Monday mornings: individual investor trading on days of the week and times within a day

Richards, Daniel; Willows, Gizelle


Published Version: https://doi.org/10.1016/j.jbef.2019.02.009
Monday mornings: Individual investor trading on days of the week and times within a day

Abstract:
Individual investors’ demand for trading activity will vary over time according to their availability and desire to trade. Academic research has primarily investigated market wide trading activity, showing low trading activity on Mondays and high activity at the start and end of each day. It remains unknown whether individual investors’ trading behavior mimics these market patterns. Instead research on individual investors shows that they overtrade in general and are less likely to trade losses. We research trading activity for 7200 UK investors, finding these investors actually prefer trading on Mondays and trade in a W-shaped intraday pattern. Further investigation revealed that investors increased their selling of losses on Monday mornings, suggesting investors utilise spare time to process difficult trading decisions.

Keywords: Monday, W-shape, disposition effect, trading frequency, day of the week

DOI: https://doi.org/10.1016/j.jbef.2019.02.009

Dr Daniel W. Richards
https://orcid.org/0000-0001-7451-0060
RMIT University, Melbourne, Australia
Email: Daniel.richards@rmit.edu.au
Corresponding Author

Dr Gizelle D. Willows
College of Accounting, University of Cape Town, Cape Town, South Africa
Email: gizelle.willows@uct.ac.za
1. INTRODUCTION

There is growing interest in understanding individual demand for financial services as individuals often demonstrate distinctive behavior (Bolt & Mester, 2017). For individual stock market trading, two robust behaviors have been observed; investors trade too frequently (a behavior ascribed to overconfidence by Barber and Odean (2000)) and demonstrate a reluctance to sell losses and an eagerness to sell gains (coined the disposition effect by Shefrin and Statman (1985)). While research has shown that individual investors are prone to these behaviours, there is little consideration about when investors are prone to these biases. However, this ‘when’ aspect of individual investor behavior is worthy of the attention of academic research for the following two reasons.

Firstly, cognate research in finance has sought to understand anomalies that occur in stock markets which challenge the long-held notion of market efficiency. Analysis has uncovered seasonal (Kamstra, Kramer, & Levi, 2003, 2012), month-of-the-year (Sahin, Topaloglu, & Ege, 2017), day-of-the-week (Dicle & Levendis, 2014) and time of the day (Foster & Viswanathan, 1993) effects which shape trading activity and returns in stock markets around the world. This literature indicates that the ‘when’ aspect of trading influences market conditions. However, it remains unknown whether individual investors follow the same market patterns and it is incorrect to generalize market-based findings to individual investors because their trades make up a meagre fraction of the trading which occurs in the market (Morse, Nguyen, & Quach, 2014). Our research contributes to this literature.

A second reason is that an individual investor’s susceptibility to bias may vary over short time frames. This concept is often overlooked by research on individual differences in behavioral biases, which has shown that gradually investors reduce their susceptibility to bias through gaining experience (Seru, Shumway, & Stoffman, 2010) and increasing sophistication (Feng
& Seasholes, 2005). However, Mukherjee and De (2018) argue that rationality can be conceived as a continuum where variation in rationality occurs within an investor (over short time frames). That is, he/she varies between behavioral and rational positions. Investor rationality is a choice because it requires strong cognitive effort to be fully rational. Our paper focuses on the ‘when’ aspect of trading by investigating whether susceptibility to behavioural bias is different at different times of the day and days in a week. Specifically, we research if trading frequency and the disposition effect is influenced by when individual investors trade. We argue that individual investors face constraints which institutional investors do not. Namely, individual investors work during the day and thus their ability to devote cognitive and emotional resources to trading decisions will occur more often over the weekend and in the evenings. For this reason, the trading frequency and susceptibility of individual investors to bias will be different following the weekend and at the market opening in the mornings. The research we report on fills a gap in the literature about when individual investors trade within a week and within a day. Using propriety trading data on UK investors over a 3½ year period, we examine trading activity during days of the week and during 30-minute windows within a day. Results show that contrary to market activity, investor’s trade more on Mondays with an increase in selling behavior being the cause thereof. During the day, the trading activity follows a W-shape, where investors trade most frequently at the start of the day, followed by the end of the day and thirdly between the times of 13:00 to 13:30. Further investigation of the selling patterns on Mondays and in the mornings indicates that investors use this time to sell stocks at a loss. These results are important because they present a new influence on the trading behavior of individual investors. That is, they are heavily influenced by days of the week and by time within a day. This has not previously been detected and may have been overlooked because individual investors make up a meagre fraction of the total market. Our results show that
individual investors follow a different trend to market level data and therefore it is incorrect to generalize market-based findings to individual investors going forward. The practical implications are far-reaching with further research being called for to better understand how individual investors process information and emotions, then relating this to trading decisions by individual investors in the evenings and over the weekend.

The paper is structured as follows. The next section reviews research on investor trading behavior, market trading activity on days of the week and market intraday trading activity. Following this, the methodology and data description section provide context to the method employed. The results are then presented inclusive of statistical testing and a discussion of the findings. To end, conclusions are made, limitations are addressed and future research proposed.

2. LITERATURE REVIEW

2.1 Individual investor trading behavior

The trading behavior of individual investors is of importance for many reasons. Most noteworthy, as a means of understanding why individual investors do not maximize returns. Two behaviors with robust evidence supporting them are that investors trade too frequently (Daniel & Hirshleifer, 2016) and that investors show a disposition to sell stocks at a gain while holding stocks at a loss (Odean 1998).

