Testing the effect of technical analysis on market quality and order book dynamics

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Abstract

We find empirical support for the theoretical finding in agent-based models of limit order book markets that the effect of technical trading on market quality is not positive. When signals occur, technical traders lower liquidity as proxied by the relative spread, the effective spread, the realized spread, the dispersion and the slope in the order book. Technical trading is also found to be accompanied by rising volatility. There is overall strong empirical support against the hypothesis that technical trading has no effect on order book dynamics.

JEL Classification: G14, D82, C5

Keywords: Agent-based model, Liquidity, Technical Analysis, Limit Order Market

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1 Introduction

With a recent focus on uninformed traders, agent-based models have been rising to the challenge of designing realistic microstructure models of limit order book markets. Still, much work remains to be done to determine what traders can exactly learn from market information in these markets (Chiarella et al., 2015). This is especially true given the lack of empirical evidence for a large set of agent-based models. We attempt to fill this gap by using a unique tick-by-tick Euronext 100 stock dataset to evaluate Chiarella and Ladley (2016)'s agent-based model into which the effect of technical analysis (TA) on order book dynamics is studied. We zoom in on this model because of its use of a numerical technique to identify a Markov perfect equilibrium and hence determine the optimal trading strategies followed by technical traders.

TA is about the use of information contained in past market data to predict future returns. A variety of tools based on data analysis and visualization techniques is employed. TA includes the use of moving averages, break out rules, and technical indicators, such as the Moving Average Convergence/Divergence (MACD), the Relative Strength Index (RSI) or the Stochastic Oscillator (STOCH). Once signals are identified, technical traders take positions in the predicted direction to benefit from future price movements.

Although there is rather strong evidence that TA strategies are not effective in generating abnormal returns (Duvinage et al., 2013; Bajgrowicz and Scaillet, 2012; Park and Irwin, 2007; Marshall et al., 2006; Allen and Karjalainen, 1999), these strategies are still used by retail investors. Hoffmann and Shefrin (2014) show that retail investors who employ TA perform much worse than the other investors: not only is their trading activity higher but they also take higher risks. According to Etheber et al. (2014), moving averages are used by around 10% of the retail investors and overall trading activity increases by 30% on days for which there are trading signals based on moving averages.

TA strategies are also widely implemented by professional investors, such as fund managers (Menkhoff, 2010) and forex traders (Cheung et al., 2004). In Wang et al. (2012), trading activity by institutional investors is estimated to increase around signals based on the Stochastic Oscillator. Allen and Taylor (1990) and Taylor and Allen (1992) find that 90% of traders employed TA tools, at short horizons in particular. Schulmeister (2009) confirm that TA is increasingly used at the intra-day level. This has coincided with shifts in the market landscape where algorithmic trading is now the dominating strategy. According to Brogaard et al.

(2014), high-frequency traders would even be able to predict price changes several seconds in advance.

Despite the shortening of timescales over which TA may be used, there is still very little empirical work considering the effect of technical traders in a microstructure context. In this paper, we test Chiarella and Ladley (2016)'s theoretical predictions of the impact of TA on order books by using a unique tick-by-tick Euronext 100 stock dataset. We focus on three technical indicators: the MACD, the RSI, and the STOCH. These three indicators all depend on the use of moving averages that Chiarella et al. (2006) view as critical tools. We perform an intraday event study around technical trading signals sent by the MACD, the RSI, and the STOCH. Our median-based event study methodology enables us to zoom in on the effect of technical analysis on market quality precisely when the technical signals may be exploited by market participants. To the best of our knowledge, no intraday event study has been carried out to analyze the link between intraday market quality dynamics and properly identified technical trading signals. We complement this non-parametric study with a panel data model in which we control for the differences in trading strategy observed between technical traders, informed traders, and liquidity traders. Finally, we test whether technical trading causes liquidity dynamics in the sense of Granger causality.

We validate most of Chiarella and Ladley (2016)'s theoretical findings. In particular, we validate Chiarella and Ladley (2016)'s main conclusion that the overall effect of technical trading on market quality is not positive and much more ambiguous than previously thought. We find that technical trading at the time of the signals lowers liquidity as estimated by the relative spread, the effective spread, the realized spread, the dispersion and slope of the order book. We also find additional negative impact of technical trading on market quality, most notably in terms of rising volatility. Finally, we find strong empirical support against the hypothesis that technical trading has no effect on order book dynamics.

2 Model and hypotheses

Chiarella and Ladley (2016)'s model on which we focus in this paper has been derived from the extent literature on agent-based models. We start from Chiarella et al. (2009)'s model in which traders' order submission strategies are specified by distinguishing (uninformed) chartists and (informed) fundamentalists. Although the paper does not rely on any analytical solution, it still assumes arbitrary behavior of technical traders, as traders randomly select a price inside a range and then submit an order based on the relationship between this random price, the best quotes and the target price at which the agent would be pleased to close the position.

To allow traders to determine their order submission endogenously according to market conditions, Chiarella et al. (2015) introduce a genetic algorithm (GA) learning with a classifier system into an agent-based model of limit order markets. It examines how traders deal with market information and learn from it. It shows that uninformed traders pay more attention to technical rules and that more learning by uninformed traders enhances market efficiency, which is not necessarily the case when informed traders learn. Opposite to the learning of informed traders, learning makes uninformed traders submit less aggressive limit orders and more market orders. It also shows that private values can have significant impact in the short run, but not in the long run. One implication is that the probability of informed trading (PIN) is positively related to the volatility and the bid-ask spread.

To implement realistic strategies and sound order submission rules, Chiarella and Ladley (2016) identify optimal strategies for technical traders by using a numerical technique originally employed by Goettler et al. (2005) who extended the analytical model of Parlour (1998). To identify a Markov perfect equilibrium and to analyze the behavior of the market, Goettler et al. (2005) could only model a single type of trader who had a fixed distribution of valuations and could not modify orders after they were submitted.

In Goettler et al. (2009) the analytical framework is extended to the case of asymmetric information and traders may cancel and resubmit orders over time. As a result of these changes, the Markov perfect equilibrium requirement could not be met anymore: for the model to be numerically tractable, the current order book could not incorporate all the information contained in the recent history of order submissions. However, the optimization process leads to a stable set of strategies which were optimal given the available information.

Chiarella and Ladley (2016) use this approach to model the interaction between technical and informed traders in an order book. They focus on technical traders who use momentum based rules. They are able to derive optimal strategies in the sense that both groups of traders submit and modify their orders in order to maximize their expected payoff, conditional on the state of the market.

The main findings of Chiarella and Ladley (2016) is that the presence of technical traders has an ambiguous effect on the market quality. They write that: 'The [quoted] spread decreases but at the same time the number of orders in the book falls. The effective spread for informed traders increases indicating higher transaction costs. Price efficiency increases, i.e.

the market price tracks the fundamental more accurately and volatility goes down. Analysis of the strategies of technical traders shows that they predominantly act as liquidity suppliers, i.e. using limit order more frequently, and market orders less frequently, than informed traders with the same valuations when technical traders are not present. These results contrast with the findings of Hendershott et al. (2011) [about] high frequency traders, many of whom use momentum based strategies, increase liquidity within markets. Whilst technical traders within our model do supply liquidity their overall effect is ambiguous.' Based on these theoretical findings, we state the following hypotheses.

H1: Technical trading has no effect on ex ante and ex post liquidity.

H2: Technical trading has no effect on adverse selection costs.

H3: Technical trading has no effect on price efficiency.

H4: Technical trading has no effect on order book dynamics.

To test these hypotheses, we perform an intraday event study around technical trading signals sent by the MACD, the RSI, and the STOCH. Our median-based event study methodology enables us to zoom in on the effect of technical analysis on market quality precisely when the technical signals may be exploited by market participants. To the best of our knowledge, no intraday event study has been carried out to analyze the link between intraday market quality dynamics and properly identified technical trading signals.

To complement our nonparametric event study, we also implement a parametric analysis through a panel data model to check the link between intraday market quality and technical analysis on average, i.e. by analyzing the behavior of technical traders in general (before and after the occurrence of trading signals). To improve our understanding of Chiarella and Ladley (2016)'s model, we create five categories of traders based on their profile and strategies. The first category includes aggressive technical traders (ATT) who submit market and marketable limit orders in the direction suggested by a technical signal. They do not submit any aggressive order in the direction opposed to the signal. Second, patient technical traders (PTT) follow the same process but they submit limit orders instead of liquidity-taking orders. Those traders do not pay the spread for immediacy and compete with other limit orders to gain price and time priority. The third category is for impatient informed traders (IIT) who are trading aggressively in the dominant direction assessed through trade imbalance. They submit market and marketable limit orders at the buy side when the signed trade imbalance is bigger than

40%[1] and at the sell side when the signed trade imbalance is lower than -40%. Patient informed traders (PIT) constitute the fourth category and follow the same process, except that they do not accept to pay for immediacy. They only submit limit orders in the direction of the signed trade imbalance. Finally, the last category is for liquidity traders (LT) who submit only limit orders on both sides of the order book when the trade imbalance is larger than 40% in absolute value.

In our empirical analysis, we also assign each submitted order to a category in order to allow market members to change their behavior through time, as proposed by Chiarella et al. (2015) in their theoretical model.

In the empirical application, we focus on three mainstream technical analysis indicators: Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI) and Stochastics oscillator (STOCH). The MACD oscillator is obtained from exponential moving averages (EMA) of the price curve. It is computed as follows:

$$\begin{aligned} Diff_t &= EMA12(price)_t - EMA26(price)_t, \\ Signal_t &= EMA9(Diff)_t, \\ MACD &= Diff_t - Signal_t, \end{aligned} \tag{2.1}$$

where $Diff_t$ is also called the MACD curve, $Signal_t$, the signal line and $MACD$, the MACD histogram. The MACD histogram is an oscillator around the zero line. When the histogram is above (below) zero, the market is bullish (bearish). Orders are usually submitted when the histogram crosses the zero line, i.e., a buy (sell) order when the histogram becomes positive (negative).

The RSI is a strength oscillator evaluating the power of the current momentum and it is computed as follows:

$$\begin{aligned} RS_t &= \tfrac{EMAn_t(U)}{EMAn_t(D)} \\ RSI_t &= 100 - \tfrac{100}{1+RS_t}, \end{aligned} \tag{2.2}$$

where $EMAn(U)$ is the exponential moving averages of the upward price changes over the n periods preceding t, $EMAn(D)$ is the exponential moving averages of the downward price changes over the n periods preceding t. n is usually set to 14. By construction, the oscillator

[1] In preliminary analyzes, we have simulated the process on a set of arbitrary thresholds. The results remain unchanged if we consider 50% or 60%.

has values comprised in [0,100]. Signals generated by the RSI are assessed by comparison with two constant lines. When the RSI is bigger than 70, the asset is overbought and a price reversal is most likely to occur. When the RSI crosses the 30 line down, the asset is oversold and a price reversal is also likely to happen. Traders usually submit sell (buy) orders when the RSI crosses up (down) the 70 (30) line.

The stochastics oscillator is computed as follows:

$$\begin{aligned} \%K_t &= 100 \times \tfrac{Close_t - LL_n}{HH_n - LH_n} \\ \%D_t &= SMAd(\%K_t), \end{aligned} \tag{2.3}$$

where LL_n, HH_n and LH_n denote the lowest low price, the highest high price and the lowest high price over the n periods preceding t, respectively. n and d are usually set to 14 and 3, respectively. The mechanics are mostly similar to RSI but the levels for the two curves are set to 80 and 20 for the overbought and oversold conditions, respectively.

3 Data and market quality proxies

3.1 Data

We use tick-by-tick data for the Euronext 100 Index for 61 trading days from February 1, 2006 to April 30, 2006. The use of this dataset presents two key advantages. First, we have information on the full order book, including undisclosed data on market members' ID. By using market members' ID, we are able to disentangle buyer-initiated and seller-initiated trades without any error margin. In many market microstructure studies, the Lee and Ready (1991) algorithm is used to categorize buyer and seller-initiated trades. Although this algorithm has proved to be relatively efficient, misclassification still occurs. In our dataset, there is none since we know the order that initiates the transaction. Second, we avoid the volume shift and market fragmentation that have been occurring since the implementation phase of MiFID. As today's trading environment is much more decentralized than before, more recent datasets are often less representative and less reliable. In a number of recent studies, there is often insufficient information on the level of trading activity that prevails on the competing Multilateral Trading Facilities (MTFs) and dark pools. This exhaustive dataset allows us to calculate a large set of market quality proxies.

