

Stock market investors' use of stop losses and the disposition effect

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Abstract

The disposition effect is an investment bias where investors hold stocks at a loss longer than stocks at a gain. This bias is associated with poorer investment performance and exhibited to a greater extent by investors with less experience and less sophistication. A method of managing susceptibility to the bias is through use of stop losses. Using the trading records of UK stock market individual investors from 2006 - 2009, this paper shows that stop losses used as part of investment decisions are an effective tool for inoculating against the disposition effect. We also show that investors who use stop losses have less experience and that, when not using stop losses, these investors are more reluctant to realise losses than other investors.

Key words: behavioural finance; disposition effect; stop losses; investor experience; investor sophistication

JEL Classifications: G02, G11

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1. Introduction

Research into the decision making of individual investors has shown that their decisions often deviate from normative rational economic models. A particular decision making bias exhibited by stock market investors is the disposition effect, where investors are predisposed to hold stocks trading at a loss and to sell stocks trading at a gain (Shefrin and Statman, 1985). Odean (1998) and Seru et al. (2010) have shown that susceptibility to this bias is correlated with poor investment performance, so it is in an investor's interest to reduce their susceptibility to this bias. To a certain extent, sophisticated investors and experienced investors do learn to reduce the disposition effect in their trading (Boolell-Gunesh et al., 2009, Brown et al., 2006, Chen et al., 2007, Dhar and Zhu, 2006, Feng and Seasholes, 2005, Grinblatt and Keloharju, 2001, Seru et al., 2010, Shapira and Venezia, 2001). In this paper we argue that a relatively easy way to reduce the disposition effect is through the use of stop losses, since stop losses can automate an exit strategy, reducing reliance on an investor's impulse control. Stop losses have been researched as a method of portfolio insurance (Rubinstein and Leland, 1981) and research on stop losses has assessed the extent to which their use is optimal for a normatively rational investor (Annaert et al., 2009, Bird et al., 1988, Dybvig, 1988b, Gollier, 1997). This research has shown that a stop loss strategy is inefficient for an investor that aims to maximise portfolio

returns under the assumptions of utility maximisation (Dybvig, 1988b, Gollier 1997). However, the disposition effect illustrates a behavioural pattern in which investors do not adhere to the prescriptions of neoclassical economic models (Shefrin and Statman, 1985). The value of stop losses for stock market investors may be as a self-control mechanism that allows them manage their reluctance to sell losses and eagerness to sell gains. Stop losses can be an effective tool to counteract the disposition effect. For example, as Nolte (2012) found, the use of stop losses and take profit strategies inverted the disposition effect for foreign exchange traders.

The relationship between stop loss use, investor sophistication and experience has not been fully explored in the literature and it is unknown whether sophisticated and experienced investors adopt stop loss strategies, thereby reducing their susceptibility to the disposition effect bias. This paper reports unique research on the disposition effect because we investigate the relationship between sophistication, experience and stop loss use and compare the extent to which each of these variables reduces the disposition effect. We also investigate the use of stop losses as a self-control mechanism by analysing the susceptibility of those investors who sometimes use stop losses to the disposition effect when these same investors are not using stop losses. The paper is structured as follows: Section 2 reviews the literature on the disposition effect, investor sophistication, investor experience and stop losses, from which research hypotheses are derived. Section 3 outlines the methodology and data for this research. Section 4 outlines the results and section 5 discusses the results and the implications for theory and practice.

2. Literature

Shefrin and Statman (1985) use the term 'disposition effect' to refer to investors' decision making bias where investors tend to hold investments longer when the investments have depreciated in value than when these have appreciated in value. In layman terms, investors "sell winners too early and ride losers too long" (Shefrin and Statman, 1985). Often, prospect theory (Kahneman and Tversky, 1979) is used to explain why investors are prone to this bias (Dacey and Zielonka, 2008, Odean, 1998). A prospect theory based explanation of the disposition effect posits that investors are more risk seeking towards stocks held at a loss and are risk seeking towards stocks held at a gain due to the 'S' shaped value (utility) function (Dacey and Zielonka, 2008). However, recently, researchers have questioned whether prospect theory alone can explain the disposition effect (Barberis and Xiong, 2009, Hens and Vlcek, 2005, Lehenkari, 2012, Summers and Duxbury, 2012). Lehenkari (2012) investigated differences in the amount of disposition effect for investors who were gifted or inherited stocks and those investors who purchased stock themselves. She finds a more pronounced disposition effect for those investors who purchased the stocks than those who inherited the stocks. Similar results were found by Summers and Duxbury (2012) in experimental research where they could also measure participants' level of regret and elation to ascertain the relationship between emotions and disposition effect. They find that regret, induced by buying a stock that subsequently decreased in value, was necessary for participants to retain losers. However, elation, induced by buying a stock that subsequently increased in value, did not lead to participants selling winners. Their research suggests that the role of emotions is integral to the behavioural pattern of the disposition effect.

There are strong empirical findings verifying that stock market investors exhibit the disposition effect (Boolell-Gunesh et al., 2009, Brown et al., 2006, Chen et al., 2007, Dhar and Zhu, 2006, Feng and Seasholes, 2005, Odean, 1998, Seru et al., 2010, Shapira and Venezia, 2001). Shapira and Venezia (2001) found substantial variability in the extent to which investors exhibit this bias and estimate that one in five investors do not trade with the disposition effect. Research on the disposition effect has moved from proving evidence of the bias (Odean, 1998) to predicting individual differences in exhibiting this bias. Three variables which have been shown to decrease the disposition effect are sophistication, experience and use of automatic trading strategies (Boolell-Gunesh et al., 2009, Brown et al., 2006, Chen et al., 2007, Dhar and Zhu, 2006, Feng and Seasholes, 2005, Grinblatt and Keloharju, 2001, Seru et al., 2010, Shapira and Venezia, 2001, Nolte, 2012). Each of these variables is reviewed below.

Investor sophistication has not been clearly defined in the disposition effect literature and the demographic variables used as proxies to measure sophistication differ significantly between studies. However, the following proxies have been used to measure sophistication and are all related to a decrease in the disposition effect: investors with a professional occupation (Shapira and Venezia, 2001); corporate investors (Brown et al., 2006, Grinblatt and Keloharju, 2001); wealth proxies such as income, portfolio value, average trade size (Brown et al., 2006, Chen et al., 2007, Seru et al., 2010); male investors (Feng and Seasholes, 2005); portfolio diversification (Boolell-Gunesh et al., 2009, Feng and Seasholes, 2005); location (Chen et al., 2007); and whether investors trade complex products such as warrants and options (Boolell-Gunesh et al., 2009, Seru et al., 2010). An interesting finding by Nolte and Voev (2011) is that portfolio performance influences the disposition effect differently for sophisticated investors as

measured by trade size. They find that investors who traded in larger values were more likely to close off positions when the performance of their portfolio was at a gain. However, traders who traded in smaller values did not show the same behavior. They suggest that this may show that less sophisticated investors are more likely to narrow frame investment decisions.

An investor's experience is also measured in different ways. One measure is an investor's number of cumulative trades (Feng and Seasholes, 2005, Seru et al., 2010) and another is their number of years of investment experience (Chen et al., 2007). Feng and Seasholes (2005) show that, as new investors trade, they significantly increase their trading of losses and slightly decrease their trading of gains. Seru et al., (2010) found that experience measured in cumulative trades and years of investment experience decreased the disposition effect, although a very weak effect for experience in years was reported. However, Chen et al., (2007) showed that investors with more years of investment experience exhibited less disposition effect.

