Fear and Greed in Financial Markets: A Clinical Study of Day-Traders*

Andrew W. Lo†, Dmitry V. Repin‡, and Brett N. Steenbarger††

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Abstract

We investigate several possible links between psychological factors and trading performance in a sample of 80 anonymous day-traders. Using daily emotional-state surveys over a five-week period as well as personality inventory surveys, we construct measures of personality traits and emotional states for each subject and correlate these measures with daily normalized profits-and-losses records. We find that subjects whose emotional reaction to monetary gains and losses was more intense on both the positive and negative side exhibited significantly worse trading performance, and large sudden swings in emotional states seem especially detrimental to cumulative profits-and-losses. Psychological traits derived from a standardized personality inventory survey instrument do not reveal any specific "trader personality profile", raising the possibility that trading skills may not necessarily be innate, and that different personality types may be able to perform trading functions equally well after proper instruction and practice.

Keywords: Behaviorial Finance; Market Psychology; Market Efficiency.

JEL Classification: G12

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†MIT Sloan School of Management, 50 Memorial Drive, E52–432, Cambridge, MA 02142 (corresponding author).

‡MIT Laboratory for Financial Engineering, One Broadway, Cambridge, MA 02142.

††SUNY Upstate Medical University, Department of Psychiatry and Behavioral Sciences, 713 Harrison Street, Syracuse, New York 13210.

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1 Introduction

The rationality of financial markets has been one of the most hotly contested issues in the history of modern financial economics. Recent critics of the Efficient Markets Hypothesis argue that investors are generally irrational, exhibiting a number of predictable and financially ruinous biases such as overconfidence (Fischoff and Slovic, 1980; Barber and Odean, 2001; Gervais and Odean, 2001), overreaction (DeBondt and Thaler, 1986), loss aversion (Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Odean, 1998), herding (Huberman and Regev, 2001), psychological accounting (Tversky and Kahneman, 1981), miscalibration of probabilities (Lichtenstein, Fischoff, and Phillips, 1982), and regret (Bell, 1982; Clarke, Krase, and Statman, 1994). The sources of these irrationalities are often attributed to psychological factors—fear, greed, and other emotional responses to price fluctuations and dramatic changes in an investor's wealth. In response to the mounting evidence of departures from market efficiency, a growing number of economists, psychologists, and financial-industry professionals have begun to use the terms "behavioral economics" and "behavioral finance" to differentiate themselves from the standard orthodoxy.

However, recent research in the cognitive sciences and financial economics suggest an important link between rationality in decisionmaking and emotion (Grossberg and Gutowski, 1987; Damasio, 1994; Elster, 1998; Lo, 1999; Loewenstein, 2000; Peters and Slovic 2000), implying that the two notions are not antithetical, but in fact complementary. For example, in a pilot study of 10 professional securities traders during live trading sessions, Lo and Repin (2002) present psychophysiological evidence that even the most seasoned trader exhibits significant emotional response—as measured by elevated levels of skin conductance and cardiovascular variables—during certain transient market events such as increased price volatility or intra-day breaks in trend. In a series of case studies, Steenbarger (2002) also presents evidence linking emotion with trading performance.

In this paper, we continue this research agenda by investigating role of emotional mechanisms in financial decisionmaking using a different sample of subjects and a different method for gauging emotional response. In particular, we recruited 80 volunteers from a five-week on-line training program for day-traders offered by Linda Bradford Raschke, a well-known professional futures trader (see Schwager, 1994). Subjects were asked to fill out surveys that recorded their psychological profiles before and after their training program, and during the course of the program—involving live trading through their own personal accounts—subjects were asked to fill out surveys at the end of each trading day which were designed to measure their emotional state and their trading performance for that day.

The results from this experiment confirm and extend those of Lo and Repin (2002) and Steenbarger (2002)—we find a clear link between emotional reactivity and trading performance as measured by normalized profits-and-losses. Specifically, the survey data indicate that subjects whose emotional reaction to monetary gains and losses was more intense on both the positive and negative side exhibited significantly worse trading performance. Moreover, large swings in emotional states within a 24-hour period were even more detrimental to trading performance, implying a negative correlation between successful trading behavior and emotional reactivity. Also, contrary to common intuition regarding common personality traits of professional traders, the psychological traits derived from a standardized personality inventory survey instrument do not reveal any specific "trader personality type" in our sample. This raises the possibility that different personality types may be able to function equally well as traders after proper instruction and practice. Alternatively, it may be the case that individual differences pertinent to trading success lies below the level that can be assessed through personality questionnaires, and may become visible only at deeper physiological and neuropsychological levels, or with a larger or more homogeneous sample of traders.

In Section 2, we provide a brief review of the literature on emotion, personality, and decisionmaking under risk. We describe our experimental protocol in Section 3, and summarize our findings in Section 4. We conclude with some discussion of future research directions in Section 5.