3.2 Market Quality Proxies

Market quality is associated with liquidity, transaction costs and market efficiency. It refers to "a market's ability to meet its dual goals of liquidity and price discovery" (O'Hara and Ye, 2011). Efficient and liquid markets should therefore exhibit a high market quality. Although these concepts are well known, there is no consensus on the best way to measure them and, when there is one, the data are not always available.

In order to evaluate market quality across all its dimensions, we compute a large set of proxies.

The first set of measures relate to the spread - the effective spread (ES), the realized spread (RealS) and the relative quoted spread (RS). All of these spread measures proxy for the cost of immediacy which is an important dimension of market quality. The formulae used to compute these proxies for a trade i in stock j at time t are given by:

$$\begin{aligned} ES_{i,j} &= 2abs(p_{i,j} - m_{i,j,t}), \\ RealS_{i,j} &= 2abs(p_{i,j} - m_{i,j,t+1}), \\ RS_{j,t} &= (a_{j,t} - b_{j,t})/m_{i,j,t}, \end{aligned} \tag{3.1}$$

where $p_{i,j}$ denotes the average execution price of trade i occurring on stock j, $b_{j,t}$, $a_{j,t}$ and $m_{j,t}$ respectively correspond to the bid, ask and mid prices prevailing at time t for stock j, which is the last reporting time before the execution of trade i, and $t+1$ denotes the first reported record after trade i. The first two proxies are ex-post spread measures computed essentially from trade data while the last one is computed from quotes and is therefore related to ex-ante liquidity and market quality. These variables are computed each time a trade occurs. We then aggregate the data on a 15-minute basis by computing the mean of these proxies for each stock separately.

As outlined by Hendershott and Moulton (2011), the effective spread (ES) captures the difference between the current transaction price and the quote midpoint which is an estimate of the true value of the security. The realized spread is a similar measure but points to a spread that has been caused by the occurrence of the trade. The relative spread is a measure of the current bid-ask spread and captures the direct cost of immediacy for small quantities.

Adverse selection cost is another component of transaction costs and, as a result, also constitutes a component of market quality. As previously presented and as Hendershott and Moulton (2011) argue, the effective spread can be decomposed into a permanent and transitory component. The transitory component is estimated through the realized spread. The percentage price impact is a proxy for the permanent portion and hence reflects adverse selection. We compute the percentage price impact of a trade i for stock j at time t as follows:

$$PPI_{i,t} = 2q_{i,t}(m_{i,j,t+5} - m_{i,j,t})/m_{i,j,t}, \tag{3.2}$$

where $q_{i,t}$ is a variable that reflects trade direction, i.e. it equals 1 for buyer-initiated trades and -1 otherwise. As for spreads, the percentage price impact is computed for each transaction and averaged over 15-minute intervals to create a unique estimate for each interval.

Beside these measures for immediacy and adverse selection, we examine Amihud (2002)'s illiquidity ratio. Amihud (2002)'s illiquidity ratio is the price response to a one-unit volume. The lower the return for a given volume, the higher the liquidity. Amihud (2002)'s illiquidity ratio is computed as:

$$IL_t = \frac{|r_t|}{v_t}, \tag{3.3}$$

where r_t is the return and v_t is the volume, both associated with time interval t for a given stock.

Our dataset also encompasses depth proxies. Depth is computed by summing the quantities on each side of the book at the Best Bid and Offer (BBO) and for the five best limits.

We measure liquidity at the end of each trading interval, which enables us to measure the direct relation between the event and liquidity. We first calculate the traditional liquidity proxies such as relative spread, depths (displayed and hidden, in number of shares) and order imbalances (at different order book levels). We also use dispersion and slope measures which are respectively presented in Kang and Yeo (2008) and Naes and Skjeltorp (2006). Then, we compute trading activity measures as buyer and seller-initiated trades and imbalances, in number of trades.[2] Finally, we evaluate volatility using the High-Low measure for each time interval.

[2]These measures are computed with the sum over each interval.

We also include two proxies capturing the density of the order book. We first compute the dispersion proxy proposed by Kang and Yeo (2008), i.e., how limits are far from each other or from the quoted midpoint.

$$Dispersion_{i,t} = \frac{1}{2}\left(\frac{\sum_{j=1}^{n} w_{i,j,t}^{Bid} Dst_{i,j,t}^{Bid}}{\sum_{j=1}^{n} w_{i,j,t}^{Bid}} + \frac{\sum_{j=1}^{n} w_{i,j,t}^{Ask} Dst_{i,j,t}^{Ask}}{\sum_{j=1}^{n} w_{i,j,t}^{Ask}}\right), \tag{3.4}$$

where, for security i and interval t, $w_{i,j,t}$ are the weights which are equal to quantities, offer and bid sizes, at the j^{th} price limit normalized by the total depth of the five best limits, $Dst_{i,j,t}^{Bid} = (Price_{i,j-1,t}^{Bid} - Price_{i,j,t}^{Bid})$ and, $Dst_{i,j,t}^{Ask} = (Price_{i,j,t}^{Ask} - Price_{i,j-1,t}^{Ask})$. The midquote is used for the distance of the first best limits.

We then use the slope of the book following Naes and Skjeltorp (2006), that is:

$$SLOPE_{i,t} = \frac{DE_{i,t} + SE_{i,t}}{2}, \tag{3.5}$$

where $DE_{i,t}$ and $SE_{i,t}$ are the demand and supply elasticities respectively and are computed as:

$$DE_{i,t} = \frac{1}{5}\left(\frac{v_1^B}{|p_1^B/p_0 - 1|} + \sum_{\tau=1}^{4} \frac{v_{\tau+1}^B/v_\tau^B - 1}{|p_{\tau+1}^B/p_\tau^B - 1|}\right), \tag{3.6}$$

$$SE_{i,t} = \frac{1}{5}\left(\frac{v_1^A}{p_1^A/p_0 - 1} + \sum_{\tau=1}^{4} \frac{v_{\tau+1}^A/v_\tau^A - 1}{p_{\tau+1}^A/p_\tau^A - 1}\right). \tag{3.7}$$

p_τ^B and p_τ^A are the prices, respectively at the bid and at the ask, appearing at the quote τ. p_0 denotes the quoted midpoint. Finally, v_τ^B and v_τ^A are the natural logarithm of accumulated total share volume at the limit τ respectively for the bid and the ask.[3]

In order to calculate trade imbalances, we compute the total number of trades and quantities respectively for buyer and seller-initiated trades. With these variables, we compute the imbalance as follows:

$$ImbalanceN_{i,t} = \frac{NTrades_{i,t}^{Buy} - NTrades_{i,t}^{Sell}}{NTrades_{i,t}^{Buy} + NTrades_{i,t}^{Sell}} \tag{3.8}$$

[3]By accumulated, we mean the sum of the quantities outstanding at that limit and the sum of all quantities outstanding at each better quote.

where $NTrades_{i,t}^{Buy}$ is the number of buyer-initiated trades occurring at the t^{th} interval for stock i and $NTrades_{i,t}^{Sell}$ is the number of seller-initiated trades occurring at the t^{th} interval for stock i.

Market quality is also directly influenced by price efficiency and volatility. In order to take into account these components of market quality, we include in our full analysis one measure of market efficiency and two proxies for volatility.

We estimate price efficiency using the absolute value of the return autocorrelation. As suggested by Hendershott and Moulton (2011), we base the calculation on quote midpoint returns in order to avoid issues induced by the bid-ask bounce. We compute 1-minute returns and calculate the autocorrelation on a 15-minute basis. In the initial idea of price efficiency, if prices follow a random walk, the return autocorrelation should equal zero. We use the absolute value in order to measure the extent to which prices deviate from a random walk process, meaning that the measure is inversely related to price efficiency. [4]

Our volatility proxy includes the realized volatility, computed by aggregating all tick-by-tick movements over a 15-minute interval.

Finally, we also address order submission behavior by including in our analysis the percentage of limit, marketable limit, and market orders submitted at each interval for each stock. We also include the percentage of completely executed, cancelled, and modified orders.

4 Empirical analyses

4.1 Event Study

We perform intraday event studies of market quality around the technical signals explained in Section 2. This original median-based event study methodology has been initially proposed by Boudt and Petitjean (2014). Mazza (2015), Mazza and Petitjean (2016), and Mazza and Petitjean (2018) then apply the technique to a larger set of liquidity proxies, including those presented in the current paper. An event corresponds to the identification of a technical

[4]Hendershott and Moulton (2011) also examined two other price efficiency proxies: the 5/30-min variance ratio and the pricing error. We argue against the use of the first one since the proxy does not bring new elements in the analysis. The latter is based on Hasbrouck (1993) which uses a vector autoregressive representation (VAR) to evaluate market quality and price efficiency. This model grounds on quote revisions after trades and on the informational content of trades. We choose not to use this proxy for several reasons that are also invoked by O'Hara and Ye (2011).

signal, meaning that the signal has occurred during the interval preceding the event. The null hypothesis states that the occurrence of a technical signal is not related to a change in market quality. The alternative hypothesis postulates that the occurrence of a technical signal is related to a positive or negative change in market quality. We focus on an event window of [-3,+3] containing seven observations: three observations before the signal, the time of the signal and three observations after the signal. This leads us to consider market quality behavior 45 minutes before and after the apparition of the event. Following Boudt and Petitjean (2014), we compute the abnormal measures in the following ways.

For imbalances, percentage price impact and autocorrelation coefficients, we compute the abnormality as follows:

$$Abnormal_{i,t,p} = Proxy_{i,t,p} - Median^{NE}_{i,t,p}, \tag{4.1}$$

where $Proxy_{i,t,p}$ is the analyzed proxy p for stock i for the time interval t and $Median^{NE}_{i,t,p}$ is the median of the proxy p for stock i across all non-events occurring during the time interval t.

For the other measures, the calculation method is:

$$Abnormal_{i,t,p} = \frac{Proxy_{i,t,p} - Median^{NE}_{i,t,p}}{Median^{NE}_{i,t,p}}, \tag{4.2}$$

where $Proxy_{i,t,p}$ is the analyzed proxy for stock i for the time interval t and $Median^{NE}_{i,t,p}$ is the median of the proxy p for stock i across all non-events occurring during the time interval t.

We need to separate these two categories of variables as imbalances, percentage price impact and autocorrelation coefficients may be negative. We apply these processes separately for each market quality measure. We then aggregate the results obtained for each stock to form median patterns of market quality behavior around each event and for each proxy. Our abnormal measure deals with the intraday pattern of market quality that has been well documented in the literature (Tóth et al., 2009; Mu et al., 2010; Mazza, 2015; Mazza and Petitjean, 2016, 2018). We choose the median as it is a more robust measure of central tendency, compared to the mean, as the distributions of market quality proxies are heavily skewed. We analyze these patterns to check whether the abnormality is significantly different from zero. For this purpose, we use a standard non parametric sign test that does not require any assumptions about the shape of the distribution. Our null hypothesis postulates that the median of the abnormal measure equals zero. The alternative hypothesis postulates the opposite. The statistic M is computed as follows:

$$M = \frac{N_+ - N_-}{2}, \tag{4.3}$$

where M follows a binomial distribution, N_+ is the number of positive values and N_- is the number of negative values. Values equal to zero are discarded.

We then analyze the p-values of each time interval of the window and check whether the differences are significant or not. If the p-value at the event interval is significant, the technical signal is associated to a particular change of market quality. This signal may thus lead to a given configuration of the limit order book or a new dynamic in trading behavior. If p-values are significant before the signal, the signal may be a response to a particular state of market quality. If p-values are significant after the signal, a change in market quality may correspond to a response to the signal.

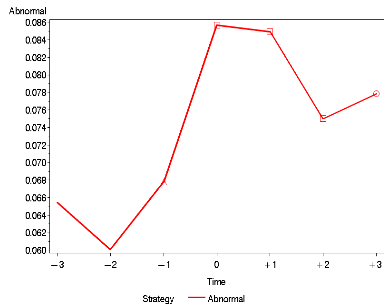
Let us turn to the empirical results regarding the five hypotheses derived from the theoretical findings of Chiarella and Ladley (2016).

H1: Technical trading has no effect on ex ante and ex post liquidity.