In relation to automatic trading strategies, Linnainmaa (2010) found that the use of sell limit order strategies which were placed above the price of a stock, increased the amount of disposition effect exhibited by investors. Linnainmaa (2010) argues that when sell limit orders are placed above the current stock price, investors are more likely to sell winners because an increase in price is needed to activate this limit order. However, Nolte (2012) investigated the influence that both take profit and stop losses limit order strategies have on the disposition effect of foreign exchange traders. Take profit are similar to sell limit orders because they are placed above the current asset price and are used to secure profits, whereas stop losses are set

below the current asset price to limit losses. Nolte (2012) found that an inverse disposition effect existed for trades of small profit and loss and that this occurrence is attributable to traders' use of stop loss and take profit strategies. In contrast, traders who closed positions using market orders exhibited the disposition effect, as has been shown in other studies on traders (Locke and Mann, 2005).

In this paper we consider the use of two automatic trading strategies; an ordinary stop loss and a tracking stop loss. An ordinary stop loss involves setting a stop loss so that if the daily price drops to a level predetermined by the investor, a sale is automatically triggered. A tracking stop loss tracks the price of a stock if it increases, recording its highest peak. If the price drops from this peak by an amount predetermined by the investor, a sale is triggered. Both types of stop losses can be used to sell gains and losses. However, an ordinary stop loss is more suitable to sell stocks at a loss because the investor has a predetermined loss exit-strategy. A tracking stop loss is more suitable to sell stocks at a gain because the investor can delay selling, then wait to see if the stock's price continues to increase. Stop losses are free to use and easily implemented by investors.

The relationship between stop loss use, investor sophistication and experience has not been fully explored in the literature and it is unknown whether sophisticated and experienced investors use stop loss strategies. As Nolte (2012) outlines, the use of these automatic strategies could be interpreted either as quite sophisticated and experienced trading since the trader is aware of the fact that she will not be able to follow the market and thus ensures her

positions against periods of high risk. On the other hand, it can be interpreted as uninformed and inexperienced trading since the trader does not expect to have access to private information which she could exploit with an active trading strategy.

From an academic perspective, earlier research on stop losses has focused on showing that stop loss strategies are a non-optimal investment strategy (Dybvig, 1988b, Gollier, 1997). Dybvig (1988b) uses a binomial, four-period model, in which stocks double or halve value in each period, in order to compare a stop loss strategy to a strategy determined by his payoff distribution pricing model (Dybvig, 1988a). Whilst the payoff distributions for both strategies are of equal values, the stop loss strategy is shown to be less efficient because an initial drop in price exits this strategy from an optimal investment path. Similarly, Gollier (1997) examines a stop-loss strategy which invests 100% in equity provided the stock price remains above a lower limit threshold, and otherwise 100% in cash. He finds that this strategy is inefficient due to second-order stochastic dominance. More recently, research has begun to show benefits of stop loss use for investors. Lei and Li (2009) applied stop loss strategies to stock historical data and found that stop losses strategies do not hurt portfolio performance and can be useful at reducing losses. Annaert et al., (2009) show that stop loss strategies produce a reduced amount of return but argue that this is compensated for by lower amounts of risk. Dichtl and Drobertz (2011) investigate whether the use of stop losses is optimal when investors have risk preferences in accordance with cumulative prospect theory (Tversky and Kahneman, 1992). They find that if an investor's value function is in accordance with prospect theory then stop loss use is optimal for these investors.

In sum, research using stock market investors has shown that sophistication and experience reduce susceptibility to the disposition effect and research on foreign exchange traders has shown that use of stop losses and profit taking strategies invert the disposition effect. In this paper we extend previous research by examining the relationship between investor use of stop losses, their sophistication and their experience. We also examine the amount of influence on the disposition effect that each of three variables have. In the next section we outline the research hypotheses.

2.1 Hypotheses

The first hypothesis that the paper addresses is evidence of the disposition effect for UK stock market individual investors. The authors know of no research into the disposition effect of stock market investors living in the UK but there are findings in many other countries which show that the disposition effect occurs (Bonanno et al., 1995, Leal et al., 2010, Odean, 1998, Seru et al., 2010, Shapira and Venezia, 2001, Talpsepp, 2010) . Thus we hypothesise that:

Hypothesis 1: UK investors will be prone to the disposition effect

We also anticipate that investors in the UK will show similar behavioural characteristics to those shown by investors studied in other research where investor sophistication and experience reduce the disposition effect. Thus we hypothesise that:

Hypothesis 2: Sophisticated investors will exhibit less disposition effect than non sophisticated investors

Hypothesis 3: Investors with more experience will exhibit less disposition effect than investors with less experience

Nolte (2012) shows that stop losses have a strong influence on the disposition effect and we anticipate that investors who use them will be less prone to this bias. We also analyse stop loss use at the transaction level and compare those transactions which involve stop losses to those transactions which do not. We expect that the transactions which involve stop losses will reverse the disposition effect. We hypothesize the following:

Hypothesis 4: Investors that use stop losses will exhibit less disposition effect than investors that do not

Hypothesis 5: Transactions in which stop losses are used will invert the disposition effect

In addition to the influence of stop losses on the disposition effect, there are still unanswered questions about why stop losses are used. One possibility is that investors who believe they are susceptible to the disposition effect may use stop losses to correct this behaviour. A method of investigating whether this occurs is to determine if investors who use stop losses are more susceptible to the disposition effect when not using them. Therefore, we hypothesise the following:

Hypothesis 6: Investors who use stop losses will be more susceptible to the disposition effect when not using them, in comparison to other investors

3. Data set and methodology

The trading data used in this analysis were provided by a brokerage company that provides an online and telephone trade execution service to investors in the UK. The trading data set contained 7,828 investors who completed 395,998 trades over the period 04/07/2006 to 14/12/2009. The observation period covers 875 trading days. Investors were selected on the basis that they had made at least two trades per year over the observation period, had an email address and that they had given consent to the brokerage firm that they could be contacted for marketing purposes. The trading data contained the following information for each trade: date of trade, time of trade (in hours:mins:seconds), International Securities Identification Number (ISIN) code of each security, gross purchase amount, gross sale amount, commission, quantity, total amount, investor identifier, gender, age (as at 14/12/2009), account type and a stop loss indicator.

In order to analyse the trading records, only relevant trades were kept and irrelevant trades were removed. We briefly outline the trades removed here. We omitted the following: 2,636 investors because they never completed a sale transaction, 253 investors because they were missing demographic information and 4 investors because they were younger than 18 years old (at the request of the brokerage firm). This left 5,085 investors who completed 318,504 trades, which we filtered into roundtrip positions. Like Feng and Seasholes (2005), we define a roundtrip transaction as beginning with the first purchase transaction and ending when the final sale returns the share balance to zero. To filter the roundtrip positions, we first ordered the data by investor, stock, account classification, date and time. After this, we removed all the sales transactions for which there was not an earlier purchase and then all buy and hold transactions where there was no sale transaction. With the remaining transactions, for each

stock in each account classification held by each investor, we created a share holding balance which increased when purchases were made and decreased when sales were made.

Roundtrips were identified when the account balance returned to zero due to a sale transaction.

Filtering the data into roundtrips reduced the number of investors to 4,344 and trades to 173,681. Accurate price data was missing on 1.25% of roundtrip transactions and these were removed. There were 137 roundtrip transactions which involved warrants and these were removed because we investigate the disposition effect on ordinary stock purchases. The final sample consisted of 4,328 investors who had completed 65,096 roundtrip positions using 169,608 trades.

