NBER WORKING PAPER SERIES

THE PSYCHOPHYSIOLOGY OF REAL-TIME FINANCIAL RISK PROCESSING

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Working Paper 8508
http://www.nber.org/papers/w8508

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2001

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NBER Working Paper No. 8508
October 2001
JEL No. G10, G14, C91, C93

ABSTRACT

A longstanding controversy in economics and finance is whether financial markets are governed by rational forces or by emotional responses. We study the importance of emotion in the decisionmaking process of professional securities traders by measuring their physiological characteristics, e.g., skin conductance, blood volume pulse, etc., during live trading sessions while simultaneously capturing real-time prices from which market events can be defined. In a sample of 10 traders, we find significant correlation between electrodermal responses and transient market events, and between changes in cardiovascular variables and market volatility. We also observe differences in these correlations among the 10 traders which may be systematically related to the traders' levels of experience.

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The spectacular rise of US stock-market prices in the technology sector over the past few years and the even more spectacular crash last year has intensified the well-worn controversy surrounding the rationality of investors. Most financial economists are advocates of the "Efficient Markets Hypothesis" (Samuelson, 1965) in which prices are determined by the competitive trading of many self-interested investors, and such trading eliminates any informational advantages that might exist among any members of the investment community. The result is a market in which prices "fully reflect all available information" and are therefore unforecastable.

Critics of the Efficient Markets Hypothesis argue that investors are often—if not always— irrational, exhibiting predictable and financially ruinous biases such as overconfidence (Fischoff & Slovic, 1980; Barber & Odean, 2001; Gervais & Odean, 2001), overreaction (DeBondt & Thaler, 1986), loss aversion (Kahneman & Tversky, 1979; Shefrin & Statman, 1985; Odean, 1998), herding (Huberman & Regev, 2001), psychological accounting (Tversky & Kahneman, 1981), mis-calibration of probabilities (Lichtenstein, Fischoff, & Phillips, 1982), and regret (Bell, 1982; Clarke, Krase, & 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. Although no clear alternative to the Efficient Markets Hypothesis has yet emerged, 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. The fact that the current value of the Nasdaq Composite Index, a bellwether indicator of the technology sector, is 1687.70 (September 7, 2001)—only 33.4% of its historical high of 5048.62 (March 10, 2000) reached less than two years ago—lends credence to the critics of market rationality. Such critics argue that either the earlier run-up in the technology sector was driven by unbridled greed and optimism, or that the precipitous drop in value of such a significant portion of US economy must be due to irrational fears and pessimism.

However, recent research in the cognitive sciences and financial economics suggest an important link between rationality in decisionmaking and emotion (Grossberg & Gutowski, 1987; Damasio, 1994; Elster, 1998; Lo, 1999), implying that the two notions are not antithetical, but in fact complementary.

In this study, we attempt to verify this link experimentally by measuring the real-

time psychophysiological characteristics—skin conductance, blood volume pulse, heart rate, electromyographical signals, respiration, and body temperature—of professional securities traders during live trading sessions. Using portable biofeedback equipment, we are able to measure these physiological characteristics in a trader's natural environment without disrupting his workflow while simultaneously capturing real-time financial pricing data from which market events can be defined. By correlating these events with the traders' psychophysiological responses, we are able to determine the relation between financial-risk measures and emotional states and dynamics. In a pilot sample of 10 traders, we find significant correlation between electrodermal responses and transient market events, and between changes in cardiovascular variables and market volatility. We also observe differences in these correlations among the 10 traders which may be systematically related to the amount of trading experience.

In studying the link between emotion and rational decisionmaking in the face of uncertainty, financial securities traders are ideal subjects for several reasons. Because the basic functions of securities trading involve frequent decisions concerning risk/reward trade-offs, traders are almost continuously engaged in the activity that we wish to study. This allows us to conduct our study *in vivo* and with minimal interference to and, therefore, contamination of the subjects' natural motives and behavior. Traders are typically provided with significant economic incentives to avoid many of the biases that are often associated with irrational investment practices. Moreover, they are highly paid professionals that have undergone a variety of training exercises, apprenticeships, and trial periods through which their skills have been finely honed. Therefore, they are likely to be among the most rational decision-makers in the general population, hence ideal subjects for examining the role of emotion in rational decisionmaking processes. Finally, due to the real-time nature of most professional trading operations, it is possible to construct accurate real-time records of the environment in which traders make their decisions, i.e., the fluctuations of market prices of the securities they trade. With such real-time records, we are able to correlate market events such as periods of high price-volatility with synchronous real-time measurements of physiological characteristics.

To measure the emotional responses of our subjects during their trading activities, we focus on indirect manifestations through the responses of the autonomic nervous system (ANS)

(Cacioppo, Tassinary, & 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.

Previous studies have focused primarily on time-averaged (over hours or tens of minutes) levels of autonomic activity as a function of task complexity or mental strain. For example some experiments have considered the link between autonomic activity and driving conditions and road familiarity for non-professional drivers (Brown & Huffman, 1972), and the stage of flight (take-off, steady flight, landing) in a jetfighter flight simulator (Lindholm & Cheatham, 1983). Recently, the focus of research has started to shift towards finer temporal scales (seconds) of autonomic responses associated with cognitive and emotional processes. Perhaps the most influential set of experiments in this area was conducted in the broad context of an investigation of the role of emotion in decisionmaking processes (Damasio, 1994). In one of these experiments, skin conductance responses were measured in subjects involved in a gambling task (Bechara et al., 1997). The results indicated that the anticipation of the more risky outcomes led to more skin conductance responses than of the less risky ones. The brain circuitry involved in anticipating monetary rewards has also been localized (Breiter et al., 2001). Another study (Frederikson et al., 1998) reported neuroanatomical correlates of skin conductance activity with the brain regions that also support anticipation, affect, and cognitively or emotionally mediated motor preparation. Recent experiments (Critchley et al., 1999) support the significance of autonomic responses during risk-taking and reward-related behavior. They provide more details on brain activation correlates of peripheral autonomic responses, and also claim the possibility of discriminating the activity patterns related to changing versus continuing the behavior based on the immediate gain/loss history in a gambling task.

