

Return Reversals and the Compass Rose: Insights from High Frequency Options Data^{*}

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Abstract:

We study the occurrence and visibility of the compass rose pattern in high frequency data from individual equity options contracts. We show that the compass rose pattern in options contracts is more complex than portrayed in prior work with other asset classes. We find that the tick/volatility ratio proposed in prior studies gives inconclusive results on the pattern's visibility. A major contribution arises from linking the compass rose pattern with return reversals, which gives new insights on the pattern's predictability. We show that return reversals are revealed as an element of the compass rose pattern and are particularly evident at higher sampling frequencies. We study the determinants of these reversals, and report that return reversals are primarily associated with high transaction frequency and decrease with the presence of additional market makers. Also, the hypothesis that there is a reaction to overnight events which is reflected in prices at the market open is not supported. Reversals are less prevalent for larger firms and when trade sizes are larger.

Keywords: compass rose, high frequency data, return reversals, equity options

JEL: G12, C22

1 Introduction

Researchers and practitioners are increasingly focused on analysis and trading at a high frequency (intraday) level. This is one of the main growth areas in financial market research in recent years. New insights on market practice and price behaviour are revealed by research on this type of data. This paper focuses on option markets, where the leverage effect magnifies the potential profit from any trading opportunities identified. This is the first study to link the compass rose pattern with intraday return reversals. This feature could significantly influence the predictability arising from the pattern. We also present a regression model which identifies many important influences on the presence of return reversals. Reversals are more evident when transaction frequency is high and when prices are high. They are less prevalent when more market makers are present, for larger firms and when trade sizes are larger.

In the market microstructure literature, the compass rose pattern dates back to Crack and Ledoit (1996). The pattern appears when plotting present and lagged returns, whereby symmetrical lines that radiate from the origin are produced. As prices must be multiples of the minimum tick size, the number of lines radiating from the zero return is restricted and lines are more prevalent at the more popular ticks. The issue of seeking predictability from the compass rose can be linked to other strands of literature e.g. on serial correlation or the random walk (dating back as far as Kendall, 1953 and Roberts, 1959). Return reversals are an additional layer to the analysis in this paper. Return reversals are embedded in the compass rose pattern but are more evident at higher sampling frequencies.

Some prior studies have concentrated on the predictive powers of the pattern (see Lee et al., 2005 and Chen, 1997), however no direct relationship between the compass rose and forecasted returns has been documented. Lee et al. (2005) suggest

that the compass rose pattern increases returns' predictability in an ARCH or GARCH model when the return from the compass rose contains (marginally) more information than the forecasted returns from the model. Szpiro (1998) argues that the discrete nature of prices is the only condition that causes the compass rose pattern to emerge. Previous evidence for the existence of the pattern has been presented for equity and foreign exchange markets (e.g. Cai et al., 2003 and Lee et al., 2005). The calculation of returns for at-the-money options involves changing strike prices over time, which can lead to more complex dynamics in the compass rose pattern. We also show that the tick/volatility ratio is not supported as a consistent indicator of the visibility of the compass rose in individual equity options. We report that the effectiveness of the ratio deteriorates as the data frequency increases. Hence, at an ultra high frequency level, the tick/volatility ratio cannot be used as a basis for implementing trading strategies.

The remainder of this paper is organised as follows. Section 2 discusses the literature on the compass rose pattern and Section 3 outlines the data sample and methods. Section 4 analyses the compass rose pattern in individual equity options and Section 5 presents the empirical evidence. Section 6 concludes the paper.

2 Literature Review

Crack and Ledoit (1996) show that the plot of daily stock returns against their lagged values (also known as a phase portrait) reveals a structure that resembles a compass rose. The plot produces symmetrical lines that radiate from the zero return, located at the origin. The number of these lines is restricted by the minimum tick size. Szpiro (1998) demonstrates that when prices do not vary, a grid pattern emerges, whereas when prices are allowed to float, a smeared pattern (in addition to being grid)

becomes apparent.¹ Extreme volatility of prices causes the pattern to disappear as the plot becomes smudged. Crack and Ledoit (1996) suggest three conditions for the pattern to appear: price discreteness, the fact that price changes are relatively small (especially over intraday intervals) and that the price level of the asset varies over a relatively wide range. However, Szpiro (1998) identifies that the “sole necessary and sufficient condition” for the pattern to emerge is that trading is in discrete prices.

The underlying motivation for the study of the compass rose pattern lies in its potential predictive power and its implications for statistical tests. It is reported that the existence of the pattern in intraday and daily returns affects the Jarque-Bera and the Lilliefors tests for normality (Annaert et al., 2004) and alters the statistical properties of the Brock-Dechert-Scheinkmann (BDS) chaos test (Kramer and Runde, 1997). Fang (2002) shows that for tick-by-tick data with a high tick/volatility ratio, the compass rose pattern distorts the asymptotic theory for the random walk test statistics. Amilon (2003) notes that the compass rose pattern affects the parameter estimates in ARCH and GARCH models. Finally, embedded nonlinearities in the pattern may increase return predictability (see Batten and Hamada, 2008; Chen, 1997; Antoniou and Vorlow, 2005).