2 Background and Literature Review

Risk-taking as an attribute or characteristic of personal preferences has been investigated extensively from both psychological and economic perspectives. Psychologists have asked whether risk propensity exists as a stable personality trait and how the tendency to take risks manifests itself across different domains of social and personal life. They have also attempted to determine a persistent connection between the biological basis of personality and risk-taking (Kuhlman and Zuckerman, 2000). Economists have put forward the notion of risk aversion, and considerable research has been devoted to parametrizing and estimating its value for individuals and for various demographic, social, and age groups. Unfortunately, neither psychologists nor economists have been particularly successful in these respective endeavors. In particular, no single psychological questionnaire predicts risk-taking behavior across multiple domains, or explains why someone highly risk-averse in financial decisionmaking contexts would pursue extremely dangerous sports (Nicholson et al., 2002). Similarly, the scant differences in risk aversion coefficients that financial advisors are able to collect from their clients seem to lose much of their value in the face of naive asset-allocation rules—dividing wealth equally among all available assets, or the so-called "$1/n$" heuristic—that Benartzi and Thaler (2001) have documented among individual investors. Moreover, there has been little direct evidence of correlation between hypothetical financial decisions made on paper versus real financial decisions involving live market transactions.

These limitations suggest that risk-taking may be context-dependent, and that characterizing the context along some standardized dimensions may be a more productive line of inquiry. We propose that the emotional or affective state of the decision-maker and certain affective properties of the environment are plausible candidates for such a characterization. In various studies, risk preferences have been linked to the affective state of the subject and/or affective characteristics of the task. For example, more risk-taking is reported for negatively framed situations than for positively framed ones (Sitkin and Weingart, 1995; Mittal and Ross, 1998). When in a positive mood, people tend to be more risk-averse (Isen and Geva, 1987; Isen et al., 1988). When positive affect is induced, people report losses to be worse than when no affect is induced (Isen et al., 1988). When the affective state is manipulated through artificially generated outcome histories, a history of success leads to higher risk-taking in gambling experiments (Thaler and Johnson, 1990) and in assumed-role decision experiments (Sitkin and Weingart, 1995).

Mano (1992, 1993) suggests that a two-dimensional representation of affect—valence (positive/negative emotion) and arousal (strength of emotional response)—leads to better understanding of the interaction between affect and risk-taking (see Section 2.2 below for further details). In particular, Mano (1994) demonstrates that higher arousal is correlated with more risk-taking in willingness to pay for lotteries and insurance experiments. Recently, Lerner and Keltner (2002) observe that most of the previous risk studies (e.g., Johnson and Tversky, 1983; Wright and Bower, 1992) have taken a valence-based approach, focusing exclusively on positive versus negative affective states. Lerner and Keltner (2002) propose a more subtle differentiation for negative affect, arguing, for example, that fear and anger influence judgments of risk in opposite ways: whereas fearful individuals make pessimistic judgments about future events, angry individuals seem to make optimistic judgments instead.

With respect to the role of emotion in the context of real-time financial risk-processing, Lo and Repin (2002) demonstrated a clear link using psychophysiological measurements—skin conductance, breathing rate, heart rate, blood volume pulse, and body temperature—for 10 professional traders during live trading sessions. However, an important limitation of their study was the lack of any information about the traders' financial gains and losses because of confidentiality requirements at the participating financial institution. Therefore, they were unable to relate psychophysiological responses directly to trading profits-and-losses, and had to settle for indirect inferences using price data for the instruments being traded by the subjects. We remedy this shortcoming in the current study, where the subjects do provide their daily profits-and-losses as well as the number of trades executed.

The specific emotional context of an individual is often influenced by external factors such as market events, family history, and even weather and other environmental conditions. In particular, the non-specific influence on the emotional states of market participants—as reflected in the systematic depression of stock prices—has been documented with respect to the amount of sunshine (Hirshleifer and Shumway, 2003), the duration of daylight (Kamstra, Kramer, and Levi, 2003), and even geomagnetic activity (Krivelyova and Robotti, 2003). These findings suggest the possibility of gauging the aggregate affective state of the market through indirect means, and may provide yet another motivation for multi-factor asset-pricing models where certain common factors are affect-related.

2.1 Emotion, Personality, and Preferences

There is substantial evidence from the personality and social-psychology literature that preferences are fairly heterogeneous across the general population. Several studies have established links between specific personality traits and performance in experimental economics paradigms. For example, higher extraversion and emotional stability—the opposite of neuroticism—appear to be related to a higher level of stability in intertemporal consumption patterns (Brandstatter and Guth, 2000). In Dictator and Ultimatum games, higher benevolence as a personality trait facilitated more equitable choices in offers to powerless opponents, and reciprocity orientation induces powerful recipients to set higher acceptance thresholds (Brandstatter and Guth, 2002). Greater internal locus of control, better self-monitoring ability, and higher sensation-seeking have all been linked to higher levels of cooperative behavior in Prisoner's Dilemma experiments (Boone et al., 1999).