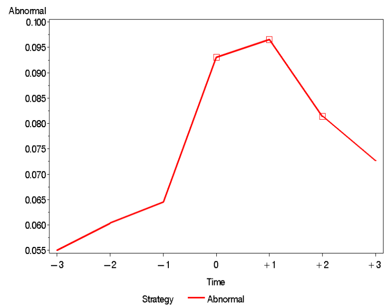
We clearly reject this null hypothesis. Most liquidity proxies go in the same direction: technical trading at the time of the signals lowers liquidity. With respect to the first dimension of liquidity (as measured by width), market liquidity is indeed worsened by the occurrence of technical trading signals. Both ex ante and ex post trading costs increase. Figure 1 points to a significant increase in the relative (quoted) spread, which measures ex-ante liquidity and the direct cost of immediacy for small quantities. Figure 2 shows that the effective spread widens as well. Finally, the realized spread, which is a enhanced measure of ex-post trading costs, shows a significant peak around the trading signals, as shown on Figure 3. The spread difference during these intervals is also economically significant.

Although no clear pattern can be observed for the second dimension of liquidity (as measured by depth, on Figures 4 and 5), we nevertheless observe that depth at the ask seems to drop before buy signals and that it seems to peak before sell signals. Both of these patterns occur with low resiliency.

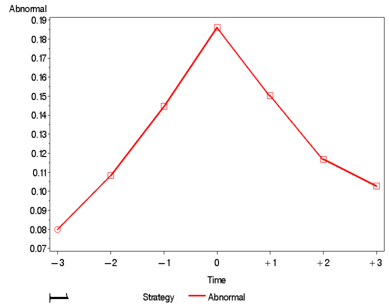
Figure 1:



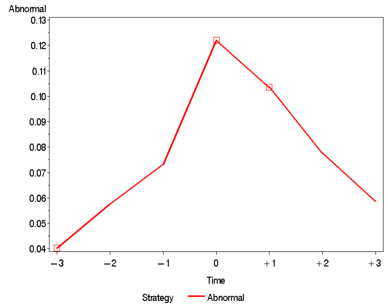
(a) Relative Spread - MACD (Buy)



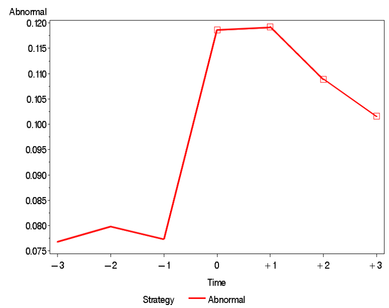
(b) Relative Spread - MACD (Sell)



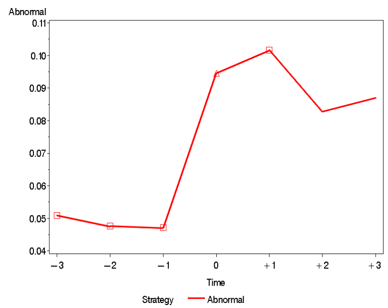
(c) Relative Spread - RSI (Buy)



(d) Relative Spread - RSI (Sell)



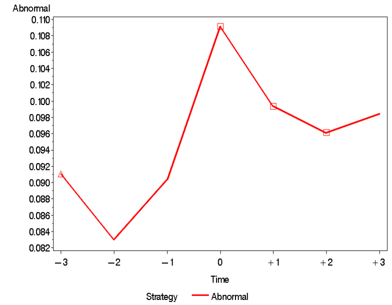
(e) Relative Spread - STOCH (Buy)



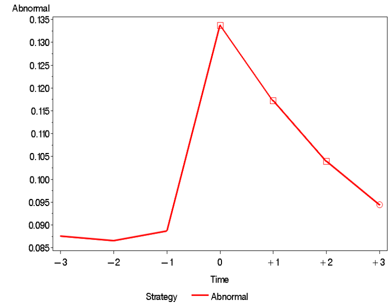
(f) Relative Spread - STOCH (Sell)

These figures show the intra-window pattern for the relative spread. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

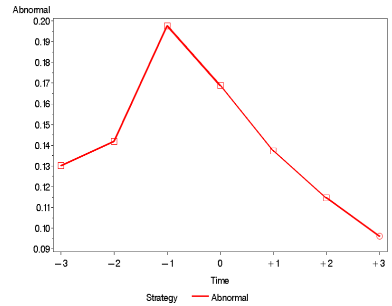
Figure 2:



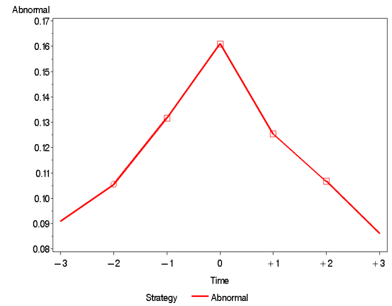
(a) Effective Spread - MACD (Buy)



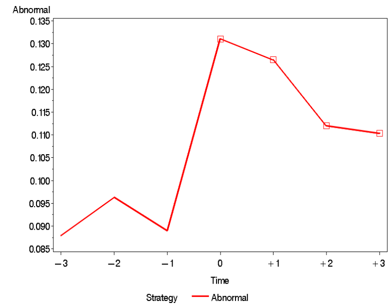
(b) Effective Spread - MACD (Sell)



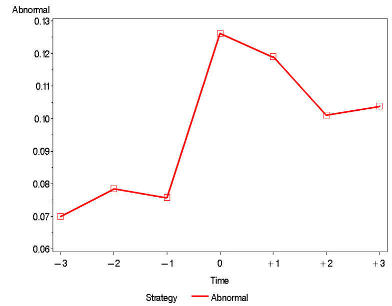
(c) Effective Spread - RSI (Buy)



(d) Effective Spread - RSI (Sell)



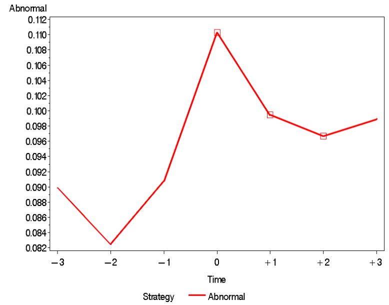
(e) Effective Spread - STOCH (Buy)



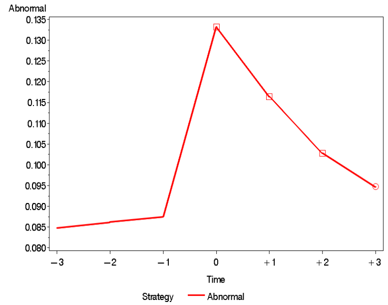
(f) Effective Spread - STOCH (Sell)

These figures show the intra-window pattern for the effective spread. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

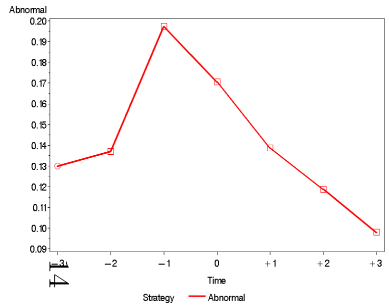
Figure 3:



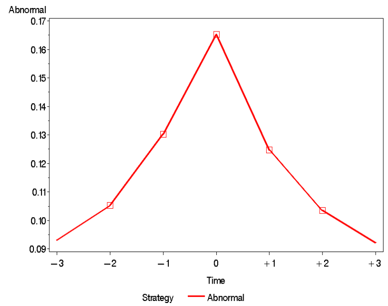
(a) Realized Spread - MACD (Buy)



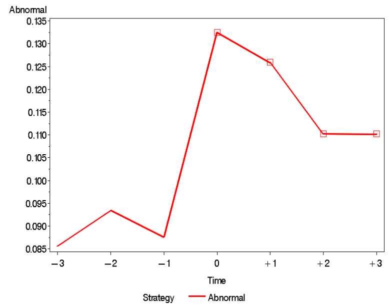
(b) Realized Spread - MACD (Sell)



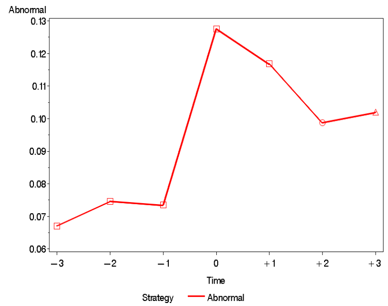
(c) Realized Spread - RSI (Buy)



(d) Realized Spread - RSI (Sell)



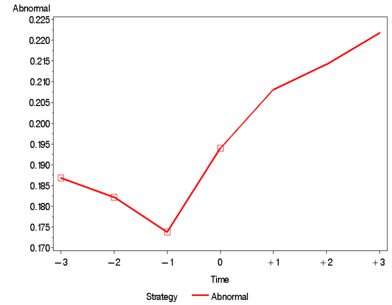
(e) Realized Spread - STOCH (Buy)



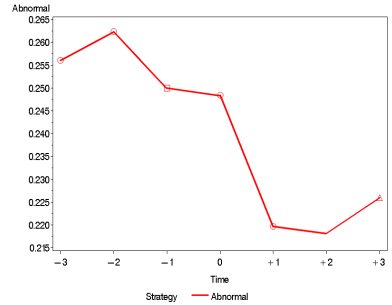
(f) Realized Spread - STOCH (Sell)

These figures show the intra-window pattern for the realized spread. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

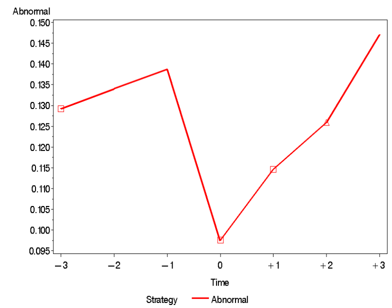
Figure 4:



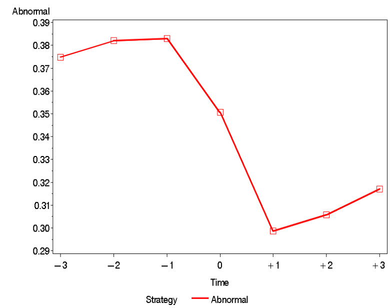
(a) Depth 5 Best Ask - MACD (Buy)



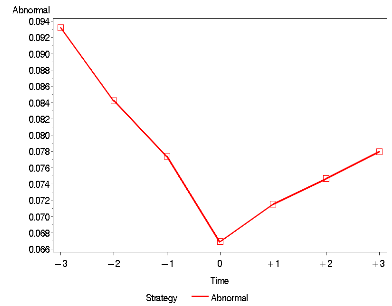
(b) Depth 5 Best Ask - MACD (Sell)



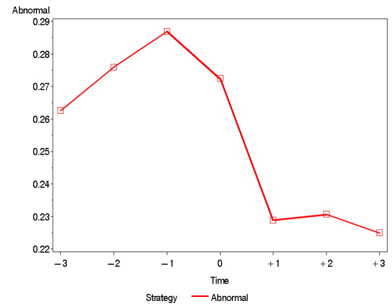
(c) Depth 5 Best Ask - RSI (Buy)



(d) Depth 5 Best Ask - RSI (Sell)



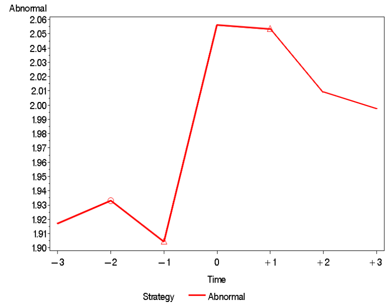
(e) Depth 5 Best Ask - STOCH (Buy)



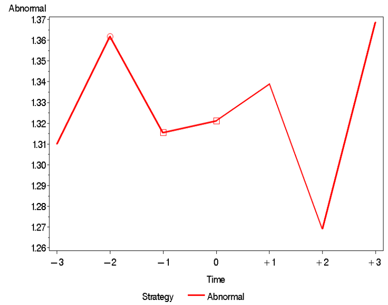
(f) Depth 5 Best Ask - STOCH (Sell)

These figures show the intra-window pattern for the quantities displayed at the five best quantities at the ask side. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

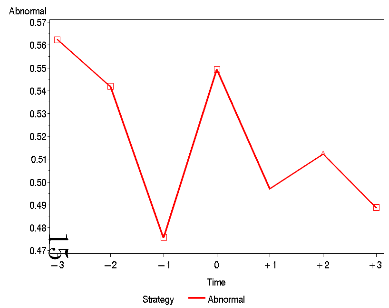
Figure 5:



