Are the least successful traders those most likely to exit the market? A survival analysis contribution to the efficient market debate

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Abstract

Concerns regarding the assumptions of the Efficient Market Hypothesis have led to a greater emphasis on how the behaviour of different groups of traders might impact the evolution of financial markets; ideas encapsulated in the Adaptive Markets Hypothesis (AMH). A key assumption of the AMH is that the dynamics of competition and natural selection will drive 'noise traders', those least likely to push prices to efficient levels because they follow sub-optimal trading strategies, to exit the market. To test the key assumptions of the AMH, survival analysis is employed to examine the behaviour of retail spread-traders, a group who are widely reported to include many noise traders. Analysis of the trades executed by 5,164 individuals in the period 24th March 2006 to 7th February 2012 found that the least profitable and those who adopted ill-disciplined trading strategies tended to cease trading sooner than others. These findings are consistent with the AMH. However, profitable traders were also found to be more likely to cease trading than the average trader and a V-shaped relationship was found between a trader's Sharpe ratio and their likelihood of ceasing to trade (cf. the average trader). Furthermore, during the financial crisis of 2008-09, the disposition effect of traders and the proportion of noise traders increased and throughout the period of the study, the ill-discipline of new generations of traders increased. The results suggest that the forces underpinning the AMH are complex and the move towards market efficiency may not be as straightforward as some expect.

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1. INTRODUCTION

False assumptions regarding the efficiency with which financial markets process information can lead to the misallocation of resources. A prevailing view for half a century was that prices fully discount all available information; reflected in the efficient markets hypothesis (EMH) (Fama, 1970). However, Grossman and Stiglitz (1980) challenged the existence of perfectly efficient markets, ones in which information is instantly discounted in market prices. They argued that those who buy and sell financial instruments (traders) only have an incentive to acquire costly information if profit opportunities exist. This led some to argue that the efficiency of markets may change over time (Campbell, et al., 1997). More recent empirical studies confirm that the assumptions of the EMH may not hold. For example, market returns do not simply follow random walks (e.g., Doyle and Chen, 2013; Shiller, 2000) and a linear dependency between past and future prices can occur (Urquhart and Hudson, 2013). Furthermore, statistical analysis has shown that the assumptions underpinning widely used models of financial behaviour, based on the EMH, are questionable (e.g., Akerlof and Shiller, 2009; Gan et al., 2017).

Psychologists and behavioural economists have also argued that the human rationality assumptions underlying the EMH do not match individual behaviour and that information overload may result in traders making poor decisions (e.g., Goodwin et al., 2010; Frino et al., 2008). This led to a shift to studying financial markets in terms of the behaviour of traders, leading to Lo (2004; 2005) arguing that markets should be viewed as a continuously evolving process; ideas encapsulated in a revised version of the EMH, the Adaptive Markets Hypothesis (AMH). Proponents of the AMH postulate that traders act in their own interests but make mistakes. As they seek to adapt, an evolutionary process based on the dynamics of competition and natural selection occurs. This results in changes in market efficiency as the populations of traders with different characteristics evolve (Urquhart and McGroarty, 2014). In particular, market forces drive those who are least likely to push prices to efficient levels under the prevailing conditions to exit the market.

The AMH suggests that "survival is ultimately the only objective that matters for all financial traders" (Lo, 2004, p25). However, most literature exploring the relationship between traders' behaviour and survival has focused on theoretical supposition and analysis. For example, Hirshleifer (2001) postulated how judgement and decision biases incorporated in Prospect Theory (Kahneman and Tversky, 1979) may affect investors' behaviour and asset pricing. Beyond this theoretical analysis, support for the AMH is largely based either on narrative descriptions or on market-level empirical work. Lo's (2004) work is a good example of a narrative account. He provides a description of and rationale for the AMH but offers no supporting empirical evidence. Research providing

empirical support for the AMH is exclusively based on market price analysis (e.g., Ghazani and Araghi, 2014; Urquhart and McGroarty, 2014; Zhou and Lee, 2013). Despite this growing evidence in favour of the AMH, the EMH is still a widely accepted theory in the finance literature and Paul Volcker, the former Federal Reserve Chairman, claimed that "among the causes of the 2008-09 financial crisis was an unjustified faith in rational expectations [and] market efficiencies" (Volcker, 2011, p. 1).

This highlights the need for further research to deepen our understanding of the relative merits of AMH *vs.* EMH. A vital missing element is the empirical analysis of the individual trader's behaviour and how this impacts their probability of continuing to trade. This is important because a key assumption of the AMH is that market forces lead to changes in the relative proportions of 'noise traders', those whose decisions are based on incorrect analysis or perceptions, and traders who behave more in line with rational expectations (i.e., individuals who make decisions based on their human rationality, the information available to them, and their past experiences), referred to as 'more informed' traders. However, no previous studies examining the AMH (e.g., Hirshleifer, 2001; Lo, 2004; Urquhart and McGroarty, 2014) have conducted empirical analysis to explore to what extent a trader's decision to cease trading is related to the degree to which they act in accordance with rational expectations. We fill this research gap by using operational research (OR) modelling techniques, particularly survival analysis (e.g., Cox, 1972), to analyse the trades of a large data set of individuals.

The strength of OR methods for this task is that they offer the prospect of estimating mathematical models to quantify the effect of different factors on an individual's probability of ceasing to trade. This approach has been successfully employed to develop insights regarding other aspects of financial markets (e.g., Bellini and Figà-Talamanca, 2005; Doyle and Chen, 2013; Krauss et al., 2017; Lessmann et al., 2012; Moreno and Olmeda, 2007; Sermpinis et al., 2013; Tabak and Lima, 2009).

Survival analysis is the most appropriate OR method to help answer the key research question addressed here: *Are noise traders (cf. more informed traders) those most likely to cease trading?'* It is widely accepted that noise traders are those most likely to display ill-disciplined, sub-optimal trading strategies and to lose money. Consequently, a methodology is employed that facilitates exploration of whether those most likely to cease trading are (i) the least profitable, and (ii) those who employ sub-optimal, ill-disciplined trading strategies.

Data related to trading in the two most popular instruments (FTSE 100 and DAX 30 futures) were provided by a large UK spread trading brokerage. These data were employed to examine the trading history of 5,164 of their clients through the years 2006 to 2012. The robustness of the results was confirmed when testing the conclusions using two supplementary data sets from different spread trading brokerages based in the UK and South Africa.

To the best of our knowledge, this is the first empirical analysis of individual trader behaviour designed to test the predictions of the AMH and the first time that survival analysis has been used to

study market evolution processes. Empirical evidence is presented that supports the view that changing market conditions have an impact on the mix of traders remaining in the market. In accordance with the AMH, the least profitable and the most ill-disciplined traders are found to be those more likely to cease trading than the average trader. However, the most profitable traders are also found to be more likely to cease trading than the average trader. In addition, throughout the period of the study, the ill-discipline of new generations of traders increased and during the financial crisis of 2008-09 the disposition effect of traders (the tendency to close winning positions more readily than losing positions) and the proportion of noise traders increased. We discuss how these complex new dimensions might require an adaption of the AMH.

The results are based on a specific data set drawn from one brokerage in the spread trading market and are predicated on the assumption that an individual who ceases trading with that brokerage, ceases trading completely. These facts may appear to limit the applicability of the results, but evidence is presented (see section 3.1.2) to suggest that a spread trader who ceases trading with one broker is likely to cease trading completely. In addition, analysis of the supplementary data yielded similar results to those from the main data set, suggesting that the results have wider applicability. However, further research is needed to confirm that these results hold in other financial markets and over a longer time.

The remainder of the paper proceeds as follows. In section 2, the literature surrounding the roles that noise traders and more informed traders may play in markets is reviewed. This literature is employed to motivate the hypotheses, which are designed to shed light on which type of trader is most likely to cease trading. In section 3, the data set and the survival-analysis methodology employed to test the hypotheses are described. In section 4, the results are reported and discussed. Conclusions are drawn in section 5.

2 HYPOTHESES

Employing earlier theoretical and empirical research, Lo (2004, 2005) developed a modified version of the EMH (the AMH), based on the view that, like natural ecological systems, financial markets follow an evolutionary process. The AMH assumes that the behaviour of different groups of traders, distinguished by their behavioural characteristics, dictates market prices and the availability of resources (e.g., profits) and that traders who are least likely to drive prices to efficient levels under current market conditions are those most likely to cease trading. We test if this assumption is justified based on the behaviour of real traders. To achieve this objective, existing literature is employed to design hypotheses concerning the degree to which a trader's market survival is related to their profitability and the degree of their trading ill-discipline.

2.1 Traders' profitability and their decision to cease trading

An important concept underpinning the AMH is that "survival is ultimately the only objective that matters for all financial traders" (Lo, 2004, p25) and that the trading gains that individuals secure affect their relative ability to survive. Recent empirical studies at the market level have supported a principle underpinning the AMH, that if competition results in the population of traders increasing substantially relative to the resources, the population declines (e.g., Charles et al., 2012; Urquhart and Hudson, 2013; Urquhart and McGroarty, 2014). This reduces competition and the cycle begins again (Lo, 2004). It has been suggested that the most profitable traders are those most likely to survive, even if they are not profit maximisers (Blume and Easley, 2007), or they hold inaccurate beliefs (Delong et al., 1991), or apply sub-optimal portfolio rules (Evstigneev et al., 2002) or have limited access to information (Figlewski, 1978). The implication is that the least profitable are those most likely to cease trading. We, therefore, test the 'Profitability' hypothesis: *H1: The least profitable traders are more likely to cease trading than traders who achieve average returns.*

Humans can explore the hypothetical consequences of actions (Evans, 2007) and can evolve ideas more rapidly than physical attributes. This suggests that traders may change their risk-related views through time, and the AMH assumes that by doing this they improve their ability to thrive in the prevailing market conditions. For example, Prospect Theory suggests that individuals become more risk averse/preferring in the face of gains/losses; a view supported by several empirical studies. For example, Barberis and Xiong (2011) found that investors gain utility from realising profits and that the probability of realising a gain increases as the value of the gain increases. It has also been argued that the desire to realise profits stems from a desire to avoid the regret of subsequent losses (Barber and Odean, 1999) or because individuals keep mental accounts related to a group of transactions and gain utility from accounts which show a profit (Thaler, 1985). In the context of the AMH, this could imply that, in apparent contrast to H1, traders who are the most profitable may be those most likely to cease trading. This view is explored by testing the 'Profit Protection' hypothesis: *H2: The most profitable traders are more likely to cease trading than traders who achieve average returns.*

Fraser-Mackenzie et al. (2019) found that the break-even point was important in a trader's decision to cease trading. Consequently, if, as suggested by the preceding hypotheses, the probability of ceasing to trade increases as a trader makes larger gains or bigger losses, a level of symmetry may exist, with traders whose profitability is around zero having the highest probability of remaining in the market. Other V-shaped relationships associated with trading have been found. For example, Odean (1998b) identified an inverted V-shaped function associated with traders' buying behaviour, Ben-David and Hirshleifer (2012) discovered that the probability of a trader selling an individual asset was a V-shaped function pivoting at the break-even point, and Strahilevitz et al. (2011) found a lower probability of an investor re-purchasing an asset on which they had previously made a loss or on which they had made a profit but whose price had subsequently risen. The idea of a V-shaped relationship between profitability and the likelihood of ceasing trading is explored by testing the 'V-

shape' hypothesis: *H3: The increase in likelihood of an individual ceasing to trade is a V-shaped function of profitability, pivoting around the point at which a trader breaks even.*

If the results support H1-H3, this will suggest that market forces drive a combination of those least and most likely to push prices to efficient levels from the market. This is likely to have implications for how quickly markets achieve efficiency.

2.2 Traders' ill-discipline and their decision to cease trading

Combining behavioural theory frameworks with evidence from financial markets, some theorists have argued that noise traders will tend to exit markets, because they lose money to more informed traders in the long run (e.g., Blume and Easley, 2006; Sandroni, 2000; Yan, 2008). As a result, prices are then driven towards underlying asset values. Consequently, noise traders, whose actions deviate from rational expectations, are assumed to play a key role in market mechanics by providing liquidity and a financial incentive to gather costly information to those traders whose actions are dictated by rational expectations (Milgrom and Stokey, 1982).

A widely recognised characteristic of noise traders is that they adopt the sub-optimal trading strategy of closing winning positions more readily than losing positions; referred to as the disposition effect (DE) (Harris, 1988; Odean, 1998b). This behaviour is often described by financial market professionals as 'ill-disciplined' and has been found more frequently amongst traders with poor financial market literacy (Dhar and Zhu, 2006). The DE can be explained by Prospect Theory, which suggests that individuals are risk--preferring for gains and risk-averse for losses (Kahneman and Tversky, 1979) or from a strong desire to self-justify one's own past decisions (e.g., Barberis and Xiong, 2009; Dhar and Zhu, 2006). Traders who behave in this ill-disciplined manner tend to lose money to those who hold winning positions relatively longer than losing positions (e.g., Blume and Easley, 2006; Locke and Mann, 2005). In order to examine the assumption that traders displaying ill-discipline are those most likely to be driven from the market, the following 'Ill-discipline' hypothesis is tested: *H4: Individuals displaying greater trading ill-discipline are more likely to cease trading.*

2.4 Market Conditions and Population Changes

Should the market evolution/adaptation processes suggested by AMH exist, then they are most likely to be evident during harsh market conditions, such as those that prevailed during the 2008-09 global financial crisis. During this period, the Dow Jones fell over 50% in 18 months, including the largest one-day fall ever recorded up to that time (777.68 points on 20th September 2008). Such volatile conditions would have resulted in many traders incurring extremely large losses and it might be expected that the most ill-disciplined and the least profitable traders would be forced from the market, as they lose money to those who trade in accord with rational expectations.

However, even under extreme conditions, it is unlikely that all ill-disciplined traders will be driven from the market since they are not all unprofitable. By trading randomly some may secure high

returns (Samuelson, 1977). Second, 'limits-to-arbitrage' prevent some ill-disciplined and unprofitable traders being driven from the market due to legislative or practical barriers (Dow and Gorton, 1994). For example, rational traders may be unable to arbitrage away pricing inefficiencies (by buying and selling differently priced items of the same value) because the actions of noise traders may cause assets to remain mispriced for protracted periods of time; presenting rational traders with, for example, cash flow problems (Shleifer and Summers, 1990).

In addition, new generations of traders that entered the market during a crisis period must also be considered. Seru et al. (2010) pointed out that"[i]f newer traders are particularly subject to behavioural biases, periods in which many new investors are trading may correspond with periods in which prices do not reflect fundamental values" (p.706). Therefore, in examining changes in the population structure, it is important to examine the behavioural biases of new generations of traders entering the market. The AMH predicts that those traders who are likely to survive are those most likely to be successful under prevailing market conditions. However, the above discussion suggests that it is difficult to predict the relative populations of noise and informed traders following a financial crisis. Consequently, the following 'Market Evolution' hypothesis is tested: *H5: There was a decrease in the proportion of unprofitable and ill-disciplined traders after the 2008-09 financial crisis.*

The relative proportions of noise and more informed traders will have implications for the speed of recovery following a financial crisis, since the presence of a high proportion of noise traders has been shown to reduce efficiency and to increase the chances of bubbles and crashes (Witte, 2013).

3. DATA, VARIABLES and METHODOLOGY

In this section, the nature of spread trading data is outlined, details of the specific data sets analysed are provided, and the advantages of using these data for testing the hypotheses are discussed. Second, details of the independent and control variables employed in the study are outlined. Third, the Cox Proportional Hazard Model (CPH), which was used to determine to what extent a trader's decision to cease trading is impacted by their profitability, trading ill-discipline and changing market conditions, is described.

3.1 Data

3.1.1 Transactions in spread trading markets

In order to test the hypotheses, the behaviour of traders in the spread trading market is examined. These traders do not own the underlying asset. Rather, they speculate on the movement of an underlying security (e.g., Index futures). Spread traders will execute a long or short trade if they believe that the market will rise or fall, respectively. Whether a profit or loss is made depends on the direction of the trade, the stake size, and the price change which takes place. For example, a trader who expects the FTSE 100 to rise might open a long position by *buying* the market with, say, a £50 stake per point. Suppose the current price is 6,000 and it rises 20 points, then the trader would have an unrealised profit of £50 × 20= £1000. However, if the FTSE 100 fell by 20 points and the trader

closed their position, they would realise a loss of £1000 (£50 × -20). Spread trades are usually opened and closed in a day and spread traders often execute several trades per day. For example, individuals in the data set executed 3.52 trades per day on average, on the days they traded.

The number of spread traders in the UK alone has been estimated to exceed one million (Pryor, 2011) and Brady and Ramyar (2006) indicate that, of the £1.2 trillion traded annually on the London Stock Exchange, 40% is equity derivative-related and 25% of this relates to spread trading (£120 billion). Spread trading companies hedge their risks into the underlying markets. Consequently, behaviour in these markets has an impact on the underlying financial markets.

3.1.2 The spread-trading data set

Account data of individuals who traded with a leading UK spread-trading brokerage were secured. The data included the 2,263,012 trades of their 5,164 clients who traded the most popular indices in these markets, the FTSE 100 and DAX 30 futures, at some point in the period between 24th March 2006 and 7th February 2012. Table 1 displays descriptive statistics for the data set.

To check the robustness of the conclusions drawn from the main study, two further data sets were secured:15,636,230 trades of 22,481 individuals and the 2,966,385 trades of 18,910 individuals placed with different brokerages in the UK and South Africa, respectively. In Appendix 2, the appropriateness of the size of the data sets for testing the hypotheses are discussed and further details of these additional data sets are provided. These supplementary data sets did not include demographic information and we were not able to compute all the variables used in the main analysis. However, the results which could be compared were very similar to those from the original data set.

3.1.2 Advantages of spread trading data for exploring the hypotheses

The data sets employed offer several advantages for examining the factors influencing an individual's decision to cease trading. First, in spread trading, a position opened with one broker must be closed with that same broker. Consequently, a complete picture from the purchase to the close of a trade can be developed. In traditional financial markets, traders can buy a position with one broker but can sell it – and possibly exit the market – with another broker. Consequently, unless one had data from all brokers in the market it would not always be possible to identify when a trade was closed.

Second, profits from spread trading are not subject to capital gains tax in the UK or South Africa, so individuals have no reason to close trades or to cease trading for tax purposes. By contrast, tax considerations can produce seasonal trading factors in regular financial markets (Dhar and Zhu, 2006; Odean, 1998b).

Third, spread trading managers we interviewed from three different leading UK brokers were unanimous that the vanilla nature of spread trading (i.e. identical/very similar products and costs associated with different brokers) means that there are few incentives to move between brokers. Their experience is that spread traders rarely switch brokers. Equally, given the specialist knowledge needed to effectively trade a given instrument, they argued that it is rare for spread traders to switch between

instruments. This feature of spreading trading is helpful, as it suggests that it is possible to analyse a trader's decision to cease trading from the records of one broker.

Clearly, it is possible that profitable spread traders cease trading to realise their profits and look for alternative investments. In fact, Lakonishok and Smidt (1986) found that some traders realise winning trades at a faster rate than losing trades simply to rebalance their portfolio. However, recent evidence (e.g., Brown, et al., 2006; Odean 1998b) contradicts this finding. This suggests that the drive for diversification may not play a role in our results. In addition, one of the reasons Lakonishok and Smidt (1986) found for investors realising their returns was for tax planning purposes. However, no capital gains tax is payable on profits from spread trading, so this is unlikely to be a factor.

Spread traders behave very much like day traders in traditional financial markets, in that trades are generally opened and closed within a day (as credit costs are high). In fact, in the data set, the median length of time a trade is open is only 10.14 minutes, with 79% of trades being open for less than 60 minutes. Several studies have found that the vast majority of day traders and retail investors (non-professional investors) in traditional financial markets quit the market within two years (e.g., Barber et al., 2014; Linnainmaa, 2011; Mahani and Bernhardt, 2007; Seru et al., 2010). This is similar to the average time that traders in the data set employed here remain active (834 days), supporting the view of the interviewed managers of spread trading firms that individuals who ceased trading did not commence trading with another broker or engage in alternative forms of investment.