When individual investors are overconfident, they place an unreasonable amount of emphasis on prior experiences and act on personal information when trading. Overconfidence makes investors trade more actively and research in behavioral finance has found the detrimental effect that frequent trading has on portfolio performance (Daniel & Hirshleifer, 2016). Barber and Odean (2000) found that investors who traded the most earned an annual return of 11.4%, compared to the market’s 17.9%. This is because individual investors trade stock in a different manner to that which is expected by a rational investor and yield to increased transaction costs and bid-ask spreads when overtrading.
The impact of trading frequency on portfolio returns is not limited to the US market only. Willows and West (2015) found a statistically significant negative correlation between trading frequency and investor returns at a South African Investment house. In China, Chen, Kim, Nofsinger, and Rui (2007) noted that individual investors made trading mistakes (the stocks they sold outperformed the stocks they bought) and 43% of the sample tested exhibited more than one bias, namely the disposition effect, overconfidence, and representativeness. Kim and Nofsinger (2007) found Japanese individual investors to make poor trading decisions, but particularly during the bull market. Glaser and Weber (2009) also found evidence that German individual investors trade more frequently following positive market and portfolio return. All these studies support the overconfidence theory of trading. However, Richards and Willows (2018) found trading frequency to be positively skewed across individual investors, in that a small proportion of individual investors are responsible for most of the trading. Moreover, advised investors make statistically significantly more trades than non-advised investors (Allie, West, & Willows, 2016; Richards & Willows, 2018). These studies emphasize that the behavior of trading frequently amongst individual investors occurs globally.

A limitation of research on individual investor trading frequency is that it does not investigate when investors trade. Whilst research has investigated the influence of market returns on trading frequency (Glaser & Weber, 2009; Zhang, Wang, Wang, & Liu, 2014), there has been little research on what days of the week and what times of the day individual investors prefer when trading. However, this is an interesting avenue because individual investors, who trade on a part-time basis, face constraints during the day, due to work, which inhibits them from acquiring and processing information. These constraints force individual investors to process information on weekends and during the evenings. After processing information at these times, an investor’s confidence in his/her trading decisions would increase and thus we would expect
more trading frequency at these times. Hence, understanding the intricacies of when investors trade is a contribution of this paper.

Another widely-researched theme affecting trading behavior is the disposition effect i.e. the tendency to sell winning stocks and hold losing stocks (Shefrin & Statman, 1985). This investment behavior is associated with underperformance (Frazzini, 2006; Odean, 1998a). Research has shown this bias to be prevalent among a variety of investors, including individuals (Grinblatt & Keloharju, 2001; Odean, 1998b), futures traders (Locke & Mann, 2005) and mutual fund managers (Frazzini, 2006). Evidence for the disposition effect is robust, yet there exists great variability between investors in their susceptibility to this bias. Research has shown that investor based factors, such as their experience (Seru et al., 2010), sophistication (Feng & Seasholes, 2005) and use of automatic trading strategies (Richards, Rutterford, Kodwani, & Fenton-O’Creevy, 2017) reduce an investors susceptibility to the disposition effect. However, while the disposition effect was present amongst Chinese individual investors, the experience of the investor did not succeed in reducing this bias (Chen et al., 2007).

Beyond individual investor based differences in the disposition effect, research has shown that the amount of disposition effect exhibited varies depending on market conditions (Cheng, Lee, & Lin, 2013; Muhl & Talpepp, 2017). Muhl and Talsepp (2017) find that a greater disposition effect occurs in a bear market, even though the disposition effect still occurs in a bull market. Similarly, Japanese individual investors are more likely to prefer riskier stocks and hold onto poorly performing stocks in a bear market (Kim & Nofsinger, 2007). The prevalence of the disposition effect is greater when market-wide attention-grabbing events succeed in raising the overall level of attention that investors might pay to their portfolios (Yuan, 2015). This results in investors being more active in processing information and making trading decisions. Added to this, investors also try to rebalance their portfolios to their desired weighting across asset classes. In doing so, many stocks that yielded positive returns since their previous trade will be
sold to rebalance the portfolio. The disposition effect is influenced by information and emotional factors which would vary within an investor so that the amount of disposition effect exhibited could change in accordance with when an investor trades. Mukherjee and De (2018) contend that when investors process more information, their disposition effect is muted. They find that investors who have acquired private information, indicated by trading activity prior to earnings announcements, exhibit less disposition effect after the earnings announcement. Furthermore, there is a growing amount of research which suggests that the disposition effect is heavily influenced by the emotions an investor experiences. Summers and Duxbury (2012) show that regret is associated with the reluctance to sell a loss and positive emotions, such as elation or rejoice, are associated with an increase in the disposition effect. Richards, Fenton-O’Creevy, Rutterford, and Kodwani (2018) find that an investors reliance on emotion-based cognition increases their susceptibility to the disposition effect but effective regulation of emotions reduces susceptibility to the disposition effect.

In this research, we contend that individual investors will access and process information over weekends and in the evenings due to work constraints. Specifically, the ability to use information to make more informed trading decisions and the ability to effectively regulate emotions will occur more frequently for individual investors over the weekends and during evenings. Thus, in the trading periods following these times (Mondays and mornings), investors will exhibit less disposition effect.

In summary of the literature on individual investors, research shows that investors tend to trade too frequently and are more likely to trade a gain than a loss, but little research exists to show when these investors trade. However, ‘when’ investors trade is of interest as they face constraints which institutional investors do not. Individual investors’ ability to acquire information and process both information and emotions that influence trading decisions will occur more frequently on the weekends and in the evenings due to work constraints. Following
weekends and evenings, we hypothesize that investors will be less susceptible to the disposition effect. Therefore, one research question this paper aims to answer is:

*Are investors more inclined to sell losses or gains on Mondays and in the morning than at other times?*

Next, the literature on market-wide trading patterns over days of the week and then market wide patterns at times within a day will be reviewed. This literature is used to identify market trends in trading activity, so this research can determine whether individual investors follow the same trading patterns as seen in markets.

### 2.2 Market trading activity over days of the week

Global markets have been shown to display patterns in returns and trading volumes based on the season in the year (Kamstra et al., 2012), month in the year (Sahin et al., 2017) and day of the week (French, 1980). The focus of this research is on the volume traded on different days of the week. This research has been derived from research that shows that returns in stock markets are different on different days of the week. Initially, it was found that common stock returns are, on average, less on Mondays than other days of the week; a finding called the day of the week effect (French, 1980).