In addition to the trading data, price data on each stock and market data over the period July 2006 – December 2009 was obtained using Datastream. The price data on each stock was downloaded for each day and all stocks priced in foreign currencies were converted into pounds sterling (GBP). Information about each stock's corporate actions (splits, consolidations, rights issues, scrip dividends) was obtained via Datastream and adjusted for in the trading data. This adjustment involved creating an artificial trade to represent any change in each investor's holding and any value in GBP they had invested. Including this trade updated an investor's holding and purchase price to reflect the influence of the corporate action. Whilst there were a number of corporate actions over the observation period, the adjustments only pertained to 1% of the trades in the final sample. This shows that corporation actions did not significantly influence our analysis.

The final step in data preparation was to combine the price data and roundtrip transactions into one large dataset. This dataset tracked each roundtrip position from the day of purchase to the day of first sale, making daily calculations of gains and losses. We used Stata 11 to analyse the final data and the model adopted is outlined next.

3.1 Methodology

The method of calculating the disposition effect is based on a survival analysis method described by Feng and Seasholes (2005). For each day after an investor purchases a stock, we calculate the conditional probability of that stock being sold. A proportional intensity model that allows for time varying covariates is used to calculate this conditional probability. As we leave the baseline hazard unspecified, our model becomes an extended Cox (1972) proportional hazard model. In our model, time t is measured in days that the UK stock markets are open. When an investor i first purchases a stock, this starts a position k where $t = 1$. A position ends on the first sale of this stock, which is tracked by a sale dummy variable taking the value of 0 when stocks are held and 1 on the day of sale. The sale variable is used to track the survival time T for each position k . The extended Cox model is defined as:

$$h_{i,k}(t|X, Z(t)) = h_0(t)e^{\{\sum_{i=1}^p \beta_i X_i + \sum_{i=1}^p \delta_i Z_i(t)\}} \quad (1)$$

Where $h_{i,k}(t|X, Z(t))$ refers to the probability of position k being sold by investor i at time T , conditional on it not being sold at time t . $h_0(t)$ is the baseline hazard function, which is left unspecified in a Cox model as it is semi-parametric. Calculations to estimate β_i and δ_i are made

using maximum likelihood. In our model we have both time independent variables X_i that remain fixed over time and time dependent variables $Z_i(t)$ that are allowed to change for each change in t . All dependent variables in our analysis take on positive values but one control variable, market returns, does not. For the dependent variables, we report their influence using hazard ratios. Their interpretation is as follows: a hazard ratio of 1 means that the covariates have no effect; a hazard ratio below 1 means that the covariates decrease the conditional probability of selling stocks, relative to baseline; and a hazard ratio above 1 means that the covariates increase the conditional probability of selling stocks, relative to baseline. A representation of the baseline hazard rate over time is outlined in Figure 1. It shows a steep decline over the first 100 days, with over 75% of the roundtrips being sold, followed by a gradual decline over the remaining time. Now we briefly outline how the variables are used in the analysis and will later outline the exact models used to test our research hypothesis.

3.2 Variables

Time: Time is the dependent variable in our analysis and is measured in the number of days a stock is held until it is first sold. We only consider days that the UK stock exchange is open for trading, with weekends and public holidays being excluded. In total there are 875 trading days over the observation period but the longest roundtrip transaction is 852 days. Trading days, instead of hours or weeks, are an apt measurement of time because they are continuous throughout our data set. For instance, there are low proportions of intraday roundtrips (4.14%) and one day roundtrips (6.43%) with most roundtrips are longer than five days (78.03%). Also sales occur on the majority of days within the data. The risk set used to make our calculations

consists of 852 days and at least one sale occurred on 775 of these days. Figure 1 provides a graphical representation of sales over the analysis time.

Gains and losses: A share weighted average purchase price (SWAPP) is adopted as the reference point by which gains and losses are calculated. We use the same method as Grinblatt and Keloharju (2001) which updates the SWAPP as additional purchases are made within roundtrip transactions. Gains and losses are determined by comparing the SWAPP to stock market prices on a daily basis. Specifically, a gain is measured by comparing the SWAPP to the stock's daily low price; if the SWAPP is below the daily low, then it is considered a gain (i.e. it could have been sold at any time that day as a gain). A loss is measured by comparing the SWAPP to the stock's daily high price; if the SWAPP is higher than the daily high, it is considered a loss. From these calculations two time varying covariates were created to analyse the disposition effect: the trading loss indicator (TLI) and the trading gain indicator (TGI). For the TLI, if a stock is held or sold at a loss on any day, then it takes a value of one, otherwise a value of zero. For the TGI, if a stock is held or sold at a gain, then it takes a value of one, otherwise a value of zero.

We compare SWAPP to market prices obtained from Datastream on the days that stock is held and sold, even though the trading data has more accurate selling prices. In earlier analyses, we used market prices on the days stock was held but trading data on the day that stock was sold. However, this approach created an artefact in our analysis due to the differences in accuracy of the data. It made it seem that stocks were often held at break-even, yet very rarely sold at break-even, and in turn, increased our hazard ratios. Thus we use market data when stock was

held and when stock was sold, in order to overcome this issue. A representation of the hazard rates for selling stocks at a gain, loss and break-even are outlined in Figure 2. Break-even refers to those stocks which could not be classified as a gain or a loss. The curve depicting stocks sold at a loss is the highest curve. It also has a more gradual decrease over time when compared to stocks sold at a gain and at break-even.

Sophistication: We base our proxy on those investors who trade more complex financial products because these investors have demonstrated more knowledge of finance than other investors (Boolell-Gunesh et al., 2009, Seru et al., 2010). Some of the investors in this data set are entitled to trade warrants on margin. To earn this entitlement they must pass a screening process with the brokerage firm. This involves testing their financial understanding using an appropriate assessment (refer to Appendix 1) outlined by the Financial Services Authority (2009) and analysing their previous investment decisions. The trading data was analysed to identify if an investor had traded warrants because this demonstrates that they had successfully passed the appropriate assessment. Based on this, a dummy variable was created where sophisticated investors take the value of one and non-sophisticated investors take the value of zero. There are 79 investors classified as sophisticated and they completed 2,808 roundtrip positions. A limitation of this measure is that there are only a small number of sophisticated investors but these investors completed a sufficient number of transactions to show a significant effect in the analysis. Furthermore, the results for this proxy of sophistication were more significant than others, such as value of trade or frequency of trades which, when tested, did not have a significant effect on the disposition effect.

Experience: The proxy we use for experience is the investor's age as this is the only possible proxy for experience available in the trading data. This proxy has both limitations and advantages because it does not directly reflect investment experience but could represent other factors influencing investment decision making. For example, older investors may have different attitudes towards money when they are nearing or in retirement. Older investors also tend to be wealthier as they have had longer to build savings. Despite these factors, Korniotis and Kumar (2011) found that older investors display weaker behavioural biases than younger investors, suggesting the measure has relevance for the kind of experience we are trying to measure. Also age better encapsulates life experience, as well as investment experience, that investors use in investment decisions and may steer them away from the disposition effect. The investors' ages ranged from 19 to 95, but to make interpretation easier, the variable was centred on the lowest value and then scaled to a lower range. Thus, 18 was subtracted from all values and then the covariate was divided by 10. The hazard ratios reported below reflect the change that an increase of 10 years in age has on the disposition effect.

Stop loss user: The trading data contain a record of each sale which took place using a stop loss (ordinary and tracking stop losses). The brokerage house did not provide us with data on other types of automatic trading strategies such as take profit orders. This variable includes only stop losses that were triggered. If an investor set and subsequently removed a stop loss, it would not be included in this variable. Also, we cannot differentiate between the two types of stop losses, ordinary or tracking stop loss, used by investors. Nonetheless, it was possible to distinguish those investors who used a stop loss from those investors who did not use them,

over the sample period. A dummy variable was created where stop loss users take the value of one and non-stop loss users take the value of zero. There are 1,027 investors who used stop losses and 3,301 investors who never used a stop loss during the sample period.