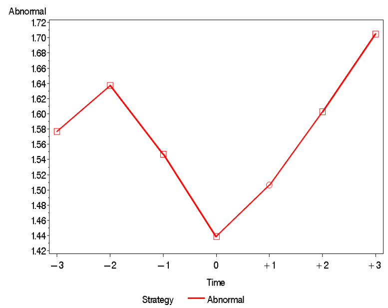
(a) Depth 5 Best Bid - MACD (Buy)



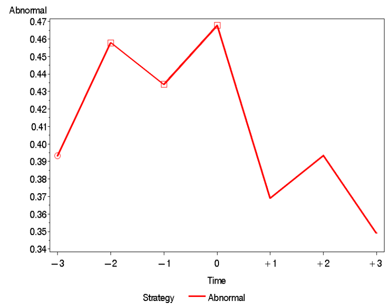
(b) Depth 5 Best Bid - MACD (Sell)



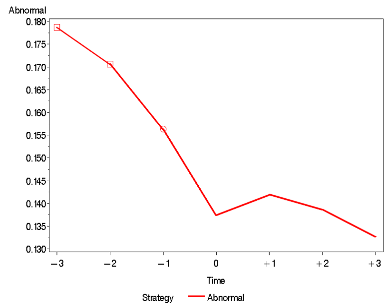
(c) Depth 5 Best Bid - RSI (Buy)



(d) Depth 5 Best Bid - RSI (Sell)



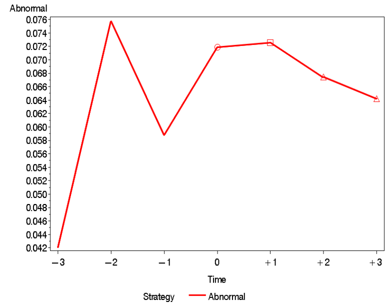
(e) Depth 5 Best Bid - STOCH (Buy)



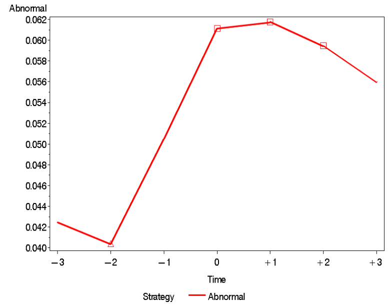
(f) Depth 5 Best Bid - STOCH (Sell)

These figures show the intra-window pattern for the quantities displayed at the five best quantities at the bid side. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

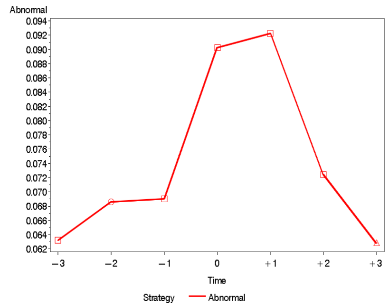
Figure 6:



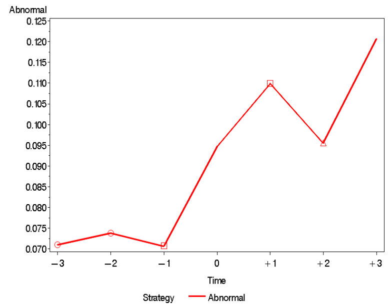
(a) Dispersion - MACD (Buy)



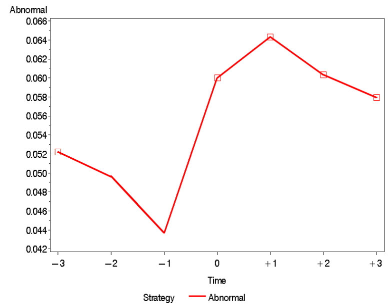
(b) Dispersion - MACD (Sell)



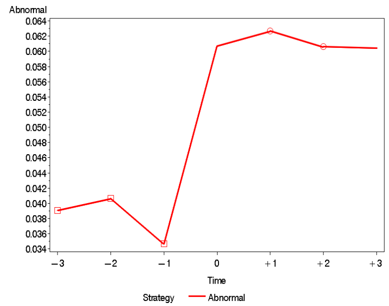
(c) Dispersion - RSI (Buy)



(d) Dispersion - RSI (Sell)



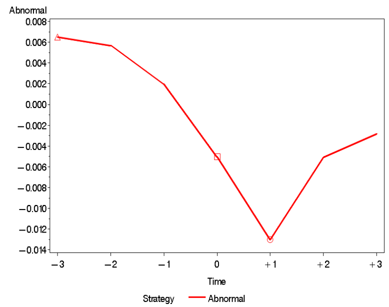
(e) Dispersion - STOCH (Buy)



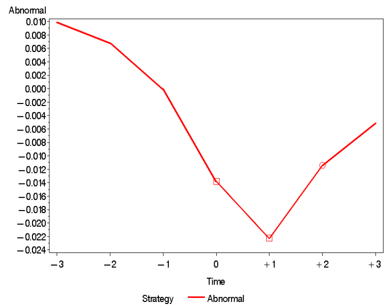
(f) Dispersion - STOCH (Sell)

These figures show the intra-window pattern for the dispersion measure. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

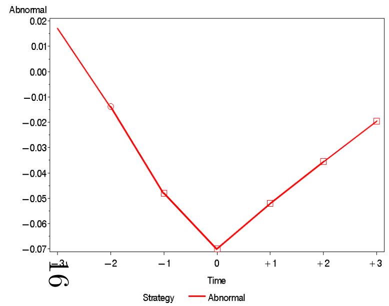
Figure 7:



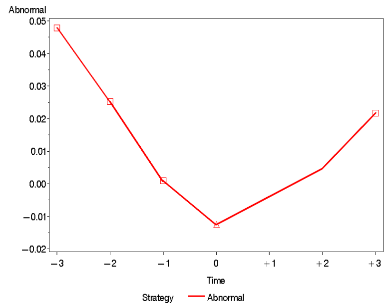
(a) Slope - MACD (Buy)



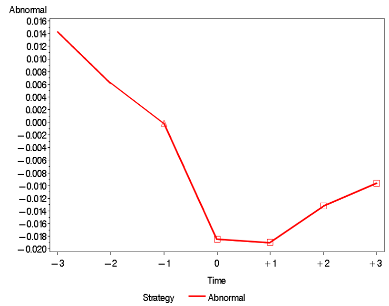
(b) Slope - MACD (Sell)



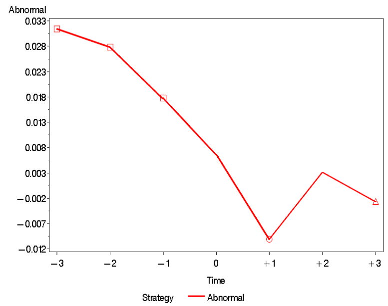
(c) Slope - RSI (Buy)



(d) Slope - RSI (Sell)



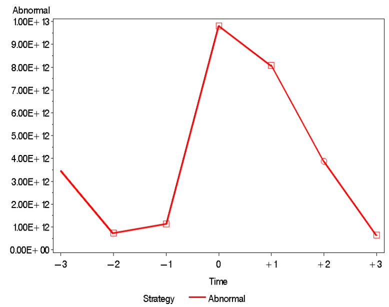
(e) Slope - STOCH (Buy)



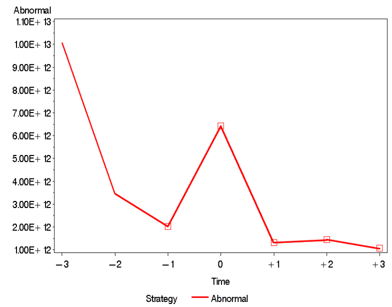
(f) Slope - STOCH (Sell)

These figures show the intra-window pattern for the slope measure. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

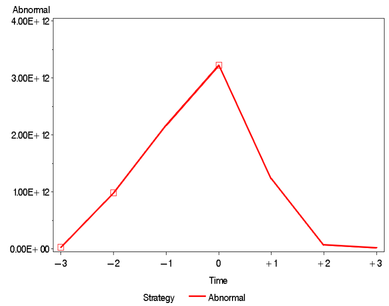
Figure 8:



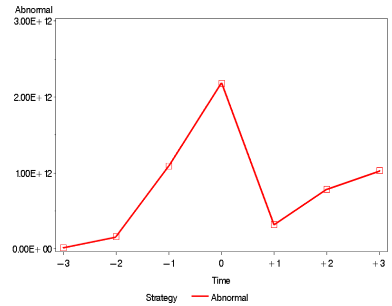
(a) Amihud - MACD (Buy)



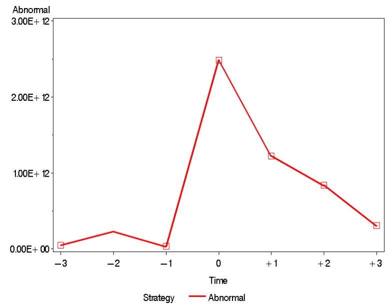
(b) Amihud - MACD (Sell)



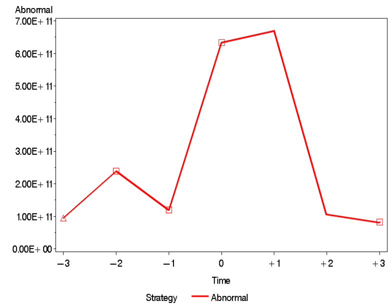
(c) Amihud - RSI (Buy)



(d) Amihud - RSI (Sell)



(e) Amihud - STOCH (Buy)



(f) Amihud - STOCH (Sell)

These figures show the intra-window pattern for the Amihud illiquidity measure. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

When we look at the density of the order book, we also conclude that ex-ante liquidity is lower around technical signals. First, the dispersion in the order book rises at the time of the signal or just after (Figure 6). Dispersion tend to increase when competition among traders is lower and traders do not try to gain price priority. By not fighting for price priority, market members increase the spread and the distance between each price limit, decreasing the density of the order book. Second, the slope falls down quite sharply (Figure 7). In fact, the slope tends to be positively related to liquidity and negatively correlated with volatility. Therefore, a more gentle slope indicates that volumes in the order book are less concentrated around a given price limit: because traders do not agree about the value of the security, accumulated depth quickly decreases when a small price variation occurs (low elasticity). So, accumulated depth only increases for larger price variations because traders have different views on the price of the security.

Finally, the Amihud illiquidity ratio leads to the same conclusion (Figure 8): At the time of the signal, illiquidity increases significantly at a 1% level for all signals, either buy or sell, and then significantly drops in $t+1$.

H2: Technical trading has no effect on adverse selection costs.

As shown on Figure 9, we can also reject this hypothesis since the percentage price impact of a trade increases, with some degree of anticipation. As a proxy for adverse selection, the rise in the percentage price impact may be the reason behind the rise in the effective spread, which is also derived from the Chiarella and Ladley (2016) model.

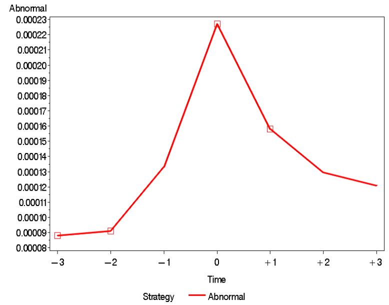
H3: Technical trading has no effect on price efficiency.

The autocorrelation in midquote returns significantly peaks for the MACD and the stochastics (Figure 10). For the RSI, it peaks with some anticipation (at $t-1$). Consistent with the previous results, the realized volatility also increases (Figure 11). Overall, price efficiency seems to decrease around the occurrence of a technical signal.

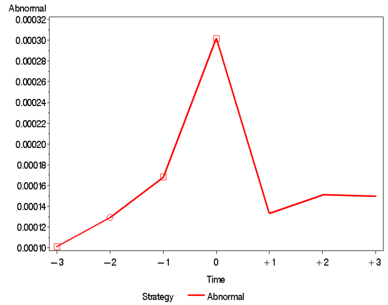
H4: Technical trading has no effect on order book dynamics.