Previous research has studied daily or intraday versions of the compass rose pattern in equity markets (Amilon, 2003; Cai et al., 2003; Fang, 2002; Wang et al., 2000), the foreign exchange market (Lee et al., 2005, Szpiro, 1998), and futures markets (Lee et al., 1999). Wang and Wang (2002) show that the compass rose pattern may be visible in returns on equally weighted portfolios. Chen (1997) and Lee et al. (1997) note that the existence of daily price limits influences the appearance of the pattern.

¹ These patterns refer to simulated scenarios. For a detailed illustration, see Szpiro (1998).

Gleason et al. (2000) demonstrate that the ratio of the tick size to returns' volatility (measured as the standard deviation of returns), determines the threshold value above which the pattern is visible (see also Lee et al., 2005 and McKenzie and Frino, 2003). Wang et al. (2000) show that the pattern might not be visible for thinly traded stocks as too few observations fall into each radiant. Cai et al. (2003) show that there is an optimal frequency of observations that produce the clearest compass rose. Although a quantifiable measure of the pattern's visibility is proposed by Wang and Wang (2002), the large amount of zero returns in the context of high frequency data tends to lead to inconsistent results on the application of this measure (Mitchell and McKenzie, 2006).

3 Data and Methodology

The data include all trades and quotes for individual equity option contracts traded at the NYSE-Euronext London International Financial Futures Exchange (Euronext-LIFFE) during 2005. In order to avoid stale pricing problems while capturing a sufficient number of contracts, we select equity options that report at least one trade per day for the data period. The total number of observations for the 28 firms included in the sample is 133,375,200.²

To calculate the returns on individual equity options, we follow the procedure introduced by Sheikh and Ronn (1994). Returns are calculated only for the at-the-money, nearest to mature contracts. Using the midpoint quote, even for the highly traded options, may lead to the use of stale prices, hence only ask prices are used in

² 6 (22) firms have a tick size of 0.25 (0.50). No tick size changes are reported during the sample period.

the returns calculation (see ap Gwilym et al., 1997 and Bollerslev and Melvin, 1994). At each time interval, the first ask price is obtained. For the closing return calculation, the last ask price of the day is obtained. The closing ask price and the first ask quote of the next day are used for the computation of the opening returns. Different strike prices can meet the at-the-money criteria for a given asset in consecutive intervals. The procedure adopted is the following: at every interval³ t , the first ask price for the at-the-money nearest maturity contract is obtained. Then, at the next time interval $t + 1$, the ask price with the same strike price is obtained. The logarithmic return is calculated from these two prices. If however, there is no ask with the same strike price in the next interval $t + 1$, we search for the last available ask price in interval t which satisfies the criteria. When the return for the interval t to $t + 1$ is calculated, the same procedure is repeated for the next interval $t + 2$.

Previous studies have focused solely on trade data to generate the pattern, whereas, for options, calculating returns on trades is not recommended because of the thin trading in options with specific exercise price and maturity combinations. In order to demonstrate the effect of thin trading on the visibility of the pattern, we also compute returns using trade data only. For comparison purposes, we also calculate returns using Ultra High Frequency (UHF) quotes data (i.e. all observations).

A further section of the analysis is dedicated to the linkage between return reversals and the compass rose pattern. A regression model is applied to test several hypotheses. We expect that return reversals are less common for high-priced securities, since these securities tend to be followed by more analysts, hence they

³ The regression variables are calculated on an hourly basis. In order to show the effect of sampling frequency on the visibility and properties of the compass rose pattern, we also compute returns using 15- and 30-minute intervals (following the same procedure).

should be more efficiently priced on an intraday basis (see Gosnell, 1995). TS is the average trade size per interval and controls for differences in the traded size per interval. Similarly, in order to control for the trading frequency effect, Liq is defined as the average number of observations per interval. It is expected that a low proportion of reversals will be observed at the market open associated with a reaction to overnight events, and a higher proportion of reversals observed at the close associated with less information arrival (Buckle et al., 1998). We expect that the designated market maker scheme⁴ increases the dissemination of information, such that a lower proportion of reversals is expected for options contracts included within this scheme. Also, we hypothesize that options approaching the maturity date will exhibit a higher proportion of reversals as a result of the increased certainty about option value (assuming the absence of other major news events). Finally, higher valued firms will tend to have greater liquidity hence a lower proportion of reversals.

The model studied is the following:

$$RR_{i,t} = \alpha_1 + \alpha_2 Pr_{i,t} + \alpha_3 TS_{i,t} + \alpha_4 Liq_{i,t} + \alpha_5 OD_t + \alpha_6 CD_t + \alpha_7 DMM_i + \alpha_8 TTM_{i,t} + \alpha_9 FV_{i,t} + \epsilon_{i,t} \quad (1)$$

Where RR is the percentage of return reversals per asset i and at each hourly time interval t . Expected signs (discussed above) for coefficients are given in Table 2. Pr is the natural log of the average trade price at each time interval per contract. TS is the natural log of the average trade size at each time interval per contract. Liq denotes the average number of observations at each time interval per contract. OD and CD are the open and close dummies respectively. DMM is the Designated Market Maker dummy.

⁴ Designated Market Makers are assigned by NYSE-Euronext to increase liquidity in specific individual equity options. Out of 28 firms in this sample, 16 are covered by DMMs.

TTM is the average time to maturity at each time interval. FV denotes the firm size as the natural log of market capitalization per day for each contract.