In securities trading, the heterogeneity of preferences implies potential differences in attitudes toward risk-taking across individuals. Various personality assessment methods developed by social psychologists have been used to examine the relationships between specific personality traits and risk-taking in different domains. In particular, Nicholson et al. (2002) examine the relation between personality dimensions from a five-factor personality model and risk propensity in recreational, health, career, finance, safety, and social domains. In a study with over 1,600 subjects, they use the NEO PI-R personality inventory (McCrae and Costa, 1996),[1] and find that sensation-seeking, which is a subscale of the Extraversion dimension, was found to be highly correlated with most risk-taking domains, while overall risk propensity was higher for subjects with higher Extraversion and Openness scores and lower for subjects with higher Neuroticism, Agreeableness, and Conscientiousness scores.[2] The five-factor model has been independently developed by several investigators, e.g. Goldberg (1990) and Costa and McCrae (1992), and is currently the most widely accepted theory of personality traits. Meta-analytic studies by Barrick and Mount (1991), Tett, Jackson, and Rothstein (1991), and Hurtz and Donovan (2000) suggest that the personality dimensions from the five-factor model may provide some utility for selecting employees. Barrick and Mount (1991) aggregate results from 117 studies using meta-analysis and find that Conscientiousness exhibits consistent relationships with all job-performance criteria for five

[1]The NEO PI-R consists of 240 items each rated on a five-point scale, and can usually be completed within 40 minutes. The five dimensions or factors of personality captured by this instrument are: (see Costa and McCrae, 1992 for details): Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness. A shorter version containing 120 items has also been developed and calibrated, and we use the public-domain version of this shorter survey. See Goldberg (1999), International Personality Item Pool (2001), and the IPIP website http://ipip.ori.org/ for further details.

[2]In their study, "risk propensity" is defined as in Sitkin and Pablo (1992), i.e., as "the tendency of a decision-maker either to take or avoid risks".

occupational groups, and other dimensions were related to job performance for certain types of occupations. In a cross-cultural study, Salgado (1997) conducts a similar meta-analysis using European data, and his findings indicate that Conscientiousness and Emotional Stability were valid predictors across job criteria and occupational groups.

2.2 Measuring Emotional Response

Historically, emotion has been one of the most intriguing and challenging psychological concepts to define and study. After the seminal work of William James (1884) and Wilhelm Wundt (1897), emotion became a bona fide subject of investigation among psychologists. Measuring emotion is an inherently complicated task for a number of reasons. By nature, emotion is a highly subjective experience, and imposing a common scale across individuals is likely to yield a fair amount of estimation error. If an introspective or an instantaneous report is used to assess an individual's emotional state, the very act of asking the individual about his or her feelings may change those feelings in some way.

Laboratory studies have some advantages over field studies because one can employ indirect measures such as physiological responses of the autonomic nervous system (ANS) (Cacioppo, Tassinary, and Bernt, 2000). The ANS innervates the viscera and is responsible for regulation of internal states that are mediated by internal bodily as well as emotional and cognitive processes. ANS responses are relatively easy to measure since many of them can be measured non-invasively from external body sites without interfering with cognitive tasks performed by the subject. ANS responses occur on the scale of seconds, which is essential for investigation of real-time risk-processing. In fact, using sensors attached to a portable data acquisition unit and a laptop computer, Lo and Repin (2002) have demonstrated the feasibility of conducting psychophysiological field studies of real-time trading activity, in which five types of physiological data are collected: skin conductance, cardiovascular data (blood volume pulse and heart rate), electromyographic (EMG) data, respiration rate, and body temperature. A related set of techniques for measuring emotional response is to employ some method of facial-expression recognition by an independent observer or through facial EMG sensors.

However, despite the advantages of indirect measures of affect, none of these approaches has been shown to work reliably for an arbitrary emotional expression except for cases where a well-defined finite set of specific emotions is experienced by the subject during the course of an experiment (Davidson and Ekman, 1994; Cacioppo et al., 2000; Collet et al., 1997). Moreover, although generally non-invasive, physiological measurements are still fairly difficult to obtain and properly calibrate, and may not be feasible for many larger-scale field studies such as the on-line training program of this current study.

State	Mood Adjectives
Pleasant	happy, pleased, content
Unpleasant	miserable, troubled, unhappy
Activated	aroused, alert, hyperactivated
Deactivated	sleepy, still, quiet
Unpleasant Activated	distressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, afraid
Pleasant Deactivated	relaxed, at rest, serene, calm, at ease
Pleasant Activated	interested, excited, strong, enthusiastic, proud, inspired, determined, attentive, active
Unpleasant Deactivated	tired, sluggish, droopy, dull, drowsy, bored

Table 1: UWIST Mood Adjectives Checklist, grouped into eight emotion categories.

A more traditional method for measuring emotional response is the University of Wales Institute of Science and Technology (UWIST) Mood Adjective Checklist (MACL), a survey instrument developed by Matthews, Jones, and Chamberlain (1990) consisting of 42 adjectives that a subject must rate on a seven-point scale (1 = "not at all true" to 7 = "very true") as to how well each describes his or her mood at that moment (see Table 1). The UWIST MACL measures the emotional state of the subject along the lines of a two-dimensional emotion representation, the circumplex model of Russel (1980). In this model, each specific emotion is characterized along two dimensions: "valence", which indicates how pleasant or unpleasant the emotional state is, and "arousal", which characterizes how activated or deactivated the person experiencing the emotion feels. For example, feeling bored would imply a low-activation unpleasant emotional state, whereas feeling excited would imply a highly activated pleasant emotional state. The scores for eight emotion categories that comprise different sectors in the emotion circumplex—summarized in Table 1—are calculated based on

UWIST MACL responses: (1) Pleasant, (2) Unpleasant, (3) Activated, (4) Deactivated, (5) Pleasant Activated, (6) Pleasant Deactivated, (7) Unpleasant Activated, and (8) Unpleasant Deactivated.