Stop loss transaction: The stop loss transaction variable was created through analysis of the roundtrip positions; where all roundtrip positions that involved a stop loss take the value of one and all other transactions take the value of zero. There are 6,040 roundtrip transactions that include stop losses and 59,056 that do not.

Control variables: The financial crisis occurred during the observation period of this analysis, with the UK stock markets going through a bear period followed by a bull period. We use two five-day moving averages based on the FTSE 100 to control for stock sales in relation to market-wide activity: market returns and market volumes.

Variables not reported: Two other factors which could influence the disposition effect are tax loss selling (Odean, 1998) and gender (Feng and Seasholes, 2005, Shu et al., 2005). Tax loss selling was measured by creating a time varying covariate to represent stocks held at a loss in the month before end of the tax year. Tax exempt accounts, such as individual savings accounts (ISA) and self-invested pension plans (SIPP), were not included in this variable. The variable took the value of one if a stock was held or sold at a loss in the month before tax year end and the value of zero otherwise. We analysed whether this variable would increase the chance of a stock being sold, but found that it decreased the probability of stock being sold. Thus, it showed the opposite influence of tax loss selling and was not included in our analysis. A possible reason that tax loss selling was not prominent in the data is that the tax free

allowance for capital gains tax was £8,800, £9,200 and £9,600 for the 2007, 2008 and 2009 tax years, respectively (HMRC, 2012). This may be too high to make capital gains a concern as 75% of the investors' trades were below £2,400 on average. Similarly, we were interested in the influence that gender may have on the disposition effect. However, results found very little differences in the disposition effect based on gender, and using gender as a control variable did not influence our findings. We have omitted the results for tax loss selling and gender and omitted them as control variables, for brevity.

Hautsch (2012) shows that autocorrelations occur within high frequency financial data, with high (low) volumes of trading activity predicting adjacent high (low) trading activity¹. We tested this influence in our data using two variables. The first variable, previous roundtrip duration, was the duration of each investor's previous roundtrip, with the first roundtrip defaulting to the mean duration of her roundtrips. Thus, we tested whether the duration of an investor's previous roundtrip would predict current selling tendency. The second variable, previous day's number of sales, tested for path dependence between investors. It was defined as the total number of sales that occurred on the previous trading day. This variable was calculated from the data set before any transactions were filtered (filtered refers to the process of removing transactions outlined in Section 3 of this paper). When each of these variables was analysed by itself, it was significant. The previous roundtrip duration had a hazard ratio of $h(t) = .9942$, $p < .01$ $z = -111.36$ and the previous day's number of sales had a hazard ratio of $h(t) = 1.0038$, $p < .01$ $z = 117.33$. However, when included as controls, these variables did not significantly

¹ The authors thank the anonymous reviewer for the suggestion that path dependence might influence our trading data.

change the results and findings presented. As a result, they have not been included in this analysis. Full details of this supplementary analysis are available from the corresponding author.

3.3 The Model

Now that the variables have been outlined, we return to the model used in our analysis. In section 4.2 below we test for disposition effect on average. The left hand side of the equation is equal to zero every day an investor holds a roundtrip position and one if the investor sells. The right hand side contains the TLI or TGI and the market control covariates. The survival analysis models used to test for the disposition effect on average contain the trading loss indicator $\delta_i TLI(t)$ or the trading gain indicator $\delta_i TGI(t)$ to ascertain whether these covariates influence the conditional probability of a stock being sold. We also include the market control covariates, market volume $\delta_i Mvol(t)$ and market return $\delta_i MReturn(t)$. All investors' i positions k are pooled together so that we learn what the disposition effect is on average. The models are:

$$h_{i,k}(t|Z(t)) = h_0(t)e^{\{\sum_{i=1}^p \delta_i TLI(t) + \delta_i Mvol(t) + \delta_i MReturn(t)\}} \quad (2)$$

$$h_{i,k}(t|Z(t)) = h_0(t)e^{\{\sum_{i=1}^p \delta_i TGI(t) + \delta_i Mvol(t) + \delta_i MReturn(t)\}} \quad (3)$$

In sections 4.3 to 4.7 we assess whether certain variables influence susceptibility to the disposition effect. This involves using a pooled approach as outlined above but extra covariates are included. These covariates are interacted with the TLI or TGI and also included by themselves. The interaction of the covariate with the TLI or TGI shows whether the covariate increases or decreases investors' propensity to sell stocks at a loss or a gain. The inclusion of

each covariate by itself controls for the influence that this covariate has on the propensity to sell stock in general. For example, investors who are sophisticated and use stop losses tend to trade more frequently than those who don't and we want to control for this influence. As an example of the model, let us consider sophistication and how it influences the conditional probability of selling losses. The equation used is:

$$h_{i,k}(t|X, Z(t)) = h_0(t)e^{\{\sum_{i=1}^p \delta_i TLI(t) + \delta_i TLI \times Soph(t) + \beta_i Soph + \delta_i Mvol(t) + \delta_i MReturn(t)\}} \quad (4)$$

All results are relative to the baseline hazard function represented as $h_0(t)$. $\delta_i TLI(t)$ shows whether stocks trading at a loss have an increased or decreased probability of being sold; $\delta_i TLI \times Soph(t)$ shows the influence that sophistication has on selling stocks at a loss; and $\beta_i Soph$ controls for the direct influence sophistication has on selling stocks in general. Finally, $\delta_i Mvol(t)$ and $\delta_i MReturn(t)$ control for market wide influences on the conditional probability of selling.

<insert Figures 1 to 4 around here>

3.4 Test of the proportional hazard assumption and goodness of fit

All fixed covariates were tested for the proportional hazard assumption using graphical tests. Graphs of scaled Schoenfeld (1982) residuals over analysis time were used for continuous variables and log (-log) plots of the survival function over log analysis time were used for dummy variables (Kleinbaum and Klein, 2005). The graphs were omitted for brevity. The only variable which violated the proportional hazard assumption was age. This violation was corrected by including an additional control variable of age interacted with log time.

We also tested goodness of fit using graphical tests of the Cox-Snell residuals (Cox and Snell, 1968). This involved running an analysis of the TLI with all other covariates and the TGI with all other covariates to obtain Cox Snell residuals for these models. These residuals are then plotted alongside a Nelson-Aalen cumulative hazard estimator based on the same data (Cleves et al., 2008). The goodness of fit graphs for the TLI with explanatory covariates and the TGI with explanatory covariates are outlined in Figure 3 and Figure 4, respectively. Goodness of fit is shown by two matching lines (Cleves et al., 2008). Our graphs show strong goodness of fit up to Cox-Snell residuals with values of 6, with slight variation above these values. Despite this variation, these graphs show goodness of fit between a Cox model and our data for two reasons. Firstly, some variability in the right hand tail of these graphs is to be expected (Cleves et al., 2008) and secondly, the vast majority of roundtrip transactions have Cox-Snell residuals below the value of 6. For the TLI analysis there are 64,898 out of 65,096 roundtrip transactions that have Cox-Snell residuals below 6 and for the TGI analysis there are 64,884 out of 65,096 roundtrip transactions that have Cox-Snell residuals below 6. Overall, these graphs provide evidence that there is very little misfit for a Cox model with our data.