Fourth, spread trading is avoids the need for large capital holdings relative to the effective position size. For example, a trader who suspects the FTSE 100 might rise from its current position of 6,000 may buy the market with, say £10 per point. This is equivalent to a £60,000 position in the underlying market. However, traders are only required to have enough money in their account to cover 'the margin', an amount which historical data concerning market movements suggests could be lost. For the FTSE 100 at the time of this study, this was set at 150 x stake per point (i.e. £1500 in this example). The lack of a need for large capital holdings and the opportunity to trade multiple times in a day means that large gains can be made by spread traders for limited capital outlay. This reduces the need to use multiple brokers. In addition, 99% of trades in the data set involved stakes per point between £1 and £100, again suggesting that traders would have few constraints using only one broker. In the light of this evidence it seems unlikely, particularly given the added complexity involved with managing these high-frequency, short-lived trades across multiple platforms, that many traders would use multiple brokers. Consequently, this gives confidence that if a trader is found to cease trading, it is likely that they will have left the market.

The data set used in this paper is a subset of all spread trading activity, but there is no reason to believe that the traders examined behave in a different manner to others in the market. In addition, confidence in the conclusions is increased because the results were very similar to those drawn from analysis of the two supplementary UK and South African data sets.

Table 1.

Daily trading activity descriptive statistics for the data set used in the main analysis*.

	Mean[+]	Std. Dev	Median	Min	Max	Skew	Kurtosis	20th Percentile	40th Percentile	60th Percentile	80th Percentile
Mean stake size per point (£)	4.82	2.01	4.46	1.00	24.83	2.63	14.11	3.52	4.19	4.79	5.76
Mean profit (£) per trade	-10.63	1,085.27	-1.46	-43,648.72	217.93	-39.87	1,598.81	-14.42	-4.28	0.80	6.37
Mean profit (%) per trade	-1.54	721.44	-0.11	-29,121.89	42.25	-40.31	1,623.54	-1.85	-0.43	0.18	0.74
Mean gain (£) on winning trades	41.28	102.50	34.55	0.40	4,002.80	35.69	1,379.67	24.57	31.06	38.69	51.17
Mean loss (£) on losing trades	92.11	3,081.64	68.20	1.60	123,824.19	39.93	1,609.23	45.99	60.60	76.97	105.19
Number of trades	1,385.99	1,164.22	1,136.50	1.00	6,618.00	1.29	2.15	297.00	913.20	1,358.00	2,338.00
Proportion of FTSE 100 trades	0.76	0.14	0.80	0.00	1.00	-1.56	3.86	0.67	0.77	0.82	0.86
Mean stake per point (£) on FTSE 100 trades	4.78	2.01	4.46	1.00	21.97	2.46	12.11	3.46	4.14	4.78	5.71
Number of FTSE 100 trades	1,124.68	1,009.10	885.00	0.00	5,815.00	1.37	2.27	176.00	712.00	1,061.60	1,955.20
Mean profit (£) on FTSE 100 trades	-9.83	1,337.90	-1.08	-53,801.30	215.41	-39.92	1,604.14	-14.37	-3.83	1.47	7.26
Proportion of DAX 30 trades	0.24	0.14	0.20	0.00	1.00	1.56	3.86	0.14	0.18	0.23	0.33
Mean stake (£) on DAX 30 trades	4.80	4.20	3.92	1.00	100.00	10.82	204.79	2.87	3.54	4.47	6.09
Number of DAX 30 trades	260.92	196.51	226.00	0.00	1,433.00	1.36	3.22	99.00	182.00	279.00	406.00
Mean profit (£) on DAX 30 trades	-9.71	99.15	-1.38	-2,450.00	483.00	-15.95	363.02	-19.38	-5.81	2.19	11.11

The table displays daily trading activity descriptive statistics for a variety of variables calculated on the basis of the trades placed by the 5,164 individuals in the main data set, between 24th March 2006 and 7th February 2012, where $Skew = m_3/m_2^{3/2}$ and $Kurtosis = m_4/m_2^4$; $m_r = \sum_i (x_i - \mu)^r/n$). 'Mean stake (£) size per point' is the mean stake per point on the trades closed on a given day. 'Mean profit (£) per trade' is the mean profit or loss earned per trade over all trades that were closed on a given day. 'Mean profit (%) per trade' is the mean profit or loss earned on the margin, per trade over all trades that were closed on a given day. 'Proportion of trades with profit ≥ 0' is the proportion of trades that were closed on a given day which either broke-even (i.e. earned back the spread) or earned a profit. 'Mean gain (£) on winning trades' is the mean profit earned by trades closed on a given day which at least broke even. 'Mean loss (£) on losing trades' is the mean loss on the trades closed on a given day that lost money. 'Number of trades' is the total number of trades in the data set closed on a given day. 'Proportion of FTSE 100 trades' is the proportion of FTSE 100 trades (*vs.* DAX 30 trades) closed on a given day. 'Mean stake (£) per point on FTSE 100 trades' is the mean stake per point on the FTSE 100 trades closed on a given day. Number of FTSE 100 trades' is the number of FTSE100 trades closed on given day. 'Mean profit (£) on FTSE 100 trades' is the mean profit or loss earned on FTSE100 trades closed on a given day. 'Proportion of DAX 30 trades' is the proportion of trades on the DAX 30 market (*vs.* FTSE 100 market) closed on a given day. 'Mean stake (£) on DAX 30 trades per day' is the mean stake per point placed on the DAX 30 trades closed on a given day. 'Mean number of DAX 30 trades' is the mean number of DAX 30 trades closed on a given day. 'Mean profit (£) on DAX 30 trades' is the mean profit or loss earned on DAX30 trades closed on a given day.

*The descriptive statistics relate to the values across all trading days in the sample (e.g., Mean of 'mean stake size per point' is mean across all trading days in the data set).

[+]To provide a robust measure of central tendency, 0.1% trimmed means are reported.

3.2 Variables

In order to test the hypotheses, a range of independent and control variables were developed to account for a trader's ill-discipline and profitability, and to control for demographic factors and diverse aspects of a trader's behaviour and market conditions. In this section, the independent variables are first described. Second, each of the control variables that may influence a trader's longevity is defined, including, in turn, their trade frequency, gender, capital held, average profits, the risk of loss to which they expose themselves, the transaction costs they experience, how close to the censor date their last trade was recorded, and the market conditions when they traded.

3.2.1 Trader Risk and Profitability

The profit on trade i for trader k, R_k^i, was calculated as follows:

$$R_k^i = Stake_k^i \times Direction_k^i \times (Closing\ Price_k^i - Opening\ Price_k^i), \qquad (1)$$

where $Stake_k^i$ is the stake per point of individual k on trade i, $Direction_k^i$ is 1 when position i opened by trader k is a long position and -1 when it is a short position and $Closing\ Price_k^i$ and $Opening\ Price_k^i$ are, respectively, the closing and opening prices of the security traded.

The entire set of returns for trader k are referred to as $\boldsymbol{R}_k$, where $\boldsymbol{R}_k = [R_k^1, R_k^2, R_k^i, \ldots, R_k^n]$. The mean profit per trade for trader k in GBP (Mean $(\boldsymbol{R}_k)$) across all trades i=1,2,3,…,n_k, is a crude measure of their profitability. However, to compare performance between traders, it is necessary to recognise that they have different risk appetites. Consequently, we computed a risk-adjusted measure of profitability of individual k using the expected return to risk ratio (i.e. Sharpe ratio):

$$S_k = \frac{mean(\boldsymbol{R}_k)}{sd(\boldsymbol{R}_k)}, \qquad (2)$$

The seminal work on behavioural finance by Kahneman and Tversky (1979) indicated that losses are perceived in a different way to gains. Consequently, depending on the extent of the previous losses/gains made by an individual trader and their relative risk aversion/preference for gains/losses, this could result in them either ceasing or continuing trading. Consequently, to test H1-H3, that both the least profitable and the most profitable traders were those most likely to cease trading, two further variables were developed (S_k^+ and S_k^-) for those with profitable and unprofitable Sharpe ratios, respectively; defined as follows:

$$S_k^+ = \begin{cases} S_k, & S_k > 0 \\ 0, & S_k \leq 0 \end{cases}, \qquad (2a)$$

$$S_k^- = \begin{cases} 0, & S_k \geq 0 \\ S_k, & S_k < 0 \end{cases}. \qquad (2b)$$

The use of two-sided statistics such as this are well established in the finance literature. For example, dual betas have been employed to capture the volatility of individual stocks compared to market systematic risk under different market conditions (e.g., Balbás et al, 2016).

3.2.2 Trader Discipline

Three measures of trading discipline were employed to test H4. The first was a standard measure of the DE (Dhar and Zhu, 2006), which captures a difference in the propensity of a trader to realise gains and losses. To develop this measure, the paper gain or loss made in each minute m for trade i, by trader k was determined by subtracting the price at the beginning of minute m from the price at the end of minute m, multiplied by the direction of that trade ($Direction_k^i$). The number of minutes in which a given trade i exhibits paper gains G_i or losses L_i was determined. These minutes were summed for all trades undertaken by trader k to produce a count of the number of minutes across all their trades, which show an unrealised gain (*Paper Gain$_k$*) or an unrealised loss (*Paper Loss$_k$*). In the minute that a trade is closed, it will result in a realised gain or a realised loss. For trader k, the number of trades resulting in realised gains (*Realised Gain$_k$*) and the number of trades resulting in realised loss, (*Realised Loss$_k$*) was calculated. Using these variables, the proportion of gains that are realised (*PGR$_k$*) and the proportion of losses that are realised (*PLR$_k$*) were calculated, as follows:

$$PGR_k = \frac{Realised\ Gain_k}{Realised\ Gain_k + Paper\ Gain_k}, \tag{3a}$$

$$PLR_k = \frac{Realised\ Loss_k}{Realised\ Loss_k + Paper\ Loss_k}. \tag{3b}$$

This led to the standard measure of the DE, defined as:

$$DE_k = PGR_k - PLR_k. \tag{4}$$

When considering trading discipline, it is also important to consider how far a trader allows a position to fall into unrealised *loss* compared with how far they allow a position to accumulate unrealised *profit*. Consequently, a measure of trading discipline was developed which accounts for the ratio of trader k's average sizes of maximum paper (i.e. unrealised) losses and gains across all their trades. To achieve this, the maximum paper gain (MPG_k^i) and the maximum paper loss (MPL_k^i) for trader k over the lifetime of trade i were calculated, where the paper return (gain or loss) on trade i at time τ ($PR_k^{i\tau}$) was calculated as the difference between the natural logarithm of the price of trade i at time τ and the natural logarithm of the opening price, multiplied by the direction of that trade ($Direction_k^i$), as follows:

$$PR_k^{i\tau} = Ln\left(\frac{Price_k^{i\tau}}{Open\ Price_k^i}\right) \times Direction_k^i \ . \tag{5}$$

The Ill-discipline index (Y_k) was then calculated as the average maximum paper loss across all trades of trader k ($AvgMPL_k$), divided by their average maximum paper gain across all trades, $AvgMPG_k$:

$$Y_k = \frac{AvgMPL_k}{AvgMPG_k} \ . \tag{6}$$

Thus, $Y_k = 2$ suggests that trader k allowed their average maximum paper losses to be double the size of their average maximum paper profits.

The final measure of ill-discipline employed was simply the average maximum paper loss across all trades of trader k ($AvgMPL_k$), called 'Loss Ill-discipline'. Clearly, there is a temptation to allow losses to reach high levels hoping that the market will turn in one's favour, thereby enabling

reduced losses or even profits to be secured. However, there is a danger that allowing paper losses to run to high levels can lead to significant losses being incurred, and most professional traders employ 'stop loss' controls to prevent paper losses reaching such levels.

3.2.3 Control Variables

When testing the hypotheses concerning the relationship between a trader's market longevity and their profitability and ill-discipline, the effects of overconfidence and other factors that may influence their longevity were controlled.

Traders can survive in financial markets in the long run, even if they are not profit maximisers (e.g., Evstigneev et al., 2002), since profits flow to those who out-perform their competitors, even though they are not perfectly rational (Blume and Easley, 2007). For example, traders who are over-confident may display a tendency to overestimate their abilities, knowledge or precision of information. However, they may remain in markets longer than a rational expectation view of markets would suggest. For example, Delong et al. (1991) demonstrated that traders who are overconfident may achieve better returns because they accept higher risks by overestimating returns or underestimating risk. Theoretical analyses (e.g., Hirshleifer, 2001; Hirshleifer and Luo, 2000) have also suggested that overconfidence bias may enable traders to survive longer in markets.

Theoretical models suggest that high trading frequency indicates overconfidence (e.g., De Bondt and Thaler, 1985) and empirical evidence supports this view (e.g., Barberis and Thaler, 2003; Odean, 1998a; Statman et al., 2006). Consequently, to control for over-confidence, the mean number of trades closed by trader k on days on which they traded (*Trade Frequency$_k$*) was incorporated into the models. It has also been demonstrated that those who trade infrequently are more likely to make decisions which do not accord with rational expectations (e.g., Dhar and Zhu, 2006). It might be expected, therefore, that those individuals who trade infrequently will be forced to leave the market before more informed traders. Consequently, by incorporating *Trade Frequency* in the model, this potential confound was also avoided.

Several psychological studies have suggested that males are more predisposed to overconfidence (e.g., Barber and Odean, 2001; Lundeberg et al., 1994)). In addition, females (Sapienza et al., 2009) and older individuals (Albert and Duffy, 2012) have been shown to be more risk averse, and this may influence their decisions concerning the length of time they continue to trade. Consequently, we controlled for trader *k's* gender (*Gender$_k$*: 1=male, 0=female) and age (*Age$_k$*).

Dhar and Zhu (2006) found that individuals with the least capital demonstrate the strongest DE. Consequently, in testing H4 related to trading discipline, it was important to control for a trader's capital. This was achieved in two ways. The first was by incorporating the trader's total savings (*TS$_k$*) into the model as notified to the brokerage at the time their account was opened. Clearly, a trader's total savings may vary from this figure at any later point in time and, as it is self-reported, may not be completely accurate. Consequently, we also controlled for the average amount per point, in pounds

sterling (£), that trader k staked when opening their positions (*Mean stake$_k$*). This was used as an additional proxy for the capital controlled by a trader because, as indicated in section 3.1.2, the maximum amount an individual can trade is directly related to the total funds they hold in their account, and this in turn is likely to be influenced by their capital, or at least, the capital they are prepared to commit to spread trading.

The tests of H1 and H2, exploring the relationship between an individual's trading success and their market survival, were based on their Sharpe ratio. However, to account for variation in traders' average profits, we also controlled for Mean ($\boldsymbol{R}_k$). In addition, to control for the risk of loss to which they expose themselves, the 'Value at Risk' for each trader (VaR ($\boldsymbol{R}_k$)) was determined. This takes the value of the .05 percentile of $\boldsymbol{R}_k$ for each trader, whereby, on average, trader k has a 0.05 probability that a trade will lose more than VaR ($\boldsymbol{R}_k$).

It has been argued that transaction costs may play a role in trading volume and in the incidence of the DE (Harris, 1988), since lower-priced assets have proportionally higher transaction costs relative to price. However, later studies such as by Brown, et al.(2006) and Odean (1998b) concluded that the DE is not driven by diversification motives, or by higher transaction costs associated with lower-priced stocks. Nevertheless, transaction costs are controlled for by incorporating trading frequency (*Trade Frequency$_k$*), since transaction costs generally increase as trading frequency increases.

The definition of ceasing to trade is based on the date of the trader's last trade (t_k^n). However, for some traders, their last observed trade in the data set will not be their final trade, as they will continue to trade past the final date in the data set ('D': 7th February 2012). Those traders whose final recorded trade was within B days of D, were treated as if they may have continued trading, and they are right-censored. To determine an appropriate value for B, the inter-trade duration (in days) between the i-1 and i'th trades (i=1,2,…m_k) of trader k was calculated and depicted as ITD_i^k. The mean inter-trade duration across all N traders (MITD) was calculated as follows:

$$MITD = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=1}^{m_k}\frac{ITD_i^k}{m_k}. \tag{7}$$

The standard deviation (SD) of the MITD distribution, SD(MITD) was also calculated. The value of B was set to MITD + 3SD(MITD), because, according to Chebyshev's inequality, this interval ensures that for an inter-trade duration which follows a Gaussian distribution or an arbitrary inter-trading distribution, the probability of those who continued trading beyond D is less than 0.3% or 11%, respectively. The censor date (t_c) was, therefore set to 11th July 2011, suggesting that k's final trade T_k will occur in the interval ($t_c, +\infty$).

It is important that the model accounts for the possibility that there may be a trend through time in the likelihood of ceasing to trade. This ensures that the true effects of the variables are identified, rather than spurious effects related to the time individuals were trading. Consequently, trader k's

'Trading period' was included in the model, defined as the number of days prior to the censor date they last traded (n_d^k). If the individual traded after the censor date, then n_d^k takes a negative value and this trader is right-censored.

Market conditions when k had trades open are also controlled for by including the mean market return (r_m^k) and the mean volatility(v_m^k), between the opening and closing times of each of their trades in markets which formed the basis of those trades. It is important to control for market conditions, as it is expected that they (e.g., the crash beginning in September 2008) may play a role in a trader's decision to cease trading (directly addressed in H5).

3.3 Modelling the 'Cease Trading' Decision using Survival Analysis

The Cox Proportional Hazard Model (CPH) is used to model the probability distribution of a trader ceasing to trade at time t if they had not ceased before t. The description in this section follows Cox (1972), which may be referred to for further details. The CPH facilitates the testing of the hypotheses.

The CPH is a powerful multiplicative regression model and has been applied in many fields to study the interval between or before pre-defined events. [See Kiefer (1990) for a literature review.] In finance, the CPH model has been used to analyse a variety of time-based events, such as bank failures and personal loan defaults (e.g., Gregoriou, 2002; Lane et al., 1986; Ma et al., 2016; Ongena and Smith, 2001; Stepanova and Thomas, 2002). The CPH model is able to handle time-dependent variables. This is particularly helpful in a spread-trading context, where characteristics associated with individual traders may change across different trades (e.g., age, stake size).

Consider a population of individual traders; for each trader k we observe the time to the "cease trading" event. Denote by T_k a random variable representing the cease trading time. Let $h_k(t)$ be the hazard function for trader k at time t, that is:

$$h_k(t) = \lim_{\Delta t \to \infty} \frac{Pr(t + \Delta t > T_k \geq t | T_k \geq t)}{\Delta t} \qquad . \tag{8}$$

The hazard rate $h_k(t)$ represents the instantaneous probability of k ceasing to trade at time t, conditional on $T_k \geq t$. Cox (1972) showed that $h_k(t)$ is a log-linear function of covariates $\mathbf{x}_k(t)$ and a baseline hazard, $h_0(t)$, as follows:

$$h_k(t) = h_0(t) \exp(\beta' \mathbf{x}_k(t)), \tag{9}$$

where $\mathbf{x}_k(t)$ represents a set of characteristics of k (e.g., age, gender, mean stake) and where the baseline hazard $h_0(t)$ captures the basic rate in the hazard when $\mathbf{x}_k(t)$ equals zero and β is a vector of estimated coefficients of $\mathbf{x}_k(t)$ measuring the impact of the explanatory and control covariates.