4 Analysis of the compass rose pattern in options contracts

Let R_t be the simple arithmetic return for the period $t-1$ to t , P_t be the price at the close of the interval t , n_t is the price change in ticks h at interval t , and S_i the strike price, $i \in T$, where T is the time series of prices for a single contract. When the strike price, S , is uniform across all contracts (or not applicable e.g. in other asset classes), the ratio of R_{t+1} over R_t gives the following:

$$\frac{R_{t+1}}{R_t} = \frac{n_{t+1}}{n_t}, \text{ when } P_t \approx P_{t-1} \text{ (Crack and Ledoit, 1996)} \quad (2)$$

or

$$\frac{R_{t+1}}{R_t} = \frac{n_{t+1}}{n_t} \left(1 - \frac{n_t h}{P_t} \right), \text{ when } P_t \neq P_{t-1} \text{ (Szpiro, 1998)} \quad (3)$$

In options markets, the assumption that prices are continuously distributed cannot be achieved, as the appropriate computation of intraday returns is not contract-specific but depends on the relevant (at-the-money) strike prices at each consecutive interval. This makes it unlikely that $P_t \approx P_{t-1}$, and differences between P_t and P_{t-1} can be relatively large. Also, Equation 3 is true only for a uniform S . Hence, equation 3 is not universal; sub-formulas arise because of the restrictions applied for the strike price, S . When we expand these restrictions, the ratio of R_{t+1} over R_t gives the following:

$$\frac{R_{t+1}}{R_t} = \frac{(P_{t+1,k+1} - P_{t,k})/P_{t,k}}{(P_{t,i} - P_{t-1,i-1})/P_{t-1,i-1}}, \forall S_k = S_{k+1}, S_i = S_{i-1} \quad (4)$$

Where $\{k, k + 1, i, i - 1\} \in S$, and $t \in T$. It follows that the assumption of a uniform S for all T , namely $k = i$, cannot be inferred.⁵ Since, $n_t \equiv (P_t - P_{t-1})/h$ and h is constant, equation 4 becomes:

$$\frac{R_{t+1}}{R_t} = \frac{n_{t+1,k+1}/P_{t,k}}{n_{t,i}h/(P_{t,i} - n_{t,i}h)} = \frac{n_{t+1,k+1}}{n_{t,i}} \left(\frac{P_{t,i} - n_{t,i}h}{P_{t,k}} \right) \quad (5)$$

Even though the use of nearest-to-mature, at-the-money contracts significantly reduces the variability of strike prices included in the final returns' sample, we cannot preclude the use of different strike prices for consecutive returns, hence, the following functions are true for R_t and R_{t+1} :

$$R_t = f(n_t h, P_t, S_i) \text{ and } R_{t+1} = g(n_t h, P_t, S_k) \quad (6)$$

The latter implies that the compass rose pattern in options contracts is more complex than that portrayed in Szpiro (1998) for other asset classes.

⁵ As the returns' calculation formula is for the nearest-to-mature contracts only, the formulae discussed refer only to different strike prices. If maturity was also allowed to float, the complexity of the formulae would increase.

5 Empirical Evidence on the Compass Rose Pattern in High Frequency Options Data

5.1 The Tick/Volatility Ratio as a Determinant of the Compass Rose Pattern

Gleason et al. (2000) and Lee et al. (2005) demonstrate the potential importance of the tick/volatility ratio as an indicator of the quality of the compass rose pattern. Wang and Wang's (2002) Q measure for the pattern's visibility is not reliable for assets with a tick/volatility ratio greater than 0.5 (see Mitchell and McKenzie, 2006). Following from these studies, this section analyses the tick/volatility ratio in order to achieve further insights on its applicability in high frequency data and in options contracts. We propose that the visual inspection of the pattern is ultimately necessary because the existing attempts to propose quantitative measures are not adequate for options contracts or for any application based on ultra high frequency data (for any asset class).

Insert Table 1 about here

Table 1 presents the tick/volatility ratio for all 28 firms (only calls are presented) for different time intervals. Panel A is based on employing the ultra high frequency (full, quotes) dataset. Panels B and C present the results for tick/volatility ratios and visual quality at 15-minute and 30-minute intervals respectively. Panel D results are based on actual trades. Panels A and D (UHF and trades) demonstrate the importance of time in the appearance of the pattern, which will be discussed later. The

other important category of information documented in Table 1 is the percentage of observations that fall on the horizontal and vertical axes.

Based on Panels B and C of Table 1, it is easily asserted that the quality of the pattern is not only determined by the tick/volatility ratio, as this would mean that the quality would actually improve for decreasing volatility levels (taking into account tick size changes, i.e. intra-tick levels). In particular, Table 1 shows that the quality of the pattern is not an increasing function of the tick/volatility ratio. As an example, Figures 1a and 1b show two option contracts (OAZA and OCPG) that exhibit contrasting results on the appearance of the pattern when sampled at 15 minute intervals. It is clear that the pattern is more (less) visible for OCPG (OAZA), which contrasts with the tick/volatility ratio supposition of Lee et al. (2005), as OCPG has the lower ratio.

Insert Figure 1 about here

At relatively high tick/volatility ratios (within a given tick size), the pattern is clearly visible at higher sampling frequencies. For lower sampling frequencies, there are not enough data points to make the pattern appear. The latter is demonstrated in Figure 2 for OBBL, where the pattern starts to emerge at the higher sampling frequency (Figure 2b in contrast to Figure 2a). Table 1 shows that when a higher frequency of data is studied, the quality of the pattern consistently increases.