The accuracy of the valence/arousal representation of emotion is not universally accepted in psychological literature (e.g., Ekman and Davidson, 1994). Moreover, factors such as the specific process for eliciting emotion, insufficient emotional intensity in a laboratory setting, and the purity of emotional experience (i.e., experiencing only one emotion at a time) all contribute to the challenges of distinguishing individual emotions (Parkinson, 1995). However, distinguishing specific emotions is significantly more difficult than identifying valence and arousal (for a discussion see Davidson, 1999; Levenson, 1994), hence the UWIST MACL often serves as a useful first-order approximation.

3 Experimental Protocol

For this study, we recruited participants from Linda Bradford Raschke's (LBR) five-week on-line training program for day-traders. This program was centered around the Observe-Orient-Decide-Act (OODA) paradigm developed Col. John R. Boyd as an efficient framework for aiding decision-making processes in a combat environment (Steenbarger, 2002). The notable aspects of this paradigm are the emphasis on the speed of information processing by the trader and frequent drills of the OODA loop applied to a given trading context multiple times during the trading day. The LBR training program was conducted through a series of on-line lessons and chat sessions conducted by Raschke and her colleagues. Each participant was expected to complete a daily set of specific paper-trades, i.e., hypothetical trades, but were also free to engage in actual trades through their personal accounts. The program was completely anonymous: all communication was done through anonymous e-mail addresses of the type `tr1234@yahoo.com,` where "`tr1234`" served as a unique identifier for each trader.

Volunteers for our study were recruited through an on-line announcement during one the initial LBR training program sessions. The subjects were told that a study independent of the LBR training would be conducted by the MIT Laboratory for Financial Engineering. All interested traders then received an e-mail inviting them to participate in the "Emotions and Personality in Trading" study, and were promised personalized results after the completion of the study; no other incentives were provided. The timeline of the study and subject consent form were provided in the invitation e-mail. The study began on July 7, 2002 and was completed on August 9, 2002 for a total of 25 trading days.

Because our subjects were geographically dispersed throughout the United States, and because the duration of the study was several weeks, the most practical methods for assessing emotional state and psychological profile were on-line questionnaires. Therefore, we asked the participants to complete several survey instruments prior to, during each day of, and after the training program. Subjects filled out all questionnaires on-line using our website (`http://www.riskpsychology.net`), using their trading identifiers to obtain authorized access.

At the start of the training course, all participants in our study were asked to complete the following three questionnaires:

A1 **Zung Self-Rating Anxiety Scale (SAS) and Self-Rating Depression Scale (SDS)**. The SDS and SAS insruments are widely used 20-item depression and anxiety scales, respectively (Zung, 1965; 1971). SDS is aimed to assess "psychic-active", physiological, psychomotor, and psychological manifestations of depression, and is useful for discriminating between depressed and non-depressed individuals (Shaver and Brennan, 1991). SAS measures affective and somatic symptoms of the anxiety disorder; scores above a cutoff value suggest presence of a clinically meaningful anxiety. These instruments are used only to screen out subjects with clinical levels of depression and/or anxiety, and none were eliminated by this filter.

A2 **International Personality Item Pool (IPIP) NEO**. This is the shorter (120-item) public-domain version of the McCrae and Costa (1996) NEO IP-R five-factor personality inventory instrument, which can typically be completed within 15–25 minutes. Responses from over 20,000 individuals have been used to calibrate this questionnaire. See Goldberg (1999), International Personality Item Pool (2001), and the IPIP website http://ipip.ori.org/ for further details.

A3 **Demographics and Strengths and Weaknesses**. The demographics component includes basic background information for each subject such as age, trading experience, account size, educational background. Each subject is also asked to report, as free-form text, his or her trading-related strengths and weaknesses. These reports are then analyzed by the experimenters and similar strengths and weaknesses are grouped into categories with a single common underlying theme. Each subject may report several or no strengths and weaknesses. See Table 3 for a summary.

Then, at the end of each trading day during the duration of the training program, each subject was asked to provide the following information:

B1 **UWIST Mood Adjective Checklist**. This is a 42-item questionnaire, each item rated on a seven-point scale, that is meant to capture the emotional state of the subject at the end of the trading day. The responses are then converted into the eight-category emotional circumplex model of Russel (1980) to reduce estimation error (see Section 2.2 and Table 1). The score for each of the eight emotion categories is calculated as the sum of raw scores for individual mood adjectives in that category.

B2 **Daily Trading Information**. Each subject is asked to report: (1) the total profit/loss on paper-trades for the day; (2) the total profit/loss on actual trades for the day; and (3) the number of actual trades for the day.

In their daily routine, the subjects first reported their trading results followed by the emotional state questionnaire. During the course of the study, the subjects were reminded several times that they had to fill out daily emotion and trading reports. The web interface allowed users to fill out daily reports only for the current day or the day before, which facilitated late-night reporting and accommodated subjects living in different time zones, but ensured timely responses.

Finally, at the end of the five-week program, subjects were asked to complete the following concluding questionnaires:

C1 **Internality, Powerful Others, and Chance (IPC)**. The IPC questionnaire (Levenson, 1972) measures personality traits related to the locus of control, which is a term from social psychology that reflects "a generalized expectancy pertaining to the connection between personal characteristics and/or actions and experienced outcomes" (Lefcourt, 1991). This 24-item questionnaire consists of three subscales consisting of eight questions each, rated on a 6-point scale. The Internality Scale (I) measures how much of the control of their lives subjects attribute to themselves; the Powerful Others Scale (P) measures the extent subjects believe that their lives are controlled by other people; and the Chance Scale (C) is related to how much people believe that pure chance influences their experiences and outcomes.

