(0.0069)**	**(0.0001)**
(AR)	1.1134	**(0.0710)**	**(0.0022)**	**(0.0000)**	1.1081	**(0.0828)**	**(0.0062)**	**(0.0001)**
30 min	.	1.2475	1.2466	1.2349	.	1.2406	1.2403	1.2280
(RW)	1.2518	**(0.0296)**	**(0.0095)**	**(0.0009)**	1.2448	**(0.0343)**	**(0.0198)**	**(0.0013)**
(AR)	1.2496	**(0.0614)**	**(0.0135)**	**(0.0006)**	1.2424	**(0.0812)**	**(0.0276)**	**(0.0009)**
45 min	.	1.5292	1.5282	1.5103	.	1.5251	1.5241	1.5046
(RW)	1.5349	**(0.0122)**	**(0.0092)**	**(0.0002)**	1.5303	**(0.0172)**	**(0.0131)**	**(0.0002)**
(AR)	1.5311	**(0.0652)**	**(0.0391)**	**(0.0002)**	1.5266	**(0.0788)**	**(0.0569)**	**(0.0002)**
1 hr	.	1.7656	1.7669	1.7441	.	1.7655	1.7668	1.7432
(RW)	1.7739	**(0.0289)**	**(0.0311)**	**(0.0001)**	1.7736	**(0.0292)**	**(0.0334)**	**(0.0001)**
(AR)	1.7698	**(0.1011)**	**(0.0970)**	**(0.0002)**	1.7691	**(0.1137)**	**(0.1153)**	**(0.0002)**
2 hr	.	2.5255	2.5280	2.4582	.	2.5303	2.5327	2.4609
(RW)	2.5433	**(0.0106)**	**(0.0182)**	**(0.0000)**	2.5476	**(0.0119)**	**(0.0191)**	**(0.0000)**
(AR)	2.5355	**(0.0414)**	**(0.0403)**	**(0.0001)**	2.5398	**(0.0446)**	**(0.0407)**	**(0.0001)**
4 hr	.	3.6412	3.6194	3.4652	.	3.6411	3.6230	3.4722
(RW)	3.7055	**(0.0107)**	**(0.0004)**	**(0.0000)**	3.7085	**(0.0079)**	**(0.0003)**	**(0.0000)**
(AR)	3.6827	**(0.0303)**	**(0.0061)**	**(0.0000)**	3.6848	**(0.0246)**	**(0.0061)**	**(0.0000)**

Table 11: Results for the price change **in-sample** prediction on different sampling frequencies (Freq). The out-of-sample prediction horizon, though for different frequencies, corresponds to the week from 9^{th} of May 2004 to 14^{th} of May 2004. The model selection period covers the period from 1^{st} of October 2003 to $8^{th}$of May 2004. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second cell entry in parenthesis is the p-value from the modified Diebold-Mariano Test with the null hypothesis, that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding benchmark model. Cell entries in bold are those, where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model.