Insert Figure 2 about here

The above analysis implies that the tick/volatility ratio alone gives inconclusive results on the strength of the pattern. Cai et al.'s (2003) analysis captures the fact that trading frequency, and especially the percentage of observations that lie on the axes, play an important role in the quality of the pattern. The latter partially explains why contracts with similar tick/volatility ratios do not produce similar quality patterns. The second explanation of the above is associated with differences in the price level of securities, which is embedded in the calculation of returns and is discussed in previous research (see Gleason et al., 2000, McKenzie and Frino, 2003 and Lee et al., 2005).

We argue that prior studies have failed to grasp the full extent of the trading process by imposing artificial restrictions (clock time) on the trading process. That is, by using data collected at 1-minute, 5-minute intervals and at lower frequencies, a substantial amount of information is lost when observations are discarded. Panel A of Table 1 confirms that the compass rose pattern is easily visible at the UHF level. Figure 3a shows that even for very low tick/volatility ratios, the compass rose pattern is easily discernible. For the UHF level, Table 1 indicates that there is no close link between tick/volatility ratios and the pattern's visual quality. This result is very much affected by the fact that, as the number of observations increase, the price and volatility levels remain relatively stable. Even at the UHF level, when prices vary sufficiently, the compass rose pattern becomes "smudged" and "smeared" (as expected by Szpiro (1998)). This means that some rays overlap and cause the pattern to disappear, which is demonstrated to some extent in Figure 3b. Finally, Panel D of Table 1 shows that the appearance of the pattern deteriorates when trade data are used. Hence, the tick/volatility ratio, when used for trade data, gives no indication on the strength of the pattern. The high proportion of observations on the axes is at least

partially one of the reasons for the low visibility of the compass rose pattern in trade data (see Cai et al., 2003).

Insert Figure 3 about here

5.2 The Compass Rose Pattern and Return Reversals

An issue that has not been previously documented in the literature is the relationship of the compass rose pattern with return reversals. A price reversal is defined as “a price change in the opposite direction to the previous price change” (Gosnell, 1995, p. 226). Similarly, a return reversal occurs when a positive (negative) return follows a negative (positive) return.

Evidence of intraday price reversals is previously documented (see Buckle et al., 1998 and Grant et al., 2005). The frequency of reversals is closely linked to the rate of information arrival to the market and the correction of previous mispricings (see Cox and Peterson, 1994). That is, when a price change (return) is followed by another price change (return) in the same direction, it is assumed that new information is being incorporated into prices. If a return reversal occurs, there is no new information. Gosnell (1995) identifies that controlling for price reversals is important for testing market efficiency. Also, Grant et al. (2005) note that price continuations at the market open may lead to an overreaction and any jump in prices at the market open will often be followed by a correction, which means that price reversals will appear. While the latter suggests that a contrarian strategy may potentially exploit this overreaction, Grant et al. (2005) report that positive returns generated by this strategy are eroded by transaction costs.

In a compass rose plot, price reversals are found in the north-west (*NW*) and south-east (*SE*) quadrants. These are cases where negative returns are followed by positive (*NW*) and positive returns are followed by negative (*SE*). Zero lagged returns and/or zero returns fall on the axes, hence, are neither reversals nor continuations. The existing literature on the compass rose pattern has shown no clear indications of a prevalence of return reversals.

Insert Figure 4 about here

Figure 4a reveals that when UHF returns are plotted, a parabolic line that declines from the *NW* to the *SE* through the origin can emerge.⁶ Before we investigate the properties of the pattern, we discuss some explanations found in the literature. Firstly, the non-linearity of the pattern arises from the arithmetic computation of returns. The use of logarithmic returns would replace the parabolic line with a straight line. Secondly, Park (1995) shows that bid-ask bounce i.e. successive quotes or trades where ask and bid prices follow each other generates price reversals. However, in the context of the findings presented in Figure 4, bid-ask bounce explanations of the pattern are not feasible because these options returns series are created using only ask prices.

A question remains as to why the magnitude of this pattern varies and in some cases is not noticeable (e.g. Figure 4b). Figure 5 presents the average duration observed between two consecutive returns for all option contracts in the UHF sample. The horizontal axis denotes duration in seconds and the vertical axis denotes the

⁶ A similar effect is observed in electricity prices (see Batten and Hamada, 2008). Lee et al. (2005) note that the same feature can emerge using a Monte Carlo simulation.

percentage of observations reported during the particular time interval. The columns are observations-weighted so that transaction frequency differences across firms do not affect the results. We hypothesize that, if trading differences exist between the four quadrants, these will be exploited by traders and duration will reveal the speed of adjustment in ways similar to that found in Christie and Schultz (1994), where it is reported that traders react differently in assets with clustered prices. The hypothesis is also closely linked to the fact that volume is evenly distributed across the four quadrants.

Insert Figure 5 about here

Figure 5 shows that at a duration of one second positive momentum is the most common observation and as the plot is observations-weighted, duration differences across the four quadrants disappear. However, the results also reveal that there is a greater tendency for return reversals at durations of 15 seconds or more. The latter is documented across all options contracts and it might be partially explained by strategic quote behaviour.