C2 **Zung Self-Rating Anxiety Scale (SAS) and Self-Rating Depression Scale (SDS)**. We asked participants to complete these questionnaires again to check for any changes in their levels of anxiety and depression. No significant differences were found.

4 Results

During the course of our study, the U.S. stock market experienced a significant decline of over 20%.[3] Therefore, it was not surprising that a number of traders dropped out of our study,

[3]For example, from June 20 to July 23, 2002, the S&P 500 Index dropped from 1006,29 to 797.70.

expressing their frustration with trading in general. Of the 80 participants that initially enrolled in our study, only 33 subjects provided valid responses to the final questionnaires. In addition to demographic information, we asked traders to identify the main strengths, weaknesses, and mistakes in their trading. Their responses clearly indicated that their primary motivation for participating in the LBR program was to eliminate trading mistakes and improve on their weakneses. We assume that a similar motivation applied to their participation in our study. Moreover, many of the subjects did not explicitly distinguish between our study and the LBR program, often asking us questions that pertained exclusively to the LBR program.

Variable	Mean	SD	Percentiles				
			Min	5%	50%	95%	Max
Entire Sample							
Extraversion	47.0	25.3	1.0	5.5	45.0	91.7	98.0
Agreeableness	35.0	31.1	0.0	0.0	26.0	89.0	93.0
Conscientiousness	44.6	29.3	1.0	2.0	41.0	93.9	99.0
Neuroticism	34.5	24.9	0.0	2.2	33.0	81.6	99.0
Openness	34.3	25.3	0.0	0.2	28.0	84.8	99.0
IPC-Internality	36.5	6.2	21.0	26.1	38.0	46.0	48.0
IPC-PowerfulOthers	8.7	5.7	0.0	0.1	8.0	19.8	26.0
IPC-Chance	8.5	5.7	0.0	0.0	8.0	17.9	21.0
Age	46.0	12.9	0.0	28.3	45.0	65.0	70.0
Experience (Years)	5.9	8.1	0.1	0.5	3.0	23.0	44.0
Account Size ($)	$118,004	$269,748	$0	$50	$30,000	$500,000	$1,800,000
Three Years or Less of Experience							
Extraversion	46.4	24.5	1.0	4.4	50.0	87.8	92.0
Agreeableness	21.8	24.5	0.0	0.0	11.0	68.5	77.0
Conscientiousness	40.7	26.7	1.0	1.0	40.0	87.3	89.0
Neuroticism	36.8	28.6	0.0	0.9	34.0	99.0	99.0
Openness	35.6	27.8	0.0	0.9	27.0	91.4	99.0
More Than Three Years of Experience							
Extraversion	47.5	26.5	2.0	6.8	44.0	94.8	98.0
Agreeableness	48.7	31.7	0.0	0.0	54.5	91.4	93.0
Conscientiousness	48.7	31.7	2.0	2.0	43.5	96.6	99.0
Neuroticism	32.2	20.7	4.0	5.6	30.5	75.6	82.0
Openness	33.0	22.8	0.0	0.0	29.5	71.6	78.0

Table 2: Summary statistics for subject demographic profiles and personality traits.

Table 2 provides a summary of the demographics and personality traits of our sample of 80 participants, each of whom acknowledged that he or she was engaged in high-frequency securities trading, i.e., day-trading, for his or her own personal account. The personality-profile data reflect raw scores for the five main scales of the IPIP NEO five-factor model, and the IPC scores reflect raw scores assessed through the IPC Locus of Control instrument. Figure 1 contains histograms of each of the five IPIP NEO personality dimensions for the entire sample of subjects.

Table 3 shows that account sizes varied from $200 to $1,800,000 with a mean of about $116,000 and a median of $35,000. Subjects' reported trading experience varied from virtually none to 44 years, with an average of 5.75 years and a median of 3 years. More than half of the subjects indicated that trading was their full-time occupation. When asked to rate their own trading performance, 20 subjects indicated that they "mostly break even"; for 16, trading was "mostly profitable"; for 14, "mostly unprofitable"; for 10, "consistently profitable"; and for 4 subjects, trading was "consistently unprofitable". Among the 64 subjects who provided their demographics, 57 were males and 7 were females, with ages ranging from 24 to 70 and a mean age of 45. 34 subjects were college educated, 17 held graduate degrees, and 13 completed high school only.

Figure 1 contains a few interesting regularities. Our sample of subjects scored quite low in the Agreeableness dimension, and the histograms for Neuroticism and Openness are also skewed to the left, though not nearly to the same degree. These patterns may seem to suggest a certain "personality type" for traders, but such a conclusion is unwarranted for several reasons. First, our sample of day-traders is quite heterogeneous—even with respect to trading experience—as Table 2 illustrates. Second, these histograms are "point estimates" of the true distribution of personality traits in the population, and estimation error is likely to be quite significant in such a small sample. Finally, we do not have a set of benchmark distributions of these five factors in the general population, hence there is no way to determine whether the histograms in Figure 1—even if measured perfectly—are distinct from those of non-traders.