Freq	BM-SOF	OP-SOF	IP-SOF	BM-OOF	OP-OOF	IP-OOF
1 min	.	4.3279	4.3275	.	6.0346	6.0344
(RW)	4.3936	**(0.0000)**	**(0.0000)**	6.6445	**(0.0000)**	**(0.0000)**
(AR)	4.3485	**(0.0000)**	**(0.0000)**	6.1613	**(0.0000)**	**(0.0000)**
2 min	.	6.4813	6.4809	.	10.0115	10.0219
(RW)	6.5998	**(0.0000)**	**(0.0000)**	10.9510	**(0.0000)**	**(0.0000)**
(AR)	6.5269	**(0.0000)**	**(0.0000)**	10.2133	**(0.0000)**	**(0.0000)**
5 min	.	11.0878	11.0924	.	19.5562	19.5612
(RW)	11.2896	**(0.0000)**	**(0.0000)**	21.0475	**(0.0000)**	**(0.0000)**
(AR)	11.1317	**(0.0001)**	**(0.0005)**	19.8634	**(0.0000)**	**(0.0000)**
10 min	.	16.6775	16.6804	.	31.8179	31.8382
(RW)	17.0066	**(0.0000)**	**(0.0000)**	33.9662	**(0.0000)**	**(0.0000)**
(AR)	16.6981	**(0.1279)**	**(0.1550)**	32.1138	**(0.0000)**	**(0.0000)**
15 min	.	20.9078	20.8962	.	42.2575	42.2904
(RW)	21.4578	**(0.0000)**	**(0.0000)**	44.8326	**(0.0000)**	**(0.0000)**
(AR)	20.9063	(0.5218)	**(0.3847)**	42.5043	**(0.0013)**	**(0.0050)**
20 min	.	25.0185	25.0171	.	50.7607	50.7849
(RW)	25.7517	**(0.0000)**	**(0.0000)**	54.1697	**(0.0000)**	**(0.0000)**
(AR)	25.0626	**(0.0966)**	**(0.0958)**	51.0548	**(0.0001)**	**(0.0001)**
25 min	.	28.7056	28.7046	.	59.2042	59.2337
(RW)	29.5486	**(0.0000)**	**(0.0000)**	62.8549	**(0.0000)**	**(0.0000)**
(AR)	28.7239	**(0.3469)**	**(0.3424)**	59.4306	**(0.0016)**	**(0.0041)**
30 min	.	31.8507	31.8593	.	69.2663	69.2880
(RW)	33.0771	**(0.0000)**	**(0.0000)**	72.6962	**(0.0000)**	**(0.0000)**
(AR)	32.0495	**(0.0093)**	**(0.0141)**	69.1807	(0.6543)	(0.6883)
45 min	.	41.2116	41.2203	.	90.0485	89.6734
(RW)	43.1033	**(0.0000)**	**(0.0000)**	94.7285	**(0.0000)**	**(0.0000)**
(AR)	41.4252	**(0.1541)**	**(0.1617)**	90.0408	(0.5140)	**(0.0139)**
1 hr	.	48.0816	48.0999	.	110.1289	110.1457
(RW)	50.9275	**(0.0000)**	**(0.0000)**	115.7915	**(0.0000)**	**(0.0000)**
(AR)	48.3953	**(0.1516)**	**(0.1627)**	110.3570	**(0.1219)**	**(0.1282)**
2 hr	.	71.5228	71.5105	.	179.7910	179.7933
(RW)	78.4165	**(0.0000)**	**(0.0000)**	187.5252	**(0.0008)**	**(0.0008)**
(AR)	72.2455	**(0.0346)**	**(0.0333)**	180.2294	**(0.1394)**	**(0.1612)**
4 hr	.	115.7755	115.7275	.	277.7545	277.8107
(RW)	129.6756	**(0.0000)**	**(0.0000)**	295.2749	**(0.0006)**	**(0.0006)**
(AR)	116.3498	**(0.0763)**	**(0.0704)**	280.9705	**(0.0078)**	**(0.0086)**

Table 12: Results for the standard and the OANDA order flow measures **in-sample** predictions on different sampling frequencies (Freq). The forecasting study is conducted over a period of 32 weeks starting on Monday the 6^{th} of October 2003 and ending on Friday the 14^{th} of May 2004. These 32 weeks are divided into 8 periods of 4 weeks each, where always the first 3 weeks are considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second and third cell entries in parenthesis are the p-value from the modified Diebold-Mariano (mDM) test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).