Buckle et al. (1998) show for the Short Sterling and FTSE100 futures contracts that price reversals are relatively low at the market open and high at the market close. The findings on the market open and close imply information arrival at the open and the implementation of trading strategies by day traders at the market close. Also, the authors suggest that there is a strong link with scheduled macroeconomic announcements, thus, the intraday proportion of reversals reaches its lowest point at the time of these announcements. Similarly, Gosnell (1995) shows that

price reversals for NYSE stocks are low at the market open and relatively stable during the trading day and near the market close.

Insert Figure 6 about here

Figure 6 shows that a clear intraday pattern of return reversals emerges from our dataset. In particular, reversals are most prevalent at the market open and the market close, whereas during the middle of the trading day, they are less common. This does not support the hypothesis that overnight news is disseminated at the market open. In contrast, Figure 6 suggests that information arrival is maximised two hours after the market open (10:00am). This coincides with the release time of the scheduled macroeconomic announcements from the Bank of England and the Office of National Statistics.⁷

Table 2 presents the results for the regression model of return reversals.⁸ Hypotheses for the signs of the coefficients were discussed in Section 3. We anticipate that higher-priced securities exhibit fewer return reversals due to being more efficiently priced. However, the results show that there is a strong positive association between the price level and the percentage of return reversals. This finding is in contrast with Gosnell (1995). Hence, return reversals are more common for high-priced options. As hypothesized, larger trade size is associated with a lower proportion of return reversals. In line with the price level variable, we hypothesize that the more liquid firms will exhibit less return reversals (see Gosnell, 1995). The

⁷ The release time for the scheduled macroeconomic announcements is 09.30GMT and the figure uses hourly data.

⁸ Estimation is by OLS. No autocorrelation or heteroskedasticity is detected.

liquidity variable shows that higher trading frequency is associated with more return reversals which may reflect strategic trading or quotation.

Insert Table 2 about here

The opening and close dummies are both highly significant and positive confirming the U-shaped pattern of Figure 6. The result for OD is not consistent with Buckle et al. (1998), but supports the hypothesis that liquidity traders operate at the market open (see Cox and Peterson, 1994). The CD dummy is consistent with a lack of information arrival at the market close.

The DMM dummy is highly significant and positive which reflects the Euronext designated market makers' obligation to offer continuous prices at each price level (hence, a lower proportion of reversals). The time-to-maturity variable is significant for calls only. The findings suggest that return reversals marginally increase close to expiration dates. Finally, the firm value variable is negative and highly significant, which is consistent with the hypothesis of Gosnell (1995) that assets of larger firms are more liquid.

Table 2 indicates that return reversals in individual equity options are more common at higher price levels and when liquidity levels are higher. Liquidity seems more important than information at the market open. The Designated Market Maker scheme enhances the dissemination of information, thus more market makers lead to fewer reversals. Finally, options that are closer to the expiration date tend to exhibit more frequent return reversals.

6 Conclusions

The paper studies the occurrence and visibility of the compass rose pattern in high frequency individual equity options data. We show that the compass rose pattern in options contracts is more complex than for other asset classes (e.g. Szpiro (1998)) because the at-the-money strike price can change over time. The tick/volatility ratio is not a reliable indicator for the strength of the compass rose pattern and its effectiveness decreases at higher data frequencies. This point is very important because it is widely claimed that the compass rose pattern is an inherent feature of discrete asset prices, thus identifying a measure of its visibility is of great significance.

Lee et al. (2005) suggest that the visibility of the compass rose pattern may give rise to increased returns' predictability. Such indications have particular significance for options contracts because their relatively low price levels enhance the implications of discreteness (Amilon, 2003), while the leverage effect in options magnifies potential profits from any market inefficiencies. The manifestation of return reversals in the compass rose pattern may indicate an increase in returns' predictability in some situations, arising from serial correlation. High frequency traders are well placed to capitalise on any such predictability. The paper contributes new evidence that the pervasiveness of the compass rose pattern is strongly associated with trading frequency. However, our findings do not indicate clear trading strategies based on any metric for the visibility of the pattern.

A major element of the paper's contribution arises from linking return reversals with the compass rose pattern. We show that return reversals are captured within the compass rose pattern, especially at higher sampling frequencies. The parabolic diagonal line that can distort the compass rose pattern when UHF data are

used is caused by an increased presence of return reversals. Duration estimates show that strategic trading may be associated with the timing of reversals. In contrast with Gosnell (1995), return reversals are found to increase with price level and with the frequency of price observations. However, reversals are inversely related to trade size, as hypothesised. Hence, the evidence on the relationship between return reversals and liquidity proxies is mixed. This is a potential avenue for future research.

The hypothesis that there is a reaction to overnight events which is reflected in prices at the market open is not supported. Return reversals could remain prevalent at this time due to heterogeneous expectations among market participants. However, intraday news arrival does have an impact by reducing the percentage of reversals observed in a given interval. Finally, a lower proportion of return reversals is associated with assets which have designated market makers, implying an increase in the information content of quotes in these cases.

Table 1: Price level, tick/volatility ratios and visual inspection of the compass rose pattern for all contracts.