Table 3 contains a summary of the self-reported strengths and weaknesses reported by the subjects, stratified by account size and trading performance. A number of common traits and behavioral patterns emerge from these strengths and weaknesses. Persistence, tenacity, perseverance, and commitment were common among 14 subjects; good technical analysis or "tapereading" skills among 9 subjects; enthusiasm or desire to succeed among 6 subjects; discipline among 5 subjects; intuition or market "feel" among 4 subjects; ability to

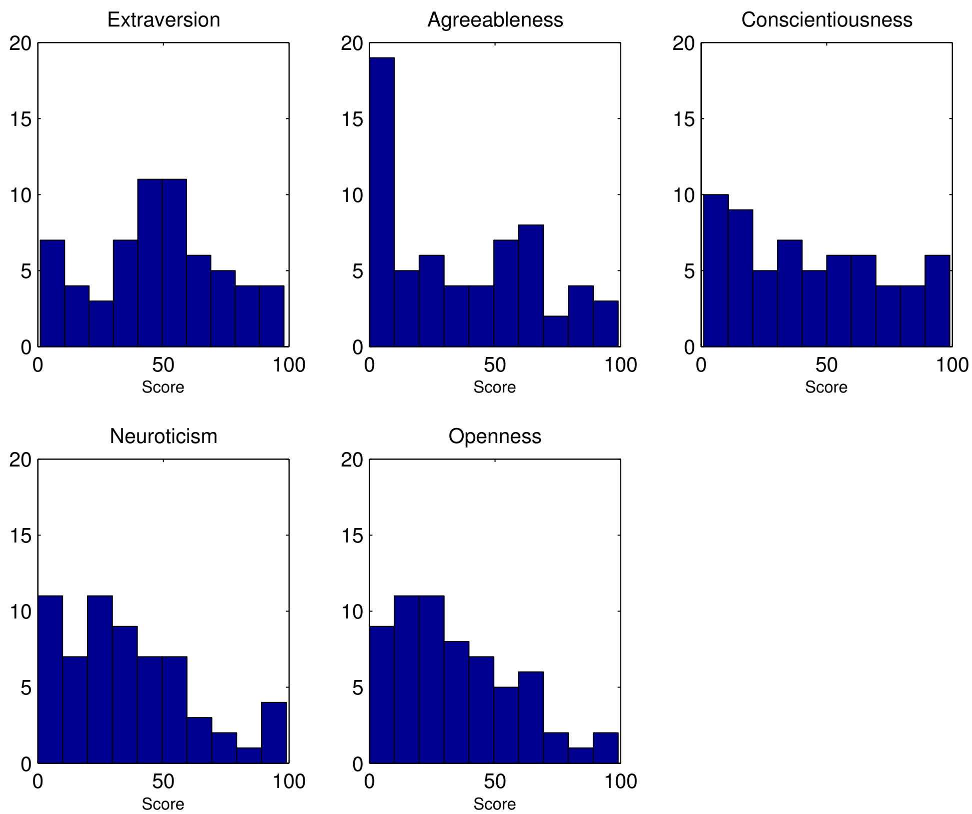

Figure 1: Histogram of personality traits for all subjects.

cut losses among 3 subjects; and focus or concentration among 3 subjects. Among the most common weaknesses reported were: lack of discipline, overtrading or unplanned trades (12 subjects); being too emotional or impulsive (11 subjects); lack of confidence, procrastination or inability to "pull the trigger" (9 subjects); lack of patience (5 subjects); lack of knowledge or experience (5 subjects); and unwillingness to accept or fear of losses (4 subjects).

In Section 4.1 we consider links between personality traits and trading performance for our sample, and in Section 4.2 we turn to the relation between emotional state and trading performance.

Characteristics	Number of Subjects	Account Size ($)			Average Daily P&L ($)			SD(|ΔV|) / Mean(|ΔV|)		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Strengths:										
Persistence / tenacity / perseverance / commitment / patience as related to trading	16	34,000	15,000	46,921	96	85	155	1.63	1.25	0.92
Technical analysis / tapereading	18	100,333	32,500	173,906	90	30	207	1.40	1.38	0.43
Enthusiasm / desire to succeed	13	24,385	25,000	17,149	27	25	105	2.00	1.53	1.15
Discipline	6	265,000	225,000	195,832	2,306	1,792	2,125	0.82	0.92	0.44
Intuition / market "feel"	5	24,000	25,000	12,942	150	43	254	1.31	1.33	0.24
Ability to cut losses	3	41,667	40,000	7,638	479	163	640	1.14	1.11	0.25
Concentration / focus	9	269,444	50,000	578,362	412	280	421	1.23	1.23	0.14
Weaknesses:										
Lack of discipline / Overtrading / Unplanned trades	23	69,174	35,000	109,929	279	157	433	1.39	1.23	0.77
Too emotional / impulsivity	14	189,571	17,500	482,063	176	27	377	1.42	1.28	0.41
Too cautious / cannot pull the trigger / not enough confidence / procrastination	7	121,571	40,000	178,906	1,591	619	2,279	1.42	0.90	1.36
Not exiting losing trades soon enough	10	159,600	45,000	219,029	389	67	747	1.47	1.40	0.45
Exiting winning trade too early	15	153,067	30,000	457,298	183	48	346	1.56	1.39	0.93
Lack of experience / lack of knowledge	8	15,250	14,500	11,081	68	42	135	2.20	1.54	1.18
Lack of patience	5	63,000	50,000	31,145	66	0	225	1.48	1.48	1.03
Unwillingness to accept losses / fear of losses	7	75,000	50,000	81,803	150	104	195	1.32	1.24	0.42

Table 3: Trading results of subjects, stratified by self-assessed strengths and weaknesses.