4. Analysis

4.1 Descriptive statistics

Table 1 outlines the descriptive statistics for the final sample of investors and their transactions in our analysis. The mean number of times an investor traded during the observation period is 70.72 and the mean value of their trades is £2163.21. Both of these statistics were positively skewed with a small number of investors trading frequently and with large values. 23.73% of

the investors used stop losses at least once during the observation period and 1.83% of the investors can be defined as sophisticated because they traded warrants. Finally, the average age of the investors was 51.65 and this variable was close to a normal distribution.

Descriptive statistics on sophisticated investors and stop loss users investors are also outlined in Table 1. These statistics are presented as an overview of the relationships between the constructs for our sample. They are not presented to draw inferences about the population of investors who use stop loss or trade warrants because our data and methodology do not permit such conclusions. Nonetheless, the statistics show some information about the constructs we are analyzing. Firstly, stop loss use and sophistication are not mutually exclusive but the statistics cannot show that a higher or lower proportion of sophisticated investors use stop losses ($\chi^2 = 1.42$, $p = .16$). One noticeable relationship is with age in that stop loss users tend to be younger than other investors ($t = 5.84$, $p < .01$) and sophisticated investors tend to be older than other investors ($t = -1.98$, $p < .05$). This suggests that stop loss users may have less experience and that sophisticated investors have more experience. This would fit with a depiction of stop loss use as a learning tool for novice investors to manage risk. Both stop loss users and sophisticated investors sell stocks more frequently than other investors. It may seem more likely that stop losses users would trade less than other investors as it is a passive strategy. An alternative way of understanding this is that the more times an investor sells stocks, the more opportunities she has to use stop losses. Finally, there seems to be a smaller proportion of female investors that use stop losses and that are sophisticated. This finding may also be related to trading frequency as research suggests that female investors trade less frequently than male investors (Barber and Odean, 2001).

4.2 Disposition effect

In this section we test for the disposition effect on average using equations 2 and 3 outlined in section 3.3 above. Tests are completed by analysing all positions from all investors together.

The left hand side of the equation takes the value of 0 every day a stock is held and the value of 1 on the day of the first sale. On the left hand side we include the TLI or TGI and two market control variables. The results in Table 2 show evidence of the disposition effect for this sample.

The data demonstrates evidence of the disposition effect because the TGI hazard ratio is significantly above 1 and the TLI hazard ratio is significantly below 1. The hazard ratio can be interpreted as showing that stocks trading at a gain have a 67.04% ($1 - 1.6704 = -.6704$) increased conditional probability of being sold, relative to baseline. Stocks trading at a loss have a decrease in the conditional probability of being sold of 40.82% ($1 - .5918 = .4082$), relative to baseline. This evidence supports hypothesis 1, that individual investors in this sample of UK investors exhibit the disposition effect.

<insert Table 2 around here>

4.3 Sophistication

In this section and the following four we report the influence of certain variables on the disposition effect. The method of doing this is outlined in section 3.3 and an example of the model is shown in equation 4 above. Each variable of interest is included in the model and interacted with the TLI and TGI. These interactions show the influence that the variable has on the propensity to sell stock either at a gain or at a loss. By including the variable by itself, we control for the general influence that the variable has on the propensity to sell stock. The same

market-based control variables are also included to control for market wide influences on selling stock. Table 3 contains the results of the regression which combines the TLI with sophistication. Regression 1 shows that the hazard ratio for the TLI interacted with sophistication is significantly above 1. This shows that sophisticated investors are 10.78% ($1 - 1.1078 = -.1078$) more likely to sell stocks at a loss, relative to baseline. Table 4 regression 1 shows the hazard ratio for the TGI interacted with sophistication. The hazard ratio is significantly below 1 showing that sophistication decreases the conditional probability of selling stocks at a gain by 13.52% ($1 - .8648 = .1352$), relative to baseline. This confirms hypothesis 2, that sophisticated investors exhibit less disposition effect than other investors.

4.4 Experience

The influence of age on the TLI and TGI are outlined in regression 2 of Table 3 and regression 2 of Table 4, respectively. A 10 year increase in age increases the probability of selling stocks at a loss by 10.01% ($1 - 1.1001 = -.1001$), relative to baseline. Also, a 10 year increase in age decreases the probability of selling stocks at a gain by 5.68% ($1 - .9432 = .0568$), relative to baseline. Overall, this analysis confirms hypothesis 3, that experienced investors are less prone to the disposition effect.

<Insert Table 3 around here>

<Insert Table 4 around here>

4.5 Stop loss users

Regression 3 in Table 3 shows the influence that being a stop loss user has on the probability of selling stocks at a loss. The hazard ratio for the interaction between the TLI and stop loss user indicates that being a stop loss user increases the conditional probability of selling stocks at a loss by 14.27% ($1 - 1.1427 = -.1427$), relative to baseline. Regression 3 in Table 4 shows that being a stop loss user significantly decreases the probability of selling stocks at a gain. The hazard ratio for the interaction between the TGI and stop loss user indicates that being a stop loss user decreases the conditional probability of selling stocks at a gain by 25.57% ($1 - .7443 = .2557$), relative to baseline. These results support hypothesis 4, that being a stop loss user decreases the disposition effect. Also, these hazard ratios for stop loss users are of a similar value to that of sophisticated investors.

Regression 4 in Table 3 and regression 4 in Table 4 combine sophistication, age and stop loss user to ascertain whether each covariate explains unique variance in the disposition effect. In relation to the TLI, the interaction of the TLI with age and with stop loss user both increase the probability of selling stocks at a loss, relative to baseline, but the interaction with sophistication does not have a significant influence. A relationship between sophistication and age exists where sophisticated investors tend to be older. This could cause the TLI interaction with sophistication to be insignificant when age is also considered. In addition, there are a small number of roundtrips completed by sophisticated investors in this sample ($n = 2,808$), and this could also cause the insignificant result. In relation to the TGI, the results in regression 4 of Table 4 show that all the variables which interacted with the TGI significantly decrease the probability of selling stocks at a gain, relative to baseline.

A comparison between the influence that sophistication, stop loss use and experience have on the disposition effect can be made by comparing the hazard ratios in regression 4 in Table 3 and Table 4. In relation to selling stocks at a loss, experience and stop loss use have a large influence. A 10 year increase in age increases the conditional probability of selling stocks at a loss by 11% and stop loss use increases it by 17%, whereas sophistication increases it by 4%, relative to baseline. For selling stocks at a gain, stop loss use has a large influence, decreasing the conditional probability of selling stocks at a gain by 26%. Whereas, sophistication decreases the selling of stocks at a gain by 10% and a 10 year increase in age decreases the selling of stocks at a gain by 5%, relative to baseline.

4.6 Stop loss transactions

Table 5 contains the analysis for the amount of disposition effect exhibited in stop loss transactions. It shows that the interaction between the TLI and stop loss transactions is significantly above 1 and increases the trading of stocks at a loss by 115.46% ($1 - 2.1546 = -1.1546$). The interaction between the TGI and stop loss transaction is significantly below 1 and decreases the trading of stocks at a gain by 47.75% ($1 - .5225 = .4775$). As stop loss transactions have a large influence, it worth estimating the disposition effect for these transactions. To do this we multiply the TLI hazard ratio with the TLI interacted with the stop loss transactions hazard ratio, and multiply the TGI hazard ratio with the TGI interacted with the stop loss hazard ratio. It shows that the disposition effect is reversed. The combined hazard ratio for the TLI of stop loss transactions is 1.1854 ($.5502 \times 2.1546$) and the combined hazard ratio of the TGI of stop loss transactions is .9246 ($1.7695 \times .5225$). Thus, stocks trading at a loss have an increased

chance of being sold and stocks trading at gain have a decreased chance of being sold, when a stop loss is used to sell the stock. These results support hypothesis 5, that transactions which involve stop losses invert the disposition effect. The results are similar to Nolte (2012) who showed that use of stop losses and of take profit strategies by foreign exchange traders inverted the reluctance to realise losses and the eagerness to realise gains.