Using the hazard function (Eq. 9), and assuming that there is only one cease trading event, (e.g., no two traders cease at exactly the same time), the probability that k ceases to trade at time t_k, conditional on the risk set of individuals, $\hbar(t_k)$ (i.e. those at risk of ceasing to trade at time t_k), can be represented by:

$$\frac{h_0(t)\exp(\beta'\mathbf{x_k}(t))}{\sum_{j\in \hbar(t_k)}h_0(t)\exp(\beta'\mathbf{x_j}(t))} = \frac{\exp(\beta'\mathbf{x_k}(t))}{\sum_{j\in \hbar(t_k)}\exp(\beta'\mathbf{x_j}(t))} \qquad . \tag{10}$$

The numerator and denominator are proportional to the risk of k ceasing to trade at t_k, and the total risk of ceasing to trade of all traders j in the risk set $\hbar(t_k)$, respectively. Using Cox (1972, 1975), the partial likelihood can be calculated with l ordered cease trading times in the data, as follows:

$$L(\beta) = \prod_{k=1}^{l}\frac{\exp(\beta'\mathbf{x_k}(t))}{\sum_{j\in \hbar(t_k)}\exp(\beta'\mathbf{x_j}(t))}. \tag{11}$$

Eq. 11 uses the parameters of interest to assess the likelihood function for estimating β and partial information concerning time. The likelihood function is derived by taking the product of the conditional probabilities (from Eq. 10) of all traders in $\hbar(t_k)$. Given that some traders have already ceased trading, this calculation estimates the probability that it is k, from the remaining risk set $\hbar(t_k)$, , that will cease trading at time t_k. This partial likelihood does not depend on the baseline hazard $h_0(t)$. Consequently, β can be estimated without knowing the underlying baseline hazard. The method developed by Efron (1977) is employed to approximate the partial likelihood in Eq. 11. This is computationally efficient and is designed to handle ties.

A set of coefficients (β) associated with the covariates can then be derived, where Exp(coef) indicates the change in the likelihood of 'ceasing to trade', based on a covariate value. For example, given a value for covariate x for a particular trader, say a Sharpe ratio of 1, and a coefficient for that covariate of $\beta = 0.1$, the hazard of this individual ceasing to trade compared to the baseline (i.e. a trader with a Sharpe ratio of zero) is Exp (0.1(1)) =1.105; i.e. this trader has a 10.5% higher chance of ceasing to trade on a given day compared to an individual with a Sharpe ratio of zero, assuming that they have not ceased trading before.

4. RESULTS AND DISCUSSION

4.1 Descriptive statistics

Descriptive statistics of the data used in the main analysis are displayed in Table 2. These relate to demographic details of the traders (e.g., age and savings) and the nature of their trading activity (e.g., staking levels, trading frequency per day, Sharpe ratios achieved). Only 25% of spread traders in the data set achieved positive average returns per trade, a similar proportion to that of profitable day traders in traditional financial markets (Barber et al., 2005). Whilst 61% of trades in the data set were profitable, the average return across all the profitable trades (£69.90) was considerably less than the average loss across all losing trades in the data set (£143.30). This is typical of behaviour associated with the disposition effect (DE), where traders are reluctant to close losing positions but close winning positions relatively quickly.

Two measures of the DE were employed, discussed more fully in section 3.2.2. The first was the standard measure (DE_k); i.e. the difference between the proportion of winning and losing positions that a trader realises; i.e. PGR_k - PLR_k. The means across all traders of the proportions of gains

realised ($\frac{1}{N}\sum_{k=1}^{N}PGR_k$) and losses realised ($\frac{1}{N}\sum_{k=1}^{N}PLR_k$) were 0.052 and 0.030, respectively. Overall, 72.9% of the spread traders were found to display a disposition effect (DE_k>0), and on average, they were 1.4 times more likely to realise a paper profit than a paper loss. The second measure of the DE, discussed in section 3.2.2, was the ratio of a trader's average maximum open loss per trade and their average maximum open profit per trade (i.e. Ill-discipline index (Y_k)). The majority of traders (68.5%) had average maximum open losses greater than their average maximum open profits. The descriptive statistics displayed in Table 2 suggest, as expected, that there is a large proportion of ill-disciplined and unprofitable traders in the retail spread-trading market.

4.2 Testing the Profitability-related Hypotheses

The results of estimating the CPH Model are presented in Table 3. The model diagnostic and fit tests suggest that the variables provide sufficient information concerning the probability of a trader ceasing to trade to be statistically significant and that the model fits the data reasonably well.

The results show a negative coefficient for traders with an unprofitable Sharpe ratio, indicating that the greater a trader's losses (relative to risk accepted) the greater the probability of their ceasing to trade, compared to the average trader. This result supports H1. Equally, the results support H2, since the coefficient for those with profitable Sharpe ratios are positive and significant, indicating that the greater a trader's profit relative to risk accepted, the greater the probability of their ceasing to trade, compared to the average trader.

The Sharpe ratios achieved by traders (x-axis) were plotted against the increase in their likelihood of ceasing to trade compared to the average trader (y-axis). This shows an interesting, tilted V-shape, with a Sharpe ratio = 0 (the baseline risk of ceasing to trade) as the pivot (see Figure 1). We examined whether the relationship between the Sharpe ratio and the likelihood of ceasing trading is simply linear, rather than V-shaped. To test this, we fitted another model which replaced the positive and negative Sharpe ratio variables with just a single Sharpe ratio variable. A log likelihood ratio test between these two models was significant, suggesting the additional complexity of the V-shaped model is warranted (χ^2 (1) = 15.97, p < .01). These results support H3; namely, that the most unprofitable and profitable traders are those least likely to continue trading. Confidence in the results employed to test H1-H3 is increased because these are obtained after controlling for several factors outlined in section 3.2.3, that could confound the impact of profitability on market survival.

To explore the robustness of these findings, alternative measures of some of the control variables were explored. In particular, the CPH model was re-estimated using median stake in place of mean stake, median profit/loss in place of mean profit/loss, and $VaR(R_k)(10\%)$ and $VaR(R_k)(1\%)$ in place of $VaR(R_k)(5\%)$. In addition, the CPH model was re-estimated using alternative censor dates defined as MITD + SD(MITD) (i.e. 22nd November 2011) and MITD +6SD(MITD) (i.e. 23rd December 2010) in place of MITD + 3SD(MITD) (i.e. 11th July 2011) (see section 3.2.3). In all these

Table 2.

Descriptive statistics for the variables (defined in section 3.2) used in the main analysis.

	Mean[+]	Std. Dev	Median	Min	Max	Skew	Kurtosis	20th Percentile	40th Percentile	60th Percentile	80th Percentile
Age_k	44.93	13.10	43.72	18.00	90.00	0.48	-0.28	33.03	40.00	47.19	56.34
Total Savings (TS_k)(£'000)	46.79	93.88	15.00	0.00	1,000.00	5.48	41.16	0.00	8.00	30.00	100.00
$Mean\ Stake_k$ (£)	3.64	8.10	1.60	1.00	182.68	10.26	160.30	1.01	1.33	2.03	4.20
$Trade\ Frequency_k$	3.47	3.74	2.38	1.00	97.05	6.27	95.08	1.38	2.00	2.86	4.76
Sharpe Ratio (S_k)	-0.10	0.85	-0.06	-29.80	4.25	-24.01	721.89	-0.19	-0.09	-0.04	0.02
Profit/loss per trade (R_k) (£)	-8.25	1,371.23	-2.61	-88,669.64	42,486.00	-46.57	3,560.42	-11.98	-4.20	-1.53	0.88
Value at risk ($VaR(R_k)$(5%)	149.19	755.32	60.00	-42,486.00	15,440.00	-31.39	2,013.08	23.86	44.35	82.02	160.04
Loss Ill-discipline ($AvgMPL_k$)	0.42	0.46	0.29	0.00	5.83	4.30	28.47	0.17	0.24	0.34	0.57
Ill-discipline Index (Y_k)	1.50	3.08	1.17	0.00	120.70	21.08	630.15	0.86	1.07	1.29	1.68
Disposition Effect (DE_k)	0.02	0.10	0.01	-1.00	1.00	0.59	53.59	0.00	0.00	0.01	0.04
Market Return (r_m^k)	0.00	0.09	0.00	-1.48	2.04	2.75	93.63	-0.03	-0.01	0.00	0.02
Market volatility (v_m^k)	0.42	0.24	0.38	0.04	7.05	9.55	200.03	0.29	0.35	0.42	0.52
Trading period (n_d^k)	522.85	495.22	605.00	-210.00	1,929.00	-0.05	-1.12	-70.00	409.00	781.80	999.00

The table presents descriptive statistics for variables calculated for the 5,164 individuals (4,664 males (90.3%) and 500 females (9.7%)) who executed trades in the FTSE 100 and DAX 30 futures with the UK brokerage, at some point between 24th March 2006 and 7th February 2012. Definitions of the variables are provided in section 3.2.
[+]To provide a robust measure of central tendency, 0.1% trimmed means are reported. Skew = $m_3/m_2^{3/2}$ and Kurtosis = m_4/m_2^4 ; $m_r = \sum_i (x_i - \mu)^r/n$).

Table 3

Results of estimating the CPH model for assessing the likelihood (at time t) that an individual ceases trading, based on their profitability and their trading discipline (DE), whilst controlling for demographic factors, trading behaviour and market conditions.

		Exp(Coef)[1]	SE(coef)	Z	p-value	
Age_k	<0.01	1.00	<0.01	0.31	0.76	
$Gender_k$ (Male)	0.01	1.01	0.05	0.16	0.87	
Total Savings (TS_k)(£)	<0.01	1.00	<0.01	0.25	0.80	
$Mean\ stake_k$ (£)	>-0.01	1.00	<0.01	-1.70	0.09	
$Trade\ Frequency_k$	0.01	1.01	<0.01	1.61	0.11	
Mean Profit/loss per trade (Mean (R_k)(£)	<0.01	1.00	<0.01	1.23	0.22	
Value at Risk ($VaR(R_k)$)(5%)	>-0.01	1.00	<0.01	-1.14	0.25	
Profitable Sharpe Ratio (S_k^+)	0.28	1.32	0.08	3.62	<0.01	***
Unprofitable Sharpe Ratio (S_k^-)	-0.07	0.93	0.02	-4.74	<0.01	***
Loss Ill-discipline ($AvgMPL_k$)	>-0.01	1.00	<0.01	-1.29	0.20	
Ill-discipline Index (Y_k)	>-0.01	1.00	0.01	-0.12	0.91	
Disposition Effect ($DE_k > 0$)	1.49	4.46	0.21	7.02	<0.01	***
Market Return (r_m^k)	0.37	1.44	0.14	2.62	0.01	**
Market Volatility (v_m^k)	0.64	1.89	0.04	16.53	<0.01	***
Trading period (n_d^k)	<0.01	1.00	<0.01	72.24	<0.01	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.84 (SE <0.01)
Rsquare= 0.73 (max possible= 1.00)
Likelihood ratio test= 6,740 (15), p= <0.01
Wald test = 5,593 (15), p= <0.01
Score (Logrank) test = 6,583 (15), p= <0.01
Total Observations (Total Traders) = 5,164
Total Events = 5,135

The Table presents the results obtained from estimating the CPH model assessing the likelihood (at time t) that an individual ceases trading, based on their profitability and trading discipline, for the 5,164 individuals who traded at any time between 24th March 2006 and 7th February 2012. Definitions of the variables are provided in section 3.2.

alternative specifications, the significant variables in the model remained the same (i.e. median stake, median profit/loss, $VaR(R_k)$(10%) and $VaR(R_k)$(1%) were not significant at the 5% level) and coefficient magnitudes associated with alternative censor dates were almost identical to those displayed in Table 3. Alternative risk-adjusted measures of profitability were also explored. In particular, the Sharpe ratio was replaced with (i) the Sortino ratio, $SR_k = \frac{mean(R_k)}{sd(NegR_k)}$, where $NegR_k$ represents only the negative returns of trader k; thus differentiating harmful (negative) volatility from total overall volatility, and (ii) a Sharpe ratio based on median returns, $MS_k = \frac{median(R_k)}{sd(R_k)}$. Both SR_k

and MS_k were split into positive (SR_k^+ and MS_k^+, respectively) and negative (SR_k^- and MS_k^-, respectively) variables, for the same reasons the Sharpe ratio was split in this manner.
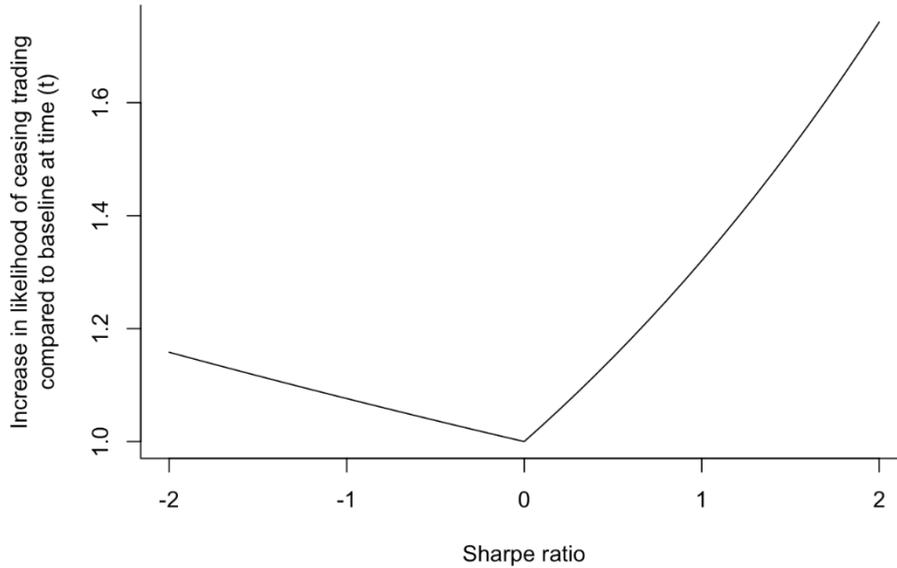
Figure 1. The figure displays estimates, derived from the CPH Model, for the effect of a trader's Sharpe ratio on the expected increase in likelihood of ceasing to trade at any given time (*t*) compared to a trader with a Sharpe ratio of zero (baseline). [$h(t, S_k^+) = \exp(2.8 \times 10^{-1} \cdot S_k^+)$; $h(t, S_k^-) = \exp(-7.0 \times 10^{-2} \cdot S_k^-)$].

MS_k^+ was significant at the 0.1% level (with a positive coefficient). However, MS_k^- and both the SR_k^+ and SR_k^- were not significant at the 5% level. Consequently, it appears that a trader's decision to cease trading is influenced by their mean return, adjusted for both positive and negative return volatility, but not by their return simply adjusted for harmful (negative) volatility. In addition, the simpler measures of a trader's success (*Mean*($\boldsymbol{R}_k$), *Median*($\boldsymbol{R}_k$) and *VaR*($\boldsymbol{R}_k$)) were not significant. Consequently, those most likely to cease trading are not those who are simply more (or less) profitable. Rather, they are those who achieve the greatest or least return to risk ratios. These may be, respectively, those who are particularly shrewd (or lucky) and those who are particularly poor (or unlucky) when making trading decisions.

Support for H1-H3 was also provided by the results of estimating the CPH model on supplementary data provided by another UK brokerage and a South African brokerage. Full details of these additional data sets are provided in Appendix 2. The results are reported in Table 4. A V-shaped relationship is again observed (see Figure A2, Appendix 2), with a Sharpe ratio = 0 as the pivot. Models that allow a V-shaped relationship between the Sharpe ratio and the chance of a trader ceasing trading were found to better account for the data than models that only allowed a linear relationship, for both the additional UK and South African data sets (χ^2 (1) = 107.29, p < .001 and χ^2 (1) = 290.08,

p < .001, respectively). Similar robustness checks to those outlined above were performed on the two supplementary data sets. The results mirror those for the main data set, other than the fact that, in this case, both MS_k^+ (with a positive coefficient) and MS_k^- (with a negative coefficient) were significant at a 0.1% interval, possibly due to the larger sample sizes associated with the supplementary data sets. The fact that a V-shaped relationship is observed in two large data sets related to different forms of spread trading, and in different periods from that covered by our main data set, provides confidence that the relationship is robust through time, across different forms of trading, and in different countries.

Previous research has identified V-shaped relationships associated with various aspects of trading, including both buying and selling behaviour (Ben-David and Hirshleifer, 2012; Odean, 1998b; Strahilevitz, et al., 2011). However, this is the first time a V-shaped relationship has been identified between a trader's profitability and their increased probability of ceasing to trade.

Table 4

Results of estimating CPH models assessing the likelihood that an individual ceases trading, based on their profitability, using supplementary data provided by (a) UK and (b) South African brokerages.

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Mean Stake$_k$ (Volume)	<0.01	1.00	<0.01	1.03	0.31	
	[>-0.01]	[1.00]	[<0.01]	[-0.11]	[0.91]	
Trade Frequency$_k$	0.01	1.01	<0.01	11.24	<0.01	***
	[0.01]	[1.01]	[<0.01]	[6.61]	[<0.01]	***
Profit/loss per trade Mean (R_k)(£)	>-0.01	1.00	<0.01	-0.70	0.48	
($)	[>-0.01]	[1.00]	[<0.01]	[-1.63]	[0.10]	
Value at Risk ($VaR(R_k)$(5%)	>-0.01	1.00	<0.01	-0.54	0.59	
	[>-0.01]	[1.00]	[<0.01]	[-1.65]	[0.10]	
Profitable Sharpe Ratio (S_k^+)	0.96	2.60	0.11	8.52	<0.01	***
	[0.81]	[2.24]	[0.05]	[16.19]	[<0.01]	***
Unprofitable Sharpe Ratio (S_k^-)	-0.58	0.56	0.03	-20.26	<0.01	***
	[-0.27]	[0.76]	[0.01]	[-19.17]	[<0.01]	***
Trading period (n_d^k)	-0.03	0.97	<0.01	-32.58	<0.01	***
	[-0.04]	[0.96]	[<0.01]	[-54.88]	[<0.01]	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.919 [0.79], se <0.01[<0.01]
Rsquare= 0.37[0.40], max possible = 0.95 [1.00]
Likelihood ratio test= 10,333.00 (7) [9,778.00(7)], *p*<.01 [<0.01]
Wald test = 1,442.00(7) [3,520.00(7)], *p*<0.01 [<0.01]
Score (logrank) test = 3,488.00(7) [3,354.00(7)], *p*<0.01 [p<0.01]
Total Observations (Total Traders) =22,481 [18,910]
Total Events =3,753 [7,380]

The finding that traders with the largest negative return to risk ratios are those most likely to cease trading chimes with previous research which predicts that less profitable traders leave the market in the long term (Blume and Easley, 2006, 2007; Delong et al., 1991; Evstigneev et al., 2006). This supports the evolutionary processes at the heart of the AMH (e.g., Urquhart and McGroarty, 2014) – namely, that the proportion of traders who are likely to drive prices to efficient levels increases in the long run (Lo, 2004). These results cannot be explained by Prospect Theory's prediction that individuals are risk-preferring for losses (Kahneman and Tversky, 1979); this would imply that those who make losses continue taking risks. Rather, the results are better explained by Lo's (2004) view that survival is the main objective of traders and this is facilitated by success, measured by profits.

The observation that traders who achieve greater profits are more likely to cease trading accords with Barberis and Xiong's (2011) finding that investors gain utility from realising profits and that this behaviour increases as profits increase. The finding can be explained by a desire to avoid the regret of gains turning to losses (Barber and Odean, 1999) or by Prospect Theory's assertion that individuals are generally risk-averse for gains (Kahneman and Tversky, 1979).

Overall, the results of testing the Profitability-related Hypotheses suggest that the relationship between profitability and the probability of ceasing to trade is complex. The V-shaped function tilts to the left, indicating that traders with a Sharpe ratio of +s have a higher expected increase in their likelihood of ceasing to trade than traders with a Sharpe ratio of -s. Protecting returns may, therefore, be a more powerful motive for ceasing to trade than depletion of capital or a realisation that the return to risk ratio is unattractive. This implies that traders who are more likely to drive prices to efficient levels are those most likely to cease trading. However, most spread traders make losses and, consequently, the mix of traders which emerges may be harder to predict than the AMH assumes.

4.3 Testing the Trading Ill-discipline Hypothesis

The Trading Ill-discipline hypothesis, H4, was tested by examining the degree to which traders display the disposition effect (DE_k). The coefficient of this variable in Table 3 is positive and significant. This result supports H4, since ill-disciplined traders are often defined by higher levels of DE_k (Harris, 1988; Odean, 1998b). However, the coefficient of the Ill-discipline index (Y_k), which measures a trader's ratio of average maximum paper losses and gains, across all trades, was insignificant. Equally, their decision to cease trading was not influenced by their loss ill-discipline, since the average maximum paper loss incurred ($AvgMPL_k$) was insignificant.