The literature on seasonal changes in stock markets has argued that a change in an investors mood, induced by the changing seasons, explains why returns tend to be negative in later winter months (Kamstra et al., 2012). Similarly, explanations of the day-of-the-week effect, particularly the lower returns seen on a Monday, are underpinned by an investor based mood explanation, with a greater proportion of investors being more pessimistic earlier in the week than later in the week. Abu Bakar, Siganos, and Vagenas-Nanos (2014) investigate this thesis with empirical evidence through the analysis of mood data from Facebook across twenty international markets. They also measure the day-of-the-week effect on a Monday and find that the day of the week effect disappears after controlling for mood (Abu Bakar et al., 2014).
Empirical evidence in support of the day of week effect is mixed. There is some recent research that found a day of the week effect occurs in Pakistan (Jebran & Chen, 2017), Indian (Mitra & Khan, 2014), Indonesian (Murhadi, 2015) and Chinese Markets (Khanna & Mittal, 2016). However, other research has found that the day of the week effect did not always occur in the USA (Xiao, 2016), Mexico and Turkey (Murhadi, 2015), Australia and New Zealand (Chia, 2014) and South Africa (Ioffe, 2008). In the UK market, a slight day of the week effect was found but this effect was ameliorated by transaction costs (Gregoriou, Kontonikas, & Tsitsianis, 2004). Overall, there is mixed evidence for a day of the week effect on market returns.

The above literature researched the day of the week effect through the analysis of market-wide averages and indexes. Different to this, Dicle and Levendis (2014) used a portfolio of stocks in their analysis. Using 37,631 stocks traded in 51 equity markets in 33 countries for the period between January 2000 and December 2007, the day of the week effect was visible in a statistically significant proportion of individual stocks (Dicle & Levendis, 2014). These results provide evidence that the day of the week effect may be stock specific rather market specific. Furthermore, 22 of the 51 markets analyzed showed negative returns on a Monday.

While there is ample research of the day of week effect for market returns, there is limited evidence for a day of the week effect for the volume of trading. Yet there is some evidence that this is an area worth investigating. Firstly, Foster and Viswanathan (1993) find that there is a day of the week effect for the volume traded on the New York Stock Exchange, with Monday having lower trading volumes than Tuesday and Wednesday for frequently traded stocks. Secondly, Battrinca, Hesse, and Treleaven (2018) conducted an analysis on pan-European stock markets which comprised of 7,197,065 daily observations for the period between 1 January

---

1 The authors also tested for a day of the week effect using the Financial Times Stock Exchange (FTSE) 100 index over the periods 2006 to 2009 but found no evidence of it occurring.
2000 and 10 May 2015. They found that the trading volume on Monday was less than other days of the week. Specifically, the Monday coefficient was consistently negative even after correcting for overnight returns in the intervening nights and their research shows robust results for less trading activity on Mondays. This confirms the existence of a day of the week effect on trading volumes at the market level. Despite evidence that markets trade less frequently on Mondays, research by Morse, Nguyen, and Quach (2014) suggests that individual investors trade more actively on Mondays. Their research investigated a random sample of 300 common stocks listed on the NYSE and compared the proportion of trading conducted by individual vs. institutional investors. They found that market volume decreased on Mondays and that institutional investors were the cause of this. But, while institutional investors decreased trading activity, individual investors increased trading volume. This paradox suggests that institutional investors are the cause of a trading volume day of the week effect but individual investors are contrarian to this market effect. This poses further impetus to understand the trading activity of individual investors on different days of the week. Therefore, this paper will also answer the following research question:

*Are individual investors more inclined to trade actively on Mondays compared to other days of the week?*

### 2.3 Intraday market trading activity

While the previous section focused on trading patterns on different days of the week, this section will focus on these same patterns, but focusing on different times within a day. This is done to further narrow down the volatility of trading to specific times on specific days. The literature can be classified according to each of the trading patterns found, namely, U-shapes, W-shapes and reverse J-shapes (or L-shapes) during the day.

Jain and Joh (1988) found that, on average, trading volume is the highest during the first hour of the day, every day. The average first-hour trading volume was found to be at least 50 percent
more than the average hourly trading volume for the rest of the day. Furthermore, trading volumes increased before the end of the day, suggesting that investors hedge their positions before they cannot be changed overnight (Jain & Joh, 1988). This suggests that a U-shaped trading pattern is seen in market trading data of the US. Using New York Stock Exchange (NYSE) data from 1988, Foster and Viswanathan (1993) found strong evidence of intraday variations in trading volume, with the volume being the highest in the first half-hour of trading and the lowest in the middle of the day. This U-shaped pattern in trading volume was confirmed by Allen, Wee, and Yang (2016) when looking at the Australian Securities Exchange between 2003 and 2009. The lunch-time session was associated with lower order placement activity (Allen et al., 2016).

Other research has found that markets sometimes follow a W-shaped pattern. While the institutional arrangements on the Tokyo Stock Exchange (TSE) are different to the NYSE, with closing for lunch being between 11:00 and 13:00, the variance of intraday stock returns still show a U-shape pattern (Ito & Lin, 1992). However, when investigating the liquidity of this same market two decades later, but specifically, in trading of government bonds, Tsuchida, Watanabe, and Yoshiba (2016) noted a W-shaped pattern for each day. That is, a U-shaped pattern, separated by a lunch break. This W-shaped pattern in the Japanese market was also found by Anderson, Bollerslev, and Cai (2000).

In Central European stock markets, Gurgul and Syrek (2017) showed differences in intraday trading volume patterns across markets at a company level, from a microstructural perspective, for the Austrian Traded Index (ATX) and Deutscher Aktien Index (DAX). Overall, a disturbed U-shape or reverse J-shaped (L-shaped) pattern is seen for Austrian and German companies. For Polish companies on the WIG20 index of the Warsaw Stock Exchange (WSE), a disturbed U-shape or reversed L-shaped (J-shaped) pattern is observed where heightened trading activity is seen at the close of day. However, these were not as frequent with some days showing no
typically recognizable shapes. When volatilities and trading volumes for each day of the week were assessed separately, ATX and DAX companies also showed peaks on a Friday, when announcements are for these companies are made. Finally, Wagner and Margaritis (2017) found that individual investors engaged in late trading activity of mutual funds in France and Germany, to ascertain pricing advantages when price information on the fund had been released.