<insert Table 5 around here>

4.7 Stop loss users without stop loss transactions

In light of the above findings, an interesting avenue to explore in the data is whether the process of using a stop loss reduces the disposition effect or whether the investors who use stop losses are less prone to the disposition effect. To investigate this research question in the data, the stop loss roundtrips were removed decreasing the number of roundtrip positions to 59,056. Then the same model as reported in section 4.5 above is used to investigate the stop loss users' inclination towards the disposition effect when their stop loss transactions are not considered (refer to Table 6). The hazard ratio for the interaction between the TLI and stop user variable is significantly below 1, indicating that stop loss users have a greater propensity to hold stocks at a loss than other investors, when their stop loss transactions are excluded. In relation to selling stocks at a gain, the hazard ratio for the interaction between the TGI and stop loss user is significantly below 1. This indicates that stop users are less likely than other investors to sell stocks at a gain, when their stop loss transactions were excluded. The amount of influence that the stop loss user covariate has on reducing selling of stocks at a gain is less when stop loss transactions are removed ($h(t) = .8419$, $p < .01$), than when these transactions are included

($h(t) = .7443$, $p < .01$). This shows that stop loss users are less inclined to sell stocks at a gain when using stop loss transactions than when not using them. Overall, this evidence only partially supports hypothesis 6, because stop loss users are only more susceptible to the holding stocks at a loss aspect of the disposition effect when their stop loss transactions have been removed, and less susceptible to selling stocks at a gain.

<insert Table 6 around here>

5. Summary

Research has shown that the disposition effect is exhibited by investors in many different countries such as the USA (Odean, 1998), China (Feng and Seasholes, 2005), Israel (Shapira and Venezia, 2001), France (Boolell-Gunesh et al., 2009), Portugal (Leal et al., 2010) and Finland (Seru et al., 2010). Our research shows that investors in the UK are also prone to this bias. As with other research on investor susceptibility to the disposition effect (Boolell-Gunesh et al., 2009, Brown et al., 2006, Dhar and Zhu, 2006, Feng and Seasholes, 2005, Seru et al., 2010), we also find that investors who are sophisticated and who have more experience exhibit this bias to a lesser extent. However, sophistication and experience are positively related so that sophisticated investors tend to have more experience. When both variables were combined in the analysis of the disposition effect, sophistication only reduced the trading gains aspect of the disposition effect.

As well as investigating investor sophistication and experience, we also analysed the influence of stop losses on the disposition effect. Stop losses were adopted by investors to sell both gains and losses, showing they are used to both preserve profits and limit losses. We found that stop

loss users tend to be younger than investors who do not use stop losses, implying that they are a trading strategy more often used by investors with less experience. However, there was no evidence that stop users are more or less likely to be sophisticated investors. Our research does not support a theory that stop loss use in trading is a tool employed by sophisticated investors. However, we do show that stop losses influence the disposition effect in several ways. Firstly, we show that investors who use stop losses exhibit less of the disposition effect than investors who do not. Secondly, a comparison between stop losses users (when using stop losses) and sophisticated investors shows that they both exhibit similar amounts of the disposition effect. Thirdly, like Nolte (2012), we find that stop loss transactions invert the disposition effect. Future research on this topic should consider all automatic trading strategies, such as take profit and limit orders, to ascertain a more in-depth understanding of how these influence individual investors' trading patterns.

An implication of this research is that stop loss use is not always detrimental for investors. Earlier research on stop losses has shown that their use is non-optimal for a rational investor (Dybvig, 1988b, Gollier, 1997). We show that investors are not rational, in that they exhibit the disposition effect. Stop losses serve a purpose to manage this bias and are most beneficial for investors more prone to this bias. Thus, less sophisticated and less experienced investors could use stop losses when learning to invest, thereby safeguarding their portfolio whilst gaining knowledge. After an investor has gained experience, they may choose to maintain or cease adopting stop loss strategies. Our findings, which show that stop loss users are younger but not

necessarily sophisticated, are coherent with this theory. Future research into the adoption of stop losses by investors could explore factors that explain why some investors choose to use and others not to use these investment tools.

The final analysis investigated the levels of disposition effect exhibited by stop loss users when not using stop loss transactions. This analysis showed that these investors are more prone to holding losses longer. This result suggests that stop losses may be adopted as a form of self-control mechanism. That is, through using stop losses, some investors counteract their own reluctance to sell losses by setting an automatic tool to exit the market. It is difficult to understand the specific motivations for stop loss use in this research, but this could be an interesting avenue for future research.

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Figure 1: Baseline survival curve estimate for the sale of stocks in roundtrip positions

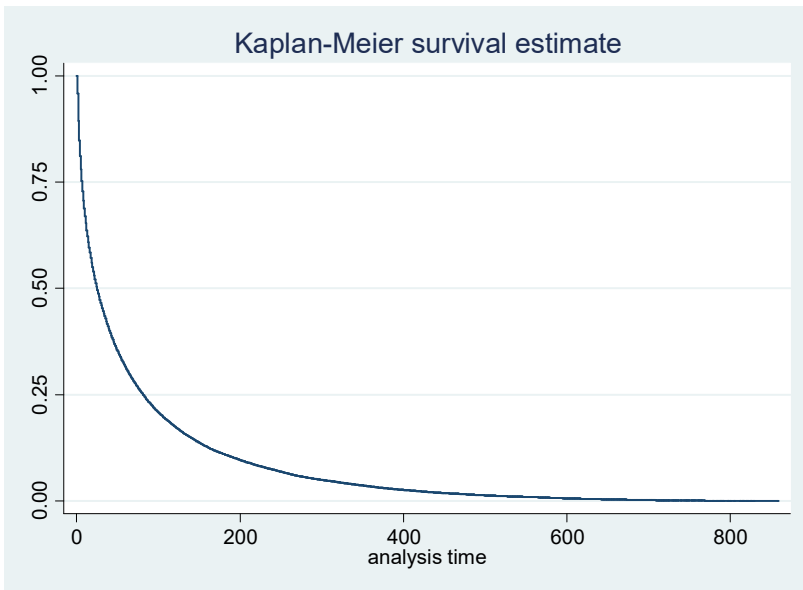


Figure 2: Baseline survival curve estimate for the sale of stocks at a gain, loss and break even in roundtrip positions

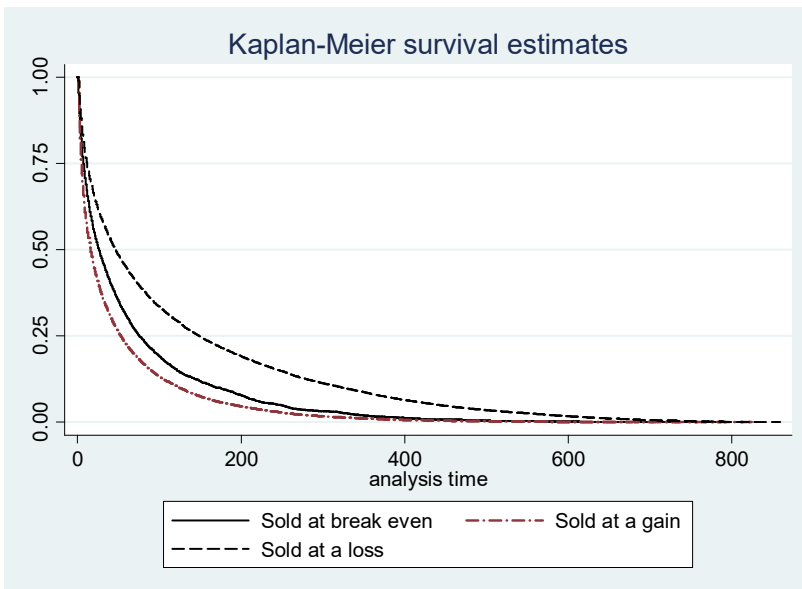


Figure 3: Goodness of fit test for the TLI with explanatory variables using Cox-Snell residuals