Name	Tick Size	Average Price Level	Panel A: UHF Quotes			Panel B: 15-min			Panel C: 30-min			Panel D: Trades		
			Tick/Vol	% on Axes	Visual Quality	Tick/Vol	% on Axes	Visual Quality	Tick/Vol	% on Axes	Visual Quality	Tick/Vol	% on Axes	Visual Quality
OAWS	0.25	13.85	7.26	30.80	Good	11.06	38.24	Fair	9.91	31.07	Poor	15.65	72.73	Bad
OBBL	0.25	16.36	1.05	33.51	Good	10.35	34.32	Fair	9.47	29.29	Bad	13.37	66.19	Bad
OBTG	0.25	7.04	1.22	44.21	Excellent	13.01	67.40	Fair	11.32	62.23	Poor	16.73	80.92	Bad
OSAN	0.25	10.86	1.52	33.76	Good	10.80	44.89	Fair	9.67	38.08	Poor	16.22	78.26	Bad
OTCO	0.25	11.36	6.02	43.13	Excellent	11.36	46.48	Good	9.89	40.55	Fair	11.60	60.68	Bad
OVOD	0.25	3.67	1.01	52.40	Excellent	17.69	88.05	Fair	14.74	82.32	Poor	20.53	92.26	Bad
OAAM	0.5	60.15	18.98	37.45	Fair	21.99	27.65	Poor	19.31	20.75	Bad	23.07	41.84	Bad
OAZA	0.5	72.89	1.99	25.16	Fair	21.39	21.83	Bad	19.11	16.07	Bad	24.95	52.30	Bad
OBLT	0.5	31.91	16.55	39.23	Good	22.30	36.83	Fair	19.65	29.02	Fair	22.79	50.63	Bad
OBOT	0.5	22.82	11.98	36.74	Excellent	21.79	40.71	Good	19.55	34.66	Fair	24.88	65.10	Bad
OBP	0.5	32.06	2.16	36.90	Good	21.90	42.69	Good	19.65	37.79	Bad	27.59	67.96	Bad
OBSK	0.5	18.87	2.01	37.67	Excellent	22.74	53.77	Good	19.67	44.25	Fair	31.51	77.72	Bad
OCPG	0.5	18.35	9.44	9.99	Excellent	18.23	26.85	Good	18.66	33.62	Good	25.85	73.61	Bad
OCUA	0.5	18.60	2.18	38.08	Excellent	21.30	46.57	Fair	20.03	44.68	Poor	22.48	64.29	Bad
OEMG	0.5	55.97	23.42	13.80	Fair	22.48	24.13	Poor	19.41	18.13	Bad	28.15	63.91	Bad
OGNS	0.5	19.55	1.97	39.38	Good	21.72	52.19	Fair	20.43	48.07	Poor	34.34	78.25	Bad
OGXO	0.5	38.02	2.15	33.99	Fair	21.08	31.97	Poor	18.84	23.77	Bad	23.97	58.92	Bad
OHSB	0.5	21.43	2.21	39.23	Good	23.41	50.09	Good	20.83	41.71	Fair	32.43	81.07	Bad
OKGF	0.5	20.32	11.98	27.93	Excellent	20.08	39.59	Good	19.07	36.08	Fair	34.34	81.25	Bad
OLS	0.5	42.68	14.60	21.15	Fair	21.52	26.05	Fair	18.88	22.92	Bad	26.33	54.44	Bad
OPRU	0.5	28.86	3.29	36.48	Fair	21.39	38.74	Poor	19.73	37.21	Bad	24.34	65.78	Bad
ORBS	0.5	43.39	1.96	26.57	Fair	21.02	29.02	Poor	19.30	23.68	Bad	26.04	63.88	Bad
ORTZ	0.5	70.97	2.04	21.85	Fair	22.08	23.92	Poor	18.72	17.26	Bad	24.69	43.68	Bad
ORUT	0.5	29.59	16.29	36.81	Good	22.42	35.85	Fair	20.29	31.34	Poor	24.13	60.16	Bad
OSCB	0.5	38.22	16.75	46.00	Fair	21.77	31.11	Poor	19.43	24.27	Bad	26.55	59.70	Bad
OSPW	0.5	14.93	8.91	24.88	Excellent	21.20	52.24	Good	20.45	53.16	Fair	30.10	80.50	Bad
OTAB	0.5	33.30	2.18	26.26	Good	20.89	33.58	Poor	19.39	27.75	Bad	30.51	71.17	Bad
OTSB	0.5	24.08	2.05	38.59	Good	21.82	46.83	Fair	20.03	40.68	Poor	24.38	65.00	Bad

The table presents the tick/volatility ratio for all 28 contracts (call only) for different time intervals. Panel A uses the ultra high frequency (full, quotes) dataset and Panel B is created using trades. Panels 2 and 3 show tick/volatility ratios and visual quality at 15-minute and 30-minute intervals respectively. The visual quality of the pattern is ranked as follows: bad, poor, fair, good, excellent (see Wang and Wang, 2002).