This hypothesis is clearly rejected for several reasons. First, the number of limit orders increases at the time of the signals (Figure 12). Second, this rise is accompanied by a fall in the number of market orders (Figure 13) and marketable limit orders (Figure 14). Following Bloomfield et al. (2005), we conjecture that informed traders tend to become less aggressive and provide more liquidity around technical signals which they typically disregard when determining the fair value: They become more patient and avoid to pay the wider spread. It

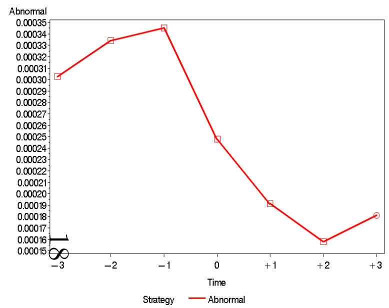
Figure 9:



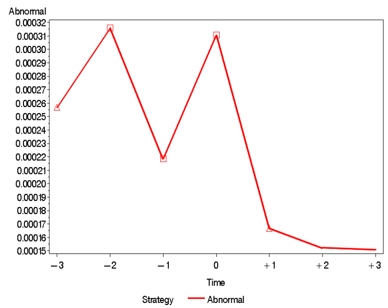
(a) Percentage Price Impact - MACD (Buy)



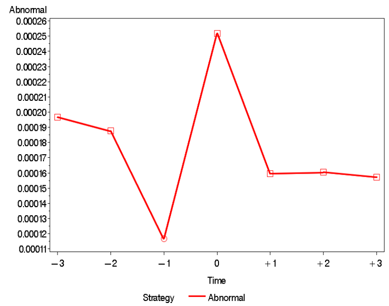
(b) Percentage Price Impact - MACD (Sell)



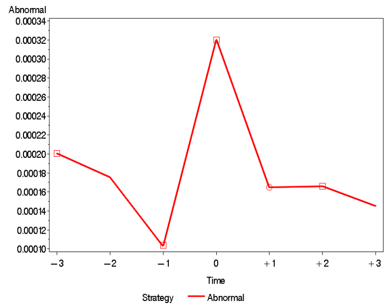
(c) Percentage Price Impact - RSI (Buy)



(d) Percentage Price Impact - RSI (Sell)



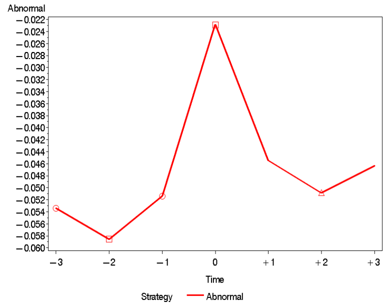
(e) Percentage Price Impact - STOCH (Buy)



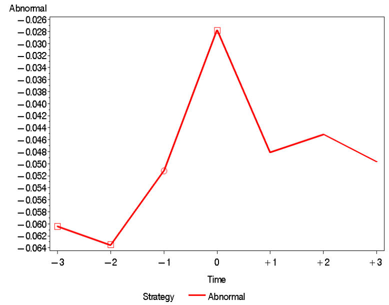
(f) Percentage Price Impact - STOCH (Sell)

These figures show the intra-window pattern for the percentage price impact. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

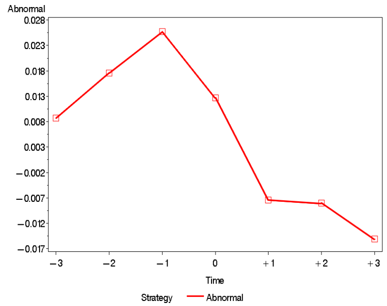
Figure 10:



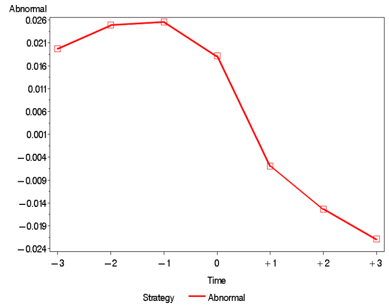
(a) Autocorr - MACD (Buy)



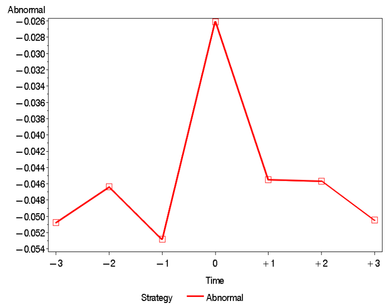
(b) Autocorr - MACD (Sell)



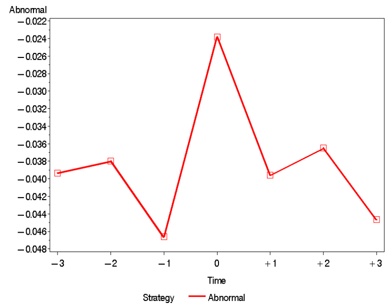
(c) Autocorr - RSI (Buy)



(d) Autocorr - RSI (Sell)



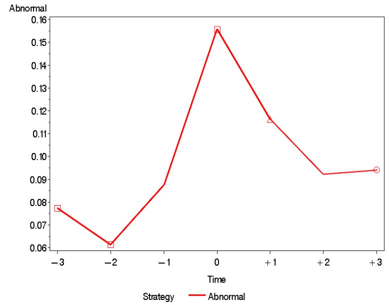
(e) Autocorr - STOCH (Buy)



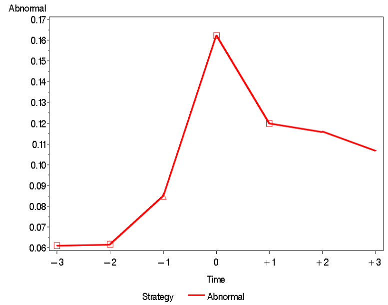
(f) Autocorr - STOCH (Sell)

These figures show the intra-window pattern for the autocorrelation coefficient. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

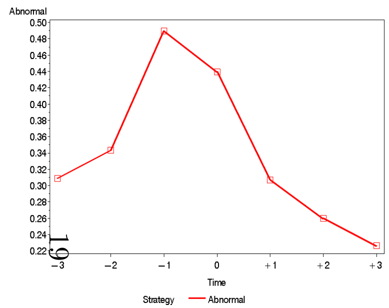
Figure 11:



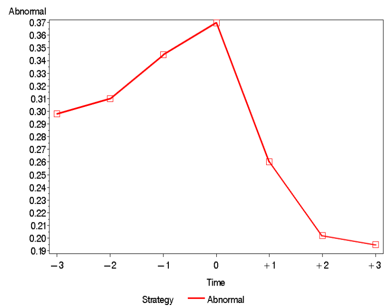
(a) Realized Volatility - MACD (Buy)



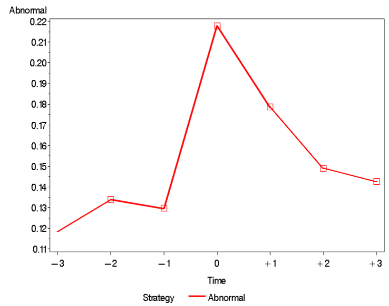
(b) Realized Volatility - MACD (Sell)



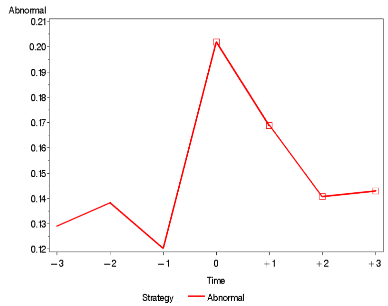
(c) Realized Volatility - RSI (Buy)



(d) Realized Volatility - RSI (Sell)



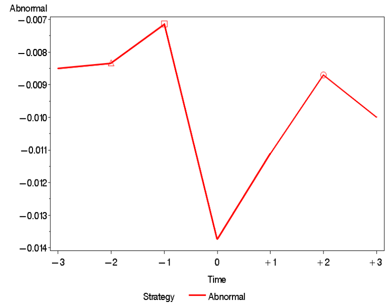
(e) Realized Volatility - STOCH (Buy)



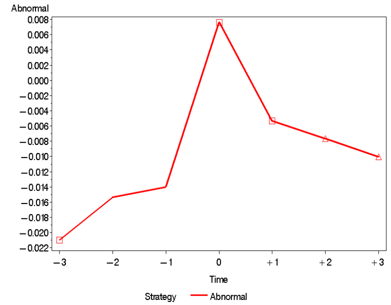
(f) Realized Volatility - STOCH (Sell)

These figures show the intra-window pattern for the realized volatility. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

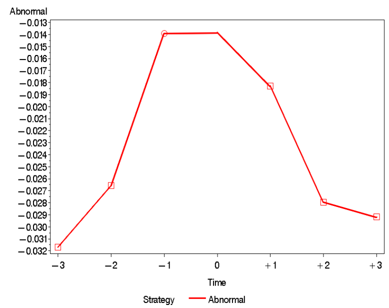
Figure 12:



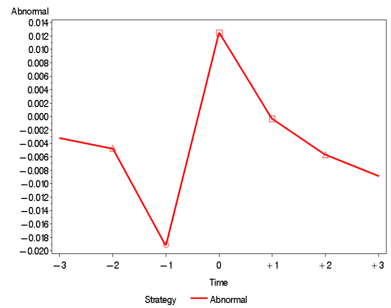
(a) Number of limit orders - MACD (Buy)



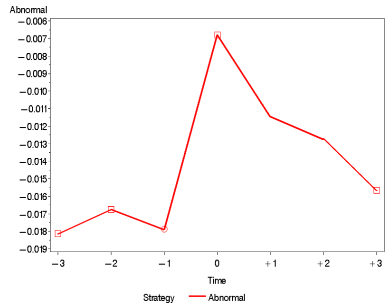
(b) Number of limit orders - MACD (Sell)



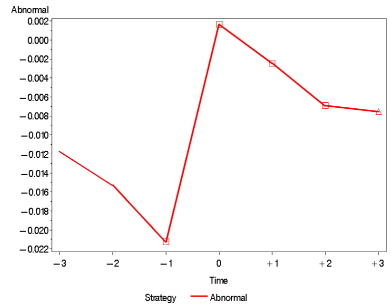
(c) Number of limit orders - RSI (Buy)



(d) Number of limit orders - RSI (Sell)



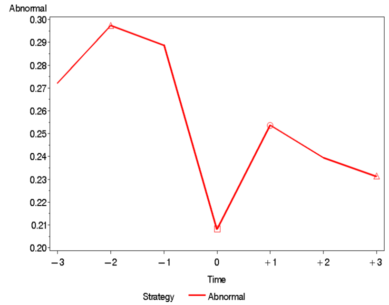
(e) Number of limit orders - STOCH (Buy)



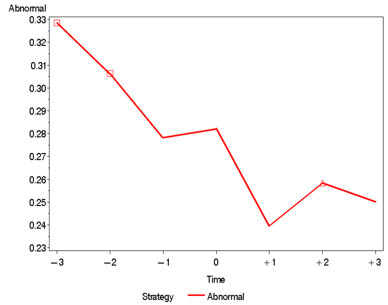
(f) Number of limit orders - STOCH (Sell)

These figures show the intra-window pattern for the number of limit orders. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

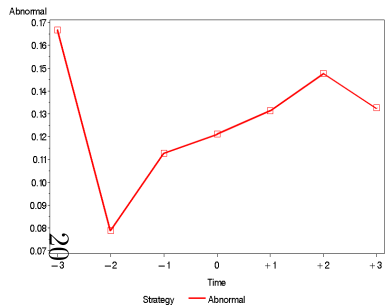
Figure 13:



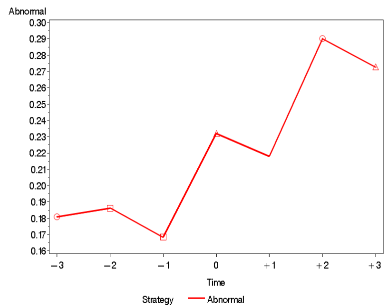
(a) Number of market orders - MACD (Buy)



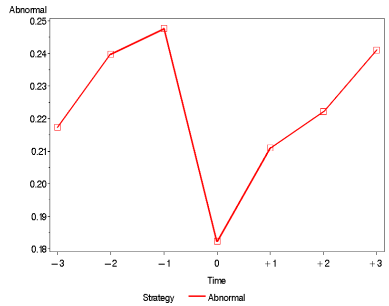
(b) Number of market orders - MACD (Sell)



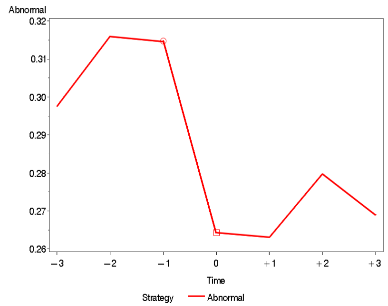
(c) Number of market orders - RSI (Buy)



(d) Number of market orders - RSI (Sell)