Freq	BM-1	OP-1	IP-1	BM-2	OP-2	IP-2	BM-3	OP-3	IP-3	BM-4	OP-4	IP-4
1 min	.	1.4445	1.4445	.	1.6203	1.6175	.	0.6316	0.6315	.	1.9774	1.9770
(RW)	1.6623	(**0.0000**)	(**0.0000**)	1.6741	(**0.0000**)	(**0.0000**)	0.6346	(**0.0002**)	(**0.0004**)	2.0869	(**0.0000**)	(**0.0000**)
(AR)	1.4454	(**0.0000**)	(**0.0000**)	1.6270	(**0.0596**)	(**0.0976**)	0.6330	(**0.0004**)	(**0.0010**)	1.9857	(**0.0000**)	(**0.0000**)
2 min	.	2.4484	2.4484	.	2.5177	2.5158	.	0.9080	0.9073	.	3.0703	3.0700
(RW)	2.8375	(**0.0000**)	(**0.0000**)	2.6031	(**0.0000**)	(**0.0000**)	0.9136	(**0.0003**)	(**0.0002**)	3.3068	(**0.0000**)	(**0.0000**)
(AR)	2.4518	(**0.0002**)	(**0.0002**)	2.5267	(**0.0375**)	(**0.0726**)	0.9106	(**0.0020**)	(**0.0019**)	3.0876	(**0.0000**)	(**0.0000**)
5 min	.	5.1238	5.1219	.	4.5231	4.5236	.	1.4946	1.4948	.	5.5516	5.5518
(RW)	5.8003	(**0.0000**)	(**0.0000**)	4.6923	(**0.0000**)	(**0.0000**)	1.5016	(**0.0000**)	(**0.0000**)	6.2090	(**0.0000**)	(**0.0000**)
(AR)	5.1312	(**0.0803**)	(**0.0599**)	4.5255	(**0.2283**)	(**0.2658**)	1.4973	(**0.0004**)	(**0.0011**)	5.5784	(**0.0000**)	(**0.0000**)
10 min	.	9.0440	9.0444	.	7.1435	7.1464	.	2.1721	2.1722	.	9.0972	9.0985
(RW)	9.8777	(**0.0000**)	(**0.0000**)	7.4598	(**0.0000**)	(**0.0000**)	2.1829	(**0.0001**)	(**0.0001**)	10.3735	(**0.0000**)	(**0.0000**)
(AR)	9.0484	(**0.3475**)	(**0.3588**)	7.1240	(0.9372)	(0.9509)	2.1762	(**0.0007**)	(**0.0010**)	9.1244	(**0.0009**)	(**0.0019**)
15 min	.	12.2743	12.2766	.	9.1503	9.1475	.	2.7153	2.7143	.	12.1089	12.1397
(RW)	13.2220	(**0.0000**)	(**0.0000**)	9.6777	(**0.0000**)	(**0.0000**)	2.7314	(**0.0002**)	(**0.0002**)	14.0151	(**0.0000**)	(**0.0000**)
(AR)	12.2393	(0.8425)	(0.8578)	9.1686	(**0.1705**)	(**0.1799**)	2.7164	(**0.4301**)	(**0.3744**)	12.1184	(**0.3619**)	(0.7651)
20 min	.	15.1468	15.1480	.	10.7382	10.7400	.	3.1521	3.1526	.	14.4882	14.4889
(RW)	16.2260	(**0.0001**)	(**0.0001**)	11.4944	(**0.0000**)	(**0.0000**)	3.1769	(**0.0001**)	(**0.0001**)	17.2043	(**0.0000**)	(**0.0000**)
(AR)	15.1778	(**0.1428**)	(**0.1501**)	10.7343	(0.5849)	(0.6278)	3.1611	(**0.0023**)	(**0.0032**)	14.5709	(**0.0338**)	(**0.0335**)
25 min	.	17.9774	17.9766	.	12.2339	12.2353	.	3.5632	3.5638	.	17.3613	17.3621
(RW)	19.0826	(**0.0002**)	(**0.0002**)	13.2318	(**0.0000**)	(**0.0000**)	3.5951	(**0.0002**)	(**0.0003**)	20.6539	(**0.0000**)	(**0.0000**)
(AR)	17.9797	(**0.4833**)	(**0.4771**)	12.1639	(0.8484)	(0.8521)	3.5789	(**0.0086**)	(**0.0105**)	17.4819	(**0.0102**)	(**0.0088**)