In testing H4, other factors associated with trading discipline were controlled; namely, an individual's capital holdings (e.g., Dhar and Zhu, 2006) and their transaction costs (Harris, 1988). Two proxies for a trader's capital were employed: their total savings (TS_k) and their *Mean stake$_k$*. Clearly, the maximum paper loss a trader can incur is dependent on their deposit (i.e. the amount of cash held in their account) and traders with larger deposits are less likely to need to cease trading due to liquidity constraints. We did not have access to deposit data. However, a useful proxy is the total funds at a trader's disposal – i.e. total savings (TS_k). Neither of the proxies for a trader's capital is significant at the 5% level, suggesting that, after controlling for all the other factors contained in the CPH model, a trader's capital has no impact on their probability of ceasing to trade.

Transaction costs were controlled using the mean number of trades closed by k on days on which they traded (*Trade Frequency$_k$*). This variable was not significant at the 5% level.

The variables accounting for market volatility (v_m^k) and the period when the individual was trading (n_d^k) were both significant at the 1% level, suggesting that traders are more likely to cease trading during periods of higher market volatility and when their last trade was nearer to the start of the data set. Both these results support H4. In particular, ill-disciplined traders (displaying DE) are unlikely to be able to sustain increasingly large paper losses under volatile conditions. Equally, managers of the spread trading brokerage which provided data indicated that a significant proportion of those who stopped trading in the earlier years were ill-disciplined, citing the immaturity of the market; spread trading being advertised as offering high leverage, with the potential to secure large returns with relatively small outlay. This attracted many inexperienced traders, particularly those most likely to display the DE (Feng and Seasholes, 2005).

The results presented in Tables 3 and 4, which are used to test H1-H4, include variables measured on different scales. Consequently, to explore the robustness of the results, the CPH models were re-estimated using the same data, with only the significant independent variables included. The results are presented in Table 5, and mirror those shown in Tables 3 and 4, with the coefficients for the independent variables remaining largely similar. Consequently, these results also support H1-H4, providing further confidence in the conclusions drawn.

Table 5: Results of estimating CPH models assessing the likelihood that an individual ceases trading, based on their profitability and their trading discipline, with only significant variables included.

	Coef	Exp(Coef)[1]	SE(coef)	Z	p-value	
Profitable Sharpe Ratio (S_k^+)	0.27	1.31	0.08	3.56	<0.01	***
	(0.95)	(2.58)	(0.11)	(8.46)	(<0.01)	***
	[0.79]	[2.21]	[0.05]	[16.10]	[<0.01]	***
Unprofitable Sharpe Ratio (S_k^-)	-0.07	0.93	0.02	-4.61	<0.01	***
	(-0.58)	(0.56)	(0.03)	(-20.38)	(<0.01)	***
	[-0.27]	[0.76]	[0.01]	[-19.19]	[<0.01	***
Disposition Effect ($DE_k > 0$)	1.59	4.9	0.20	7.90	<0.01	***

	(-)	(-)	(-)	(-)	(-)	
	[-]	[-]	[-]	[-]	[-]	
Market Return (r_m^k)	0.38	1.47	0.14	2.75	<0.01	**
	(-)	(-)	(-)	(-)	(-)	
	[-]	[-]	[-]	[-]	[-]	
Market Volatility (v_m^k)	0.62	1.87	0.04	17.27	<0.01	***
	(-)	(-)	(-)	(-)	(-)	
	[-]	[-]	[-]	[-]	[-]	
Trading period (n_d^k)	<0.01	1.00	<0.01	2.60	<0.01	***
	(-0.03)	(0.97)	(<0.01)	(-32.57)	(<0.01)	***
	[-0.04]	[0.96]	[<0.01]	[-54.88]	[<0.01]	***
Trade Frequency$_k$	-	-	-	-	-	
	(0.01)	(1.01)	(<0.01)	(11.25)	(<0.01)	***
	[0.01]	[1.01]	[<0.01]	[6.71]	[<0.01]	***

*, **, *** Significant at 0.05, 0.01, and 0.001.

[1]See section 3.3 for an explanation of Exp(coef).

Concordance= 0.84, (0.91), [0.79]; SE < 0.01, (<0.01), [<0.01]

Rsquare= 0.73, (0.37), [0.40]; max possible= 1, (0.95), [1.00]

Likelihood ratio test= 6,724 (6), (10,331.00 (4)), [9,764.00 (4)]; p <0.01, (<.01), [<0.01]

Wald test = 5,589 (6), (1,442.00 (4)), [3,513.00 (4)]; p <0.01, (<0.01), [<0.01]

Score (Logrank) test = 6,558 (6), (3,456.00(4)), [3,349.00(4]; p <0.01, (<0.01), [<0.01]

Total Observations (Total Traders) =5,164; (22,481), [18,910]

Total Events =5,135, (3,753), [7,380]

The Table presents results from estimating CPH Models (Eq. 9) with only significant variables from Tables 3 and 4 included, for assessing the likelihood (at time *t*) that an individual ceases trading, based on their profitability and, for the main study, the UK brokerage data set only, their trading discipline, for the 5,164, 22,481 and 18,910 individuals executing trades with, respectively, the UK brokerage from the main study between 24th March 2006 and 7th February 2012, the supplementary UK brokerage between 21st June 2010 and 10th October 2018 and the supplementary South African brokerage between 16th June 2016 and 23rd April 2019. Definitions of the variables are provided in section 3.2. Results for the traders with the supplementary UK and South African brokerages are shown in round and square brackets, respectively.

4.3 Testing the Market Evolution Hypothesis

To test the Market Evolution Hypothesis: H5, that there was a decrease in the proportion of those that were both unprofitable and displayed the DE ('noise traders') in the years following the 2008-09 financial crisis, the proportions of noise and more informed traders (profitable and did not display the DE) were examined through time. A trader was defined as a noise or informed trader in a given month, based on the performance of their trades closed in that month, and the proportions of noise and informed traders in each month are plotted in Figures 2A and 2B. The proportion of noise traders in month *m* was calculated as $PNT_m = \frac{1}{r}\sum_{k=1}^{r}[S_k^m < 0 \text{ and } DE_k^m > 0 \text{ then } 1 \text{ else } 0]$, where S_k^m is the Sharpe ratio, DE_k^m is the disposition effect over all the trades closed in month *m* by trader *k*, and *r* is the number of traders that closed at least one trade in month *m*. The proportion of informed traders in month *m* was calculated as $PIT_m = \frac{1}{r}\sum_{k=1}^{r}[S_k^m > 0 \text{ and } DE_k^m \leq 0 \text{ then } 1 \text{ else } 0]$. Figure 2C shows the mean of the disposition effects of the *r* individuals who closed trades in month *m*. Precisely, $DE_m = \frac{1}{r}\sum_{k=1}^{r} DE_k^m$. Figure 2D shows the mean Ill-discipline index of each generation of

traders, grouped by the month in which they first placed a trade. Precisely, $\gamma_m = \frac{1}{s}\sum_{k=1}^{s}\gamma_k^m$, where γ_k^m is the Ill-discipline index for all trades executed by trader k obtained from the set of s traders whose first ever trade was in month m.

The best fitting lines shown in Figure 2 were estimated by fitting successively higher power polynomial models, stopping when an analysis of variance (ANOVA) indicated that the polynomial of greater power no longer increased fit significantly. The ANOVA results are displayed in Table A12 and the corresponding models of the fitted lines in Figure 2 are shown in Table A13, in Appendix 3. These results indicate that a third-degree polynomial best fits the data related to changes in the proportions of noise traders through time, with these proportions increasing throughout 2007 and 2008 followed by a slight decrease in subsequent years until 2011. There was no significant change in the proportion of informed traders through time, the best fitting line (Figure 2B) being the average proportion of informed traders (0.07). A fourth-degree polynomial best modelled the disposition effect through time (see Figure 2C). The results showed a large increase in the proportion of traders displaying the disposition effect from 2007 until the end of 2008, falling through 2009 and 2010 and then increasing again from 2011 onwards. A first-degree polynomial best modelled the degree of ill-discipline shown by new generations of traders through time (see Figure 2D), In particular, there was a gradual increase in ill-discipline of traders who commenced trading throughout the period from 2006-2012. Taken together, the results suggest changes in the proportion of noise traders through time and this seems to be related to increases in ill-discipline exhibited by new generations of traders entering the market.

These results may arise as an artefact of the time period, rather than from the nature of the financial crisis. Consequently, to determine the factors influencing these results, a further survival analysis was conducted. The version of the CPH model shown in Table 5 was re-estimated, this time including interaction terms between Market Volatility $\left(v_m^k\right)$ and (i) the Sharpe ratio variables (S_k^+ and S_k^-) and (ii) a variable identifying traders who displayed the disposition effect ($DE_k > 0$). The results from estimating this model are displayed in Table 6.

A log likelihood ratio test revealed that the addition of an interaction term between market volatility and the disposition effect did significantly improve the fit of the model (χ^2 (1) = 13.55, p < .01), suggesting that there was a significant difference in the impact of the disposition effect in high and low volatility conditions on the likelihood of ceasing to trade. Log likelihood ratio tests also revealed a significant interaction between volatility and profitable Sharpe ratio (χ^2 (1) = 6.59, p< .01), but no significant interaction between unprofitable Sharpe ratio and volatility (χ^2 (1) = 0.01, p > .99). The coefficient for the disposition effect alone indicates that in zero volatility conditions, those with a higher disposition effect tend to cease trading more readily than those exhibiting low disposition effects. The interaction term (Market Volatility × Disposition Effect) indicates that, as volatility increases, the increased chances of those with higher disposition effects ceasing to trade reduces. This

is the opposite of what we would expect given H5. The coefficients for the interaction between the Sharpe ratio coefficients and volatility indicates that the right side of the V-shape will drop as volatility increases while the left side will remain fixed in different volatility conditions.

In order to more directly test H5, the data were split into three groups: trades executed pre- (before 1st January 2007), during- (1st January 2007 to 31st December 2008) and post- (after 31st December 2008) crisis periods. A logistic regression model was fitted to the data with the dependent variable being the indicator variable of a noise trader (i.e. if $S_k^m < 0 \text{ and } DE_k^m > 0$ then 1 else 0). The independent variable was the time period categorical variable ('pre', 'during' or 'post' crisis). A log likelihood ratio test revealed a main effect of time period ($\chi^2 (2) = 9.43$, $p < 0.01$), indicating that the proportion of noise traders changed with time period. Post-hoc analysis, involving pairwise (Bonferroni adjusted) proportions tests between the time-period groups on the proportion of noise traders, found that there were significantly more noise traders during the crisis period ($p < 0.01$)
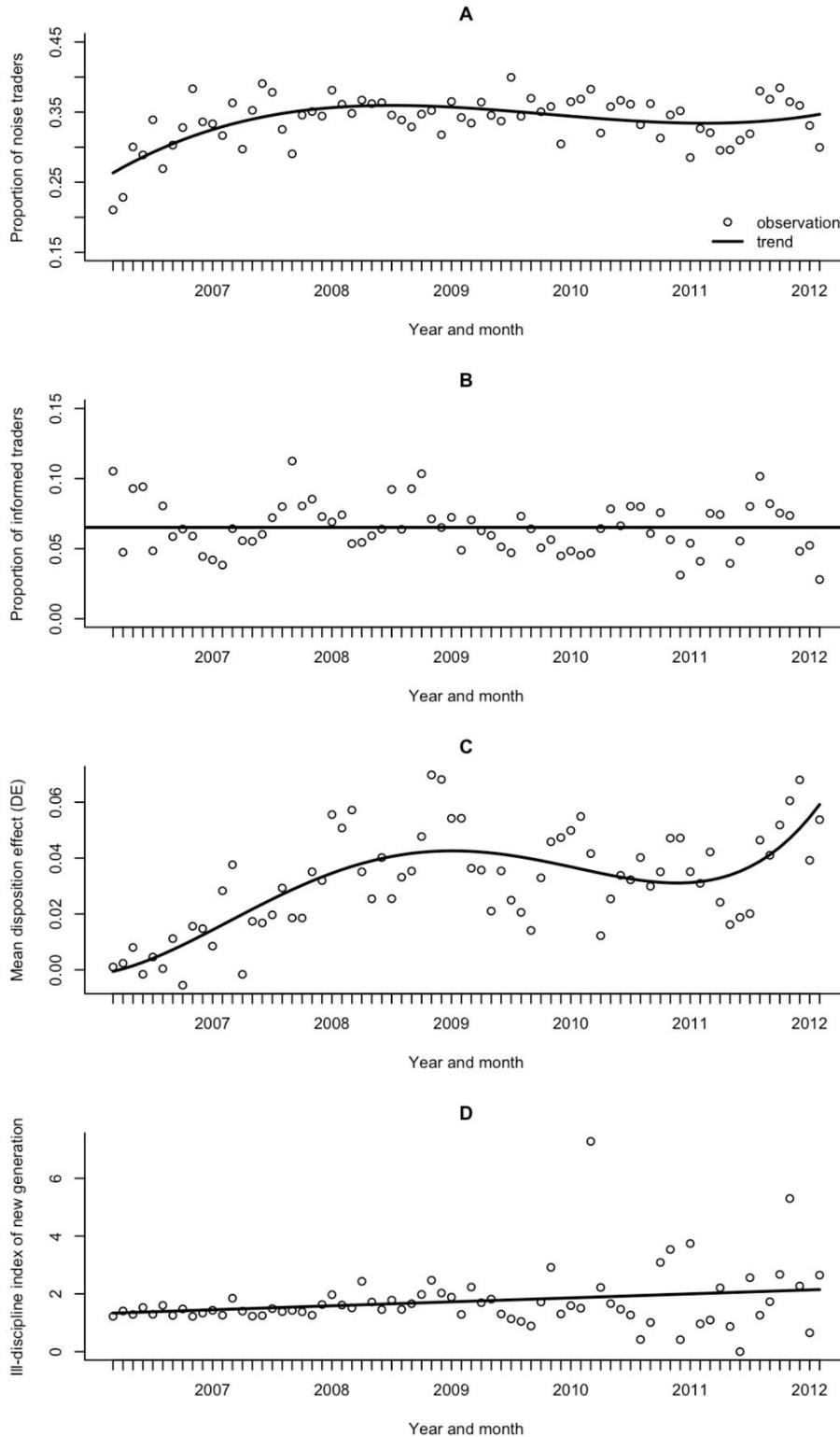
Figure 2. Characteristics of the population of spread traders with the UK brokerage explored in the main analysis, for each month from March 2006 to February 2012.

Figure 2A displays the proportion of noise traders in each month (PNT_m). The line of best fit was: $PNT_m = 0.25 + (8.58 \times 10^{-3})x - (2.19 \times 10^{-4})x^2 + (1.63 \times 10^{-6})x^3$, where x is the number of months since January 2006. Figure 2B displays the proportion of more informed traders in each month (PIT_m). The line of best fit was: $PIT = 0.07$. Figure 2C displays the average disposition effect of traders in each month (DE_m). The line of best fit was: $DE_m = -1.31 \times 10^{-3} + (6.17 \times 10^{-4})x + (1.09 \times 10^{-4})x^2 - (6.67 \times 10^{-6})x^3 + (3.05 \times 10^{-8})x^4$. Figure 2D displays the mean Ill-discipline Index of each generation of traders, grouped by the month in which they first placed a trade (γ_m). The line of best fit: was $\gamma_{m=} 1.32 + 0.01x$.

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Table 6. Results of re-estimating the robust CPH model (shown in Table 5) for assessing the likelihood (at time t) that an individual ceases trading, based on their profitability and their trading discipline (DE_k), whilst also accounting for possible interactions between these factors and market volatility.

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Profitable Sharpe Ratio (S_k^+)	0.54	1.72	0.14	3.97	<0.01	***
Unprofitable Sharpe Ratio (S_k^-)	-0.07	0.93	0.02	-2.94	<0.01	**
Market Volatility (v_m^k)	0.81	2.25	0.07	11.93	<0.01	***
Disposition Effect (DE_k)	2.29	9.83	0.26	8.71	<0.01	***
Market Return (r_m^k)	0.18	1.20	0.16	1.08	0.28	
Trading period (n_d^k)	<0.01	1.00	<0.01	72.53	<0.01	***
Disposition Effect × Market Volatility	-1.19	0.30	0.30	-3.93	<0.01	***
Profitable Sharpe Ratio × Market Volatility	-0.70	0.50	0.29	-2.39	0.02	*
Unprofitable Sharpe Ratio × Market Volatility	<0.01	1.00	0.08	-0.01	1.00	

* significant at 0.05, ** significant at 0.01, *** significant at 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.84 (SE <0.01)
Rsquare= 0.73 (max possible= 1.00)
Likelihood ratio test= 6,737(10), p= <0.01
Wald test = 5,566 (10), p= <0.01
Score (Logrank) test = 6,568 (10), p= <0.01
Total Observations (Total Traders) = 5,164
Total Events = 5,135

The Table presents results from estimating CPH Models (Eq. 9) with only significant variables from Tables 3 and 4 included, for assessing the likelihood (at time t) that an individual ceases trading, based on their profitability and their trading discipline, for the 5,164 individuals executing trades with the UK brokerage from the main study, at some point between 24th March 2006 and 7th February 2012. Definitions of the variables are provided in section 3.2.

compared to the pre-crisis period, and no significant difference compared to the post-crisis period (p > 0.05). These results were consistent with Figure 2A and led us to reject H5. A similar analysis was undertaken for the proportions of 'informed traders' in the pre-, during- and post-crisis periods. A log likelihood ratio test revealed that the time period was not a significant predictor of the proportion of informed traders (χ^2 (1) = 1.85, p = 0.40), confirming the conclusion from Figure 2B that the proportion of informed traders did not change over time.

As a further robustness check, the CPH model was estimated using data from each of the pre-, during- and post-crisis periods. The descriptive statistics for these periods and the results of this analysis are shown in Tables A1-A6 and are discussed more fully in Appendix 1. The key conclusions from this analysis are that, in each of the periods, some evidence in line with H1-4 was identified. However, the increasing likelihood of an individual ceasing to trade is related to diverse aspects of profitability and trader ill-discipline in these different periods. A notable finding was that, while disposition effect was a significant predictor of the likelihood of ceasing to trade in the pre-crisis period, in the crisis and post-crisis periods the disposition effect was no longer significant, indicating that those with greater disposition effects were not more likely to cease trading in those periods. Indeed, in those periods, an increase in the proportions of those with high disposition effects occurs, and as a result, there was an increase in noise traders in the population.

As shown in Appendix A1.1, a pronounced V-shaped relationship was found in the pre-, and during-crisis periods between a trader's Sharpe ratio and their expected increase in the likelihood of ceasing to trade at any given time, compared to a trader with a Sharpe ratio of zero. The V-shape was significant over a simple linear relationship in both these periods, although the effect was less pronounced in the during-crisis period. The V-shape was not significant over a simple linear relationship in the post-crisis period (see A1.1 for detailed results). The lack of significance in this period may have arisen because the smaller number of traders led to diminished statistical power of the test. However, it also possible that these results suggest that the V-shaped relationship may be periodic in nature. To explore this view, analysis of the supplementary data from an additional UK brokerage and a South African brokerage was undertaken (see details in Appendix 2.3).