We focus on five types of physiological characteristics in our study: skin conductance, cardiovascular data (blood volume pulse and heart rate), electromyographic data, respiration rate, and body temperature.

Skin conductance response (SCR) is measured by the voltage drop between two electrodes

placed on the skin surface a few centimeters apart. Changes in skin conductance occur when eccrine sweat glands, that are innervated by the sympathetic ANS fibers receives a signal from a certain part of the brain. Three distinct "brain-information systems" can potentially elicit SCR signals (Boucsein, 1992). The affect arousal system is capable of generating a phasic (on the scale of seconds) response that is associated directly with the sensory input indicating attention focusing or defense response, and the amygdala is the primary brain region involved. The emotional response to a novel or highly complex is an example of affect arousal. Another system that can initiate a phasic SCR centers on the basal ganglia and is related to a preparatory activation, mediated by internal cognitive processes. The body exhibits increased perceptual and motor readiness, and high attention levels. Expectation of an event or preparation to an important action illustrates the operation of this system. The third system, often called the "effort system", produces tonic changes in the level of skin conductance and is related to the long-term changes of a general emotional ("hedonic") state or attitude, indicating a nonspecific increase inattention or arousal. Hippocampal information-processing is believed to be behind this system, which is associated with a higher degree of conscious awareness, while the first two are mostly attributed to subconscious processes.

The cardiovascular system consists of the heart and all the blood vessels, and the variables of particular interest are blood volume pulse (BVP) and heart rate (HR). BVP is the rate of flow of blood through a particular blood vessel, and is related to both blood pressure and the diameter of the vessel. Constriction or dilation of the vessels is controlled by the sympathetic branch of the ANS, and along with electrodermal activity, has been shown to be related to information processing and decisionmaking (Papillo & Shapiro, 1990). HR refers to the frequency of the contractions of the heart muscle or myocardium. Specialized neurons— the so-called "pacemaker" cells—initiate the contraction of myocardium, and the output of the pacemakers is controlled by both parasympathetic (HR decrease) and sympathetic (HR increase) ANS branches. BVP and HR track each other closely, so that HR deceleration usually causes an increase in BVP. Compared to SCR arousal indications that refer mostly to cognitive processes, changes in cardiovascular variables register higher levels of arousal which are often somatically mediated. These variables may provide supplemental information for interpreting high SCR signals—elevated SCR accompanied by an increase in HR may be

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an indication of extreme significance of the task or stimulus or, alternatively, simply indicate that some physical activity is being performed simultaneously (Boucsein, 1992).

Electromyographic (EMG) measurements are based on the electrical signals generated by the contraction process of striated muscles. Muscle action potentials travel along the muscle and some portion of the electrical activity leaks to the skin surface where it can be detected with the help of surface electrodes. The activation of particular muscles reflects different types of actions. For example, activation of the facial muscle (i.e., the "masseter" muscle) indicates ongoing speech; activation of the forearm muscle group (i.e., the "flexor digitorum" group) corresponds to finger movements such as typing on a keyboard. In addition to their role in motor activity, certain muscle groups exhibit strong correlations with emotional states. Most of the research in this literature has focused on facial muscles since facial expressions have been linked to emotional states (Ekman, 1982). For example, an increase in EMG activity over the forehead is associated with anxiety and tension, and an increase in activity over the brow accompanied by a slight decrease in activity over the cheek often corresponds to unpleasant sensory stimuli (Cacioppo, Tassinary, & Bernt, 2000). Therefore, EMG measurements can capture very subtle changes in muscle activity that can differentiate otherwise indistinguishable response patterns. However, in our current implementation, the role of EMG measurements is limited to identifying and eliminating anomalous sensor readings caused by certain physical motions of a subject.

Respiration influences the heart rate through vascular receptors (Lorig & Schwartz, 1990), and although this variable is usually is not of primary psychological importance, it is a reliable indicator of physically demanding activities undertaken by the subject, e.g., speaking or coughing, which can often yield anomalous sensor readings if not properly taken into account. Respiration can be measured by placing a sensor that monitors chest expansion and compression.

Finally, body temperature regulation involves the integration of autonomic, motor and endocrine responses, and several studies have related the temperatures of different parts of the body to certain cognitive and emotional contents of the task or stimuli. For example, forehead temperature (a proxy for brain temperature) increases while experiencing negative emotions; cooling enhances positive affect, while warming depresses it (McIntosh et al., 1997). Another study reports hand skin temperature increases with positive affect, and decreases

with threatening and unpleasant tasks (Rimm-Kaufman & Kagan, 1996).

Results

Our sample of subjects consisted of 10 professional traders employed by the foreign-exchange and interest-rate derivatives business unit of a major global financial institution based in Boston, Massachusetts. This institution provides banking and other financial services to clients ranging from small regional startups to Fortune 500 multinational corporations. The foreign-exchange and interest-rate derivatives business unit employs approximately 90 professionals, of which two thirds specializes in the trading of foreign exchange and related instruments, and one third specializes in the trading of interest-rate derivative securities. In a typical day, this business unit engages in 1,000 to 1,200 trades, with an average size of \$3 million to \$5 million per trade. Approximately 80% of the trades are executed on behalf of the clients of the financial institution, with the remaining 20% motivated by the financial institution's market-making activities.