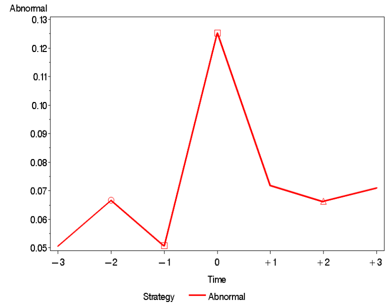
(e) Number of market orders - STOCH (Buy)



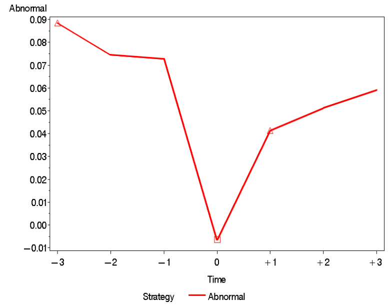
(f) Number of market orders - STOCH (Sell)

These figures show the intra-window pattern for the number of market orders. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

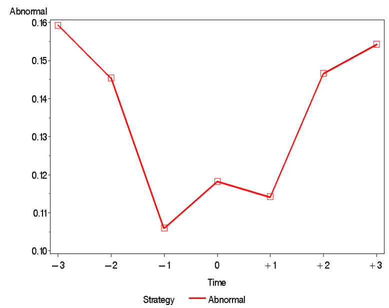
Figure 14:



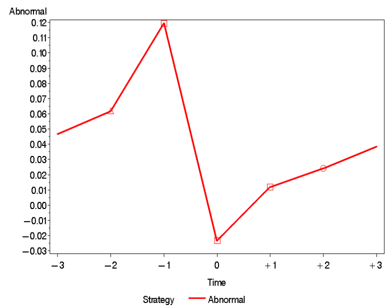
(a) Number of marketable limit orders - MACD (Buy)



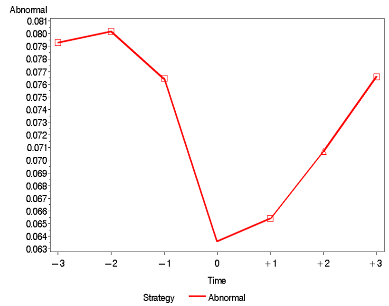
(b) Number of marketable limit orders - MACD (Sell)



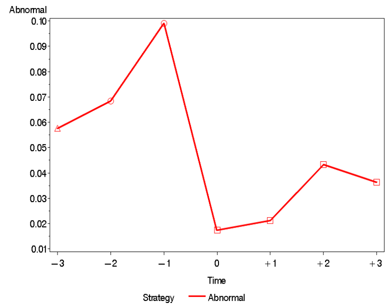
(c) Number of marketable limit orders - RSI (Buy)



(d) Number of marketable limit orders - RSI (Sell)



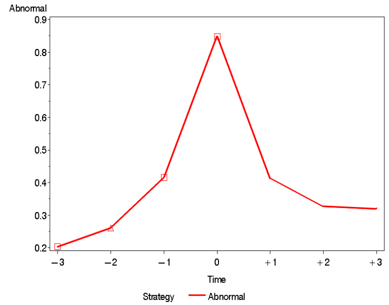
(e) Number of marketable limit orders - STOCH (Buy)



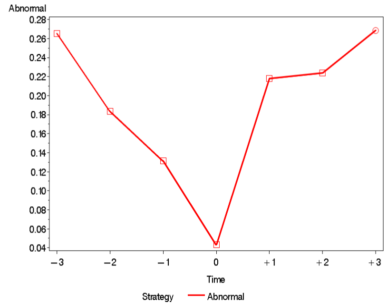
(f) Number of marketable limit orders - STOCH (Sell)

These figures show the intra-window pattern for the number of marketable limit orders. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

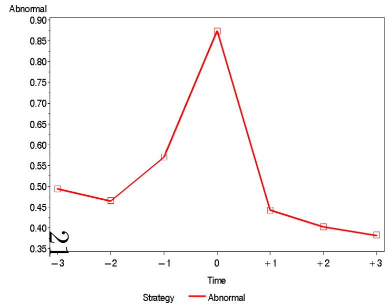
Figure 15:



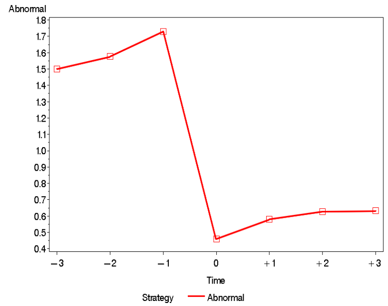
(a) Number of buyer-initiated trades - MACD (Buy)



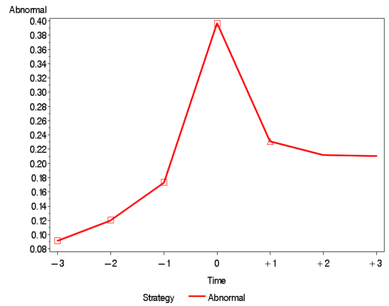
(b) Number of buyer-initiated trades - MACD (Sell)



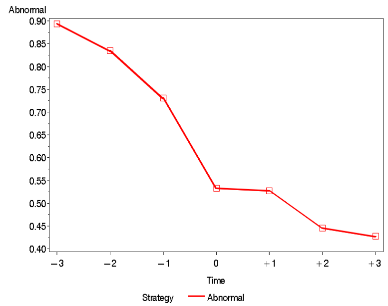
(c) Number of buyer-initiated trades - RSI (Buy)



(d) Number of buyer-initiated trades - RSI (Sell)



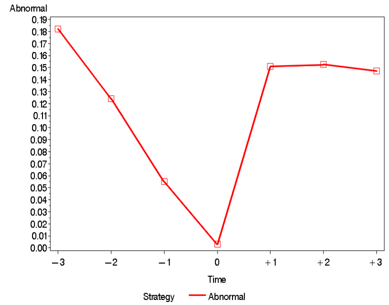
(e) Number of buyer-initiated trades - STOCH (Buy)



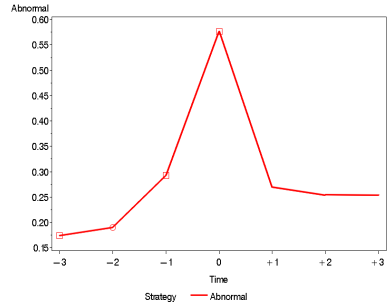
(f) Number of buyer-initiated trades - STOCH (Sell)

These figures show the intra-window pattern for the number of buyer-initiated trades. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

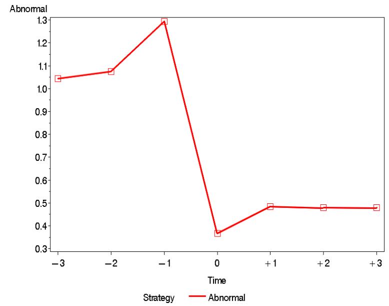
Figure 16:



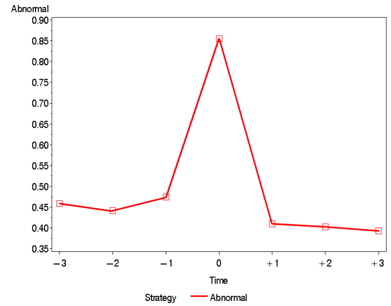
(a) Number of seller-initiated trades - MACD (Buy)



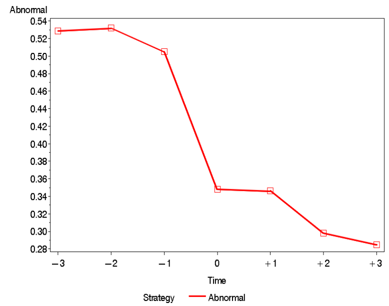
(b) Number of seller-initiated trades - MACD (Sell)



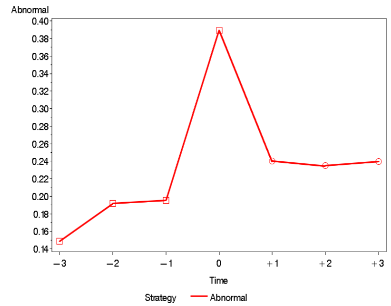
(c) Number of seller-initiated trades - RSI (Buy)



(d) Number of seller-initiated trades - RSI (Sell)



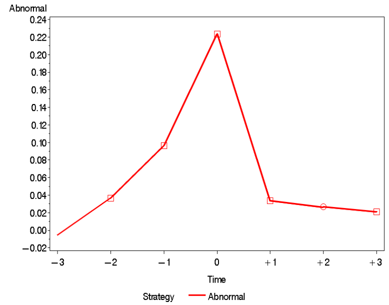
(e) Number of seller-initiated trades - STOCH (Buy)



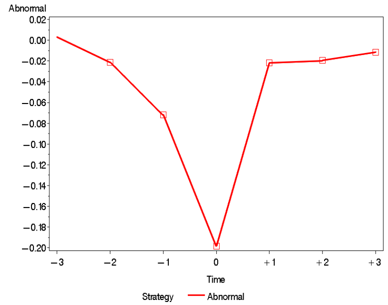
(f) Number of seller-initiated trades - STOCH (Sell)

These figures show the intra-window pattern for the number of seller-initiated trades. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

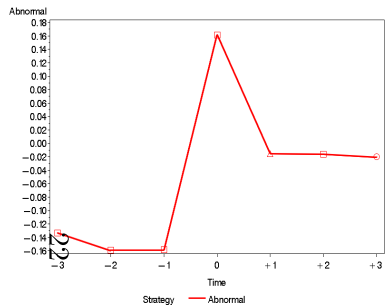
Figure 17:



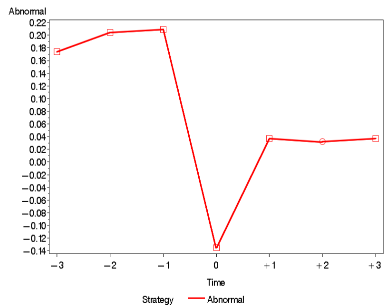
(a) Trade Imbalance - MACD (Buy)



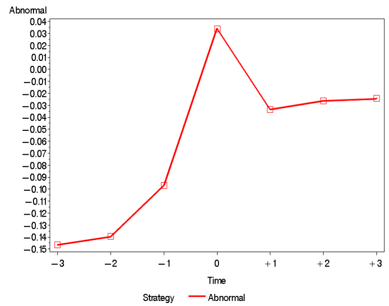
(b) Trade Imbalance - MACD (Sell)



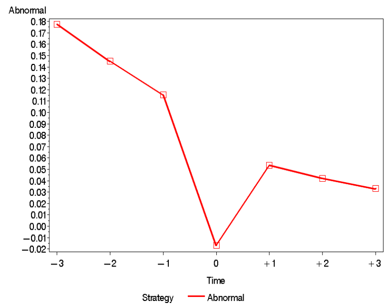
(c) Trade Imbalance - RSI (Buy)



(d) Trade Imbalance - RSI (Sell)



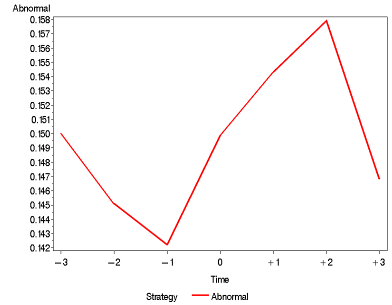
(e) Trade Imbalance - STOCH (Buy)



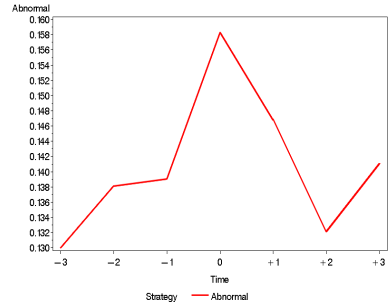
(f) Trade Imbalance - STOCH (Sell)

These figures show the intra-window pattern for the trade imbalance. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

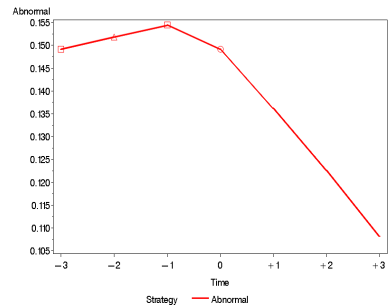
Figure 18:



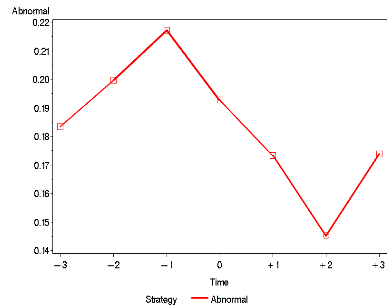
(a) 5 Best Limits Imbalance - MACD (Buy)



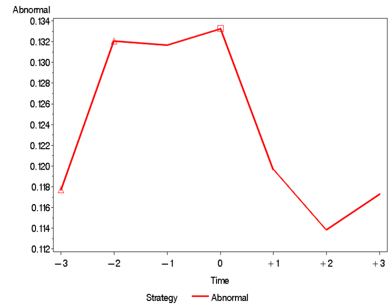
(b) 5 Best Limits Imbalance - MACD (Sell)



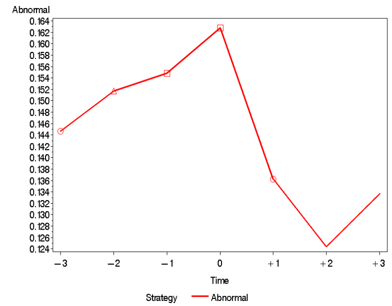
(c) 5 Best Limits Imbalance - RSI (Buy)



(d) 5 Best Limits Imbalance - RSI (Sell)



(e) 5 Best Limits Imbalance - STOCH (Buy)



(f) 5 Best Limits Imbalance - STOCH (Sell)

These figures show the intra-window pattern for the 5 best limits imbalance. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

seems to be a wise strategy since the total number of trades increase as well, as indicated by the rise in both the number of buyer-initiated trades when the signal is bullish and the number of seller-initiated trades when the signal is bearish (Figures 15 and 16).