Details of the trades of a much larger number of individuals were captured by these supplementary datasets and this provided the opportunity to split the data into a number of different periods, each containing the trades of a far greater number of traders than those in the post-crisis period in the main data set. Importantly, the supplementary UK dataset involved trades in a similar post-crisis period to that examined in the main dataset. Analysis of this period using the supplementary data showed a pronounced and significant V-shaped relationship (see Table A9 and Figure A4); those traders with Sharpe ratios of -2 /2 having a 4-/14-fold increase in the likelihood of ceasing trading compared to an individual with a Sharpe ratio of zero. Furthermore, the supplementary UK data afforded the opportunity to explore the V-shaped relationship in three later time periods. In addition, the South Africa supplementary data was sufficiently large to split into two periods. The UK and South Africa data sets were sufficiently large such that the trades of significantly more individuals were captured in each of these periods than was the case in the post-crisis period in the main study. Analysis of each of these periods revealed a significant and pronounced V-shaped relationship between a trader's Sharpe ratio and their expected increase in the likelihood of ceasing to trade at any given time, compared to a trader with a Sharpe ratio of zero (see Appendix 2.3 for detailed results). The impact of an increase/decrease in Sharpe ratio from 0 to 2/-2 was over three-fold in all but one of these periods, and in the remaining period there was an 80% increase in the likelihood of ceasing trading for those with a Sharpe ratio of -2, compared to a trader with a Sharpe ratio of zero.

The fact that a significant and pronounced V-shaped relationship exists between a trader's Sharpe Ratio and their likelihood of ceasing to trade across all the time periods examined using the supplementary data from two different brokerages, suggests that the lack of significance of the V-shape in the post-crisis period in the main study may have arisen because the smaller number of traders led to diminished statistical power of the test.

The exact V-shaped relationship between a trader's Sharpe Ratio and their likelihood of ceasing to trade does appear to vary in different periods and its economic significance is less

pronounced in certain periods. This variability is in line with the results related to the testing of the ill-discipline hypothesis in different periods.

Taken together, these results suggest that the evolutionary processes which form an integral part of the AMH are complex. Clearly, these results do not enable us to definitively determine a differential impact in trading patterns during and outside a financial crisis. However, throughout the pre-, during- and post-2008/09 financial crisis periods, we did find that different aspects of trader profitability and trading discipline have a relationship with the probability of a trader ceasing to trade. We also found that the degree and nature of the V-shaped relationship between a trader's Sharpe ratio and their likelihood of ceasing to trade varied in different periods and across different brokerages. These results are in line with a key prediction of the AMH – that populations of traders with different characteristics will rise and fall at different times. However, contrary to the expectations of the AMH, the proportions of those who were made profit and did not display the DE (i.e. more informed traders), who might be expected to drive prices to efficient levels, did not change during and after the financial crisis. It should be noted that Figure 2D revealed new generations of ill-disciplined traders who allowed their paper losses to run to levels five times greater than their paper profits. In addition, an increase in the proportion of noise traders (those who made losses and displayed the DE) throughout much of the period of the study was observed. Ill-disciplined traders may trade more aggressively (Ben-David and Hirshleifer, 2012) and this is particularly dangerous during periods of turbulence. This behaviour is highly likely to lead to losses in the long term.

5. CONCLUSION

This paper tests the voracity of a key assumption of the AMH, that the dynamics of competition and natural selection will drive ill-disciplined, unprofitable traders from the market. The results indicate that such traders are *not* necessarily those most likely to cease trading. However, the results conform with some of the evolutionary processes that underpin the AMH, with populations of traders with different characteristics rising and falling at different times. However, the results do not show, as suggested by the AMH, that the individuals who are most likely to continue trading are those best able to handle the prevailing market conditions; rather, the most and the least successful traders are those most likely to cease trading. Many commentators argue that financial crises lead to a shake-out of noise traders, resulting in efficient markets in the long run. However, the results demonstrate that, at least amongst spread traders, during the period of the 2008-09 financial crisis, the disposition effect of traders increased and the percentage of noise traders increased. In addition, it is interesting to note the V-shaped relationship between a trader's Sharpe ratio and their probability of ceasing to trade changes through time (see Appendix 1) and possibly for different forms of spread trading (see Appendix 2), suggesting that the relative proportions of more unprofitable/profitable traders ceasing to trade may change with time and circumstance. This supports the notion encapsulated in the AMH, of populations of traders evolving in different ways at different times.

The paper makes four contributions: First, it offers an empirical analysis of the factors influencing a trader's decision to cease trading. The results provide support for one of the predictions of the AMH – that the most unprofitable and ill-disciplined traders tend to cease trading. However, the finding that highly profitable traders also cease trading may help explain why the proportion of noise traders following the 2008-09 financial crisis was no lower than before the crisis. Taken together, the results suggest that the evolutionary assumptions associated with the AMH need to be suitably modified. Further research exploring whether it is risk aversion for gains, or some other factor which causes profitable traders to cease trading, would help in this process.

Second, the results support the view that the evolutionary processes underlying the AMH are likely to be slow and that individuals with erroneous beliefs may persist in markets for long periods. We observe that a new generation of ill-disciplined traders entered the market following the 2008-09 crash. Inexperienced traders may have been attracted to the market to offset losses incurred elsewhere (e.g., loss of employment), particularly in the light of the low entry barriers in this market. Whilst their motivation for entering the market requires further research, ill-disciplined traders can impact market efficiency and our results suggest that the AMH needs to account for this behaviour.

Third, we demonstrate how survival analysis can help study the veracity of the behavioural assumptions underlying the AMH and, more broadly, the impact of trader behaviour and characteristics on market structure and the processes of market evolution. Previously, survival analysis has been employed to shed light on other aspects of finance operations. However, even though trader survival is a central feature of the AMH, no studies have employed survival analysis to study its evolutionary processes. Future research may use survival analysis to study the behaviour explored here on alternative data sets and to formally test the effects of crises.

Fourth, the finding that it is possible to predict the likelihood of an individual ceasing to trade, based on their profitability, demographic factors, trading discipline, and other behavioural factors, is important for spreading trading firms. Their business model relies on a sustainable number of clients, a large proportion of whom lose in the long run. The ability to predict who is likely to cease trading can help spread trading firms manage their business profitability.

The data employed, whilst offering many benefits for the exploration of the AMH, have some limitations. In particular, the data are drawn from the spread trading and forex markets and further research is needed to confirm that the behaviour of ill-disciplined and unprofitable traders in other financial markets mirrors the behaviour observed. The results of analysing the large supplementary data sets from an additional UK brokerage and a South African brokerage, across different time periods (shown in Appendix 2), were in line with the results found in the main study. This provides a level of confidence in the main conclusions reached. However, further research employing the CPH model is needed, with larger data sets of traders over even longer time horizons. This would enable more detailed analysis of changing patterns of behaviour across different periods.

The data for the main study relate to the behaviour of those who traded in the most popular markets (i.e. FTSE 100 and DAX 30 futures) with one spread trading brokerage. The results are predicated on the assumption that a trader who ceased trading with that brokerage ceased trading completely. We explain in section 3.1.2 why this is likely to be the case. However, we could not eliminate the possibility that those who ceased trading continued to invest in the market. To cater for this possibility, further research would need to capture *all* the global investments made by a sample of traders across multiple brokerages and financial markets and ensure that these individuals had not traded through proxy accounts, such as those of family members.

A further potential limitation is that there may be unobserved heterogeneity in a trader's decision to cease trading. We have attempted to reduce this possibility by incorporating a range of variables which previous research has suggested may impact the cease trading event, including demographic factors, various aspects of trading behaviour, and market conditions. However, further research, incorporating an even wider range of variables, would be valuable.

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Appendix 1: Analysis of the years before, during and after the 2008-9 financial crisis

To examine whether the 2008-09 financial crisis resulted in changes in the factors which led to individuals deciding to cease trading, the CPH model, represented in Eq. 9, is estimated using data from each of the pre-, during- and post-crisis periods, namely, prior to 2008, during 2008 and 2009, and from 2010 onwards. The descriptive statistics for the variables calculated for these years are shown in Tables A1, A2 and A3, respectively, and the results from estimating the CPH model for these years are shown in Tables A4, A5 and A6, respectively.

A1.1 Testing the Profitability-related Hypotheses

When comparing the results for the pre-, during- and post-crisis periods, caution must be exercised in drawing strong conclusions based on differences in significance, due to the varying sample sizes. However, with this caveat, we do identify some potentially interesting differences in behaviour.

For the period prior to 2008, the results are similar to those based on data for the whole period (2006-2012). In particular, traders who made the greatest losses and the greatest profits relative to the risk taken in this period were those more likely to cease trading. These results provide further support for H1 and H2.

During the crisis period and post-crisis period, the unprofitable Sharpe ratio variable was significant at the 5% level but the profitable Sharpe ratio was not significant. However, during both these periods, other variables related to a trader's profitability were significant. In particular, during the crisis years of 2008 and 2009, profit/loss per trade was significant at the 0.1% level, suggesting that those traders who were least profitable were more likely to cease trading. In the post-crisis period, profit/loss per trade was no longer significant at the 5% level. Taken together with the fact that S_k^-

was significant throughout all periods, the findings suggest that those traders with the greatest losses were more likely to cease trading, which is consistent with H1.

Plotting the effect of a trader's Sharpe ratio on the expected increase in the likelihood of ceasing to trade at any given time, compared to a trader with a Sharpe ratio of zero (baseline), using data from the pre-, during- and post-crisis periods, resulted in a tilted V-shaped function for all three periods, although more pronounced in the pre-crisis period (see Figure A1). This V-shape was significant over a simple linear relationship in the pre- and during-crisis periods (χ^2 (1) = 26.84, p < .01 and χ^2 (1) = 4.24, p < .05), but not post-crisis (χ^2 (1) = 0.76, p = .38).

The function in the pre-crisis period is similar in shape to the one found when estimating the model across the whole 2006-12 period. In particular, the function shows a steeper increase in the probability of a trader ceasing to trade associated with increases in positive (cf. negative) Sharpe ratios. The effect is less pronounced in the crisis period and is undetectable in the post-crisis period, although this may be the result of the diminished sample size in this period.

Taken together, the results across all three periods provide support for H1-H3. In particular, the results in the pre- and during-crisis periods provide direct evidence supporting H1 and H2. In addition, H3 was supported in the pre-crisis period, and to a lesser extent in the post-crisis period. The coefficients of the Sharpe ratio variables in the latter period indicate a stronger V-shape than during the crisis. The lack of significance of the variables in this period may have arisen because the smaller number of traders led to diminished statistical power of the tests.

A1.2 Testing the Trading Discipline Hypotheses

In the crisis period, the disposition effect was significant at the 5% level, suggesting, in accord with H4, that traders with the greatest levels of ill-discipline were those most likely to cease trading. The 'loss ill-discipline' index was also significant at the 0.1% level in this period, indicating that traders with the highest average maximum paper losses were those most likely to cease trading. Given the significant turbulence during this period, it is not surprising that traders who allowed their losses to reach particularly high levels were likely to be forced from the market. During the pre-crisis (pre-2008) and the recovery periods (post-2009), the ill-discipline index was significant at the 0.1% and 5% levels, respectively and in the pre-crisis period the loss ill-discipline index was also significant at the 1% level. Taken together, the results from across all three periods suggest that ill-discipline affected the likelihood of ceasing trading.

Overall, throughout the pre- and during-crisis periods there is evidence in line with hypotheses 1-4, but it is clear from the results presented in Tables A1-A6, that different patterns of behaviour occurred in these different periods. Importantly, in relation to the hypotheses, different aspects of profitability and trader ill-discipline were differentially related to the probability of an individual ceasing to trade at different times. Consequently, in addition to these results being broadly supportive of the hypotheses related to trader profitability and ill-discipline, they are also in line with

the AMH, which predicts that populations of traders with different characteristics will rise and fall as market conditions change.

Table A1.   Descriptive statistics for the variables calculated for the years before the financial crisis (before 2008).

	Mean[+]	Std. Dev	Median	Min	Max	Skew	Kurtosis	20th Percentile	40th Percentile	60th Percentile	80th Percentile
Age$k$	43.89	12.64	43.00	19.00	90.00	0.46	-0.29	32.59	39.00	46.00	55.00
Total Savings (TS_k)(£'000)	47.40	88.80	15.00	0.00	1,000.00	5.77	47.30	0.00	14.00	30.00	100.00
Mean Stake$k$ (£)	4.26	10.11	1.75	1.00	200.00	9.12	118.52	1.00	1.37	2.24	5.00
Trade Frequency$k$	3.03	3.44	2.00	1.00	53.68	5.08	42.37	1.14	1.65	2.43	4.00
Sharpe Ratio (S_k)	-0.12	1.42	-0.07	-53.74	25.93	-17.91	750.13	-0.25	-0.11	-0.03	0.04
Profit/loss per trade (R_k) (£)	-13.32	3,694.37	-3.23	-202,301.43	1,883.50	-54.53	2,982.23	-17.25	-5.56	-1.52	2.77
Value at risk ($VaR(R_k)$ 5%)	159.37	513.73	55.45	-947.50	12,000.00	11.47	189.46	19.70	40.26	77.46	174.56
Loss Ill-discipline ($AvgMPL_k$)	0.33	0.35	0.23	0.00	4.17	3.87	24.88	0.12	0.19	0.27	0.45
Ill-discipline Index (Y_k)	1.54	3.89	1.14	0.00	122.01	19.91	516.99	0.72	1.02	1.28	1.76
Disposition Effect (DE_k)	0.01	0.12	0.00	-1.00	1.00	-0.14	47.79	0.00	0.00	0.01	0.03
Market Return (r_m^k)	0.00	0.06	0.00	-1.28	0.75	-3.4	91.56	-0.02	0.00	0.00	0.02
Market volatility (v_m^k)	0.27	0.09	0.26	0.00	1.59	3.24	29.67	0.21	0.24	0.27	0.32
Trading period (n_d^k)	1,383.00	127.74	1,334.00	1,288.00	1,931.00	2.21	4.80	1,299.00	1,316.00	1,356.00	1,434.00

The Table presents descriptive statistics for variables calculated for the 3,009 individuals who executed trades during the pre-crisis period (24th March 2006 - 31st December 2007); i.e. they opened and closed the trade during this period with the UK brokerage which supplied data for the main study. Only traders who executed trades in the FTSE 100 and DAX 30 futures were included. Definitions of the variables are provided in section 3.2.   Skew $= m_3/m_2^{3/2}$ and Kurtosis $= m_4/m_2^4$; $m_r = \sum_i (x_i - \mu)^r/n$).
[+]To provide a robust measure of central tendency, 0.1% trimmed means are reported.

Table A2
Descriptive statistics for the variables calculated for the crisis years (2008-2009).

	Mean[+]	Std. Dev	Median	Min	Max	Skew	Kurtosis	20th Percentile	40th Percentile	60th Percentile	80th Percentile
Age_k	44.85	13.07	43.52	18.00	90.00	0.49	-0.27	33.00	40.00	47.05	56.00
Total Savings (TS_k)(£'000)	47.44	95.25	15.00	0.00	1,000.00	5.40	39.81	0.00	7.00	30.00	100.00
Mean Stake$_k$ (£)	3.27	7.50	1.42	1.00	198.26	11.12	191.74	1.00	1.17	1.80	3.78
Trade Frequency$_k$	3.54	4.09	2.31	1.00	110.39	6.80	114.17	1.30	1.94	2.85	4.83
Sharpe Ratio (S_k)	-0.12	2.75	-0.06	-108.19	85.56	-15.14	906.90	-0.22	-0.09	-0.03	0.04
Profit/loss per trade (R_k) (£)	-7.67	628.59	-2.35	-4,243.53	42,486.00	65.47	4,428.54	-13.52	-4.08	-1.22	2.35
Value at risk ($VaR(R_k)$ 5%)	140.58	774.40	53.89	-42,486.00	15,965.00	-32.11	1,995.46	20.65	39.84	74.67	150.00
Loss Ill-discipline ($AvgMPL_k$)	0.50	0.65	0.32	0.00	18.07	7.91	144.76	0.18	0.26	0.39	0.68
Ill-discipline Index (Y_k)	1.73	3.66	1.19	0.00	94.46	13.04	237.04	0.81	1.07	1.33	1.86
Disposition Effect (DE_k)	0.03	0.13	0.01	-1.00	1.00	2.04	33.30	0.00	0.00	0.02	0.05
Market Return (r_m^k)	0.00	0.13	0.00	-1.52	2.04	0.16	47.46	-0.04	-0.01	0.01	0.03
Market volatility (v_m^k)	0.53	0.30	0.47	0.00	7.05	7.02	102.36	0.35	0.44	0.51	0.64
Trading period (n_d^k)	817.01	199.63	812.00	557.00	1,284.00	0.27	-1.07	593.00	727.40	885.00	1,007.00

The Table presents descriptive statistics for variables calculated for the 4,712 individuals who executed trades during the crisis years, 1st January 2008 and 31st December 2009; i.e. they opened and closed the trade during this period with the UK brokerage which supplied data for the main study. Only traders who executed trades in the FTSE 100 and DAX 30 futures were included. Definitions of the variables are provided in section 3.2. Skew = $m_3/m_2^{3/2}$ and Kurtosis = m_4/m_2^4 ; $m_r = \sum_i (x_i - \mu)^r/n$).
[+]To provide a robust measure of central tendency, 0.1% trimmed means are reported.

Table A3

Descriptive statistics for the variables calculated for the recovery years (after 2009).

	Mean[+]	Std. Dev	Median	Min	Max	Skew	Kurtosis	20th Percentile	40th Percentile	60th Percentile	80th Percentile
Age_k	47.97	12.82	47.00	20.17	90.00	0.45	-0.28	36.17	43.59	50.00	59.00
Total Savings (TS_k)(£'000)	37.39	57.81	15.00	0.00	1,000.00	5.70	63.13	0.00	5.00	30.00	101.00
Mean Stake$_k$ (£)	2.79	5.81	1.14	1.00	131.70	9.45	146.47	1.00	1.01	1.44	2.87
Trade Frequency$_k$	3.19	5.12	2.00	1.00	153.72	13.81	334.36	1.11	1.66	2.43	4.10
Sharpe Ratio (S_k)	-0.19	4.28	-0.07	-154.15	12.49	-28.38	901.76	-0.25	-0.11	-0.04	0.02
Profit/loss per trade (R_k) (£)	-8.19	214.77	-2.20	-1,652.00	10,000.00	40.80	1,913.76	-12.41	-3.80	-1.27	1.27
Value at risk ($VaR(R_k)$ 5%)	104.90	342.52	36.96	-10,000.00	4,672.48	-6.17	345.28	12.00	26.00	51.47	120.00
Loss Ill-discipline ($AvgMPL_k$)	0.42	0.66	0.25	0.00	15.60	8.40	134.87	0.13	0.21	0.31	0.54
Ill-discipline Index (Y_k)	2.05	54.46	1.20	0.00	2,679.72	48.28	2,367.84	0.73	1.05	1.36	2.02
Disposition Effect (DE$_k$)	0.03	0.15	0.00	-1.00	1.00	0.92	26.45	0.00	0.00	0.01	0.04
Market Return (r_m^k)	0.00	0.09	0.00	-1.50	1.56	0.79	101.45	-0.02	-0.01	0.00	0.02
Market volatility (v_m^k)	0.32	0.15	0.30	0.00	2.93	4.19	49.30	0.23	0.27	0.32	0.39
Trading period (n_d^k)	67.56	249.94	-24.00	-210.00	553.00	0.50	-1.22	-189.00	-80.00	97.60	369.00

The Table presents descriptive statistics for variables calculated for the 2,462 individuals who executed trades during the recovery period (1st January 2010 - 7th February 2012); i.e. they opened and closed the trade during this period with the UK brokerage which supplied data for the main study. Only traders who executed trades in the FTSE 100 and DAX 30 futures were included. Definitions of the variables are provided in section 3.2. Skew $= m_3/m_2^{3/2}$ and Kurtosis $= m_4/m_2^4$; $m_r = \sum_i (x_i - \mu)^r /n$).
[+]To provide a robust measure of central tendency, 0.1% trimmed means are reported.

Table A4

Results of estimating the CPH model for the years prior to the financial crisis.