The literature reviewed shows that trading volume is a function of both the day of the week and the time of the day. While intraday trading patterns reflecting a U-shape (Allen et al., 2016; Foster & Viswanathan, 1993), W shape (Anderson et al., 2000; Tsuchida et al., 2016) and reverse J shape (Gurgul & Syrek, 2017) are noted, the commonality is that trading frequency is heightened first thing in the morning. That being said, the majority of the research is on trading activity from market data. There is little research on when individual investors trade.

Individual investors might not follow the patterns of market data due to the constraints they face. Therefore, these market-based trends might not apply to individual investors, particularly because the volume they trade is relatively small compared to other market participants (Morse et al., 2014). The aim of this research is to ascertain whether individual investors trade following a U-shaped, W-shaped, or reverse J-shaped pattern or demonstrate their own behavior. Thus, the final research question that this paper aims to answer is:

*Do aggregate individual investor’s trading patterns follow a U-shaped, W-Shaped or reverse J-shaped pattern over a trading day?*

3. METHOD

3.1 Research data

Investor trading records were acquired from a brokerage firm in the UK. The brokerage firm provides its clients with a stock trading platform to buy and sell shares, bonds, and funds. The firm did not offer other trading services (such as currency trading, futures etc.). Only a few
investors at the firm (estimated to be less than 1% by the sales manager) could trade warrants which would allow them to make a leveraged position or a short position. Thus, the investors in the sample reflect individual investors who typically buy and sell stocks in their spare time and on a non-professional basis. The UK brokerage firm had approximately 6% market share of the UK brokerage market at the end of 2009.

The trading records contained all the trades that each investor conducted in the secondary market, which could be completed via the internet, telephone, written correspondence and in person. The firm provided trading records for 7,828 investors who completed 395,998 trades between 5 July 2006 and 14 December 2009 (the ‘observation period’). These investors were selected randomly by the sales manager at the brokerage firm, and the sample can be generalized to UK-based individual investors who trade more than 2 times per annum. The trading records contained information regarding the trade, such as the date, time, the value (in pounds sterling), the quantity traded, the stock name, the International Securities Identification Number (ISIN) and a unique stock identifier.

The trading records were filtered so that an appropriate sample could be used. The data removed included any investors which did not have demographic information. Investors who were younger than 19 years were removed as these investors may not be making their own investment decisions. Finally, 30,997 automatic reinvestment trades which were executed by the brokerage firm on behalf of the investor were also removed because the investor did not place the order themselves. This left 341,452 trades which were completed by 7,200 investors over a period of 874 trading days. This data is referred to as the ‘trading sample’.

To investigate whether investors are more inclined to sell losses or gains, the trading records were examined to identify any ‘round-trip’ transactions. A round-trip transaction is the buy and sell trades an investor made in one stock to open and then close that position. Put differently, an investor bought and subsequently sold the same number of shares during the observation
period. Use of such round-trip transactions allowed accurate analysis of the purchase price and sale price of a stock because it removed all trades where an investor had purchased before the observation period or sold after the observation period. Adjustments for corporate actions, such as splits, consolidations, scrip dividends, and rights issues were made whilst determining these round-trip transactions. The round-trip data contained 173,681 trades that were completed by 4,344 investors in 66,062 round-trip transactions. Please note that investors could use multiple buy and sell transactions to start and close a round-trip transaction.

The final step was to obtain daily stock price data for the stocks in these round-trip transactions. Datastream was used for this purpose. If the price data was not available from Datastream, then the round-trip transaction was removed. The final dataset consisted of 62,823 round-trip transactions completed by 4,266 investors. This dataset is referred to as the ‘round-trip sample’.

3.2 Research design

3.2.1 Descriptive analysis

Descriptive analysis was employed to investigate trading patterns relating to the day of the week and the time of the day that individual investors buy and sell stocks. To identify patterns, the number of transactions, purchases and sales completed on each day, and throughout the day in 30 minute periods, are graphically displayed.

3.2.2 Trading on days of the week

For more robust statistical analyses of when trading occurred, we use a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model with an Autoregressive Integrated Moving Average (ARIMA) model. We include three dependent variables of trading activity: total number of trades, total number of sales and total number of purchases on each trading day. A GARCH \((m,k)\) model controls for time-varying volatility in the number of trades on a calendar day. This is useful when there are changes in volatility of the dependent variable over the sample period, which occurs in our data. An ARIMA model is used to describe the
behavior of variables in terms of linear relationships with their past values. In stock market trading, autocorrelations trading activity are common where there are periods of high (low) trading activity followed by periods of high (low) trading activity (Hautsch, 2011). Furthermore, there are often trends in stock market trading activity as investors will trade more (less) actively following a month of high (low) returns (Glaser & Weber, 2009). An ARIMA model with a differenced dependent variable controls for this. Finally, in stock market trading activity there is often noise (Black, 1986), which is also controlled for in an ARIMA model.

An ARIMA \((p,d,q)\) denotes an ARIMA model with \(p\) autoregressive lags, \(q\) moving average lags, and differences in the order of \(d\). The formula for our ARIMA model is:

\[
Y_t = \mu + \sum_{i=1}^{p} Y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta \varepsilon_{t-i} 
\]

\((1)\)

\(Y_t\) represents the dependent variable, which is the number of trades completed by investors at time \(t\). \(\mu\) is a constant and \(\varepsilon\) refers to an error term. In this analysis, the model includes a differenced dependent variable (indicated with a \(d\)) to control for non-stationary trends in the trading activity. The differenced dependent variable for first-order differences is:

\[
\Delta Y_t = Y_t - Y_{t-1} \]

\((2)\)

The formula for the GARCH \((1,1)\) model is:

\[
\sigma_t^2 = \gamma_1 \varepsilon_{t-1}^2 - \delta_1 \varepsilon_{t-1}^2
\]

\((3)\)

where \(\sigma_t^2\) is the conditional variance of the residuals obtained from equation \((1)\), \(\gamma_1\) is the ARCH parameter and \(\delta_1\) is the GARCH parameter. The parameters used in the model are a GARCH \((1,1)\) model and an ARIMA \((1,1,1)\). This parameterisation was determined using graphical assessment (autocorrelations, partial autocorrelations, non-stationarity and heteroscedasticity) and by trialling models to obtain the lowest Akaike information criterion (AIC), and Bayesian information criterion (BIC) values (Sakamoto, Ishiguro, and Kitagawa, 1986)).
To identify whether a specific day of the week influences trading activity, dummy variables denoting each day of the week were created to identify if more or less trading occurs on that day. The day of the week we investigate (Monday) was excluded so a comparison between other days and a Monday could be made. Also included are a daily market return variable (natural log of Financial Times Stock Exchange (FTSE) 100 index/FTSE100t-1) and a daily market volume variable (the number of shares traded on the FTSE 100 index/10,000).