Trade imbalance clearly shows that the technical signals are heavily screened by traders as the variation is perfectly in line with the expected trading dynamics implied by the signals (Figures 17). The results further indicate that post-signal resiliency is rather slow. Order imbalance points in the same direction (Figures 18), although evidence is weaker with no clear pattern for MACD.

Finally, the occurrence of technical signals leads to some clear changes in the order submission strategies followed by market participants. The monitoring of existing orders is clearly dynamic since the number of modified and canceled orders significantly increases at $t = 0$ (Figures 19 and 20).

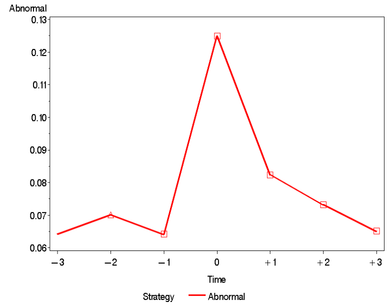
4.2 Panel regressions

As a robustness check, we also follow a parametric methodology and run the following fixed-effect panel model :

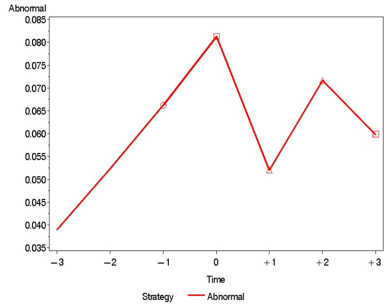
$$\begin{aligned}
&\Delta M_{i,t} = \beta_0 + \beta_1 MACD_{i,t}^{Buy} + \beta_2 MACD_{i,t}^{Sell} + \beta_1 STOCH_{i,t}^{Buy} + \beta_2 STOCH_{i,t}^{Sell} + \\
&\beta_1 RSI_{i,t}^{Buy} + \beta_2 RSI_{i,t}^{Sell} + \textstyle\sum_{k=1}^{5} \left(\alpha_{1,i,k} MO_{i,t,k}^{Buy} + \alpha_{2,i,k} MO_{i,t,k}^{Sell} \right) + \\
&\textstyle\sum_{k=1}^{5} \left(\alpha_{3,i,k} LO_{i,t,k}^{Buy} + \alpha_{4,i,k} LO_{i,t,k}^{Sell} \right) + \textstyle\sum_{k=1}^{5} \left(\alpha_{5,i,k} MLO_{i,t,k}^{Buy} + \alpha_{6,i,k} MLO_{i,t,k}^{Sell} \right) + \\
&\textstyle\sum_{k=1}^{5} \left(\alpha_{7,i,k} EXE_{i,t,k}^{Buy} + \alpha_{8,i,k} EXE_{i,t,k}^{Sell} \right) + \textstyle\sum_{k=1}^{5} \left(\alpha_{9,i,k} CAN_{i,t,k}^{Buy} + \alpha_{10,i,k} CAN_{i,t,k}^{Sell} \right) + \\
&\textstyle\sum_{k=1}^{5} \left(\alpha_{11,i,k} Modif_{i,t,k}^{Buy} + \alpha_{12,i,k} Modif_{i,t,k}^{Sell} \right) + \textstyle\sum_{i=2}^{89} \gamma_i S_i + \nu_{i,t},
\end{aligned} \tag{4.4}$$

where $M_{i,t}$ is the market quality proxy measured at interval t for stock i, and Δ indicates the percentage change of the variable, i.e. $\Delta M_{i,t} = \frac{M_{i,t} - M_{i,t-1}}{M_{i,t-1}}$. All the explanatory variables are defined in the previous sections. $MACD_{i,t}^{Buy}$ is a dummy variable which equals 1 when a buying signal for the MACD has been identified for stock i at time interval t. $MACD_{i,t}^{Sell}$, $STOCH_{i,t}^{Buy}$, $STOCH_{i,t}^{Sell}$, $RSI_{i,t}^{Buy}$ and, $RSI_{i,t}^{Sell}$ follow the same logic. Regarding the control

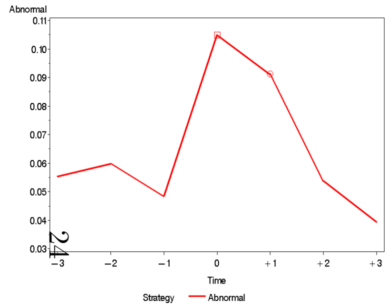
Figure 19:



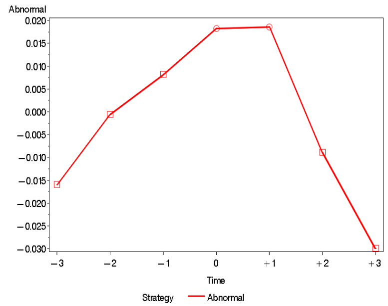
(a) Number of modified orders - MACD (Buy)



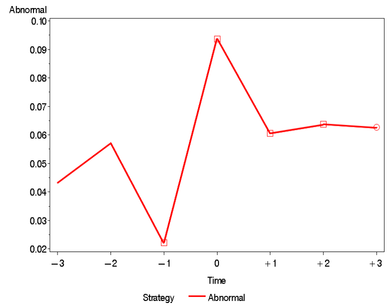
(b) Number of modified orders - MACD (Sell)



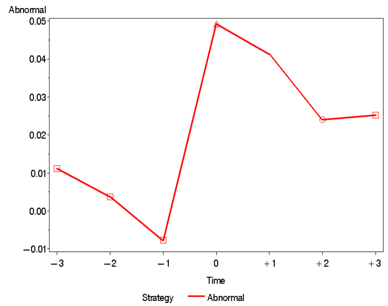
(c) Number of modified orders - RSI (Buy)



(d) Number of modified orders - RSI (Sell)



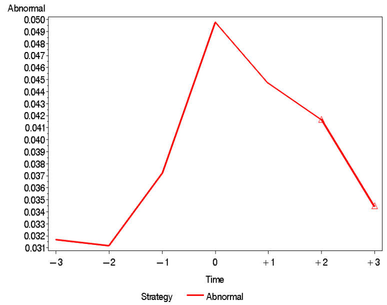
(e) Number of modified orders - STOCH (Buy)



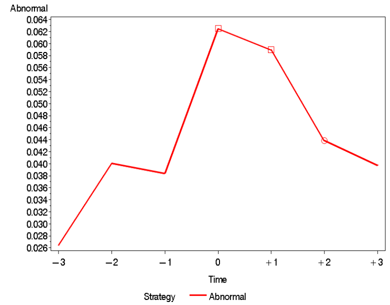
(f) Number of modified orders - STOCH (Sell)

These figures show the intra-window pattern for the number of modified orders. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

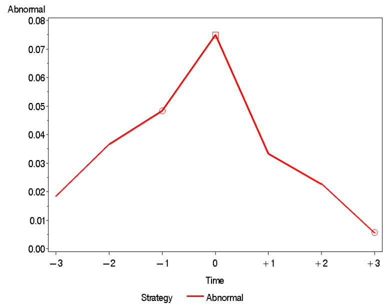
Figure 20:



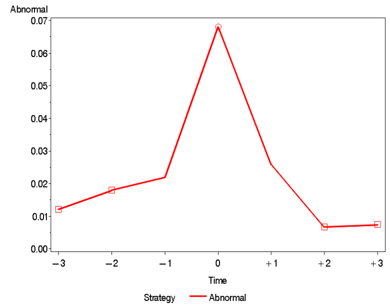
(a) Number of cancelled orders - MACD (Buy)



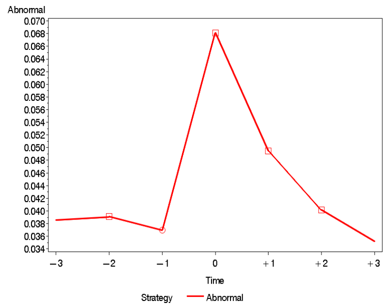
(b) Number of cancelled orders - MACD (Sell)



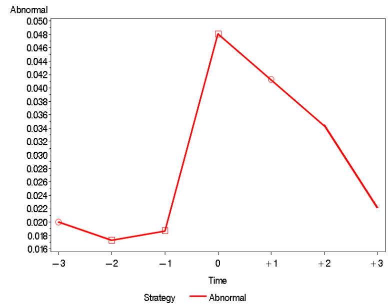
(c) Number of cancelled orders - RSI (Buy)



(d) Number of cancelled orders - RSI (Sell)



(e) Number of cancelled orders - STOCH (Buy)



(f) Number of cancelled orders - STOCH (Sell)

These figures show the intra-window pattern for the number of cancelled orders. The window encompasses 7 observations: 3 intervals before the signal, the signal and 3 intervals after the signals. Squares (□), triangles (△), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

variables. k under the summation symbol refers to the different categories of traders that have been identified previously. $MO_{i,t,k}^{Buy}$, $LO_{i,t,k}^{Buy}$, $MLO_{i,t,k}^{Buy}$, $EXE_{i,t,k}^{Buy}$, $CAN_{i,t,k}^{Buy}$, and $Modif_{i,t,k}^{Buy}$ respectively denote the percentage of market orders, limit orders, marketable limit order, executed orders, cancelled orders and modified orders submitted at the bid side by the members belonging to category k for stock i during interval t. A similar process is applied to sell orders. The $n-1$ S_i dummies denote the stocks' fixed effects that are present in the sample. As outlined in Chordia et al. (2000), we use first differences in order to deal with econometric issues that affect market quality variables, such as high persistence and/or non-stationarity.

We estimate the model by using the clustered standard errors approach that is described in Petersen (2009) to correct for the bias in the OLS standard errors that arises for panel estimation. The standard errors produced by this method are robust to within cluster correlation. As outlined by Petersen (2009), this method produces unbiased standard errors when there is a firm-specific effect and is superior to White, Newey-West, and Fama-MacBeth correction methods in such a case.

Most of the empirical findings confirm the non-parametric event study, as indicated in Table 1.[5]

H1: Technical trading has no effect on ex ante and ex post liquidity.

We reject this hypothesis, as it was the case in the event study. First, the technical dummies exhibit positive and statistically significant coefficient estimates in all the spread equations. Second, technical signals are rather associated with lower depth. Third, liquidity is also negatively associated with technical signals when dispersion and slope are used as liquidity proxies: in accordance with the event study, coefficient estimates are negative (and statistically significant) in the slope equation and positive (and statistically significant) in the dispersion equation. Nevertheless, we do not find any significant relationship between technical indicators and the Amihud ratio.

H2: Technical trading has no effect on adverse selection costs.

We fail to reject the null since the coefficient estimates related to the technical indicators are not statistically significant. We fail to confirm the non-parametric analysis which pointed to a rise in adverse selection costs,

H3: Technical trading has no effect on price efficiency.