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Age_k	>-0.01	1.00	<0.01	-2.38	0.02	*
$Gender_k$ (Male)	-0.03	0.97	0.06	-0.52	0.60	
Total Savings (TS_k) (£)	<0.01	1.00	<0.01	2.30	0.02	*
$Mean stake_k(£)$	<0.01	1.00	<0.01	1.02	0.31	
$Trade Frequency_k$	<0.01	1.00	0.01	0.57	0.57	
Profit/loss per trade (R_k) (£)	<0.01	1.00	<0.01	1.19	0.23	
Value at Risk $VaR(R_k)$(5%)	>-0.01	1.00	<0.01	-2.66	0.01	**
Profitable Sharpe Ratio (S_k^+)	0.13	1.14	0.02	6.06	<0.01	***
Unprofitable Sharpe Ratio (S_k^-)	-0.06	0.94	0.01	-5.11	<0.01	***
Loss ill-discipline ($AvgMPL_k$)	>-0.01	1.00	<0.01	-4.23	<0.01	***
Ill-discipline Index (Y_k)	0.01	1.01	<0.01	3.32	<0.01	***
Disposition Effect ($DE_k > 0$)	0.53	1.70	0.28	1.88	0.06	
Market Return (r_m^k)	1.28	3.59	0.47	2.73	0.01	**
Market Volatility (v_m^k)	2.85	17.26	0.20	14.46	<0.01	***
Trading period (n_d^k)	<0.01	1.00	<0.01	22.65	<0.01	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.65 (SE = <0.01)
Rsquare= 0.18 (max possible= 1)
Likelihood ratio test= 579.1(15), p = <0.01
Wald test = 732.6(15), p= <0.01
Score (Logrank) test = 778.0(15), p = <0.01
Total Observations (Total Traders) = 3,009
Total Events = 3,009

The Table presents results from estimating the CPH Model (Eq. 9), for assessing the likelihood (at time *t*) that an individual ceases trading, based on their profitability and trading discipline for the 3,009 individuals trading during the pre-crisis period (24th March 2006 - 31st December 2007) with the UK brokerage that supplied data for the main study. Only traders who executed trades in the FTSE 100 and DAX 30 futures at some time between 24th March 2006 and 7th February 2012, were included. Definitions of the variables are provided in section 3.2.

Table A5

Results of estimating the CPH model for the crisis years (2008 and 2009).

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Age_k	>-0.01	1.00	<0.01	-3.55	<0.01	***
$Gender_k$ (Male)	0.08	1.08	0.05	1.59	0.11	
Total Savings (TS_k) (£)	<0.01	1.00	<0.01	-0.44	0.66	
$Mean\ stake_k$ (£)	<0.01	1.00	<0.01	0.07	0.94	
$Trade\ Frequency_k$	-0.03	0.97	<0.01	-6.26	<0.01	***
Profit/loss per trade (R_k) (£)	>-0.01	1.00	<0.01	-6.75	<0.01	***
Value at Risk $VaR(R_k)$(5%)	>-0.01	1.00	<0.01	-8.95	<0.01	***
Profitable Sharpe Ratio (S_k^+)	0.01	1.01	0.01	1.41	0.16	
Unprofitable Sharpe Ratio (S_k^-)	-0.01	0.99	0.01	-2.18	0.03	*
Loss ill-discipline ($AvgMPL_k$)	<0.01	1.00	<0.01	4.71	<0.01	***
Ill-discipline Index (Y_k)	>-0.01	1.00	<0.01	-0.28	0.78	
Disposition Effect ($DE_k > 0$)	0.38	1.46	0.16	2.38	0.02	*
Market Return (r_m^k)	0.16	1.18	0.13	1.21	0.23	
Market Volatility (v_m^k)	0.18	1.20	0.05	3.31	<0.01	***
Trading period (n_d^k)	0.01	1.01	<0.01	64.35	<0.01	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.82 (SE = <0.01)
Rsquare= 0.72 (max possible= 1)
Likelihood ratio test= 6,012 (15), p = <0.01
Wald test = 4,368 (15), p= <0.01
Score (Logrank) test = 5,989(15), <0.01
Total Observations (Total Traders) = 4,712
Total Events = 4,712

The Table presents results from estimating the CPH Model (Eq. 9), for assessing the likelihood (at time *t*) that an individual ceases trading, based on their profitability and trading discipline for the 4,712 individuals who executed trades during the crisis period (1st January 2008 - 31st December 2009). with the UK brokerage that supplied data for the main study. Only traders who executed trades in the FTSE 100 and DAX 30 futures at some point between 24th March 2006 and 7th February 2012 were included. Definitions of the variables are provided in section 3.2.

Table A6

Results of estimating the CPH model for the recovery years (after 2009).

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Age_k	>-0.01	1.00	<0.01	-2.37	0.02	*
$Gender_k$ (Male)	0.12	1.12	0.07	1.61	0.11	
Total Savings (TS_k) (£)	>-0.01	1.00	<0.01	-0.17	0.86	
$Mean\ stake_k$	>-0.01	1.00	0.01	-0.40	0.69	
$Trade\ Frequency_k$	-0.04	0.96	0.01	-5.33	<0.01	***
Profit/loss per trade (R_k) (£)	>-0.01	1.00	<0.01	-1.04	0.30	
Value at Risk (VaR_k) (5%)	>-0.01	1.00	<0.01	-2.14	0.03	*
Profitable Sharpe Ratio (S_k^+)	0.01	1.01	0.04	0.37	0.71	
Unprofitable Sharpe Ratio (S_k^-)	-0.02	0.98	0.01	-4.06	<0.01	***
Loss ill-discipline ($AvgMPL_k$)	<0.01	1.00	<0.01	0.71	0.48	
Ill-discipline Index (Y_k)	<0.01	1.00	<0.01	2.24	0.02	*
Disposition Effect ($DE_k > 0$)	-0.01	0.99	0.22	-0.03	0.98	
Market Return (r_m^k)	0.48	1.62	0.34	1.40	0.16	
Market Volatility (v_m^k)	0.10	1.10	0.21	0.45	0.65	
Trading period (n_d^k)	0.01	1.01	<0.01	43.25	<0.01	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.86(SE <0.01)
Rsquare= 0.76 (max possible= 1.00)
Likelihood ratio test= 3,506 (15), p = <0.01
Wald test = 1,961 (15), p = <0.01
Score (Logrank) test = 3,712 (15), p = <0.01
Total Observations (Total Traders) = 2,462
Total Events = 2,253

The Table presents results from estimating the CPH Model (Eq. 9), for assessing the likelihood (at time *t*) that an individual ceases trading, based on their profitability and trading discipline for the 2,462 individuals who executed trades during the recovery years (1st January 2010 - 7th February 2012) with the UK brokerage that supplied data for the main study. Only traders who executed trades in the FTSE 100 and DAX 30 futures at some point between 1st January 2010 - 7th February 2012 were included. Definitions of the variables are provided in section 3.2.
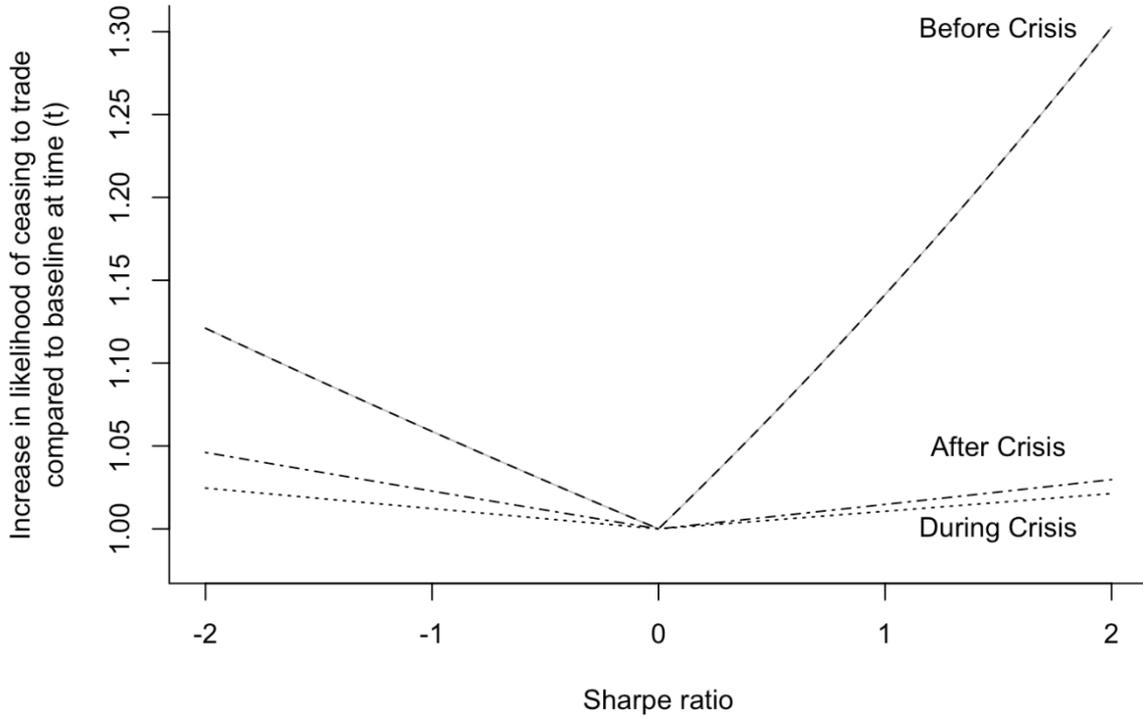
Figure A1. Relationship between a trader's Sharpe ratio and the likelihood of their ceasing trading before, during and after the crisis years.

The Figure displays estimates, derived from CPH models, for the effect of a trader's Sharpe ratio on the expected increase in the likelihood of ceasing to trade at any given time (t) compared to a trader with a Sharpe ratio of zero (baseline), for the years before (prior 2008), during (2008 and 2009) and after (after 2009) the 2008-09 financial crisis. Before crisis: $h(t, S_k^+) = \exp((1.32 \times 10^{-1})S_k^+)$; $h(t, S_k^-) = \exp((-5.71 \times 10^{-2})S_k^-)$; During crisis: $h(t, S_k^+) = \exp((1.05 \times 10^{-2})S_k^+)$; $h(t, S_k^-) = \exp((-1.22 \times 10^{-2})S_k^-)$; After crisis: $h(t, S_k^+) = \exp((1.46 \times 10^{-2})S_k^+)$; $h(t, S_k^-) = \exp((-2.25 \times 10^{-3})S_k^-)$.

Appendix 2: Data set size considerations and robustness tests of V-shaped relationship between an individual's likelihood of ceasing to trade and their Sharpe ratio.

A 2.1 Data set size

Whilst exact estimates are difficult to obtain, the total global population of spread traders and online retail forex traders almost certainly exceeds 10 million (Pryor, 2011; BrokerNotes, 2017). Consequently, in determining to what extent the data set of 5,164 traders was sufficiently large to test the hypotheses, we applied Cochran's large sample test (Cochran, 2007). This sampling technique is generally applied in designing surveys and is robust when the exact size and heterogeneity of a population is unknown. Under these conditions, the ideal sample size (n_0) is given, as follows:

$$n_0 = \frac{Z^2 pq}{e^2} \tag{A1}$$

where Z depends on the confidence interval required, $p=1-q$, is the proportion of the population having the attribute of interest, and e is the degree of precision or margin of error.

Assuming conservative parameters; i.e. that the population of traders displays the most extreme diversity in behavioural attributes ($p= 0.5$), a 99% confidence interval and a margin of error of 2%, Cochran's large sample test suggests that 4,160 traders are required to make inferences. This is less than the 5,164 traders in our main study. Furthermore, some important recent studies examining various aspects of investor decision making have employed smaller data sets. For example, Ammann and Schaub, (2020) examined investment-related messages of 1,314 traders to analyse influences on retail investor decision making, Paravisini, et al. (2017) examined risk aversion amongst 2,168 investors in a single peer-to-peer lending platform, and Heimer and Simsek (2019), when examining the behaviour of retail investors who trade the EUR/USD currency pair, analysed data sets of 1,193 American and 1,479 European traders. This suggests that the data set employed in the main study is sufficiently large to enable insights to be drawn regarding the factors which cause traders to cease trading.

A 2.2 Supplementary data sets and analysis

In order to test the robustness of the key finding – that the likelihood of an individual ceasing to trade is a V-shaped function of their Sharpe ratio, pivoting around the point at which a trader breaks even – additional data sets from large spread trading brokerages in the UK and South Africa were secured.

The additional UK data partially overlap with the period covered by the data set employed in the main study and involves trading from 21st June 2010 to 10th October 2018. The additional South African data cover the period from 16th June 2016 to 23rd April 2019. Consequently, the data offer the advantage of providing the opportunity to check if the relationship identified between the likelihood of an individual ceasing to trade and their Sharpe ratio, applied outside the date range of the main data set and for traders with different brokerages.

The supplementary data sets also had the benefit of being large, enabling analysis of 15,636,230 trades of 22,481 individuals across 708 different markets, and 2,966,385 trades of 18,910 individuals across 275 markets with the UK and South African brokerages, respectively. Cochran's large sample test suggests that data sets of this size will also reduce the margin of error associated with inferences. In particular, assuming the conservative parameters for Cochran's large sample test outlined in section A2.1, with the margin of error reduced to 1%, the formula suggests that 16,641 traders are required to make appropriate inferences.

The brokerages from which we obtained these additional data specialise in offering spread trades associated with currency pairs as opposed to index futures. Consequently, they offer the advantage of exploring a different form of spread trading. The important differences with index futures spread trading which may impact a trader's behaviour include: (i) the fact that forex trading takes place over a far longer period per day than index futures. For example, the popular US

Dollar/Japanese Yen currency pair is traded throughout 24 hours, whereas index futures such as the FTSE 100 tend to only be traded during market opening hours (0800-1630). (ii) There is a larger margin required for index future trading as indices generally change more in absolute terms and involve more volatility than in currency pairs and the forex market generally has more liquidity, which makes hedging the underlying instrument easier for brokers. (iii) As prices of forex pairs generally change very little (e.g., the typical Euro/US Dollar pair only changes an average of 0.0006 per day), traders require a much larger principal amount (amount at risk in the underlying market) when trading forex as compared to indices. As a rule of thumb, the larger the principal amount needed to trade an asset, the lower the margin. Having a much larger margin means that trades involving indices are held open for a shorter period as the cost of credit is higher (a typical index future spread trade is only open for a few hours and rarely overnight; trades rolling over more than one day is far more common in spread trading involving currency pairs). Because price fluctuations in currency pairs are small, a larger principal sum is needed to generate meaningful returns. This principal amount is known as a "lot" and for the most popular currency pairs (e.g., Euro/US Dollar) a typical lot is 100,000 units of a currency. However, most traders do not have access to such large sums. They, therefore, capitalise on the leverage provided by the spread trading brokerage. A typical leverage value is 500:1, meaning that every unit of stake provides access to 500 units of currency; thus, a stake of £200 would provide access to one lot size of the equivalent of £100,000. In these markets, 'volume' refers to the number of lots purchased: a volume of 0.21 associated with a trade means that 0.21 lots have been purchased, thereby giving the total value of the trade equal to 0.21×100,000 for a typical Euro/US Dollar pair. Profit on a trade (which can be a long trade or a short trade) is calculated by lot size * direction of movement in the currency pair * (closing price -opening price) – cost of margin/credit.

Trading profits with the UK-based spread trading provider were calculated in GBP, but traders with the South African brokerage could choose between using USD, GBP, and ZAR (South African rand). For the analysis, profits were standardised to the most popular choice, USD, based on the exchange rate at the time of closure of each individual trade.

These supplementary data sets, unlike the data used for the main analysis reported in the paper, do not contain any demographic data, and because the data sets involve several hundred different markets, we could not obtain data to calculate the market return and market volatility during the period each trade was open. This also prevented calculation of the ill-discipline index, the loss ill-discipline index and the DE for individual traders. The descriptive statistics for the supplementary UK and South Africa data sets are reported in Table A7 and the descriptive statistics for the variables used in the analysis of these datasets are reported in Table A8. Differences in the nature of trading between currency pairs and index future spread trading and cultural differences may account for differences between the three data sets in terms of the number of days traded, the number of trades executed throughout an individual's trading history, and the trade frequency.

Table A7

Daily trading activity descriptive statistics for the supplementary UK and South Africa data sets*.

	Trimmed Mean+	Std. Dev	Median	Min	Max	Skew	Kurtosis	20th Percentile	40th Percentile	60th Percentile	80th Percentile
Mean Stake	42.83	65.00	34.08	0.50	2,149.00	18.34	507.31	19.50	29.12	39.57	55.70
	[8.73]	[15.39]	[6.13]	[1.00]	[343.89]	[15.20]	[295.96]	[4.49]	[5.62]	[6.80]	[9.85]
Mean profit (£) per trade	-3.51	25.46	-1.04	-272.59	323.26	-2.55	52.77	-8.02	-2.68	0.37	4.00
[$]	[1.70]	[10.79]	[1.47]	[-84.54]	[124.07]	[1.57]	[48.55]	[-1.26]	[-0.58]	[2.38]	[4.97]
Mean Profit (%) per trade	-6.57	580.19	-2.50	-1,291.49	1,008.25	-6.22	314.52	-38.31	-8.98	0.18	12.11
[$]	[1.16]	[421.29]	[0.18]	[-876.34]	[789.56]	[0.18]	[42.6]	[-25.25]	[-3.34]	[5.78]	[10.76]
Number of trades	6,198.77	5,137.60	5,550.00	1.00	33,287.00	0.92	4.17	926.00	4,043.00	7,210.00	10,357.00
	[3,445.27]	[3,502.39]	[2,376.00]	[1.00]	[17,574.00]	[1.47]	[4.82]	[405.00]	[1,813.00]	[3,093.00]	[5,641.00]
Proportion of trades with profit ≥ 0	0.63	0.09	0.64	0.00	1.00	-1.83	12.72	0.59	0.63	0.65	0.69
[$]	[0.64]	[0.13]	[0.65]	[0.00]	[1.00]	[-2.33]	[13.74]	[0.59]	[0.62]	[0.65]	[0.68]
Mean profit (£) on winning trades	27.22	38.45	20.41	0.00	995.69	12.52	250.10	12.96	17.86	23.72	34.99
[$]	[13.10]	[8.24]	[10.13]	[0.00]	[246.32]	[8.24]	[122.80]	[6.87]	[9.00]	[11.55]	[16.71]
Mean loss (£) on losing trades	-53.96	74.76	-39.86	-2,020.43	-0.72	-11.27	225.38	-68.68	-46.31	-34.10	-22.90
[$]	[-19.17]	[22.37]	[-13.90]	[-280.67]	[-0.06]	[-5.83]	[51.77]	[-22.62]	[-15.93]	[-12.42]	[-9.37]

The table displays the mean, standard deviation, median, minimum, maximum, range, standard skew and kurtosis statistics, and the 1st to 4th quintiles for a variety of variables; where Skew = $m_3/m_2^{3/2}$ and Kurtosis = m_4/m_2^4 ; $m_r = \sum_i (x_i - \mu)^r/n$). All values are calculated on the basis of the trades placed by the 22,481 individuals in the supplementary UK brokerage (figures without square brackets), between 21stJune 2010 and 10th October 2018. The figures in square brackets are calculated from trades placed by 18,910 individuals in the South African brokerage between 16th June 2016 and 23rd April 2019.

'Mean Stake' is the mean amount staked on trades on a trading day (equates to the 'volume' of a trade). 'Mean profit (£) per trade' is the mean profit or loss earned per trade over all trades that were closed on a given day. 'Mean profit (%) per trade' is the mean profit or loss earned on the margin, per trade, over all trades that were closed on a given day. 'Number of trades' is the total number of trades in the data set closed on a given day. 'Proportion of trades with profit ≥ 0' is the proportion of trades that were closed on a given day which either broke-even (i.e. earned back the spread) or earned a profit. 'Mean gain (£) on winning trades' is the mean profit earned by trades closed on a given day which at least broke even. 'Mean loss (£) on losing trades' is the mean loss on the trades closed on a given day that lost.

*The descriptive statistics of these variables relate to the values across all trading days in the sample (e.g., Mean of 'mean stake size per point' is mean across all trading days in the data set; i.e. 44.13 implies that the mean lot size purchased of, say, a Euro/US Dollar currency pair is 44.13 x 100,000 =4,413,000). +To provide a robust measure of central tendency, 0.1% trimmed means are reported.