### 3.2.3 Trading of losses and gains

This paper investigates whether investors are more inclined to trade a loss or a gain (the disposition effect) during their periods of peak trading behavior. To investigate this, a shared frailty survival analysis model is adopted. Survival analysis models can ascertain the influence of variables on the tendency to sell stocks with greater flexibility and control than other methods (Feng & Seasholes, 2005). A shared frailty model in survival analysis is similar to adding a random effect to a linear regression as a way to account for correlations between clusters of observations. Thus, by using a shared frailty model, an investor’s characteristics (e.g. sophistication and experience) that decrease (increase) the tendency to sell stocks at a gain (loss) are controlled for, while the influence of the time of the day and day of the week is ascertained.

In the model, $i$ denotes the investor who first purchases a stock to start a roundtrip transaction $k$. We include the factor $\alpha_i$ to estimate the investor level variance of frailty. This factor has a gamma distribution with $\alpha_i > 0$, the mean of $\alpha_i$ equal to one and a variance parameter $\theta$, estimated from the data. When investor $i$ purchases a stock, time $t$ is equal to one and $t$ increases by one each day the stock market was open. Survival time, $T$ is measured by a sale covariate which takes the value of zero when a stock is held and the value of one on the day it is first
sold. Similar to Feng and Seasholes (2005), a Weibull distribution is utilized to estimate the shared frailty conditional hazard model\(^2\). The hazard model is:

\[
h_{ik}(t | \alpha_i) = \alpha_i h_{ik}(t)
\]

\[
\alpha_i h_{ik}(t) = \alpha_i \exp(X_{ik}\beta) pt^{1-p}
\]

where \(h_{i,k}(t | \alpha_i)\) is investor \(i\)'s probability of selling stock \(k\) at time \(t\), conditional on both not selling until time \(t\) and the frailty variance factor \(\alpha_i\). \(h_{ik}(t)\) is the baseline hazard function, which is a parametric model calculated using a Weibull function \(pt^{1-p}\). \(p\) in a Weibull model is a shape parameter estimated from the data. \(p > 1\) means that the hazard increases as time increases, \(p < 1\) means that the hazard decreases as time increases and \(p = 1\) means the hazard is constant over time. We calculate \(\beta\) using both investor and transaction-based covariates expressed as \(X_{ik}\). The two time-varying covariates used to measure the disposition effect are a trading gain indicator (TGI) and trading loss indicator (TLI). The TGI (TLI) takes the value of 1 when a stock is trading or sold at a gain (loss) and a value of zero otherwise.

In the survival analysis model, two dummy variables are included; a covariate to indicate stocks sold on a Monday and a covariate to indicate stocks sold before 08:30 am. Finally, a stop loss round-trip transaction covariate is used to control those transactions which are sold using a stop loss and is included as a control. These covariates are interacted with the TLI and the TGI to ascertain if there is an increase or decrease in the tendency to sell stocks at a loss or gain, respectively. Finally, the covariates are included by themselves to control for the direct influence that Monday, prior to 8:30 am and stop losses have on trading activity in general.

\(^2\) Other survival analysis models, such as Cox Proportional Hazard model and a Weibull model without shared frailty, were also used. The results were very similar to those presented in this paper and results are omitted for brevity.
4. RESULTS

The results of various descriptive statistics will be discussed, after which the output from the ARIMA and GARCH models will be presented. Finally, results on the tendency to trade losses and gains using survival analysis are presented.

4.1 Descriptive statistics

Table 1 outlines the descriptive statistics of the trades in the trading sample.

<table>
<thead>
<tr>
<th>Types of stocks traded</th>
<th>Number of transactions</th>
<th>Percentage of transactions</th>
<th>Total Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shares</td>
<td>309389</td>
<td>90.61%</td>
<td>£669,237,489</td>
</tr>
<tr>
<td>Managed funds &amp; ETFs</td>
<td>27181</td>
<td>7.96%</td>
<td>£53,995,941</td>
</tr>
<tr>
<td>Bonds</td>
<td>753</td>
<td>0.22%</td>
<td>£4,533,954</td>
</tr>
<tr>
<td>Warrants</td>
<td>803</td>
<td>0.24%</td>
<td>£2,585,155</td>
</tr>
<tr>
<td>Unidentified</td>
<td>3326</td>
<td>0.97%</td>
<td>£3,570,289</td>
</tr>
</tbody>
</table>

* calculated as total value traded (£)/number of trades per investor

Table 1 illustrates that there is a mean trade value of around £2 150 but the spread in trading value is positively skewed with few trades being in very high values and a lot of trades below the median. A pattern of positively skewed data is also illustrated in the number of trades per day, but this is less extreme because the mean trades per day (around 391) is located between the median and the 75th percentile. The types of stocks traded indicate that shares are the most popular followed by managed funds and exchange traded funds (ETF). Few investors trade in bonds or warrants. The number of trades over the observation period trading time is shown graphically in Figure 1.

Figure 1: Number of trades per day over time
Figure 1 reflects an upward trend in the number of trades towards the end of the observation period. This trend is likely due to a significant bull market over this period as the FTSE recovered from the global financial crisis. Figure 1 illustrates the need to use a GARCH model as the volatility of trading increases over the observation period, indicating Heteroscedasticity. An ARIMA model is also needed as there is autocollinearity in trading periods, an upwards trend in trading activity, and noise present in the data.

Figure 2 is a comparison of the number of trades completed on each day divided by the number of those days in the trading sample.