For each of the 10 subjects, five physiological variables were monitored in real time during the entire duration of each session while the subjects sat at their trading consoles (see Figure 1). Six sensors were used: skin conductance response (SCR), blood volume pulse (BVP), body temperature (TMP), respiration (RSP), and two electromyographic sensors (facial and forearm EMG).

The benefits of acquiring real-time physiological measurements *in vivo* must be balanced against the cost of measurement error, spurious signals, and other statistical artifacts which, if left untreated, can obscure and confound any genuine signals in the data. To eliminate as many artifacts as possible while maximizing the informational content of the data, each of the five physiological variables were preprocessed with filters calibrated to each variable individually, and adaptive time-windows were used in place of fixed-length windows to match the event-driven nature of the market variables.

After pre-processing, the following 8 features were extracted from SCR, BVP, temperature, and respiration signals:

1. times of onset of SCR responses
2. amplitudes of SCR responses

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3. average heart rates (every three-second interval)

4. BVP signal amplitudes

5. respiration rates (every five-second interval)

6. respiration amplitudes

7. temperature changes (from the 10-second lag)

These features were selected to reflect the different properties and different information contained in the raw physiological variables. Skin conductance responses were characterized by smooth "bumps", with a relatively fast onset and slow decay, hence the number of such bumps and their relative strength are excellent summary measures of the SCR signal. Three- and five-second intervals for heart and respiration rates were chosen as a compromise between the need for finer time slices to distinguish the onset and completion of physiological and market events and the necessity of a sufficient number of heartbeats and respiration cycles within each interval to compute an average. Under normal conditions, a typical subject will exhibit an average of three to four heartbeats per three-second interval and approximately three breaths per five-second interval. Temperature was the most slow-varying physiological signal, and the 10-second interval to register its change reflected the maximum possible interval in our analysis.

For each session, real-time market data for key financial instruments actively traded or monitored by the subject were collected synchronously with the physiological data. In particular, across the 10 subjects, a total of 15 instruments were considered, 13 foreign currencies and two futures contracts: the euro (EUR), the Japanese yen (JPY), the British pound (GBP), the Canadian dollar (CAD), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Mexican peso (MXP), the Brazilian real (BRL), the Argentinian peso (ARS), the Colombian peso (COP), the Venezuelan bolivar (VEB), the Chilean peso (CLP), S&P 500 futures (SPU), and eurodollar futures (EDU). For each security, four time series were monitored: (1) the bid price P_t^b; (2) the ask price P_t^a; (3) the bid/ask spread $X_t \equiv P_t^b - P_t^a$; and (4) the net return $R_t \equiv (P_t - P_{t-1})/P_{t-1}$, where P_t denotes the price at time t, and prices were sampled every second.

For each of the financial time series, we identified three classes of market events: deviations, trend reversals, and volatility events. These events are often cited by traders as

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significant developments that require heightened attention, potentially signaling a shift in market dynamics and risk exposures. With these definitions and calibrations in hand, we implemented an automatic procedure for detecting deviations, trend reversals, and volatility events for all the relevant time series in each session. Table 1 reports event counts for the financial time series monitored for each subject. Feature vectors were then constructed for all detected market events in all time series for all subjects, and a set of control feature-vectors was generated by applying the same feature-extraction process to randomly selected windows containing no events of any kind. One set of control feature-vectors were constructed for deviation and trend-reversal events (10-second intervals), and a second set was constructed for volatility-type events (five-minute intervals). A two-sided t-test was applied to each component of the each feature vector and the corresponding control vector to test the null hypothesis that the feature vectors were statistically indistinguishable from the control feature-vectors.

For volatility events which, by definition, occurred in five-minute intervals ("event windows"), we constructed feature vectors containing the following information for the duration of the event window:

1. number of SCR responses
2. mean SCR amplitude
3. mean heart rate
4. mean ratio of the BVP amplitude to local baseline
5. mean ratio of the BVP amplitude to global baseline
6. number of temperature changes exceeding 0.1^oF
7. mean respiration rate
8. mean respiration amplitude

where the local baseline for the BVP signal is the average level during the event window and the global baseline is the average over the entire recording session for each trader. Control feature vectors were constructed by applying the feature-extraction process to randomly selected 5-minute windows containing no events of any kind. For the other two types of market events—deviations and trend-reversals—"pre-event" and "post-event" feature-vectors were constructed before and after each market event using the same variables, where features were

aggregated over 10-second windows immediately preceding and following the event. Control feature vectors were generated for these cases as well.

The motivation for the post-event feature-vector was to capture the subject's reaction to the event, with the pre-event feature-vector as a benchmark from which to measure the magnitude of the reaction. A comparison between the pre-event feature vector and a control feature-vector may provide an indication of a subject's anticipation of the event. Latencies of the autonomic responses reported in previous studies were on the time scale of one to 10 seconds (see Cacioppo, Tassinary, & Bernt, 2000), hence 10-second event windows were judged to be long enough for event-related autonomic responses to occur and, at the same time, short enough to minimize the likelihood of overlaps with other events or anomalies. Five-minute windows were used for volatility events because 10-second intervals were simply insufficient for meaningful volatility calculations. For all of the financial time series used in this study, and for most financial time series in general, there are few volatility events that occur in any 10-second interval, except, of course, under extreme conditions, e.g., the stock market crash of October 19, 1987 (no such conditions prevailed during any of our sessions).