Table A8

Descriptive statistics for the data and variables (defined in section 3.2) used in the analysis of the supplementary UK and South African data sets.

|	Trimmed Mean[+]	Std. Dev	Median	Min	Max	Skew	Kurtosis	20th Percentile	40th Percentile	60th Percentile	80th Percentile
Mean Stake_k * (£)	7.33	43.45	1.25	0.01	1,627.05	16.73	387.78	0.33	0.84	1.92	5.69
[$]	[4.83]	[68.48]	[1.84]	[1.00]	[4,902.82]	[54.57]	[3,455.66]	[1.15]	[1.54]	[2.27]	[4.41]
Trade Frequency_k	9.85	44.67	5.72	1.00	7,932.67	43.94	2,245.06	2.83	4.54	7.23	12.50
	[5.67]	[4.97]	[4.42]	[1.00]	[171.50]	[6.87]	[133.86]	[2.66]	[3.78]	[5.20]	[7.74]
Sharpe Ratio (S_k)	-0.08	0.42	-0.07	-21.40	14.90	-16.62	872.02	-0.18	-0.10	-0.05	0.01
	[0.08]	[0.39]	[0.03]	[-26.72]	[4.23]	[-15.68]	[1,103.62]	[-0.15]	[-0.02]	[0.10]	[0.29]
Profit/loss per trade (R_k) (£)	-3.57	163.47	-1.27	-11,126.10	6,146.77	-14.71	1,469.79	-6.87	-2.10	-0.73	0.03
[$]	[1.85]	[170.84]	[0.17]	[-3,666.39]	[21,878.09]	[111.61]	[14,241.65]	[-0.69]	[-0.08]	[0.52]	[1.99]
Value at Risk ($VaR(R_k)$)(5%) (£)	129.46	900.75	27.41	-715.63	87,463.89	52.60	4,360.73	7.47	18.26	41.26	112.71
[$]	[17.81]	[288.26]	[5.98]	[-139.94]	[18,752.86]	[49.32]	[2,804.69]	[2.28]	[4.45]	[7.95]	[16.97]
Trading Period (n_d^k)	869.75	892.87	496.00	-41.00	2,916.00	0.69	2.02	30.00	298.00	878.00	1,930.00
	[73.23]	[155.58]	[17.00]	[-31.00]	[977.00]	[2.70]	[11.17]	[-25.00]	[2.00]	[40.00]	[129.20]

*The mean stake shown equates to the 'volume' of a trade: The mean of 8.25 implies that the mean lot size purchased of, say, a Euro/US Dollar currency pair is 8.25 x 100,000 =825,000.

The Table presents descriptive statistics for variables calculated for the 22,481 and 18,910 individuals who executed trades with the supplementary UK (figures without brackets) brokerage, in at least one of 708 currency pairs, at some point between 21st June 2010 and 10th October 2018, and the supplementary South African (figures in square brackets) brokerage, in at least one of 275 currency pairs, at some point between 16th June 2016 and 23rd April 2019. Definitions of the variables are provided in section 3.2. [+]To provide a robust measure of central tendency, 0.1% trimmed means are reported. Skew = $m_3/m_2^{3/2}$ and Kurtosis = m_4/m_2^4 ; $m_r = \sum_i (x_i - \mu)^r/n$).

Data from both the UK and South African brokerages were then used to estimate separate CPH models (shown in Eq. 9), for assessing the likelihood that an individual ceases trading, based on their profitability. The results are displayed in Table 4 in the main paper. Right-censoring dates of 41 and 31 days from the end of the UK and South African data sets were determined, using the same criteria as for the main analysis (i.e. MITD + 3SD(MITD)).

For both data sets, the coefficient for those with unprofitable Sharpe ratios is negative and significant, indicating that the greater the losses an individual incurs (relative to the risk they accepted), the greater the likelihood of their ceasing to trade, compared to the average trade). These results support H1. Equally, for both data sets, the coefficient for those with profitable Sharpe ratios is positive and significant, indicating that the greater the profit an individual achieves (relative to the risk they accepted), the greater the likelihood of their ceasing to trade, compared to the average trader. These results support H2.

The results from testing H1 and H2 are used to plot the Sharpe ratios achieved by traders (x-axis) *vs.* the likelihood of their ceasing to trade (y-axis). The graphs relating to the results based on the data from the additional UK and South African data sets are presented in Figure A2. These again show very similar V-shaped functions to those found in Figure 1 for data in the main study, with a Sharpe ratio = 0 (the baseline risk of ceasing to trade) as the pivot. Models that allow a V-shaped relationship between the Sharpe ratio and the chance of a trader ceasing trading were found to better account for the data than models that only allowed a linear relationship, for both the additional UK and South African data sets (χ^2 (1) = 107.29, p < .001 and χ^2 (1) = 290.08, p < .001, respectively). These results support H3, namely that the most unprofitable and most profitable traders are those least likely to continue trading.
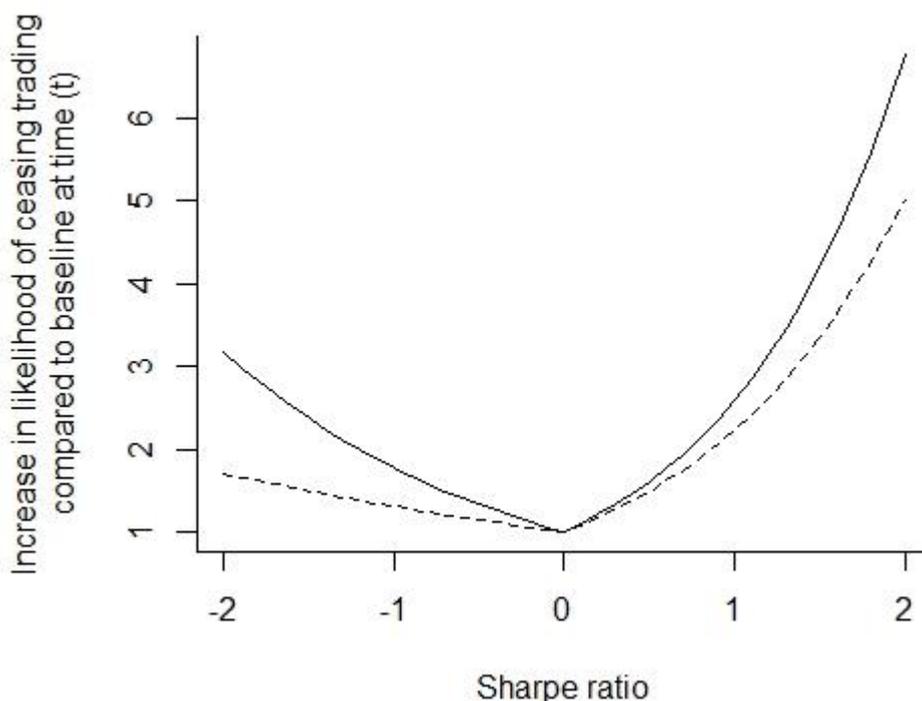
Figure A2. Relationship between a trader's Sharpe ratio and the likelihood of their ceasing trading.

The Figure displays estimates, derived from CPH Models, for the effect of a trader's Sharpe ratio on the expected increase in the likelihood of ceasing to trade at any given time (t) compared to a trader with a Sharpe ratio of zero (baseline), for the supplementary UK (unbroken line) and South African (dashed line) data sets, $(h(t, S_k^+) = \exp((9.6 \times 10^{-1})S_k^+)$; $h(t, S_k^-) = \exp((-5.8 \times 10^{-1})S_k^-)$ and $h(t, S_k^+) = \exp((8.1 \times 10^{-1})S_k^+)$; $h(t, S_k^-) = \exp((-2.7 \times 10^{-1})S_k^-)$, respectively.
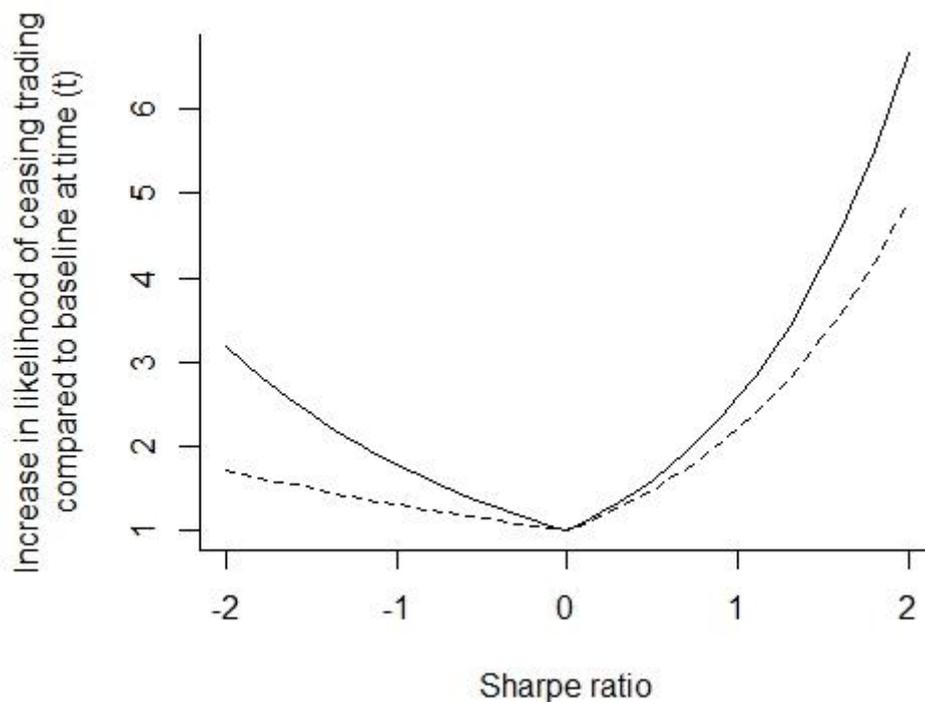
Figure A3. Relationship between a trader's Sharpe ratio and the likelihood of their ceasing trading, with only significant variables included.

The Figure displays estimates, derived from CPH Models with only significant variables included, for the effect of a trader's Sharpe ratio on the expected increase in the likelihood of ceasing to trade at any given time (t) compared to a trader with a Sharpe ratio of zero (baseline) for the supplementary UK (unbroken line) and South African (dashed line) data sets (; $h(t, S_k^+) = \exp((9.5 \times 10^{-1})S_k^+)$; $h(t, S_k^-) = \exp((-5.8 \times 10^{-1})S_k^-)$ and $h(t, S_k^+) = exp((7.9 \times 10^{-1})S_k^+)$; $h(t, S_k^-) = \exp((-2.7 \times 10^{-1})S_k^-)$, respectively.

The results presented in Table 4 in the main paper, based on the additional data sets from the UK and South African brokerages, include variables measured on different scales. Consequently, to explore the robustness of the results, the CPH models were re-estimated using the same data, with only the significant independent variables included. The results, presented in Table 5 in the main paper, indicate that the coefficients for the independent variables remain largely unchanged. The Sharpe ratios achieved by traders (x-axis) are plotted against the likelihood of their ceasing to trade (y-axis) in in Figure A3. These again show very similar V-shaped functions to those found in Figure A2. Models that allow a V-shaped relationship between the Sharpe ratio and the chance of a trader ceasing trading were found to better account for the data than models that only allowed a linear relationship (χ^2 (1) = 106.52, p < .001, and χ^2 (1) = 287.1, p < .001 for the supplementary UK and South African data sets, respectively). These results provide further support for H1-H3.

To explore the sensitivity of the results for changes in the censor dates adopted, the process discussed above was repeated with more extreme values of censor dates. In particular, these were changed to 17 and 11 days, for the supplementary UK and South African data sets, respectively (i.e. MITD+SD(MITD) and to 75 and 62 days, for the supplementary UK and South African data sets, respectively (i.e. MITD+6SD(MITD). Analysis based on these alternative censor dates resulted in similar values to those reflected in Tables 4 and 5 in the main paper and to similar plots to Figures A2 and A3, supporting the conclusions drawn from the main study.

A2.3 Exploring the periodic nature of the V-shaped relationship between a trader's Sharpe ratio and their likelihood of ceasing to trade

In testing the profitability-related hypotheses across different time periods using the data from the main study (see results in A1.1), the V-shaped relationship between a trader's Sharpe ratio and their likelihood of ceasing to trade is more pronounced in certain periods. In particular, as shown in Figure A1, in the pre-crisis period, the likelihood of an individual ceasing to trade, compared to traders with a Sharpe ratio of 0, rises sharply as their Sharpe ratio increases or decreases (e.g., by 30.2% and 12.1%, for traders with Sharpe ratios of 2 and -2, respectively). However, in the crisis and post-crisis periods, the increase in the likelihood of ceasing trading as Sharpe ratio increases above zero is more gradual (e.g., the likelihood of ceasing trading increases by 3.0% and 4.6% in the post-crisis period for individuals with Sharpe ratios of 2 and -2, respectively). In addition, whilst a log-likelihood test confirmed that a V-shaped relationship between a trader's Sharpe ratio and their likelihood of ceasing to trade is significant over a simple linear relationship in the pre- and during-crisis periods, this is not the case in the post-crisis period. These results may suggest that the V-shaped relationship is periodic in nature. However, the V-shaped relationship was also evident when analysing the supplementary data from a different UK brokerage and a South African brokerage (see A2.1). Consequently, we suspected, as indicated in A1.1, that the lack of significance of the V-shaped relationship in the post-crisis period may be connected to the fact that the main data set contained the trades of fewer individuals in the post-crisis period than was the case in the pre- and during-crisis periods.

The significantly larger size of the supplementary datasets afforded the opportunity to explore to what extent the V-shaped relationship may be periodic in nature. In particular, the large number of traders in the supplementary datasets enabled the splitting of the data into separate time periods which each included the trades of a large sample of traders.

Since the supplementary UK data overlaps with the post-crisis period, this enabled us to explore whether the V-shaped relationship was significant during this period. In particular, the period defined as post-crisis in the main study included trades executed from 1st October 2010 to 7th December 2012 (but the trades of only 2,462 individuals could be analysed). However, the supplementary UK data contained data concerning 4,916 individuals who traded in an equivalent post-crisis period (i.e. 21st June 2010 to 31st December 2012). Consequently, we split the UK supplementary data into two periods: 21st June 2010 to 31st December 2012 and 1st January 2013 to 10th October 2018. The results of estimating the CPH model for these periods are shown in Table A9.

The results for both periods show significant negative/positive coefficients for traders with unprofitable/profitable Sharpe ratios, indicating that the greater a trader's losses/profits (relative to risk accepted) the greater the probability of their ceasing to trade, compared to the average trader. For both periods, the Sharpe ratios achieved by traders (x-axis) plotted against the increase in their

likelihood of ceasing to trade (compared to the average trader) (y-axis) show a V-shape (see Figure A4) and log-likelihood tests confirmed that a V-shape fitted the data better than a simple linear model in both periods (χ^2 (1) = 16.01, p < 0.001 for 2010 to 2012 period; χ^2 (1) = 107.29, p < 0.001 for 2013 to 2018 period). Importantly, the period which most closely corresponds to the post-crisis period used in the main study shows a strong V-shape, with a 4-/14-fold increase in the likelihood of ceasing trading amongst those with Sharpe ratios of -2 /2 compared to an individual with a Sharpe ratio of zero. These results suggest that the lack of significance of the V-shape in the post-crisis period in the main study may well have resulted from the smaller number of traders, resulting in the diminished statistical power of the tests.

Table A9

Results of estimating the CPH model for the supplementary UK data for the post-crisis period, 21st June 2010 to 31st December 2012, and the period 1st Jan 2013 to 10th October 2018.

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Mean Stake$_k$ (Volume)	<0.01	1.00	<0.01	0.02	0.98	
	[<0.01]	[1.00]	[<0.01]	[1.03]	[0.31]	
Trade Frequency$_k$	<-0.01	0.98	<0.01	-0.95	0.34	
	[<0.01]	[0.98]	[<0.01]	[11.24]	[<0.01]	***
Profit/loss per trade Mean (R_k)(£)	<0.01	1.00	<0.01	0.94	0.35	
	[>-0.01]	[0.99]	[<0.01]	[-0.70]	[0.48]	
Value at Risk (*VaR(R_k)*(5%)	>-0.01	0.99	<0.01	-1.11	0.27	
	[<0.01]	[1.00]	[<0.01]	[0.54]	[0.59]	
Profitable Sharpe Ratio (S_k^+)	1.31	3.70	0.28	4.58	<0.01	***
	[0.96]	[2.60]	[0.11]	[8.52]	[<0.01]	***
Unprofitable Sharpe Ratio (S_k^-)	-0.69	0.49	0.18	-3.89	<0.01	***
	[-0.58]	[0.56]	[0.03]	[-20.26]	[<0.01]	***
Trading period (n_d^k)	<0.01	1.00	<0.01	20.00	<0.01	***
	[-0.03]	[0.97]	[<0.01]	[-32.58]	[<0.01]	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.462 , SE <0.01; [0.895, SE <0.01]
Rsquare= 0.11, max possible = 0.99; [0.39, max possible = 0.97]
Likelihood ratio test= 593.60 (7) p<.0.01; [9,259.00 (7) p<.0.01]
Wald test =433.60(7) , p< 0.01; [1,442.00(7) , p< 0.01]
Score (logrank) test = 433.06(7), p<0.01; [3,117.00(7), p<0.01]
Total Observations (Total Traders) =4,916; [18,460]
Total Events (Right Censored Traders) = 974; [3,753]

The Table presents results from estimating the CPH Model (Eq. 9), for assessing the likelihood (at time t) that an individual ceases trading, based on their profitability, for the 4,916 and 18, 460 individuals who executed trades at some point between 21st June 2010 to 31st December 2012 and 1st Jan 2013 to 10th October 2018th, respectively, with the supplementary UK brokerage. Results for the latter period shown in square brackets. Definitions of the variables are provided in section 3.2.
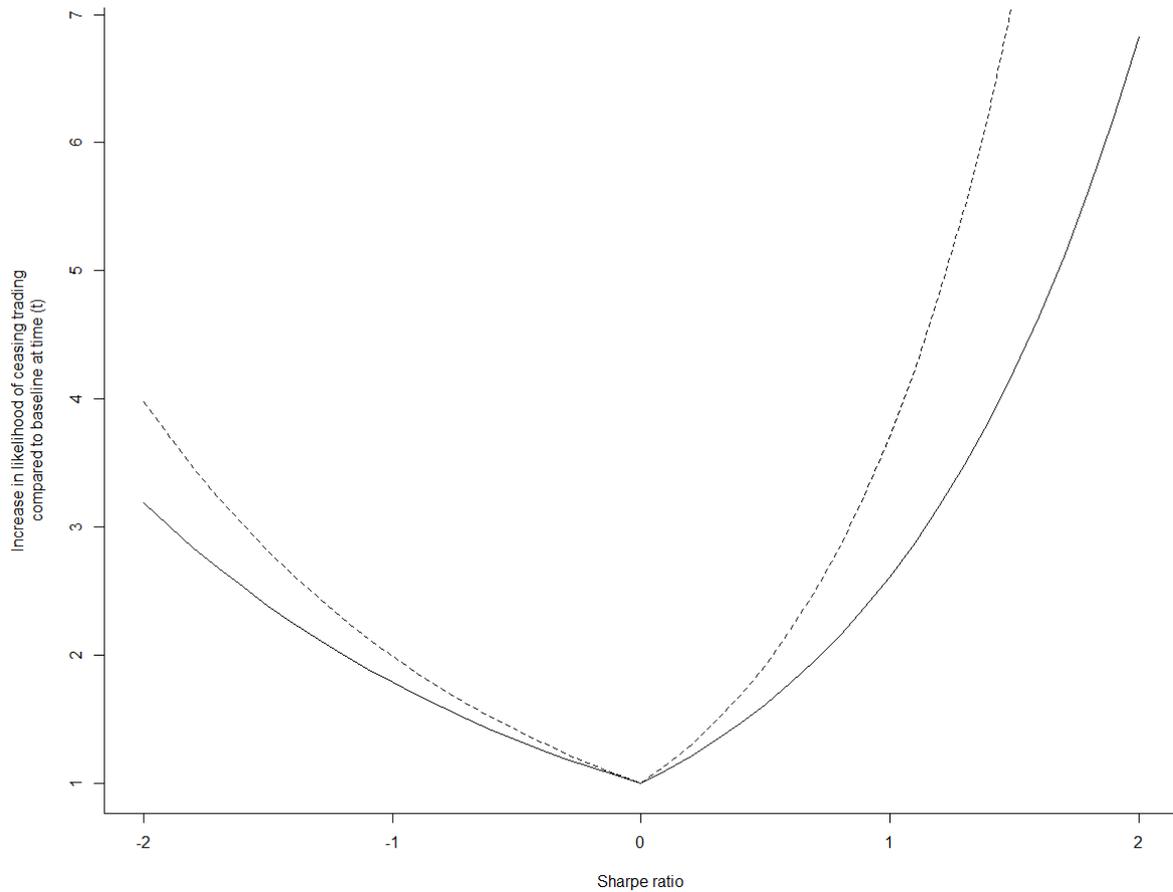
Figure A4. Relationship between a trader's Sharpe Ratio and the likelihood of their ceasing trading for individuals executing trades with the supplementary UK brokerage

The figure displays estimates, derived from CPH Models, for the effect of a trader's Sharpe ratio on the expected increase in the likelihood of ceasing to trade at any given time (t) compared to a trader with a Sharpe ratio of zero (baseline), for trades placed in the periods, 21st June 2010 to 31st December 2012 (solid line: $h(t, S_k^+) = \exp(1.31.S_k^+)$; $h(t, S_k^-) = \exp(-0.69 S_k^-)$) and 1st Jan 2013 to 10th October 2018th (dashed line: $h(t, S_k^+) = \exp(0.96.S_k^+)$; $h(t, S_k^-) = \exp(-0.58 S_k^-)$), with the supplementary UK brokerage.