**Figure 2: Mean number of trades per day**
Note: * mean represents the number of trades on each day divided number of those trading days in the data.

Figure 2 shows Monday being more active than other days of the week in terms of overall trades, purchases, and sales. Figure 3 shows the number of trades per 30-minute time-period divided by the number of trading days. In total, there are 17 time-periods, with the first period reflecting all trades before 08:30 (the market opens at 08:00). The final period of trading is after 16:00 (the market closes at 16:30). There were 43 trades which occurred prior to the market opening (included in the pre 08:30 time) and 106 trades recorded after the market was closed (included in the post 16:00 time). The trades which occurred outside of market hours could have been executed by market makers.

Figure 3: Mean trades per 30-minute period during the trading day
Note: * mean represents number of trades per 30-minute time-period divided by number of trading days.

Two trends are seen in Figure 3. Firstly, there are more trades than average during four periods of the day; pre 8:30 (market opening), 9:00-9:30, 13:00-13:30 and post 16:00 (market closing). The heightened trading activity at market opening and closing are supported in the prior literature which shows a U-shaped trading activity pattern during the day (Allen et al., 2016; Foster & Viswanathan, 1993). However, the 13:00 – 13:30 trading period and to some extent, the 9:00 – 9:30 period, are unique findings to a study on individual investors in the UK. Both increases in trading are driven by an increase in purchases by investors and not by sales. The spike over lunch-time, more commonly known as W-shaped trading activity has previously been noted in market data in Japan (Anderson et al., 2000; Tsuchida et al., 2016). Given that the trading sample consisted of individual investors only, such trading activity could be explained by the timing of trades after arriving at work and/or having a break over lunch. 

The higher number of sell trades which occur when the market is opening (around twice the frequency of sell trades occurring pre 8:30 compared to selling at any other time during the
day) denotes an interesting behavior of individual investors. It is possible that investors sell first thing in the morning after considering the decision to sell during the night or over the weekend.

A comparison of the mean number of purchases and sales per 30-minute time-period over different days of the week are outlined in Figure’s 4 and 5.

**Figure 4: Purchase transactions per day per 30-minute time-period**

Note: * mean represents number of trades per 30-minute time-period divided by number of trading days.

Figure 4 shows that the purchasing activity of individual investors is highest on a Monday morning between 9:00 and 9:30, followed by pre 8:30 of the same day. Other than this, there is consistently higher purchasing activity across all days of the week between 13:00 and 13:30 and between 16:00 to 16:30.
Figure 5: Sale transactions per day per 30-minute time-period

Note: * mean represents number of trades per 30-minute time-period divided by number of trading days.

Figure 5 shows that selling activity also occurs more frequently on a Monday morning when the market opens i.e. pre 8:30, than at any other time-period during the week. Pre 8:30 is also the most popular time-period for selling Tuesday to Friday.

4.2 Trading on days of the week

The results for the GARCH and ARIMA analyses are presented in Table 2. These results are for an ARIMA (1,1,1) and GARCH (1,1) model on the differenced number of trades ($d.trades$ in column 1), differenced number of purchases ($d.Purchases$ in column 2), and differenced number of sales ($d.sales$ in column 3). The independent variables are dummies for each day of the week, excluding Monday, to ascertain if trading, purchasing and selling is greater on a Monday when compared to other days of the week. Also included are a FTSE 100 return
variable and FTSE 100 volume variable to control for the influence of market returns and market trading in the analysis.

Table 2: ARIMA GARCH of trades, purchases and sales with days of the week dummies

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>d.Trades</td>
<td>d.Purchases</td>
<td>d.Sales</td>
</tr>
<tr>
<td>Tuesday</td>
<td>-100.6***</td>
<td>-63.68***</td>
<td>-31.92***</td>
</tr>
<tr>
<td></td>
<td>(-11.95)</td>
<td>(-11.24)</td>
<td>(-8.52)</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-55.78***</td>
<td>-39.56***</td>
<td>-16.43***</td>
</tr>
<tr>
<td></td>
<td>(-6.97)</td>
<td>(-6.78)</td>
<td>(-4.62)</td>
</tr>
<tr>
<td>Thursday</td>
<td>-35.84***</td>
<td>-21.84***</td>
<td>-9.666*</td>
</tr>
<tr>
<td></td>
<td>(-3.82)</td>
<td>(-3.32)</td>
<td>(-2.29)</td>
</tr>
<tr>
<td>Friday</td>
<td>-21.25**</td>
<td>-11.38</td>
<td>-8.061*</td>
</tr>
<tr>
<td></td>
<td>(-2.71)</td>
<td>(-1.80)</td>
<td>(-2.18)</td>
</tr>
<tr>
<td>FTSE 100 Volume</td>
<td>&lt;0.0001</td>
<td>&gt;-0.0001</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.30)</td>
<td>(-0.72)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>FTSE 100 Return</td>
<td>-185.5</td>
<td>-367.2***</td>
<td>216.2***</td>
</tr>
<tr>
<td></td>
<td>(-1.50)</td>
<td>(-3.89)</td>
<td>(4.46)</td>
</tr>
<tr>
<td>Constant</td>
<td>42.91***</td>
<td>29.55***</td>
<td>13.04***</td>
</tr>
<tr>
<td></td>
<td>(6.72)</td>
<td>(6.48)</td>
<td>(4.94)</td>
</tr>
</tbody>
</table>

ARMA

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L.ar</td>
<td>0.394***</td>
<td>0.332***</td>
<td>0.313***</td>
</tr>
<tr>
<td></td>
<td>(7.63)</td>
<td>(6.20)</td>
<td>(6.59)</td>
</tr>
<tr>
<td>L.ma</td>
<td>-0.842***</td>
<td>-0.820***</td>
<td>-0.855***</td>
</tr>
<tr>
<td></td>
<td>(-28.00)</td>
<td>(-26.67)</td>
<td>(-31.12)</td>
</tr>
</tbody>
</table>