The statistical analysis of the physiology and market data was motivated by four objectives: (1) to identify particular classes of events with statistically significant differences in autonomic responses before or after an event, as compared to the no-event control; (2) to identify particular traders or groups of traders based on experience or other personal characteristics that demonstrate significant correlation between market events and autonomic responses; (3) to identify particular financial instruments or groups of instruments that exhibit significant correlations with autonomic responses; and (4) to identify particular physiological variables that demonstrate significant response levels immediately following the event or during the event-anticipation period, as compared to the no-event control

To address the first objective, a total of eight types of events were used for each of the time series:

1. price deviations
2. spread deviations
3. return deviations
4. price trend-reversals

5. spread trend-reversals

6. maximum volatility

7. price volatility

8. return volatility

and for each type of event, a two-sided t-test was performed for the pooled sample of all subjects and all time series. The results—"p-values" or significance levels of the tests—are summarized in the left sub-panel of Table 2, labelled "All Traders". The p-value of a statistic is defined as the smallest level of significance for which the null hypothesis can be rejected based on the statistic's value (Bickel & Doksum, 1977, Chapter 5.2.B). Therefore, smaller p-values indicate stronger evidence against the null hypothesis, and larger p-values indicate stronger evidence in favor of the null. p-values are often reported instead of test statistics because they are easier to interpret (to interpret a test statistic, one must compare it to the critical values of the appropriate distribution; this comparison is performed in computing the p-value). For deviations and trend-reversals, only the number of SCRs reached statistically significant level for four (price and return deviations, price and spread trend-reversals) out of the five event-types. Volatility events were highly correlated with BVP amplitude-related features—significance levels less than 1% were obtained for both BVP amplitude features for all three types of volatility events. Because the results were so similar across the three types of volatility events (maximum volatility, price volatility, and return volatility), we averaged the p-values over the three types of events in Table 2. Such patterns of autonomic responses may indicate the presence of transient emotional responses to deviations and trend-reversal events that occur within 10-second windows, while volatility events, defined in 5-minute windows, elicited a tonic response in BVP.

To explore potential differences between experienced and less experienced traders, sample of 10 traders was divided into two groups, each consisting of five traders, the first containing highly experienced traders, and the second containing traders with low or moderate experience (see Table 5). The results for each of the two groups are reported in the two right subpanels of Table 2, labelled "High Experience" and "Low or Moderate Experience". The experienced traders exhibited low correlations for deviations and trend-reversal events for experienced traders. However, SCR responses exhibited as high correlation with volatility

events as did BVP amplitude. Less experienced traders showed a much higher number of significant correlations between deviations and trend-reversals and the number of SCRs, BVP amplitude, and even the number of temperature increases. In particular, Table 2 shows that sessions with low- and moderate-experience traders yielded 11 p-values less than 5%, while sessions with high-experience traders yielded only two p-values less than 5%. Volatility events exhibited a common pattern of high correlation with BVP amplitude. The difference in correlation patterns for deviations and trend-reversals observed in the fourth testing paradigm indicate that less experienced traders may be more sensitive to short-term changes in the market variables than their more experienced colleagues.

To address the third objective, 10-second intervals immediately preceding and immediately following each deviation and trend-reversal event were compared to control (i.e., no-event) time intervals. Two separate t-tests were conducted—one for pre- and another for post-event time intervals—for each of three types of deviations and two types of trend-reversals. Because the objective is to detect differences in how pre- and post-event feature vectors differed from the control, we used the same control feature vectors for both sets of t-tests. In all cases, the t-tests were designed to test the null hypothesis that both pre- and post-event feature vectors are statistically indistinguishable from the control feature vector. Surprisingly, these two sets of t-tests yielded very similar results, reported in Table 3, implying that none of the physiological variables were predictors of anticipatory emotional responses. These findings may be at least partly explained by the how the events were defined. In particular, the definitions of deviation and trend-reversal events are those instances where the time series achieved a prespecified deviation from the time-series mean and its moving average, respectively. In the absence of large jumps, the values of the time series near an event defined in this way are likely to be comparable to the event itself. Therefore, the traders may be responding to market conditions occurring throughout the pre- and post-event period, not just at the exact time of the event, hence the similarity between the two periods. More complex definitions of events may allow us to discriminate between pre- and post-event physiological responses, and we are exploring several alternatives in ongoing research.

Finally, to address the fourth objective, the following four groups of financial instruments were formed on the basis of similarity in their statistical characteristics:

- Group 1: EUR, JPY
- Group 2: GBP, CAD, CHF, AUD, NZD (other major currencies)
- Group 3: MXP, BRL, ARS, COP, VEB, CLP (Latin American currencies)
- Group 4: SPU, EDU (derivatives)

Table 4 shows that for the major currencies (Groups 1 and 2), none of the physiological features reached a significant level for deviations and trend-reversals. The correlation of BVP amplitude and volatility events stayed reliably high. Latin American currencies (Group 3) exhibited correlation patterns very similar to first two testing paradigms for all types of events. Derivatives (Group 4) demonstrated the same correlations for deviations and trend-reversals as in the first two paradigms, but ceased to show any correlation between BVP amplitude and volatility. The latter could be due to insufficient number of volatility events available for derivatives time series (11 to 13 events of each type of volatility only).

Discussion

Our findings suggest that emotional responses are a significant factor in the real-time processing of financial risks. Contrary to the common belief that emotions have no place in rational financial decisionmaking processes, physiological variables associated with the autonomic nervous system are highly correlated with market events even for highly experienced professional traders. Moreover, the correlation patterns among variables and events differed in important ways for less experienced traders, suggesting the possibility of relating trading skills to certain physiological characteristics that can be measured.