4.1 Personality Traits and Trading Performance

Four out of the five major personality dimensions exhibit small negative correlation with self-reported trading performance, with Agreeableness exhibiting small positive correlation, but none of these correlations are statistically significant. However, significant negative correlation ($t = -2.23$, $p < 5\%$) is observed for the Internality dimension of the IPC instrument, implying that subjects attributing more control to themselves tend to lose money. Older subjects tend to perform worse, or at least more of them report mostly or consistently unprofitable trading ($t = -3.26$, $p < 1\%$). Not surprisingly, trading performance is positively correlated with trading experience ($t = 1.73$, $p < 10\%$), and when the largest account of $1.8M was removed from the sample, account size is also positively correlated with better trading performance ($t = 2.69$, $p < 1\%$). Among all personality traits measured by both the IPIP NEO and IPC instruments, Agreeableness is the only factor to be significantly and negatively correlated with average trading frequency ($t = -2.17$, $p < 5\%$). Women tend to trade less than men, while older subjects tend to trade less than younger subjects (all with $p < 10\%$).

4.2 Emotional States and Trading Performance

Table 4 contains summary statistics for the emotional scores of the 69 subjects who filled out daily UWIST and trading-performance questionnaires, yielding a total of 755 usable individual daily reports over the five-week period. For each individual daily report, the score for each emotional category was calculated as the sum of raw scores for the individual UWIST mood adjectives in that category. Table 5 contains the correlation matrix for emotional categories, calculated with the raw scores for each emotional category across all days and all individuals. And for those subjects completing meaningful daily reports for three or more days, we computed the correlation coefficients between each emotion category and daily trading performance normalized by the standard deviation of daily profits-and-losses, reported in Table 6.

The correlations in Table 5 show that valence and arousal are related, but do capture some independent characteristics of emotion. The highest correlations are between Unpleasant and Unpleasant Activated (78.3%) and Pleasant and Pleasant Activated (73.4%), underscoring the importance of valence as a common factor, but also demonstrating the fact that the correlation is not perfect, hence arousal is responsible for additional variation. As expected, Pleasant and Unpleasant are negatively correlated (-45.0%), and the only other two correlations greater than 50.0% in absolute value are between Pleasant Activated and Pleasant Deactivated (64.0%) and Activated and Pleasant Activated (59.5%).

Variable	Mean	SD	Min	5%	50%	95%	Max
Pleasant	7.86	2.71	3	3	8	12	15
Unpleasant	4.60	2.24	3	3	4	9	15
Activated	6.85	2.05	3	4	6	11	15
Deactivated	6.27	2.08	3	3	6	10	13
Unpleasant Activated	14.65	5.52	10	10	13	26	50
Pleasant Deactivated	12.84	4.30	5	5	13	20	25
Pleasant Activated	27.47	7.04	9	16	28	40	45
Unpleasant Deactivated	8.24	3.29	6	6	7	15	24

Table 4: Summary statistics for daily emotional scores of all subjects.

Not surprisingly, we see from Table 6 that normalized daily performance is highly positively correlated with Pleasant (37.5, $p < 0.01\%$) and highly negatively correlated with Unpleasant (-31.7, $p < 0.01\%$) emotional states, but not as highly correlated with the Activated or Deactivated categories. When viewed from the valence/arousal standpoint, trading performance exhibits correlation with all four combinations of Pleasant/Unpleasant and Activated/Deactivated categories. Given the low correlations for the arousal categories, these higher correlations for the interacted categories may be attributed primarily to valence. A substantially smaller, but still statistically significant correlation is observed for the trading performance of paper-trades for the Pleasant emotional category, suggesting that paper-trading provides some of the same emotional stimuli of live trading, but is not a perfect simulacrum.

Table 6 also shows that for traders in the top trading-performance tercile, the correlations between profits-and-losses and Pleasant and Unpleasant categories are lower than for the bottom tercile. This suggests that emotional reactivity may be counterproductive for trading performance, but the differences are not large enough to render this conjecture conclusive. However, subjects whose emotional states exhibited higher correlations with their

Correlation Matrix for Emotional Categories (in percent)	Pleasant	Unpleasant	Activated	Deactivated	Unpleasant Activated	Pleasant Deactivated	Pleasant Activated	Unpleasant Deactivated
Pleasant	100.0							
Unpleasant	**-45.0**	100.0						
p-value (in percent)	**< .01**							
Activated	**48.4**	8.0	100.0					
p-value (in percent)	**< .01**	2.7						
Deactivated	**37.6**	6.1	**29.6**	100.0				
p-value (in percent)	**< .01**	9.7	**< .01**					
Unpleasant Activated	**-36.1**	**78.3**	**14.4**	4.7	100.0			
p-value (in percent)	**< .01**	**< .01**	**< .01**	20.0				
Pleasant Deactivated	**72.8**	**-29.9**	**41.8**	**57.4**	**-33.4**	100.0		
p-value (in percent)	**< .01**	**< .01**	**< .01**	**< .01**	**< .01**			
Pleasant Activated	**73.4**	**-30.5**	**59.5**	**32.0**	**-24.6**	**64.0**	100.0	
p-value (in percent)	**< .01**	**< .01**	**< .01**	**< .01**	**< .01**	**< .01**		
Unpleasant Deactivated	-9.5	**36.1**	5.3	**37.9**	**39.8**	-4.8	-13.0	100.0
p-value (in percent)	0.9	**< .01**	14.2	**< .01**	**< .01**	18.5	0.0	