30 min	.	19.8016	19.8267	.	14.5336	14.5874	.	3.9492	3.9339	.	20.0634	19.9743
(RW)	21.2259	(**0.0003**)	(**0.0003**)	15.5098	(**0.0000**)	(**0.0000**)	3.9893	(**0.0021**)	(**0.0061**)	23.8539	(**0.0000**)	(**0.0000**)
(AR)	19.8530	(**0.0556**)	(**0.2631**)	14.5193	(0.6342)	(0.8520)	3.9716	(**0.0016**)	(**0.0237**)	20.1194	(**0.2530**)	(**0.0061**)
45 min	.	26.8965	26.8938	.	18.8844	18.8847	.	4.9509	4.9513	.	26.5315	26.5359
(RW)	28.5510	(**0.0018**)	(**0.0018**)	20.3978	(**0.0000**)	(**0.0000**)	4.9974	(**0.0155**)	(**0.0159**)	32.4244	(**0.0000**)	(**0.0000**)
(AR)	26.7754	(0.7654)	(0.7577)	18.8809	(0.5323)	(0.5364)	4.9625	(**0.0836**)	(**0.0902**)	26.7991	(**0.0113**)	(**0.0112**)
1 hr	.	32.6713	32.6807	.	22.3687	22.3710	.	5.8689	5.8693	.	33.3208	33.3265
(RW)	34.6926	(**0.0007**)	(**0.0007**)	24.5455	(**0.0001**)	(**0.0001**)	5.9108	(**0.0029**)	(**0.0031**)	40.8190	(**0.0000**)	(**0.0000**)
(AR)	32.6755	(**0.4831**)	(0.5225)	22.3827	(**0.3803**)	(**0.3974**)	5.8760	(**0.2253**)	(**0.2387**)	33.6136	(**0.0310**)	(**0.0318**)
2 hr	.	52.2502	52.2478	.	36.3476	36.3494	.	8.2940	8.2904	.	56.8263	56.8558
(RW)	55.3027	(**0.0001**)	(**0.0001**)	40.0777	(**0.0003**)	(**0.0003**)	8.4684	(**0.0186**)	(**0.0184**)	71.1987	(**0.0000**)	(**0.0000**)
(AR)	52.3839	(**0.1931**)	(**0.1935**)	36.2961	(0.6031)	(0.6072)	8.3189	(**0.1240**)	(**0.1125**)	57.5232	(**0.0036**)	(**0.0050**)
4 hr	.	83.7143	83.7328	.	65.9489	65.9525	.	11.9902	11.9914	.	101.0908	101.0879
(RW)	88.4631	(**0.0003**)	(**0.0003**)	69.1170	(**0.0028**)	(**0.0028**)	12.3125	(**0.0087**)	(**0.0089**)	126.3154	(**0.0000**)	(**0.0000**)
(AR)	83.9541	(**0.2840**)	(**0.2998**)	66.0293	(**0.3017**)	(**0.3041**)	11.9968	(**0.4417**)	(**0.4525**)	102.0218	(**0.0458**)	(**0.0485**)

Table 13: Results of the **in-sample** predictions of the category specific order flow measures on different sampling frequencies (Freq). The forecasting study is conducted over a period of 32 weeks starting on Monday the 6^{th} of October 2003 and ending on Friday the 14^{th} of May 2004. These 32 weeks are divided into 8 periods of 4 weeks each, where the first 3 weeks are always considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second and third cell entries in parenthesis are the p-value from the modified Diebold-Mariano (mDM) test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).