More generally, our experiments demonstrate the feasibility of relating real-time quantitative changes in cognitive inputs (financial information) to corresponding quantitative changes in physiological responses in a complex field environment. Despite the challenges of such measurements, a wealth of information can be obtained regarding high-pressure decisionmaking under uncertainty. Financial traders operate in a controlled environment where the inputs and outputs of the decisions are carefully recorded, and where the subjects are highly trained and provided with great economic incentives to make rational trading decisions. Therefore, *in vivo* experiments in the securities trading context are likely to become an important part of the empirical analysis of individual risk preferences and decisionmaking

processes. In particular, there is considerable anecdotal evidence that subjects involved in professional trading activities perform very differently depending on whether actual gains and losses are involved or if they are trading only with "play" money. Such distinctions have been documented in other contexts; for example, it has been shown that different brain regions are activated during a subject's naturally occurring smile and a forced smile (Damasio, 1994). For this reason, measuring subjects while they are making decisions in their natural environment is essential for any truly unbiased study of financial decisionmaking processes.

In capturing relations between cognitive inputs and affective reactions that are often subconscious and of which subjects are not fully aware, our findings may be viewed more generally as a study of cognitive-emotional interactions and the genesis of "intuition". Decision processes based on intuition are characterized by low levels of cognitive control, low conscious awareness, rapid processing rates, and a lack of clear organizing principles. When intuitive judgments are formed, large numbers of cues are processed simultaneously, and the task is not decomposed into subtasks (Hammond et al., 1987). Experts' judgments are often based on intuition, not on explicit analytical processing, making it almost impossible to fully explain or replicate the process of how that judgment has been formed. This is particularly germane to financial traders—as a group, they are unusually heterogeneous with respect to educational background and formal analytical skills, yet the most successful traders seem to trade based on their intuition about price swings and market dynamics, often without the ability (or the need) to articulate a precise quantitative algorithm for making these complex decisions (Schwager, 1989, 1991; Niederhoffer, 1997). Their intuitive trading "rules" are based on the associations and relations between various information tokens that are formed on a subconscious level, and our findings, and those in the extant cognitive sciences literature suggest that decisions based on the intuitive judgments require not only cognitive but also emotional mechanisms. A natural conjecture is that such emotional mechanisms are at least partly responsible for the ability to form intuitive judgments and for those judgments to be incorporated into a rational decisionmaking process.

Our findings may surprise some financial economists because of the apparent inconsistency with market rationality, but a more sophisticated view of the role of emotion in human cognition (Rolls, 1990, 1994, 1999) can reconcile any contradiction in a complete and intellectually satisfying manner. Emotion is the basis for a reward-and-punishment system that

facilitates the selection of advantageous behavioral actions, providing the numeraire for animals to engage in a "cost-benefit analysis" of the various actions open to them (Rolls, 1999, Chapter 10.3). From an evolutionary perspective, emotion is a powerful adaptation that dramatically improves the efficiency with which animals learn from their environment and their past.

These evolutionary underpinnings are more than simple speculation in the context of financial traders. The extraordinary degree of competitiveness of global financial markets and the outsize rewards that accrue to the "fittest" traders suggest that Darwinian selection—financial selection, to be specific—is at work in determining the typical profile of the successful trader. After all, unsuccessful traders are generally "eliminated" from the population after suffering a certain level of losses. Our results indicate that emotion is a significant determinant of the evolutionary fitness of financial traders. We hope to investigate this conjecture more formally in the future in several ways: a comparison between traders and a control group of subjects without trading experience or with unsuccessful trading experiences; a more fundamental analysis of the neural basis of emotion in traders, aimed at the function of the amygdala and the orbitofrontal cortex (Rolls, 1992; 1999, Chapters 4.4–4.5); and a direct mapping of the neural centers for trading activity through functional magnetic resonance imaging (Breiter et al., 2001).

It should be emphasized that because of the small sample size of 10 subjects, our findings are, at best, suggestive and promising, not conclusive. A more comprehensive study with a much larger sample, a more diverse set of events and subjects, and a broader set of controls is necessary before coming to any firm conclusions regarding the precise mechanisms of the psychophysiology of financial risk-processing.

Methods

Subjects

The 10 subjects' descriptive characteristics are summarized in Table 5. Based on discussions with their supervisors, the traders were categorized into three levels of experience: low, moderate, and high. Five traders specialized in handling client order flow ("Retail"), three specialized in trading foreign exchange ("FX"), and two specialized in interest-rate derivative

securities ("Derivatives"). The durations of the sessions ranged from 49 minutes to 83 minutes and all sessions were held during live trading hours, typically between 8am and 5pm, eastern daylight time.

Physiological Data Collection

A ProComp+ data-acquisition unit and Biograph (Version 1.2) biofeedback software from Thought Technologies, Ltd. were used to measure physiological data for all subjects. All six sensors were connected to a small control unit with a battery power supply, which was placed on each subject's belt and from which a fiber-optic connection led to a laptop computer equipped with real-time data acquisition software (see Figure 2). Each sensor was equipped with a built-in notch filter at 60 Hz for automatic elimination of external power line noise, and standard AgCl triode and single electrodes were used for SCR and EMG sensors, respectively. The sampling rate for all data collection was fixed at 32 Hz. All physiological data except for respiration and facial EMG were collected from each subject's non-dominant arm. SCR electrodes were placed on the palmar sites, the BVP photoplesymographic sensor was placed on the inside of the ring or middle finger, the arm EMG triode electrode was placed on the inside surface of the forearm, over the flexor digitorum muscle group, and the temperature sensor was inserted between the elastic band placed around the wrist and the skin surface. The facial EMG electrode was placed on a masseter muscle, which controls jaw movement and is active during speech or any other activity involving the jaw. The respiration signal was measured by chest expansion using a sensor attached to an elastic band placed around the subject's chest. An example of the real-time physiological data collected over a two-minute interval for one subject is given in Figure 3.