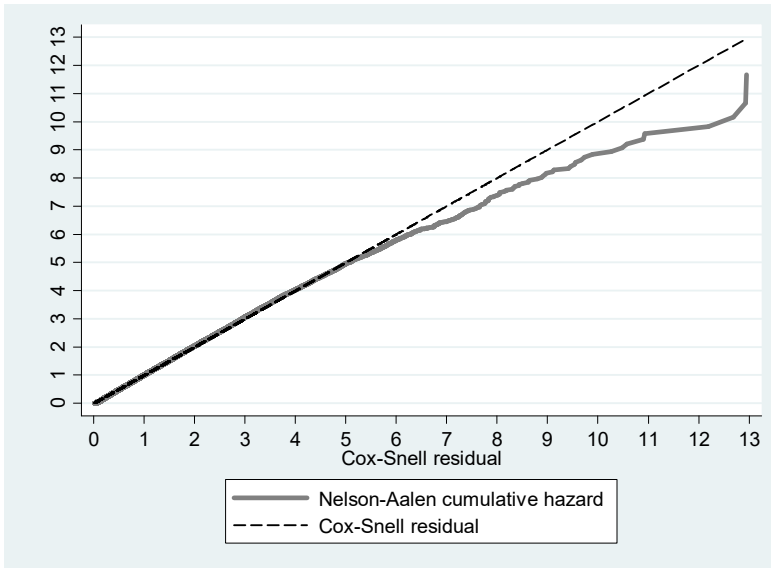


Figure 4: Goodness of fit test for the TGI with explanatory variables using Cox-Snell residuals

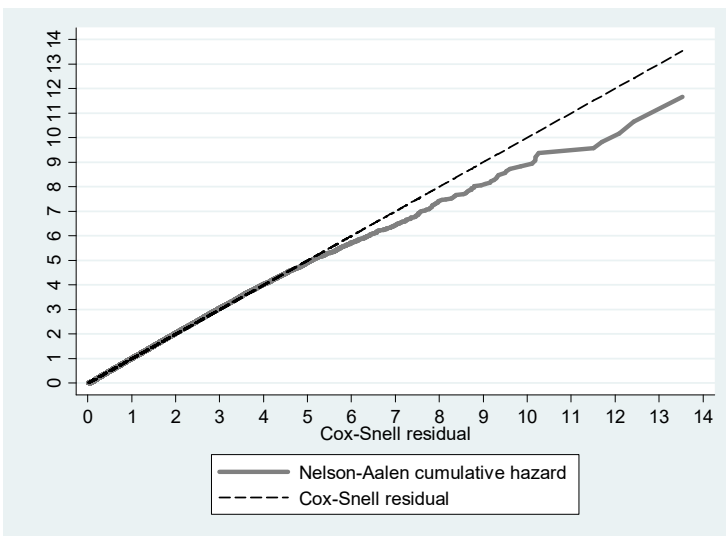


Table 1: Descriptive statistics of trading data:

Number of investors	4,328			
Number of roundtrips	65,096			
Number of stock days	4,507,142			
Number of stop loss users	1,027 (23.73%)			
Number of sophisticated investors	79 (1.83%)			
Number of stop loss roundtrips	6,040 (9.28%)			
Number of female investors	847 (19.57%)			
	Mean	25 th -tile	50 th -tile	75 th -tile
Age of investor	51.65	41	52	62
Mean value of trade (GBP)	2163.21	640.3	1202.62	2393.9
Mean number of trades made per investor	70.72	20	38	77
Comparison between stop loss investors and other investors	Stop loss investors	Other investors		Significance test
Mean age	49.43	52.34		t = 5.84***
Percentage of sophisticated investors	2.04%	1.76%		$\chi^2 = 1.42$
Mean number of sales	42.95	20.99		z = -19.17**
Mean value of trade (GBP)	£2,192	£2,154		z = -2.07**
Percentage of female investors	14.41%	21.18%		$\chi^2 = 22.77$ ***
Comparison between sophisticated investors and other investors	Sophisticated investors	Other Investors		
Mean age	54.75	51.59		t = -1.98**
Mean number of sales	76.42	25.27		z = -7.05**
Mean value of trade (GBP)	£1755	£2170		z = 2.34**
Percentage of female investors	15.19%	19.65%		$\chi^2 = 0.98$
***, ** - significant at 1 and 5 % level, respectively				

This table reports summary statistics of the data used in this study. The data set includes the individual trades between July 2006 and December 2009 placed at a brokerage firm in the UK. The stocks are traded in British Sterling (GBP). This table shows statistics on the sample data to identify relationships between investors who used stop losses and investors who did not and sophisticated investors and other investors. Tests of significance for differences between stop loss investors and other investors and sophisticated investors and other investors were conducted using the following tests: Age was conducted using Student t-test; the sophisticated, stop loss investors and female investors were conducted using a Pearson Chi-square test; and the number of sales and mean value of trades were conducted using Wilcoxon rank sum test.

Table 2: Tests for the disposition effect in aggregate:

	Reg 1	Reg 2
TLI (Z-stat)	.5918*** (-60.10)	
TGI (Z-stat)		1.6704*** (64.88)
Control Variables		
Market return (Z-stat)	1.7987 (0.92)	1.2627 (0.36)
Market volume (Z-stat)	.9923*** (-63.50)	.9922*** (-64.54)
*** - significant at 1% level		

This table presents the hazard ratios associated with investors' tendency to sell/hold stocks at a loss/gain. The dependent variable takes the value of 0 every day a stock is held by an investor and 1 on the first day it is sold. The independent variable in regression 1, the trading loss indicator (TLI), takes the value of 1 every time a stock trades at a loss and 0 otherwise. The independent variable in regression 2, the trading gain indicator (TGI), takes the value of 1 every time a stock trades at a gain and 0 otherwise. We also control for market return and market volume on the FTSE 100 using a 5 day moving average for each. The data is from a sample of 65,096 roundtrip positions made by 4,328 investors over the period July 2006 to December 2009. It was provided by a brokerage firm in the UK. Z-stats are shown in the parentheses below the hazard ratios.