To further explore whether the existence of the V-shaped relationship depended upon the period which was analysed or the country in which the trades were executed, we also split the data from the supplementary South African brokerage into two periods, each of which contained the trades of more than 4,500 individuals, namely 16th June 2016 to 16th June 2018 and 17th June 2018 to 23rd April 2019.

The results of estimating the CPH model for these periods are shown in Table A10. These again show significant negative/positive coefficients for traders with unprofitable/profitable Sharpe ratio. For both periods, the Sharpe ratios achieved by traders (x-axis) plotted against the increase in their likelihood of ceasing to trade (compared to the average trader) (y-axis) show a V-shape (see

Figure A5) and log-likelihood tests confirmed that a V-shape fits the data better than a simple linear model in both periods (χ^2 (1) = 94.31, p < 0.001 for 2016 to 2018 period; χ^2 (1) = 259.68, p < 0.001 for 2018 to 2019 period). In addition, the increases in the chance of a trader with Sharpe ratio of 2/-2 ceasing trading, compared to a trader with a Sharpe ratio of zero, are large in both these periods. In particular, in the 2016-2018 period there is nearly a 16-fold and 10-fold increase in the likelihood of ceasing trading for those with Sharpe ratios of +2 and -2 respectively. The equivalent figures in the 2018-19 period are a 5.3-fold and an 80% increase.

Table A10

Results of estimating the CPH model for the supplementary South African data for the periods 16th June 2016 to 16th June 2018 and 17th June 2018 to 23rd April 2019.

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Mean Stake$_k$ (Volume)	<0.01	1.00	<0.01	1.34	0.18	
	[>-0.01]	[0.99]	[<0.01]	[-1.92]	[0.05]	*
Trade Frequency$_k$	>-0.01	0.99	<0.01	-2.01	0.04	*
	[0.01]	[1.01]	[<0.01]	[5.71]	[<0.01]	***
Profit/loss per trade Mean (R_k)($)	<0.01	1.00	<0.01	0.54	0.59	
	[<-0.01]	[0.99]	[<0.01]	[-0.44]	[0.66]	
Value at Risk (*VaR(R_k)*)(5%)	<0.01	1.00	<0.01	1.47	0.14	
	[<0.01]	[1.00]	[<0.01]	[0.36]	[0.72]	
Profitable Sharpe Ratio (S_k^+)	1.38	3.96	0.09	15.56	<0.01	***
	[0.83]	[2.30]	[0.05]	[15.22]	[<0.01]	***
Unprofitable Sharpe Ratio (S_k^-)	-1.13	0.32	0.20	-5.73	<0.01	***
	[-0.29]	[0.75]	[0.02]	[-19.00]	[<0.01]	***
Trading period (n_d^k)	<0.01	1.00	<0.01	12.44	<0.01	***
	[-0.06]	[0.94]	[<0.01]	[-51.43]	[<0.01]	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.641 , SE <0.01; [0.808 , SE <0.01]
Rsquare= 0.07, max possible = 0.99; [0.41, max possible = 0.99]
Likelihood ratio test= 338.10 (7) p<.0.01; [9,155.00 (7) p<.0.01]
Wald test =396.10(7), *p*< 0.01; [3,090.00(7) , *p*< 0.01]
Score (logrank) test = 401.08(7), *p*<0.01; [4,439.00(7), *p*<0.01]
Total Observations (Total Traders)= 4,916; [17,305]
Total Events (Right Censored Traders) = 3,501; [6,224]

The Table presents results from estimating the CPH Model (Eq. 9), for assessing the likelihood (at time t) that an individual ceases trading, based on their profitability, for the 4,916 and 17, 305 individuals who executed trades at some point between 16th June 2016 to 16th June 2018 and 17th June 2018 to 23rd April 2019, respectively, with the supplementary South African brokerage. Results for the latter period shown in square brackets. Definitions of the variables are provided in section 3.2.
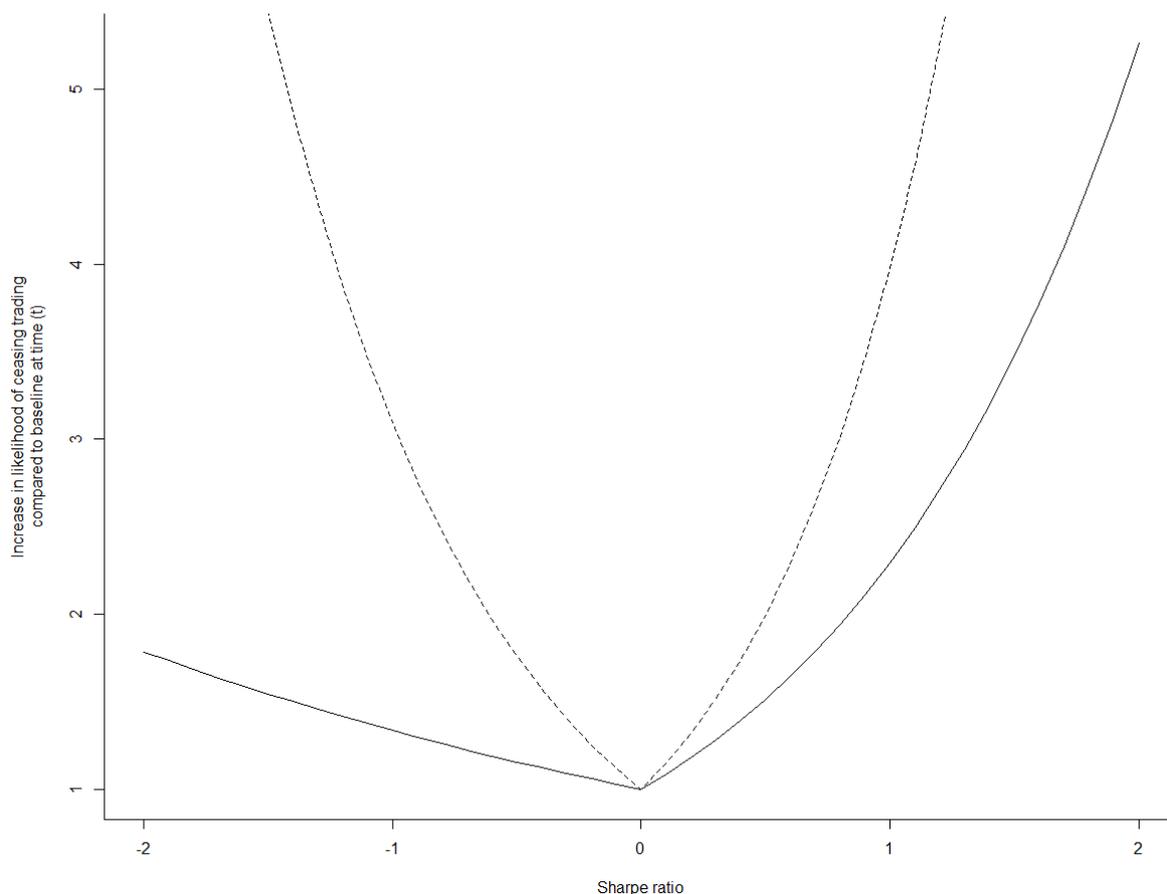
Figure A5. Relationship between a trader's Sharpe Ratio and the likelihood of their ceasing trading for individuals executing trades with the supplementary South African brokerage

The figure displays estimates, derived from CPH Models, for the effect of a trader's Sharpe ratio on the expected increase in the likelihood of ceasing to trade at any given time (*t*) compared to a trader with a Sharpe ratio of zero (baseline), for trades placed in the periods, 16th June 2016 to 16th June 2018 (dashed line: $h(t, S_k^+) = exp(1.38. S_k^+); h(t, S_k^-) = exp(-1.13 S_k^-)$) and 17th June 2018 to 23rd April 2019 (solid line $h(t, S_k^+) = exp(0.83. S_k^+); h(t, S_k^-) = exp(-0.29 S_k^-)$), with the supplementary South African brokerage.

The significantly longer period and larger number of traders in the supplementary UK data set allowed analysis of a further set of three time periods following the immediate post-crisis period, each of which captures the behaviour of over 40% more traders than operated in the post-crisis period in the dataset used in the main study.

The results of estimating the CPH model for these three periods, namely, 1st January 2013 to 31st December 2014, 1st January 2015 to 31st December 2016 and 1st January 2017 to 10th October 2018, are displayed in table A11.

Table A11

Results of estimating the CPH model for the supplementary UK data for the periods 1st January 2013 to 31st December 2014, 1st January 2015 to 31st December 2016 and 1st January 2017 to 10th October 2018.

	Coef	Exp(coef)[1]	SE(coef)	Z	p-value	
Mean Stake$_k$ (Volume)	<0.01	0.99	<0.01	1.94	0.05	*
	[<0.01]	[1.00]	[<0.01]	[1.30]	[0.19]	
	{<0.01}	{1.00}	{<0.01}	{0.94}	{0.35}	
Trade Frequency$_k$	<0.01	1.00	<0.01	0.59	0.55	
	[>-0.01]	[0.99]	[<0.01]	[-0.24]	[0.81]	
	{<0.01}	{1.00}	{<0.01}	{11.09}	{<0.01}	***
Profit/loss per trade Mean (R_k)(£)	>-0.01	1.00	<0.01	-0.87	0.38	
	[>-0.01]	[0.99]	[<0.01]	[-0.45]	[0.65]	
	{<0.01}	{1.00}	{<0.01}	{0.87}	{0.93}	
Value at Risk (*VaR(R_k)*)(5%)	>-0.01	0.99	<0.01	-3.72	<0.01	***
	[<0.01]	[1.00]	[<0.01]	[0.53]	[0.59]	
	{>-0.01}	{1.00}	{<0.01}	{-0.25	{0.80}	
Profitable Sharpe Ratio (S_k^+)	1.31	3.72	0.30	4.36	<0.01	***
	[0.72]	[2.06]	[0.12]	[6.02]	[<0.01]	***
	{1.03}	{2.80}	{0.11}	{8.69}	{<0.01}	***
Unprofitable Sharpe Ratio (S_k^-)	-1.75	0.17	0.22	-7.75	<0.01	***
	[-0.85]	[0.43]	[0.13]	[-6.79]	[<0.01]	***
	{-0.59}	{0.55}	{0.03}	{-19.80}	{<0.01}	***
Trading period (n_d^k)	<0.01	1.00	<0.01	6.57	<0.01	***
	[>-0.01]	[0.99]	[<0.01]	[-15.75]	[<0.01]	***
	{-0.04}	{0.96}	{<0.01}	{-29.67}	{<0.01}	***

*, **, *** Significant at 0.05, 0.01, and 0.001.
[1]See section 3.3 for an explanation of Exp(coef).
Concordance= 0.571 , SE <0.01; [0.578 , SE <0.01]; {0.842 , SE <0.01}
Rsquare= 0.32, max possible = 0.99 ; [0.51, max possible = 0.99]; {0.41, max possible = 0.99}
Likelihood ratio test= 116.10 (7) $p<.01$; [307.50 (7) $p<0.01$]; {6,317.00 (7) $p<.01$}
Wald test = 136.20(7) , $p< 0.01$; [301.60(7), $p< 0.01$]; {1,245.00(7) , $p< 0.01$}
Score (logrank) test = 138.00(7), $p<0.01$; [306.80(7), $p<0.01$]; {2,787.00(7), $p<0.01$}
Total Observations (Total Traders) =3,565; [5,888]; {11,887}
Total Events (Right Censored Traders) = 1,372; [1,912]; {3,480}

The Table presents results from estimating the CPH Model (Eq. 9), for assessing the likelihood (at time t) that an individual ceases trading, based on their profitability, for the 3,565, 5,888 and 11, 877 individuals who executed trades at some point between 1st January 2013 to 31st December 2014, 1st January 2015 to 31st December 2016 and 1st January 2017 to 10th October 2018, respectively, with the supplementary UK brokerage. Results for the 2015-16 period shown in square brackets and for the 2017-18 period shown in curly brackets. Definitions of the variables are provided in section 3.2.

The results presented in table A11 indicate that in each of the additional three periods examined, the positive and negative Sharpe ratios are significant at 0.001, with positive and negative coefficients, respectively. These results are consistent with the results for all the analysis of the supplementary data presented in both A2.2 and earlier in this section, indicating that the larger a trader's negative or positive Sharpe ratio, the greater is their expected increase in the likelihood of

ceasing to trade at any given time, compared to a trader with a Sharpe ratio of zero (baseline). These results confirm that for all three periods there exists a V-shaped relationship between a trader's Sharpe ratio and the likelihood of their ceasing to trade. Log-likelihood tests confirm that in each period the V-shape is significant over a simple linear relationship (χ^2 (1) = 38.08, p < 0.001; χ^2 (1) = 33.74, p < 0.001 and χ^2 (1) = 106.70, p < 0.001, for the periods 1st January 2013 to 31st December 2014, 1st January 2015 to 31st December 2016 and 1st January 2017 to 10th October 2018, respectively). In addition, the impact of an increase/decrease in Sharpe ratio from 0 to 2/-2 is over three-fold in each of these periods, suggesting a strong economic impact.

Taken together, the results of analysing the supplementary data suggest that the V-shaped relationship between a trader's Sharpe Ratio and their likelihood of ceasing to trade is persistent across time and across the three brokerages we examined (operating in both the UK and South Africa). These results suggest that the lack of significance of the V-shape in the post-crisis period in the main study may have arisen because the smaller number of traders led to diminished statistical power of the tests.

Appendix 3: The ANOVA and polynomial regression results that model, through time, changes in (i) the proportion of noise traders and informed traders, (ii) the degree of disposition effect and (iii) the Ill-discipline Index of new generations of traders.

Table A12. ANOVA table for the best fitting polynomial regression models that explain the changes in the proportion of noise traders and informed traders, in the degree of disposition effect displayed by traders and in the Ill-discipline Index of new generations of traders through time (see Figures 2A,2B, 2C and 2D, respectively).

	Residual DF	RSS	Df	Sum Sq	F value	p-value	
Month	70	0.08	1	<0.01	5.94	<0.02	*
	(70)	(0.02)	(1)	(<0.01)	(1.88)	(0.17)	
	[70]	[0.02]	[1]	[<0.01]	[41.47]	[<0.01]	***
	{70}	**{74.63}**	**{1}**	**{4.08}**	**{3.99}**	**{0.05}**	*
Month^2	69	0.06	1	0.02	22.10	<0.01	***
	(-)	(-)	(-)	(-)	(-)	(-)	
	[69]	[0.01]	[1]	[<0.01]	[15.06]	[<0.01]	***
	{69}	{70.5}	{1}	{0.04}	{0.04}	{0.85}	
Month^3	**68**	**0.05**	**1**	**0.01**	**12.01**	**<0.01**	***
	(-)	(-)	(-)	(-)	(-)	(-)	
	[68]	[0.01]	[1]	[<0.01]	[13.52]	[<0.01]	***
	{-}	{-}	{-}	{-}	{-}	{-}	
Month^4	67	0.05	1	<0.01	2.21	0.14	
	(-)	(-)	(-)	(-)	(-)	(-)	
	[67]	**[0.01]**	**[1]**	**[<0.01]**	**[6.76]**	**[0.01]**	*
	{-}	{-}	{-}	{-}	{-}	{-}	
Month^5	-	-	-	-	-	-	
	(-)	(-)	(-)	(-)	(-)	(-)	
	[66]	[0.01]	[1]	[<0.01]	[0.54]	[0.46]	

	{-}	{-}	{-}	{-}	{-}	{-}

*, **, *** Significant at 0.05, 0.01, and 0.001.

The data employed to conduct these analyses of variance relate to the 5,164 individuals who traded with the UK brokerage at any time between 24th March 2006 and 7th February 2012. The rows show analysis of variance results from fitting increasingly higher-order polynomial models to explain changes in the proportion of noise traders (in plain text) and informed traders (in round brackets), in the degree of disposition effect displayed by traders (in square brackets) and in the Ill-discipline Index of new generations of traders through time (in curly brackets).

Table A13. Polynomial regression results for the best fitting model of the changes in the proportion of noise traders (see Figure 2A), in the proportion of informed traders (Figure 2B), in the degree of disposition effect displayed by traders (see Figure 2C), and in the Ill-discipline Index of new generations of traders (see Figure 2D) through time.

	Estimate	Std. Error	Statistic	p-value	
(Intercept)	0.25	0.01	18.08	<0.01	***
	(0.07)	(<0.01)	(30.87)	<0.01	***
	[>-0.01]	[0.01]	[-0.16]	[0.87]	
	{1.32}	{0.24}	{5.54}	{<0.01}	***
Month	0.01	<0.01	5.17	<0.01	***
	(-)	(-)	(-)		
	[<0.01]	[<0.01]	[0.41]	[0.69]	
	{0.01}	{0.01}	{2.01}	{<0.05}	*
Month^2	>-0.01	<0.01	-4.15	<0.01	***
	(-)	(-)	(-)	(-)	
	[<0.01]	[<0.01]	[1.30]	[0.20]	
	{-}	{-}	{-]	{-}	
Month^3	<0.01	<0.01	3.44	<0.01	**
	(-)	(-)	(-)	(-)	
	[>-0.01]	[<0.01]	[-2.13]	[<0.05]	*
	{-}	{-}	{-}	{-}	
Month^4	-	-	-	-	
	(-)	(-)	(-)	(-)	
	[<0.01]	[<0.01]	[2.61]	[<0.05]	*
	{-}	{-}	{-}	{-}	

*, **, *** Significant at 0.05, 0.01, and 0.001.
Residual standard error: 0.03, (0.04), [0.01], {1.00} on 68, (71), [67],{70} degrees of freedom (DF)
Multiple R-squared: 0.37, (-), [0.54], {0.05}; Adjusted R-squared: 0.34, (-), [0.51], {0.04}
F-statistic: 13.11 on 3 and 68 DF, p-value: <0.01; (-); [19.33 on 4 and 67 DF, p-value: <0.01];
        { 4.04 on 1 and 70 DF, p-value: <0.05}

The rows show the statistics for the polynomial regression results for the best fit lines (shown in Figure 2) for changes in the proportion of noise traders (in plain text) and informed traders (in round brackets), in the degree of disposition effect displayed by traders (in square brackets), and in the Ill-discipline Index of new generations of traders through time (in curly brackets).