The entire procedure of outfitting each subject with sensors and connecting the sensors to the laptop required approximately five minutes, and was often performed either before the trading day began or during relatively calm trading periods. Subjects indicated that presence of the sensors, wires, and a control unit did not compromise or influence their trading in any significant manner, and that their workflow was not impaired in any way. This was verified not only by the subject, but also by their supervisors. Given the magnitudes of the financial transactions that were being processed, and the economic and legal responsibilities that the subjects and their supervisors bore, even the slightest interference with the subjects'

workflow or performance standards would have caused the supervisors or the subjects to terminate the sessions immediately. None of the sessions were terminated prematurely.

Physiological Data Feature Extraction

An initial smoothing of the raw EMG signals (sampled at 32 Hz) was performed with a moving-average filter of order 23. If the level of the filtered forearm EMG signal exceeded a threshold of 0.75mV, both SCR and BVP readings at this time were discarded because of the high probability of artifacts, e.g., typing, grasping telephone handsets, or inadvertent physical disturbances to the sensors. Similarly, if the level of the filtered facial EMG signal exceeded 0.75mV, the respiration signal at this time was excluded from further processing. A very small spatial displacement of the sensor or the electrode was able to produce a different kind of artifact—an abrupt change in the signal, of the order of 10 to 20 standard deviations within 1/32 of a second. Such jumps did not have any physiological meaning, hence they were excluded from further analysis via adaptive thresholding. Specifically, our adaptive thresholding procedure involved marking all observations that differed by more than 10 standard deviations from a local average (with both standard deviation and local average computed over the most recent 30 seconds of data which, at a sampling rate of 32 Hz, yields 960 observations) and replacing these outliers with the immediately preceding values. This procedure was then repeated until all such artifacts were eliminated. Finally, irrelevant high-frequency signal components and noise were eliminated through a low-pass filter that was individually designed for each of the physiological variables. The relatively smooth nature of the SCR signals permitted the elimination of all harmonics above 1.5 Hz, while the periodic structure of the BVP signals pushed the cut-off frequency to 4.5 Hz. Table 6 reports the means and standard deviations of the signals measured by the six sensors for each of the 10 subjects. After pre-processing, feature vectors were constructed from SCR, BVP, temperature, and respiration signals.

Financial Data Collection

At the start of each session, a common time-marker was set in the biofeedback unit and in the subject's trading console (a networked PC or workstation with real-time datafeeds such as Bloomberg and Reuters) and software installed on the trading console (MarketSheet, by

Tibco, Inc.) stored all market data for the key financial instruments in an Excel spread-sheet, time-stamped to the nearest second. The initial time-markers and time-stamped spreadsheets allowed us to align the market and physiological data to within 0.5 seconds of accuracy. Figure 4 displays an example of the real-time financial data—the euro/US-dollar exchange rate—collected over a 60-minute interval.

Financial Data Feature Extraction

Deviations of a time series $\{Z_t\}$ were defined as those observations that deviated from the series mean by a certain threshold, where the threshold was defined as a multiple k of the standard deviation σ_z of the time series. Positive deviations were defined as those observations Z_t such that $Z_t > \overline{Z} + k\sigma_z$, and negative deviations were defined as those observations Z_t such that $Z_t < \overline{Z} - k\sigma_z$. The value of the multiplier k varied with the particular series and session, and was calibrated to yield approximately five to 10 events per session. Because the volatility of financial time series can vary across instruments and over time, a single value of k for all subjects and instruments is clearly inappropriate. However, the sole objective in our calibration procedure was to maintain an approximately equal number of events for each time series in each session. Deviation events were defined for prices, spreads, and returns. Table 7 reports the average values of k for each of the 15 financial instruments in our study, which range from 0.10 for ARS and BRL (the Argentinian peso and Brazilian real) to 2.03 for EUR (the euro) for price deviations, 0.10 for ARS, BRL, and MXP (the Argentine peso, Brazilian real, and Mexican peso) to 2.85 for GBP (the British pound) for spread deviations, and 0.01 for ARS (the Argentine peso) to 15.00 for COP and MXP (the Colombian and Mexican peso) for return deviations.

Trend-reversal events were defined as instances when a time series $\{Z_t\}$ intersected its five-minute moving-average $\mathrm{MA}_{5\,\mathrm{min}}(Z_t)$ (see, for example, Figure 4, Panel 4A). Positive and negative trend-reversals were defined as those observations Z_t such that $Z_t > (1 + \delta) \cdot \mathrm{MA}_{5\,\mathrm{min}}(Z_t)$ and $Z_t < (1 - \delta) \cdot \mathrm{MA}_{5\,\mathrm{min}}(Z_t)$, respectively. The parameter δ also varied with the particular series and session (see Table 7), ranging from an average of 0.0001 to 0.1 for price series and 0.005 to 1.575 for spreads. Due to the high-frequency sampling rate (one second), prices did not vary often from one observation to the next, hence most of the return values were zero, making it difficult to define trends in returns. Therefore, we defined trend

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reversals only for prices and spreads, excluding returns from this event category.