Table 3: Trading losses and predictive variables:

	Reg 1	Reg 2	Reg 3	Reg 4
TLI (Z-stat)	.5892*** (-59.29)	.4298*** (-36.34)	.5590*** (-51.02)	.3948*** (-37.32)
TLI x sophistication (Z-stat)	1.1078*** (2.57)			1.039 (0.97)
TLI x age (Z-stat)		1.1001*** (15.00)		1.1054*** (15.67)
TLI x stop loss user (Z-stat)			1.1427*** (7.94)	1.1700*** (9.31)
Control Variables				
Sophistication (Z-stat)	.8768*** (-7.34)			.9149*** (-3.63)
Age (Z-stat)		.7849*** (-37.42)		.7904*** (-36.15)
Age x log time (Z-stat)		1.0324*** (16.86)		1.0316*** (16.40)
Stop loss user (Z-stat)			1.2793*** (25.38)	1.2487*** (22.82)
Market return (Z-stat)	1.7765 (0.90)	1.6761 (0.81)	1.6867 (0.82)	1.5705 (0.71)
Market volume (Z-stat)	.9923*** (-63.29)	.9930*** (-57.08)	.9924*** (-62.71)	.9931*** (-56.42)
***, **, * - significant at 1,5 and 10% level				

This table presents the hazard ratios associated with investors' tendency to sell/hold stocks at a loss. The dependent variable takes the value of 0 every day a stock is held by an investor and 1 on the first day it is sold. Demographic variables are fixed over time but vary across individuals. The demographic variables include a sophistication variable, the investor's age (subtracted by 18 then divided by 10) and a stop loss user variable. These variables are interacted with the trading loss indicator which takes the value of 1 every time a stock trades at a loss and 0 otherwise. The interaction allows the interpretation of cross-sectional differences in investors' propensities to sell losses. The demographic variables are also used as control variables. We also control for market return and market volume on the FTSE 100 using a 5 day moving average for each. The data is from a sample of 65,096 roundtrip positions made by 4,328 investors over the period July 2006 to December 2009. It was provided by a brokerage firm in the UK. Z-stats are shown in the parentheses below the hazard ratios.

Table 4: Trading gains with predictive variables:

	Reg 1	Reg 2	Reg 3	Reg 4
TGI (Z-stat)	1.6807*** (61.85)	2.0263*** (34.01)	1.8961*** (59.83)	2.3777*** (38.68)
TGI x sophistication (Z-stat)	.8648*** (-3.75)			.8987*** (-2.75)
TGI x age (Z-stat)		.9432*** (-10.11)		.9356*** (-11.42)
TGI x stop loss user (Z-stat)			.7443*** (-18.58)	.7409*** (-18.80)
Control Variables				
Sophistication (Z-stat)	.9698 (-1.18)			.9722 (-1.08)
Age (Z-stat)		.8094*** (-30.99)		.8195*** (-28.98)
Age x log time (Z-stat)		1.0420*** (22.34)		1.0412*** (21.86)
Stop loss user (Z-stat)			1.5414*** (39.38)	1.5197*** (37.94)
Market return (Z-stat)	1.2441 (0.34)	1.2240 (0.32)	1.2142 (0.30)	1.1605 (0.23)
Market volume (Z-stat)	.9923*** (-64.32)	.9929*** (-58.14)	.9924*** (-63.73)	.9930*** (-57.44)
***, **, * - significant at 1,5 and 10% level				

This table presents the hazard ratios associated with investors' tendency to sell/hold stocks at a gain. The dependent variable takes the value of 0 every day a stock is held by an investor and 1 on the first day it is sold. Demographic variables are fixed over time but vary across individuals. The demographic variables include a sophistication variable, the investor's age (subtracted by 18 then divided by 10) and a stop loss user variable. These variables are interacted with the trading gain indicator which takes the value of 1 every time a stock trades at a gain and 0 otherwise. The interaction allows the interpretation of cross-sectional differences in investor's propensities to sell gains. The demographic variables are also used as control variables. We also control for market return and market volume on the FTSE 100 using a 5 day moving average for each. The data is from a sample of 65,096 roundtrip positions made by 4,328 investors over the period July 2006 to December 2009. It was provided by a brokerage firm in the UK. Z-stats are shown in the parentheses below the hazard ratios.

Table 5: Trading gains, trading losses and stop losses:

	Reg 1	Reg 2
TLI (Z-stat)	.5502*** (-64.86)	
TLI x Stop loss transaction (Z-stat)	2.1546*** (27.96)	
TGI (Z-stat)		1.7695*** (69.15)
TGI x Stop Loss transaction (Z-stat)		.5225*** (-23.48)
Control variables		
Stop loss transaction (Z-stat)	.8285*** (-10.58)	1.4634*** (21.76)
Market return (Z-stat)	1.9511 (1.04)	1.3425 (0.46)
Market volume (Z-stat)	.9924*** (-63.60)	.9923*** (-64.63)
***, **, * - significant at 1,5 and 10% level		

This table presents the trading gains and losses in relation to use of stop losses. The dependent variable takes the value of 0 every day a stock is held by an investor and 1 on the first day it is sold. A transaction level stop loss variable is created which takes the value of 1 if a transaction used a stop loss and a value of 0 if a transaction didn't use a stop loss. This variable is interacted with two other independent variables to measure the extent to which it changes the propensity to sell both winners and losers. The independent variable in regression 1 is the trading loss indicator which takes the value of 1 every time a stock trades at a loss and 0 otherwise. The other independent variable is the trading gain indicator (TGI) which takes the value of 1 every time a stock trades at a gain and 0 otherwise. We also control for market return and market volume on the FTSE 100 using a moving 5 day average for each. The data is from a sample of 65,096 roundtrip positions made by 4,328 investors over the period July 2006 to December 2009. It was provided by a brokerage firm in the UK. Z-stats are shown in the parentheses below the hazard ratios.

Table 6: Trading gains, trading losses and stop loss users without stop losses:

	Reg 1	Reg 2
TLI (Z-stat)	.5610*** (-50.57)	
TLI x Stop loss user (Z-stat)	.9555** (-2.49)	
TGI (Z-stat)		1.8918*** (69.15)
TGI x Stop loss user (Z-stat)		.8419*** (-10.10)
Control variables		
Stop loss user (Z-stat)	1.3949*** (32.27)	1.4955*** (34.01)
Market return (Z-stat)	655.04*** (9.66)	473.15*** (9.17)
Market volume (Z-stat)	.9923*** (-60.64)	.9922*** (-61.81)
***, **, * - significant at 1,5 and 10% level		

This table presents the hazard rates associated with an investor's tendency to sell/hold stocks at a gain and a loss. The dependent variable takes the value of 0 every day a stock is held by an investor and 1 on the first day it is sold. Demographic variables are fixed over time but vary across individuals. The demographic variable is the stop loss user. However, all transactions that include stop losses have been removed from the data to be able to analyse stop losses users' susceptibility to the disposition effect when not using stop losses. The stop loss user variable is interacted with other independent variables to measure the extent to which it changes the propensity to sell both winners and losers. The independent variable in regression 1 is the trading loss indicator (TLI) which takes the value of 1 every time a stock trades at a loss and 0 otherwise. The other independent variable in regression 2 is the trading gain indicator (TGI) which takes the value of 1 every time a stock trades at a gain and 0 otherwise. The data is from a sample of 59,056 roundtrip positions made by 4,258 investors over the period July 2006 to December 2009. It was provided by a brokerage firm in the UK. Z-stats are shown in the parentheses below the hazard ratios.

Appendix 1: Questions used to assess whether investors could trade warrants

Some investors in our data were entitled to trade warrants in addition to stocks. To trade warrants an investor has to request permission from the brokerage firm due to the increased risk associated with these financial products. The brokerage firm would get the investor to answer some questions in order to determine whether they were appropriate to have this entitlement. Some examples of the questions used are as follows:

- Are you fully aware of the risks these types of investments carry?
- Would you be prepared to lose a significant part of your investment?
- How long have you been dealing in the stock market?
- What is your average total dealing activity per year?
- What is the approximate value of your overall investment portfolio?
- Do you believe your educational background and/or profession or former profession are relevant in understanding the risks involved?
- What level of your overall portfolio does this investment represent?

In addition to these questions, the brokerage firm would also analyse previous trades and portfolio balances to inform their decision.