Freq	BM-5	OP-5	IP-5	BM-6	OP-6	IP-6	BM-7	OP-7	IP-7	BM-8	OP-8	IP-8
1 min	.	2.6627	2.6613	.	1.9240	1.9238	.	3.1746	3.1693	.	0.7240	0.7239
(RW)	2.8578	(**0.0000**)	(**0.0000**)	1.9766	(**0.0000**)	(**0.0000**)	3.3768	(**0.0000**)	(**0.0000**)	0.7971	(**0.1475**)	(**0.1471**)
(AR)	2.7454	(**0.0000**)	(**0.0000**)	1.9344	(**0.0000**)	(**0.0000**)	3.2039	(**0.0000**)	(**0.0000**)	0.7265	(**0.0003**)	(**0.0002**)
2 min	.	4.0548	4.0575	.	3.0185	3.0210	.	5.2092	5.2056	.	1.1967	1.1954
(RW)	4.4574	(**0.0000**)	(**0.0000**)	3.0733	(**0.0000**)	(**0.0000**)	5.4727	(**0.0000**)	(**0.0000**)	1.3037	(**0.1529**)	(**0.1525**)
(AR)	4.2203	(**0.0000**)	(**0.0000**)	3.0333	(**0.0000**)	(**0.0000**)	5.2630	(**0.0000**)	(**0.0000**)	1.2003	(**0.0254**)	(**0.0022**)
5 min	.	7.5407	7.5485	.	5.2398	5.2454	.	9.7143	9.7153	.	2.5831	2.5830
(RW)	8.3385	(**0.0000**)	(**0.0000**)	5.3296	(**0.0000**)	(**0.0000**)	10.2025	(**0.0000**)	(**0.0000**)	2.6455	(**0.0393**)	(**0.0400**)
(AR)	7.8304	(**0.0000**)	(**0.0000**)	5.2662	(**0.0000**)	(**0.0000**)	9.8193	(**0.0000**)	(**0.0000**)	2.6045	(**0.0758**)	(**0.0779**)
10 min	.	12.1692	12.1819	.	7.8821	7.8903	.	15.3112	15.3124	.	3.8417	3.8418
(RW)	13.4704	(**0.0000**)	(**0.0000**)	8.0017	(**0.0000**)	(**0.0000**)	16.0741	(**0.0000**)	(**0.0000**)	3.9277	(**0.0074**)	(**0.0068**)
(AR)	12.5372	(**0.0000**)	(**0.0000**)	7.9106	(**0.0002**)	(**0.0002**)	15.3615	(**0.0591**)	(**0.0667**)	3.8643	(**0.0383**)	(**0.0347**)
15 min	.	16.1990	16.2111	.	9.9710	9.9745	.	19.8456	19.8464	.	4.8662	4.8678
(RW)	17.8872	(**0.0000**)	(**0.0000**)	10.0993	(**0.0000**)	(**0.0000**)	20.8999	(**0.0000**)	(**0.0000**)	4.9706	(**0.0111**)	(**0.0105**)
(AR)	16.5733	(**0.0000**)	(**0.0000**)	9.9829	(**0.0360**)	(**0.0798**)	19.8503	(**0.4701**)	(**0.4749**)	4.9016	(**0.0393**)	(**0.0371**)
20 min	.	19.6552	19.6528	.	11.6988	11.6999	.	22.8409	22.8464	.	5.9726	5.9750
(RW)	21.8687	(**0.0000**)	(**0.0000**)	11.8790	(**0.0000**)	(**0.0000**)	24.6665	(**0.0000**)	(**0.0000**)	6.1053	(**0.0110**)	(**0.0122**)
(AR)	20.1138	(**0.0000**)	(**0.0000**)	11.7201	(**0.0151**)	(**0.0208**)	23.0231	(**0.0001**)	(**0.0001**)	6.0462	(**0.0579**)	(**0.0642**)
25 min	.	22.9573	22.9671	.	13.2223	13.2237	.	26.9235	26.9249	.	6.3785	6.3820
(RW)	25.4635	(**0.0000**)	(**0.0000**)	13.4096	(**0.0000**)	(**0.0000**)	28.7503	(**0.0000**)	(**0.0000**)	6.5536	(**0.0082**)	(**0.0080**)
(AR)	23.3486	(**0.0000**)	(**0.0000**)	13.2341	(**0.1848**)	(**0.2025**)	27.0023	(**0.0607**)	(**0.0567**)	6.4416	(**0.0531**)	(**0.0544**)
30 min	.	27.1207	27.1266	.	15.1540	15.1554	.	32.4423	32.4378	.	7.0275	7.0261
(RW)	29.5857	(**0.0000**)	(**0.0000**)	15.3250	(**0.0000**)	(**0.0000**)	34.1397	(**0.0000**)	(**0.0000**)	7.2376	(**0.0086**)	(**0.0094**)