Table 2: OLS Regressions

Variable	Expected Sign	Call	Put
Intercept		53.67*** 42.56	56.83*** 45.37
Pr	-	4.96*** 29.70	4.55*** 26.72
TS	-	-3.00*** -15.98	-2.70*** -14.57
Liq	-	0.02*** 5.86	0.01** 2.06
OD	-	5.46*** 14.62	6.05*** 16.67
CD	+	1.10*** 3.18	1.07*** 3.18
DMM	-	-3.79*** -13.57	-3.44*** -12.65
TTM	+	-0.02* -1.80	-0.01 -0.73
FV	-	-2.10*** -13.11	-2.42*** -15.89
R-Squared		0.10	0.09
No. of Obs.		54,235	54,410

$$RR_{it} = \alpha_1 + a_2 Pr_{it} + a_3 TS_{it} + a_4 Liq_{it} + a_5 OD_t + a_6 CD_t + a_7 DMM_i + a_8 TTM_{it} + a_9 FV_{it} + \varepsilon_{it}$$

Where RR is the percentage of return reversals per time interval; *Pr* is the natural log of the average trade price at each time interval per contract; *TS* is the natural log of the average trade size at each time interval per contract; *Liq* denotes the average number of observations at each time interval per contract; *OD* and *CD* are the open and close dummies respectively; *DMM* is the Designated Market Maker dummy; *TTM* is the average time to maturity at each time interval; *FV* denotes the firm size as the natural log of market capitalization per day for each contract. *, **, *** significant at the 10%, 5% and 1% levels, respectively. T-statistics are reported.

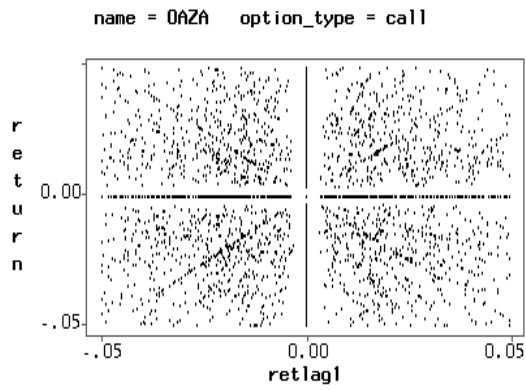


Figure 1a

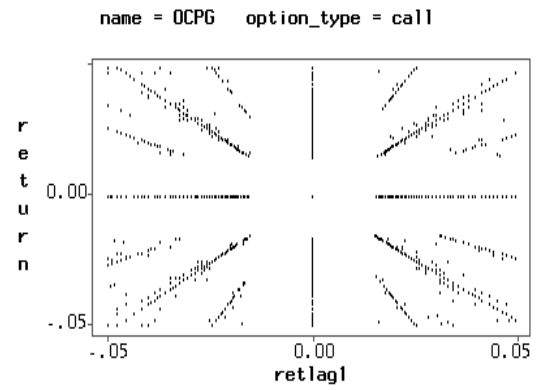


Figure 1b

Figures 1a and 1b. 15-Minute Time Interval Plots for OAZA (21.39) and OCPG (18.23) respectively. Tick/Volatility Ratios in Parentheses.

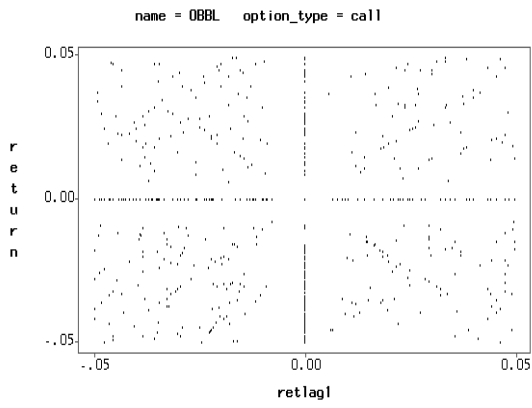


Figure 2a

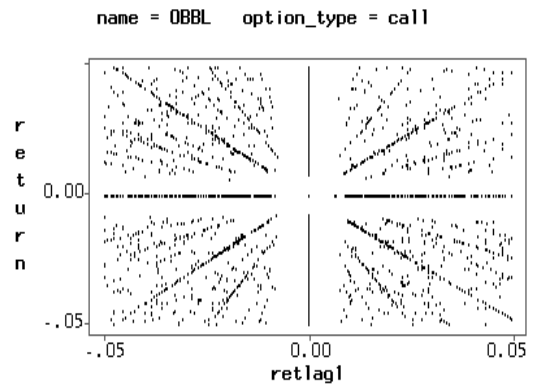


Figure 2b

Figure 2a: 30 minute Interval Plot for OBBL

Figure 2b: 15 minute Interval Plot for OBBL

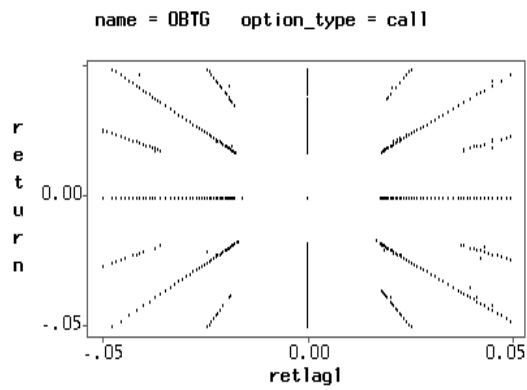


Figure 3a

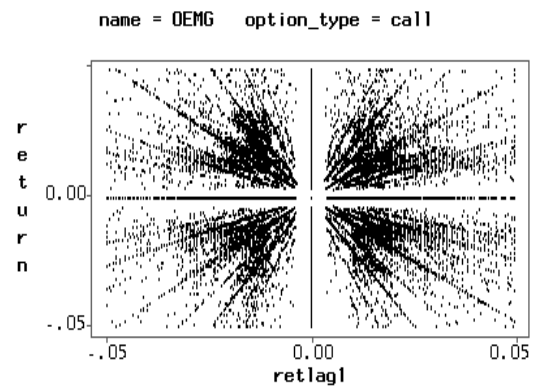


Figure 3b

Figures 3a and 3b. UHF Plots for OBTG (1.22 / 44.21%) and OEMG (23.42 / 13.80%) respectively. Tick/Volatility ratios and the Percentage of Observations on the Axes are in parentheses.