[5]To save space, we only report the dummies related to the three technical indicators, with separate buy and sell signals.

We reject the null hypothesis, although evidence in the event study was stronger. While autocorrelation in the miquote returns is unaffected by technical trading, realized volatility increases significantly.

Table 1: Technical trading, market quality and order book dynamics

Variables	Relative Spread	Effective Spread	Realized Spread	5 Best Bid	5 Best Ask	Dispersion	Slope
MACD buy	0.077***	4.23E8**	5.71E8**	−0.017**	−0.004	0.035***	−0.026***
MACD sell	0.050***	6.37E8**	5.22E8**	−0.004	−0.020***	0.022***	−0.032***
RSI buy	0.048***	2.54E8*	5.09E+08	0.018	−0.042***	0.031***	−0.033***
RSI sell	0.032**	3.54E8***	2.77E8**	0.229	0.006	0.021***	−0.027***
STOCH buy	0.069***	5.07E8***	3.04E+08	−0.011**	−0.021***	0.030***	−0.040***
STOCH sell	0.071***	2.67E+08	2.80E+08	−0.061**	−0.020***	0.034***	−0.039***

Variables	Amihud	Percentage Price Impact	Autocorrelation	Realized Vol.	N. limit	N. market	N. marketable limit
MACD buy	3.81E+12	1.12E+13	4.46E+22	0.183***	0.002	−0.092***	0.039***
MACD sell	9.05E+12	1.65E+13	1.30E+23	0.165***	0.015***	−0.094***	−0.038***
RSI buy	−2.91E10**	4.74E+12	6.00E+22	−0.056***	0.004	0.053	−0.052***
RSI sell	−6.07E+12	7.84E+11	3.65E+22	−0.018	0.017***	0.045	−0.103***
STOCH buy	7.56E+11	2.87E+13	6.78E+22	0.159***	0.013***	−0.078***	−0.035***
STOCH sell	1.07E+13	−7.11E+12	7.32E+22	0.133***	0.018***	−0.075***	−0.053***

Variables	N buy	N sell	Trade Imbalance	Order Imbalance	N. modified	N. cancelled	N. executed
MACD buy	0.286***	0.090***	−0.111**	0.042***	0.061***	0.030***	−0.006
MACD sell	0.079***	0.198***	0.119**	0.046***	0.057***	0.033***	−0.009*
RSI buy	−0.044	−0.446***	−0.392***	−0.018	0.02	−0.005	−0.039***
RSI sell	−0.445***	0.072**	−0.547***	−0.035**	0.024*	0.031**	−0.043***
STOCH buy	0.136***	−0.070***	0.176**	0.021***	0.078***	0.038***	−0.047***
STOCH sell	−0.076***	0.175***	−0.079	0.014*	0.076***	0.027***	−0.036***

H4: Technical trading has no effect on order book dynamics.

We confirm the rejection of this hypothesis. As in the event study, the technical signals are associated - all else equal- with a higher number of limit orders, a lower number of market orders and marketable limit orders.

There are nevertheless some differences found in comparison to the event study. The total number of trades increase only when the signals are sent by the MACD, and not across all signals. Trade imbalance is always significantly impacted by technical trading, but the direction of the impact depends on the technical indicator. It is also rather the case for the order imbalance.

Finally, we confirm all the findings of the event study with respect to the changes observed in the order submission strategies followed by market participants when technical signals occur. There is obviously a clear dynamic monitoring of orders since the number of modified and canceled orders significantly increases when the three technical indicators are sending a signal.

4.3 Granger Causality

We conclude the empirical analysis by testing the Granger causality between each market quality proxy and each technical indicator. The indicators are computed using the standard rules. These tests enable us to check whether changes in the indicator is a cause or consequence of a change in market quality or both of these relationships (Bidirectional causality).

Toda and Yamamoto (1995) present a procedure to produce efficient and unbiased estimators of VAR models when the processes are integrated. This methodology helps to produce unbiased Granger causality tests, as it is similar to testing zero-restrictions on a given set parameters of a VAR specification. Their first step suggests that we check for the order of integration of the time series. We use stationarity tests, ADF and Phillips-Perron statistics, and conclude that all our time series were stationary. In this case, the Wald test statistic may be directly used instead of going through the process presented in Toda and Yamamoto (1995).

Our unrestricted VAR models are specified as follows:

$$\begin{aligned} I_t = \alpha_0 + \alpha_1 I_{t-1} + \alpha_2 I_{t-2} + ... + \alpha_p I_{t-p} \\ +\beta_1 M_{t-1} + \beta_2 M_{t-2} + ... + \beta_p M_{t-p} + u_t, \end{aligned} \tag{4.5}$$

$$M_t = \alpha_0 + \alpha_1 M_{t-1} + \alpha_2 M_{t-2} + ... + \alpha_p M_{t-p} \\ +\beta_1 I_{t-1} + \beta_2 I_{t-2} + ... + \beta_p I_{t-p} + u_t, \tag{4.6}$$

where M_t denotes one of the liquidity proxies that is investigated, p denotes the number of lags and u_t is an error term. The optimal lag length, p, is determined through an optimization process based on Akaike's Information Criterion (AIC).

The null hypothesis of Granger Causality tests characterizes non-causality, i.e. "M_t does not Granger-cause I_t" for the first VAR model and "I_t does not Granger-cause M_t" for the second one. This test consists in testing that all the β_i of the models equal 0.

Tables 2 to 4 present the results of the Granger causality tests, based on the asymptotically equivalent statistic. The first column indicates the p-value of the causality from market quality to the technical signals while the second one displays the p-value from the signals to market quality.

Table 2: Granger causality tests - MACD

M_t	I_t	$M \to I$	$I \to M$
Relative Spread	MACD	0.00063	0.99726
Depth 5 Best Bid	MACD	0.99926	0.80093
Depth 5 Best Ask	MACD	0.99699	0.88561
5 limits Imbalance	MACD	0.12686	0.60938
Dispersion	MACD	0.95798	0.02222
Slope	MACD	0.31055	0.35428
Effective Spread	MACD	<0.0001	0.20251
Realized Spread	MACD	<0.0001	0.17525
Percentage Price Impact	MACD	0.00068	0.04534
Realized Volatility	MACD	0.00004	0.6046
Amihud IR	MACD	0.97918	0.98993
Autocorrelation	MACD	0.65866	0.79587
Number of buyer-initiated trades	MACD	<0.0001	<0.0001
Number of seller-initiated trades	MACD	<0.0001	0.00003
Trade Imbalance	MACD	<0.0001	<0.0001
Number of market orders	MACD	0.45897	0.2094
Number of limit orders	MACD	0.40798	<0.0001
Number of marketable limit orders	MACD	0.22315	<0.0001
Number of executed orders	MACD	0.0088	0.06139
Number of modified orders	MACD	0.00018	0.0253
Number of cancelled orders	MACD	0.2618	0.5665

This table presents the results of the Granger causality tests conducted for both directions. Column $M \to I$ shows the p-values returned by the asymptotically equivalent test for market quality proxies Granger-causing the technical analysis indicator. Column $I \to M$ presents the p-values in the opposite direction.

Table 3: Granger causality tests - STOCH

M_t	I_t	$M \to I$	$I \to M$
Relative Spread	Stochastics	0.0005	0.24181
Depth 5 Best Bid	Stochastics	0.00051	<0.0001
Depth 5 Best Ask	Stochastics	0.42728	0.00012
Imb_5	Stochastics	0.91141	0.04132
Dispersion	Stochastics	0.14557	0.01014
Slope	Stochastics	0.00021	<0.0001
ES	Stochastics	0.00208	0.00262
RealizedS	Stochastics	0.00235	0.0028
PriceImpact	Stochastics	<0.0001	0.00524
sumvolume	Stochastics	0.05348	0.19658
RV	Stochastics	0.00001	0.00268
Amihud	Stochastics	0.71844	0.16339
STDMQR1	Stochastics	<0.0001	<0.0001
AR	Stochastics	<0.0001	<0.0001
Number of buyer-initiated trades	Stochastics	<0.0001	<0.0001
Number of seller-initiated trades	Stochastics	<0.0001	<0.0001
Trade Imbalance	Stochastics	<0.0001	<0.0001
Number of market orders	Stochastics	<0.0001	<0.0001
Number of limit orders	Stochastics	<0.0001	<0.0001
Number of marketable limit orders	Stochastics	<0.0001	<0.0001
Number of executed orders	Stochastics	0.00007	<0.0001
Number of modified orders	Stochastics	<0.0001	<0.0001
Number of cancelled orders	Stochastics	<0.0001	<0.0001

This table presents the results of the Granger causality tests conducted for both directions. Column $M \to I$ shows the p-values returned by the asymptotically equivalent test for market quality proxies Granger-causing the technical analysis indicator. Column $I \to M$ presents the p-values in the opposite direction.

Table 4: Granger causality tests - RSI

M_t	I_t	$M \to I$	$I \to M$
Relative Spread	RSI	0.00009	0.00295
Depth 5 Best Bid	RSI	0.00563	0.51641
Depth 5 Best Ask	RSI	0.92301	0.17618
5 Limits Imbalance	RSI	<0.0001	<0.0001
Dispersion	RSI	0.90059	0.02436
Slope	RSI	<0.0001	<0.0001
Effective Spread	RSI	<0.0001	<0.0001
Realized Spread	RSI	<0.0001	<0.0001
Percentage Price Impact	RSI	<0.0001	<0.0001
Realized Volatility	RSI	<0.0001	<0.0001
Amihud IR	RSI	0.38077	0.85375
Autocorrelation	RSI	<0.0001	<0.0001
Number of buyer-initiated trades	RSI	<0.0001	<0.0001
Number of seller-initiated trades	RSI	<0.0001	<0.0001
Trade Imbalance	RSI	<0.0001	<0.0001
Number of market orders	RSI	<0.0001	<0.0001
Number of limit orders	RSI	<0.0001	<0.0001
Number of marketable limit orders	RSI	0.11704	<0.0001
Number of executed orders	RSI	0.00562	<0.0001
Number of modified orders	RSI	<0.0001	<0.0001
Number of cancelled orders	RSI	<0.0001	<0.0001

This table presents the results of the Granger causality tests conducted for both directions. Column $M \to I$ shows the p-values returned by the asymptotically equivalent test for market quality proxies Granger-causing the technical analysis indicator. Column $I \to M$ presents the p-values in the opposite direction.

The results show that Granger causality is mainly bidirectional. Technical trading does influence liquidity, but the opposite is true as well. Bi-directionality is particularly obvious for the STOCH indicator. When significant p-values are found, they are significant in both directions in all cases but one only. The MACD and RSI indicators are also drivers of liquidity dynamics, while being driven by it at the same time. The only cases where technical trading seems to have a unidirectional impact on liquidity, are when we consider dispersion, the number of limit orders and the number of marketable limit orders. Otherwise, results are very similar than in the case of the STOCH indicator.

5 Conclusion

Technical traders are often modeled as uninformed traders who are subject to herding behavior. They tend to act as noise traders in the sense of Black (1986) and Shleifer and Summers (1990). In the past, trading based on technical analysis was found to have a positive effect on market quality. However, theoretical evidence in agent-based models has recently evolved and the effect of technical traders on market quality is viewed as ambiguous, at best. Contrary to Kyle (1985) and Glosten and Milgrom (1985), Chiarella and Ladley (2016) do not find that noise trading, under the form of technical trading, leads to reduced spreads. Despite primarily acting as liquidity providers, Chiarella and Ladley (2016) find out that technical traders increase trading costs.

Using tick-by-tick data, we find empirical evidence in support of the theoretical finding in agent-based models of limit order markets that the effect of technical trading on market quality is not positive. We find that technical trading at the time of the signals lowers liquidity as proxied by the relative spread, the effective spread, the realized spread, the dispersion and slope of the order book. We also find empirical support indicating that technical traders can have negative effects on price efficiency when arbitrage is limited. We also find additional negative impact of technical trading on market quality, most notably in terms of rising volatility. We indeed find that realized volatility increases with technical trading, as in Foucault et al. (2011) where noise traders have a positive effect on volatility. Finally, we find strong empirical support against the hypothesis that technical trading has no effect on order book dynamics.

We join Chiarella and Ladley (2016) when they conclude that the effect of technical traders on the market is more ambiguous than previously thought. There may be underestimated negative consequences in terms of market quality that further research needs to corroborate or invalidate.

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