Three types of volatility events were defined for 5-minute time intervals, indexed by j, based on the following statistics:

$$\sigma_j^1 = \frac{\max_{t_j-300<\tau\leq t_j} P_\tau - \min_{t_j-300<\tau\leq t_j} P_\tau}{\frac{1}{2}(\max_{t_j-300<\tau\leq t_j} P_\tau + \min_{t_j-300<\tau\leq t_j} P_\tau)} \tag{1}$$

$$\sigma_j^2 = \sqrt{\frac{1}{300} \sum_{t_j-300<\tau\leq t_j} (P_\tau - \overline{P_{t_j}})^2} \tag{2}$$

$$\sigma_j^3 = \sqrt{\frac{1}{300} \sum_{t_j-300<\tau\leq t_j} R_\tau^2} \tag{3}$$

where $\overline{P}_{t_j}$ denotes the average price in the interval $t_j - 300$ to t_j, and R_τ^2 is the squared return between $\tau-1$ and τ. We refer to σ_j^1 as "maximum volatility" since it is the difference between the maximum and minimum prices as a fraction of their average, and σ_j^2 and σ_j^3 are the standard deviations of prices and returns, respectively. "Plus" and "minus" volatility events were then defined as those instances when

$$\sigma_j^l > (1+\eta) \cdot \sigma_{j-1}^l \qquad \text{(Plus Event)} \tag{4}$$

$$\sigma_j^l < (1-\eta) \cdot \sigma_{j-1}^l \qquad \text{(Minus Event)} \tag{5}$$

for $l = 1, 2, 3$. The parameter η was calibrated to yield five or less volatility events per session, and ranged from an average of 0.10 to 20.0 (see Table 7). For volatility events, we calibrated the threshold to yield five or fewer events to ensure that the combined time intervals containing volatility events comprised less than 50% of the total session time.

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Trader ID	Facial EMG (μV)		Forearm EMG (μV)		SCR (μm)		TMP (°C)		BVP (%)		RSP (%)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
B32	1.23	1.46	8.84	25.69	3.32	1.38	30.7	0.13	23.34	6.31	34.20	1.69
B34	1.36	3.15	0.88	1.86	11.54	4.55	31.4	0.39	24.93	4.05	33.28	1.15
B35	1.26	1.65	3.31	3.57	2.16	2.71	31.3	0.74	25.00	6.60	35.57	1.65
B36	2.50	4.06	1.04	2.13	10.09	2.16	29.7	0.36	24.87	3.80	33.45	1.57
B37	2.73	18.53	3.66	18.84	3.96	1.73	28.7	0.67	25.06	3.27	31.04	2.43
B38	8.35	20.12	1.51	1.93	12.24	2.21	28.4	0.25	25.09	7.61	29.75	0.61
B39	1.96	2.64	0.36	1.85	25.09	3.40	29.6	0.15	25.10	6.72	36.65	1.08
B310	1.26	0.73	1.75	2.75	1.99	0.47	32.2	0.29	24.87	5.12	36.93	1.53
B311	1.37	8.59	1.85	10.22	28.87	2.10	33.3	0.55	25.21	8.82	33.12	1.61
B312	1.64	1.19	1.08	8.22	3.59	0.71	29.2	0.08	25.10	5.12	31.32	0.79

Table 1. Summary statistics of physiological response data for all traders: means and standard deviations (S.D.) for each of the six sensors.

Physiology Features	All Traders						High Experience						Low or Moderate Experience					
	Market Events						Market Events						Market Events					
	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three
Number of SCR Responses	0.4	54.6	0.7	3.2	31.2	42.1	54.5	36.7	23.1	94.4	91.2	1.9	0.4	71.7	5.0	16.0	52.4	47.9
Average SCR Amplitude	49.7	42.5	63.6	98.9	12.3	18.2	69.0	80.9	21.8	55.9	10.3	21.1	37.9	23.6	60.6	97.3	16.9	38.7
Average Heart Rate	15.5	32.6	54.2	41.9	20.4	71.4	38.4	1.4	41.7	77.3	15.3	97.8	17.4	46.5	29.0	24.9	17.2	8.1
Average BVP Amplitude Relative to Local Baseline	85.2	84.7	46.1	8.0	84.5	0.2	65.8	58.4	50.6	19.5	30.6	4.6	17.4	97.2	0.6	1.0	99.6	0.4
Average BVP Amplitude Relative to Local Baseline	61.9	98.6	9.5	4.7	99.2	0.4	97.4	76.8	26.0	66.5	94.6	3.8	1.4	99.9	0.6	2.5	99.9	1.9
Number of Temperature Jumps	20.0	0.0	22.5	1.1	0.0	98.8	16.0	99.9	99.9	67.5	16.0	16.1	8.9	0.1	0.3	12.0	0.0	97.5
Average Respiration Rate	4.3	56.3	24.9	54.5	87.5	73.9	91.3	80.9	31.6	25.2	56.0	51.8	3.4	87.4	11.5	77.8	99.5	79.1
Average Respiration Amplitude	71.8	67.4	5.7	86.8	85.4	99.9	40.6	20.0	48.8	11.5	4.6	67.3	53.6	13.8	11.0	92.9	98.4	99.9

Table 2. Significance levels (*p*-values), in percent, for individual *t*-tests for each of the eight components of the physiology feature vectors (rows) for each type of market event (columns); *p*-values less than or equal to 5% are highlighted. The left panel gives aggregate results for all traders: in each *t*-test, values of each individual feature of the physiology feature vectors were tested against the same value of the control (no-event) feature vectors. Significance levels for traders with high experience and low or moderate experience are shown in the middle and right panels, respectively.