(AR)	27.4590	(**0.0000**)	(**0.0000**)	15.1372	(0.6326)	(0.6431)	32.6134	(**0.0012**)	(**0.0015**)	7.0998	(**0.0365**)	(**0.0401**)
45 min	.	35.4057	35.3963	.	19.0022	19.0036	.	41.7642	41.7748	.	9.4235	9.4286
(RW)	38.8158	(**0.0000**)	(**0.0000**)	19.2290	(**0.0001**)	(**0.0001**)	44.1179	(**0.0002**)	(**0.0002**)	9.6765	(**0.0297**)	(**0.0280**)
(AR)	35.8041	(**0.0015**)	(**0.0014**)	19.0306	(**0.0751**)	(**0.0917**)	41.8647	(**0.0145**)	(**0.0203**)	9.5666	(**0.0709**)	(**0.0681**)
1 hr	.	44.2274	44.2294	.	22.0024	21.9956	.	50.2901	50.3161	.	10.8078	10.8131
(RW)	48.1776	(**0.0000**)	(**0.0000**)	22.4658	(**0.0028**)	(**0.0028**)	53.3719	(**0.0002**)	(**0.0003**)	11.1289	(**0.0267**)	(**0.0274**)
(AR)	44.7921	(**0.0007**)	(**0.0007**)	22.0938	(**0.0721**)	(**0.0693**)	50.5215	(**0.0176**)	(**0.0214**)	10.9656	(**0.0523**)	(**0.0540**)
2 hr	.	72.8748	72.8933	.	31.6892	31.6867	.	83.6019	83.6420	.	16.0807	16.0723
(RW)	78.5813	(**0.0000**)	(**0.0000**)	32.8597	(**0.0073**)	(**0.0071**)	86.9648	(**0.0004**)	(**0.0003**)	16.5854	(**0.0497**)	(**0.0508**)
(AR)	73.2669	(**0.0335**)	(**0.0425**)	32.0076	(**0.0439**)	(**0.0437**)	83.8739	(**0.1859**)	(**0.1951**)	16.1938	(**0.1565**)	(**0.1540**)
4 hr	.	114.7352	114.7439	.	46.6595	46.6408	.	136.1893	136.1951	.	22.8727	22.8589
(RW)	125.9523	(**0.0000**)	(**0.0000**)	49.4934	(**0.0024**)	(**0.0024**)	141.1003	(**0.0046**)	(**0.0045**)	24.3249	(**0.0569**)	(**0.0574**)
(AR)	115.5674	(**0.0365**)	(**0.0385**)	47.2952	(**0.0294**)	(**0.0262**)	137.1682	(**0.1602**)	(**0.1650**)	22.9814	(**0.1261**)	(**0.1321**)

Table 14: Results of the **in-sample** predictions of the category specific order flow measures on different sampling frequencies (Freq). The forecasting study is conducted over a period of 32 weeks starting on Monday the 6^{th} of October 2003 and ending on Friday the 14^{th} of May 2004. These 32 weeks are divided into 8 periods of 4 weeks each, where the first 3 weeks are always considered as the in-sample estimation periods and the last weeks are always considered as the out-of-sample forecasting periods. Weekends and holidays are excluded from the analysis. The first cell entry is the Root-Mean-Squared-Prediction Error (RMSPE) of the associated forecasting model. The second and third cell entries in parenthesis are the p-value from the modified Diebold-Mariano (mDM) test with the null hypothesis that the RMSPE of the associated forecasting model is not smaller than the RMSPE of the corresponding Random Walk or AR(p) benchmark model (RW, AR). P-values in bold correspond to those cases where the RMSPE of the associated forecasting model is smaller than the RMSPE of the corresponding benchmark model (RW, AR).