ARCH

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L.arch</td>
<td>0.170***</td>
<td>0.124***</td>
<td>0.176***</td>
</tr>
<tr>
<td></td>
<td>(6.81)</td>
<td>(5.49)</td>
<td>(7.42)</td>
</tr>
<tr>
<td>L.garch</td>
<td>0.808***</td>
<td>0.846***</td>
<td>0.819***</td>
</tr>
<tr>
<td></td>
<td>(32.60)</td>
<td>(31.42)</td>
<td>(41.54)</td>
</tr>
<tr>
<td>Constant</td>
<td>280.8***</td>
<td>135.5***</td>
<td>46.71***</td>
</tr>
<tr>
<td></td>
<td>(4.45)</td>
<td>(3.99)</td>
<td>(3.87)</td>
</tr>
</tbody>
</table>

N 873 873 873

* t statistics in parentheses
| p < 0.05, ** p < 0.01, *** p < 0.001 |

Table 2 shows that the overall trading and selling activity is higher on a Monday than any other day of the week. For purchasing activity, Monday has more purchases than Tuesday, Wednesday and Thursday at a statistically significant level but the difference between Monday and Friday is not statistically significant.
4.3 Trading of gains and losses

Individual investors show a pattern of selling more frequently on Mondays and before 08:30. This behavior is investigated further to ascertain if the investors are more likely to sell losses or gains on Mondays, pre 08:30 and Mondays pre 08:30. The results of these analyses are outlined in Table’s 3 and 4. Table 3 presents the results for the trading loss indicator (TLI) and Table 4 the results for the trading gains indicator (TGI).

Table 3: Trading Loss Indicator (TLI) with Monday and market open variables

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>TLI (Z-stat)</td>
<td>.4574**</td>
<td>.4694**</td>
<td>.4725**</td>
<td>.4514**</td>
</tr>
<tr>
<td></td>
<td>(-76.61)</td>
<td>(-71.75)</td>
<td>(-77.84)</td>
<td>(-71.74)</td>
</tr>
<tr>
<td>TLI x Pre-08:30am sale</td>
<td>1.3367**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Z-stat)</td>
<td>(12.37)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TLI x Monday (Z-stat)</td>
<td></td>
<td>1.1025**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.53)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TLI x Monday x Pre-08:30am sale (Z-stat)</td>
<td></td>
<td>1.4168**</td>
<td>1.1406*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(8.31)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TLI X Stop Loss Transaction (Z-stat)</td>
<td>2.5983**</td>
<td>2.6548**</td>
<td>2.6095**</td>
<td>2.59577**</td>
</tr>
<tr>
<td></td>
<td>(32.51)</td>
<td>(33.37)</td>
<td>(32.74)</td>
<td>(32.46)</td>
</tr>
<tr>
<td>Pre-08:30am Sale (Z-stat)</td>
<td>.8329**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-11.85)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday (Z-stat)</td>
<td></td>
<td>.9335**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-5.27)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday x Pre-08:30am sale (Z-stat)</td>
<td></td>
<td>1.1229**</td>
<td>1.3590**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stop Loss Transaction (Z-stat)</td>
<td>35.4865**</td>
<td>35.2846**</td>
<td>35.2704**</td>
<td>35.4273**</td>
</tr>
<tr>
<td></td>
<td>(175.02)</td>
<td>(174.95)</td>
<td>(174.93)</td>
<td>(174.92)</td>
</tr>
<tr>
<td>p (Z-stat)</td>
<td>1.01415**</td>
<td>1.0129**</td>
<td>1.0131**</td>
<td>1.01427**</td>
</tr>
<tr>
<td></td>
<td>(4.79)</td>
<td>(4.40)</td>
<td>(4.46)</td>
<td>(4.84)</td>
</tr>
<tr>
<td>θ (Z-stat)</td>
<td>.8026**</td>
<td>.8017**</td>
<td>.8045**</td>
<td>.8020**</td>
</tr>
<tr>
<td></td>
<td>(-9.15)</td>
<td>(-9.20)</td>
<td>(-9.07)</td>
<td>(-9.18)</td>
</tr>
</tbody>
</table>

Columns 1 and 2 contain a pre-8:30 morning trade covariate and a Monday covariate, respectively. The pre-8:30 covariate interacted with the TLI has a statistically significant hazard ratio above 1 which means that sales executed before 08:30 are more likely to sell at a loss. Likewise, the results for the Monday covariate interacted with the TLI also show an increased chance of selling a loss on a Monday. Finally, when combined in column 4, there is
an increased chance of selling losses pre-8:30, on Mondays and on Mondays pre-8:30. The increased sales activity on Mondays and pre 8:30 is associated with a tendency to sell losses by individual investors. Table 4, to follow, presents the results for the trading gain indicator (TGI) with explanatory variables.

Table 4: Trading Gain Indicator (TGI) with Monday and market open covariates

<table>
<thead>
<tr>
<th>TGI (Z-stat)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>TGI x Pre-08:30 sale (Z-stat)</td>
<td>.8614** (-6.58)</td>
<td></td>
<td>.8679** (-5.56)</td>
<td></td>
</tr>
<tr>
<td>TGI x Monday (Z-stat)</td>
<td>.9882 (-0.58)</td>
<td>.9991 (-0.04)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TGI x Monday x Pre-08:30 sale (Z-stat)</td>
<td></td>
<td>.8795* (-3.10)</td>
<td>.9806 (-0.42)</td>
<td></td>
</tr>
</tbody>
</table>

Control Variables

| TGI x Stop Loss Transaction (Z-stat) | .7123** (-11.49) | .7061** (-11.79) | .7103** (-11.59) | .7137** (-11.42) |
| Pre-8:30 sale (Z-stat) | .9951 (-0.30) |       | .9172** (-4.71) |       |
| Monday (Z-stat) |       | .9679* (-2.25) |       | .9547* (-3.18) |
| Monday x Pre-08:30 sale (Z-stat) |       |       | 1.3689** (11.06) | 1.4534** (11.74) |

Stop Loss Transaction (Z-Stat) | 56.9019** (200.67) | 56.9569** 200.99 | 56.5478** 200.56 | 56.7596** 200.54 |
| p (Z-stat) | .9431** (-18.35) | .9429** (-18.40) | .9428** (-18.43) | .9431** (-18.32) |
| θ (Z-stat) | .7910** (-9.71) | .7911** (-9.71) | .7938** (-9.58) | .7903** (-9.74) |