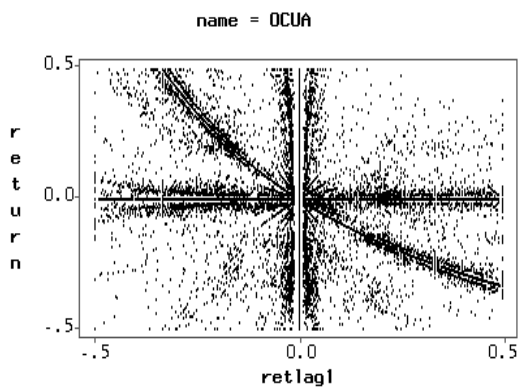


Figure 4a

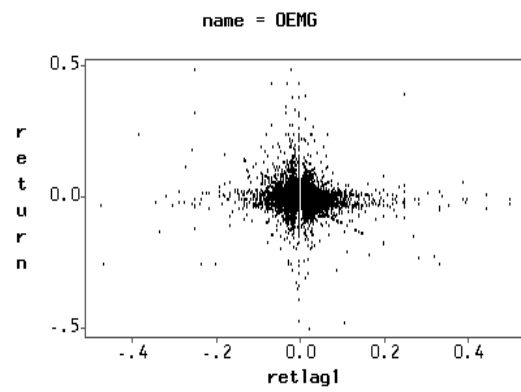


Figure 4b

Figures 4a and 4b. UHF Plot of OCUA and OEMG respectively

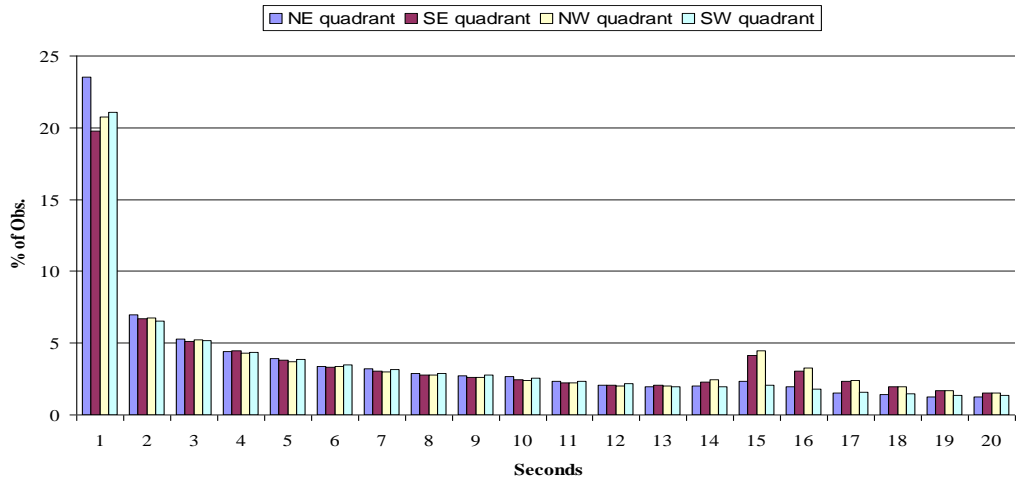


Figure 5. Average Duration Estimates

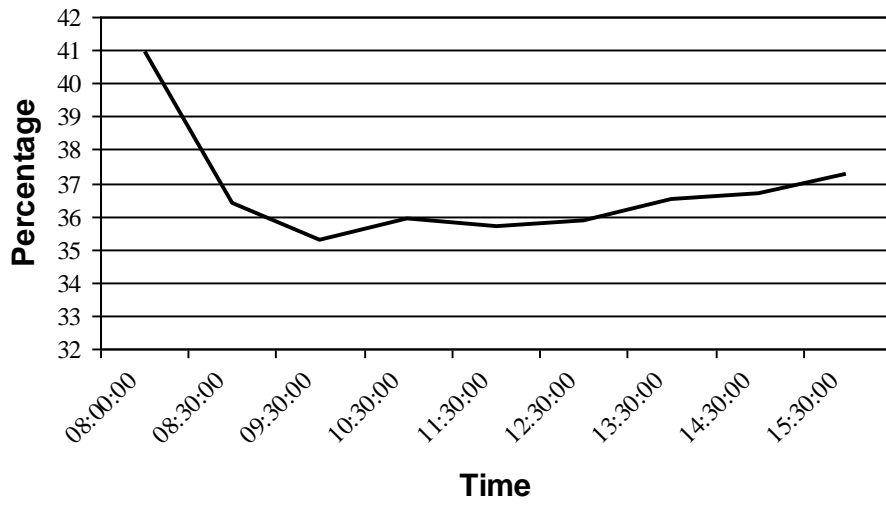


Figure 6. Intraday Distribution of Reversals

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