Table 5: Correlation matrix of emotion categories, in percent, derived from aggregate emotional scores for all subjects, all days.

normalized daily profits-and-losses (Pleasant with gains, Unpleasant with losses), do tend to have worse overall profits-and-losses records, supporting the common wisdom that traders too emotionally affected by their daily profits-and-losses are, on average, less successful.

Sample	Pleasant	Unpleasant	Activated	Deactivated	Pleasant Activated	Unpleasant Activated	Pleasant Deactivated	Unpleasant Deactivated
All Traders	**37.5**	**-31.7**	**9.5**	4.7	**30.0**	**-27.5**	**25.8**	**-13.9**
p-value	**< .01**	**< .01**	**1.4**	22.6	**< .01**	**< .01**	**< .01**	**0.0**
Top 1/3	**32.4**	**-39.3**	10.5	-0.2	**19.1**	**-25.2**	**22.1**	**-17.4**
p-value	**< .01**	**< .01**	19.7	98.1	**1.8**	**0.2**	**0.6**	**3.2**
Bottom 1/3	**52.0**	**-46.2**	4.5	9.8	**36.0**	**-44.4**	**42.5**	**-13.9**
p-value	**< .01**	**< .01**	50.8	15.0	**< .01**	**< .01**	**< .01**	**4.0**

Table 6: Correlation between profits-and-losses and eight emotion-category scores for all subjects, and those in the top and bottom cumulative profits-and-losses terciles, in percent.

We also investigated the typical temporal profile of emotional reactivity associated with trading performance by performing a linear regression analysis with daily profits-and-losses regressed on the previous day's emotional scores for each category. We find that yesterday's emotional score was significant for both Pleasant ($t=-2.26$, $p=2.6\%$) and Unpleasant ($t=3.47$, $p=0.07\%$) categories, but with opposite sign than the contemporaneous correlations. This suggests that large "emotional swings" occurring within a 24-hour time scale hurt trading performance the most.

5 Conclusions

The results of our study underscore the importance of emotional state for real-time trading decisions, extending previous findings in several significant ways. In particular, although Lo and Repin (2002) document significant emotional response among the most experienced traders, our results show that extreme emotional responses are apparently counterproductive from the perspective of trading performance, and large changes in emotional state within short periods of time are among the most detrimental.

Contrary to common folk wisdom that financial traders share a certain set of personality traits, e.g., aggressiveness or extraversion, we found little correlation between measured traits and trading performance. Of course, this may be due to a lack of power because of our small sample size and the heterogeneity of our subject pool. In a larger sample, or perhaps in a more homogeneous sample of professional traders, certain personality traits may become more pronounced. For example, in a recent study by Fenton-O'Creevey et al. (2004) of 118 professional traders employed at investment banking institutions, they find that successful traders tend to be emotionally stable introverts who are open to new experiences.

These findings suggest that typical emotional responses may be too crude an evolutionary adaptation for purposes of "financial fitness", and as a result, one component of successful trading may be a reduced level of emotional reactivity. Given that trading is likely to involve higher brain functions such as logical reasoning, numerical computation, and long-term planning, our results are consistent with the current neuroscientific evidence that automatic emotional responses such as fear and greed (e.g., responses mediated by the amygdala) often trump more controlled or "higher-level" responses (e.g., responses mediated by the prefrontal cortex).[4] To the extent that emotional reactions "short-circuit" more complex decisionmaking faculties—for example, those involved in the active management of a portfolio of securities—it should come as no surprise that the result is poorer trading performance.

A number of open research questions remain to be addressed. The lack of correlation between personality traits and trading performance begs for additional data and a more refined analysis, particularly in light of Fenton-O'Creevey et al.'s (2004) tantalizing results. The specific interaction between emotional state and trading performance also deserves further investigation, particularly the dynamic aspects that we have only begun to consider in our linear regression model with lagged dependent variables. Finally, the large body of neuro-imaging research provides a wealth of information about where certain types of decisions and actions originate in the brain. A more detailed analysis of the neuroanatomical origins of financial risk-processing may yield significant insights into the individual and aggregate behavior of market participants and market rationality. Ultimately, we hope to provide a scientific basis for the kind of recommendations for trading success made by Gilbert (2004) in his summary of Fenton-O'Creevey et al. (2004):

[4]See Camerer, Loewenstein, and Prelec (2004) for an excellent review of the neurosciences literature most relevant for economics and finance.

Be an introvert. Keep your emotions stable. Stay open to new experiences. Oh, and try not to be misled by randomness, stop thinking you are in control of the situation, and don't expect any help from your boss.

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