*,**, *** - significant at p<.01, p<.001

In Table 4, columns 1 and 2 contain the covariates for selling pre-08:30 and on a Monday, respectively. The hazard ratio for the interaction between pre-08:30 and the TGI is statistically significant and below 1, which means that gains are less likely to be sold at this time. However, the Monday covariate interacting with the TGI does not have a statistically significant hazard ratio. There is no indication that gains are more or less likely to be sold on a Monday compared to other days. Finally, in column 4, only the pre-08:30 covariate interacted with the TGI is statistically significant and below 1. This show that the gains are less likely to be sold prior to
08:30 in the morning but there is no effect on Mondays for the sale of gains. Overall, the results in Table 4 support that when the market opens, investors are less likely to sell at a gain.

5. DISCUSSION AND CONCLUSION

Research on individual investors has presented evidence that individual investors show idiosyncratic behaviours. In particular, investors trade too frequently (Barber & Odean, 2000) and have a disposition for selling gains while holding losses (Shefrin & Statman, 1985). However, there is little research that focuses on when individual investors exhibit those trading behaviours. This topic warrants investigation because prior research has shown financial markets are influenced by time effects and it is unknown whether individual investors will mimic such trends. Also, individual investors that work will face constraints in their ability to process information and emotions to make investment decisions. Thus, the extent that investors demonstrate overtrading or disposition effect will vary over different time periods. The research we report on investigates the ‘when’ aspect of individual investors trading to identify when they trade frequently and when they trade gains and losses.

Using trading records for 7 200 UK investors, our research investigates the extent to which individual investors trade on days of the week and times within a day. A useful comparison of our research is to literature that investigates market-level data to identify anomalies in global stock markets. Such research has proposed a day of the week effect (Monday effect), where market returns are poorer on Mondays (French, 1980). There is mixed evidence of a universal day of the week effect (Dicle & Levendis, 2014) but there is evidence that markets have less trading activity on Mondays compared to other days of the week (Batrinca et al., 2018; Foster & Viswanathan, 1993). Our findings show that individual investors follow a different trend; they are more likely to trade on a Monday and they are more likely to sell on a Monday than any other day of the week. As individual investors make up a meager fraction of the total market volume, their behavior is unlikely to be detected in market-level analysis of trading (Morse et
We contend that a reason for increased trading activity on a Monday is that investors utilise the weekend to both gather and analyze information to make trading decisions on a Monday.

Research on intra-day market trading volume illustrates that trading follows either a U-shaped (Allen et al., 2016), W-shaped (Tsuchida et al., 2016) or a reverse J-shaped (Gurgul & Syrek, 2017) pattern. These patterns show spikes in trading activity occurring at market opening and market closing (U-shaped), around the opening, middle and closing (W shaped), or at market opening only (reverse J-shaped). A contribution of this research is that we show individual investors in our study generally follow the W-shaped pattern of trading activity, but with some additional observations. One observation is that individual investors also exhibit an increase in trading (buying) activity between 09:00-09:30, which might coincide with arrival at work. A second observation is that the market opening spike in trading behavior is driven by an increase in both buys and sells by investors but the lunchtime and evening spikes in the number of trades occur through an increase in buy transactions only. A contribution of our research is that when investors sell stocks, they are more likely to do this in the morning and on Mondays. We investigated this pattern further by analyzing whether investors were more likely to sell gains or losses on Mondays, mornings and Monday-morning in particular.

On average, investors are more inclined to sell gains and hold losses, a bias referred to as the disposition effect. Research suggests that investor variability to this bias decreases gradually with experience (Seru et al., 2010) and sophistication (Feng & Seasholes, 2005). However, there is growing research that an individual investor may vary significantly in their disposition effect from time to time (Mukherjee & De, 2018). Firstly, there is evidence that bear market conditions make investors less susceptible to the disposition effect, implying that they learn faster during this period (Muhl & Talpsepp, 2017). Also, Mukherjee and De (2018) contend that an investor will vary in the extent they are fully rational because making rational decisions
(as opposed to behavioral decisions) requires strong cognitive effort. Our research extends this argument. We argue that individual investors face work constraints which limit their ability to obtain and process information. Therefore, the ability to use cognitive resources to make closer to rational decisions will be limited to evenings and the weekend. Our empirical evidence supports this claim. We find that investors show less disposition effect on Mondays, mornings and Monday-mornings, as they are more inclined to sell losses at these times. As these are days and times when they are more likely to sell shares in general, this suggests that loss selling activity follows periods in which individual investors have obtained and processed information to make investment decisions.

A possible explanation of this behavior is that individual investors require extra time to correct a counterfactual event. As an example, an investor invests to gain a return yet they are presented with having lost money from their investment decision. To process this and correct the behavior, they may require a weekend or the evening after work to cognitively process this and then execute a sale trade. However, an alternative theory is that generally, mornings and Mondays induce a bad mood. Realising a loss will induce negative emotions and investors may integrate the selling of losses with Monday mornings to create congruence between their state and their behavior. In other words, “Monday mornings cannot get any worse, so why not sell that loss?”

5.1 Limitations and future research

This research is somewhat exploratory as there is little literature on when individual investors trade. This presents both limitations and opportunities for future research. Firstly, the trends uncovered in this research may be specific to the country (the UK) and the time-period (between 2006 and 2009). Even though the influence of market fluctuations on trading was controlled for in the analysis, the time-period covers the financial crisis where a large bear and bull market occurred. Future research from different countries, and in different conditions, is
needed to ascertain if the trading patterns of individual investors apply elsewhere. Secondly, the thesis that investors process information during evenings and weekends is implied and not empirically researched. Whilst this is a logical assumption, more research into how and when individual investors process information is needed to better understand the relationship between information processing and trading. Finally, this research uses a somewhat modest sample size, with 7200 investors. This data-set contains adequate empirical data to draw conclusions, but future research could investigate a larger sample to compare individual investors to institutional investors.
REFERENCE LIST