Physiology Features	Pre-Event Interval						Post-Event Interval					
	Market Events						Market Events					
	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three
Number of SCR Responses	0.4	54.6	0.7	3.2	31.2	42.1	0.0	19.9	0.2	1.0	1.1	42.1
Average SCR Amplitude	49.7	42.5	63.6	98.9	12.3	18.2	20.3	78.8	97.6	23.9	14.2	18.2
Average Heart Rate	15.5	32.6	54.2	41.9	20.4	71.4	14.0	20.6	52.6	42.5	73.3	71.4
Average BVP Amplitude Relative to Local Baseline	85.2	84.7	46.1	8.0	84.5	0.2	87.3	85.7	69.0	22.1	70.3	0.2
Average BVP Amplitude Relative to Local Baseline	61.9	98.6	9.5	4.7	99.2	0.4	71.0	98.8	8.7	5.7	99.3	0.4
Number of Temperature Jumps	20.0	0.0	22.5	1.1	0.0	98.8	16.9	0.0	27.1	0.4	0.2	98.8
Average Respiration Rate	4.3	56.3	24.9	54.5	87.5	73.9	1.2	75.4	54.3	49.2	94.7	73.9
Average Respiration Amplitude	71.8	67.4	5.7	86.8	85.4	99.9	71.0	60.7	2.3	86.0	91.5	99.9

Table 3. Significance levels (p-values), in percent, for pre- and post-event time intervals for each of the eight components of the physiology feature vectors (rows) for each type of market event (columns); p-values less than or equal to 5% are highlighted. The left panel reports significance levels of t-tests for pre-event feature vectors that were tested against controls (no-event feature vectors). The right panel reports significance levels of t-tests for post-event feature vectors tested against the same controls.

Physiology Features	Group 1: EUR and JPY						Group 2: Other Major Currencies*						Group 3: Latin American Currencies**						Group 4: Derivatives***					
	Market Events						Market Events						Market Events						Market Events					
	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three	DEV, Price	DEV, Spread	DEV, Return	TRV, Price	TRV, Spread	VOL, All Three
Number of SCR Responses	5.0%	81.4%	1.2%	37.6%	54.9%	64.1%	92.8%	46.2%	53.9%	47.8%	84.5%	90.3%	0.1%	1.1%	17.1%	0.8%	44.4%	30.0%	3.3%	40.7%	2.1%	2.8%	33.8%	19.8%
Average SCR Amplitude	19.4%	25.0%	26.4%	18.8%	17.0%	36.6%	17.3%	2.7%	49.2%	83.0%	8.2%	17.3%	75.6%	21.3%	91.8%	99.0%	4.7%	88.6%	64.1%	5.0%	22.7%	88.8%	65.5%	66.0%
Average Heart Rate	58.4%	27.7%	64.4%	17.6%	66.5%	76.1%	35.8%	83.2%	65.9%	61.0%	51.0%	66.4%	2.1%	49.2%	92.9%	21.8%	61.8%	47.0%	11.7%	43.6%	25.5%	7.6%	71.9%	48.4%
Average BVP Amplitude Relative to Local Baseline	41.5%	93.9%	50.5%	45.1%	67.9%	1.4%	84.9%	9.3%	7.9%	3.0%	53.1%	1.0%	19.9%	48.1%	0.3%	50.7%	68.7%	2.5%	68.2%	99.5%	98.1%	96.2%	72.5%	98.3%
Average BVP Amplitude Relative to Local Baseline	19.6%	99.4%	1.3%	51.8%	91.8%	1.6%	12.1%	8.1%	2.1%	0.1%	29.5%	0.7%	88.8%	65.0%	34.3%	58.6%	93.0%	47.0%	78.1%	87.4%	86.4%	98.9%	80.4%	85.6%
Number of Temperature Jumps	6.2%	0.0%	98.4%	1.3%	23.9%	84.7%	14.9%	74.8%	1.1%	7.0%	0.0%	89.6%	90.7%	54.9%	96.6%	90.2%	93.4%	93.6%	96.0%	83.8%	83.9%	89.9%	96.3%	83.4%
Average Respiration Rate	93.5%	88.5%	74.1%	46.7%	95.4%	81.8%	0.0%	10.4%	17.9%	4.0%	65.8%	81.8%	49.8%	91.3%	57.7%	29.1%	78.2%	52.5%	83.3%	84.8%	60.3%	19.8%	51.4%	80.1%
Average Respiration Amplitude	59.1%	47.1%	44.7%	55.4%	97.3%	98.7%	53.1%	9.9%	5.4%	30.0%	72.4%	99.2%	8.3%	58.3%	37.7%	25.8%	61.5%	80.9%	70.1%	37.4%	29.7%	54.1%	44.7%	60.3%

*   GBP, CAD, CHF, AUD, NZD
** MXP, BRL, ARS, COP, VEB, CLP
*** EDU, SPU

Table 4. Significance levels (*p*-values), in percent, for individual *t*-tests for each of the eight components of the physiology feature vectors (rows) for each type of market event (columns); *p*-values less than or equal to 5% are highlighted. The results for each currency group are shown in one of the four panels.

Trader ID	Gender	Experience	Specialty	Market Data Available	Number of Market Time Series Recorded	Session Duration, Min and Sec	Session Start Time
B33	F	high	retail	major currencies	2	49'30"	13:20
B34	M	high	FX	major currencies	3	83'32"	08:56
B35	M	high	retail	major currencies	4	66'30"	11:02
B36	M	high	derivatives	S&P500 futures, eurodollar futures	3	79'16"	12:55
B37	M	moderate	FX	Latin American, major currencies	9	70'06"	09:17
B38	M	low	FX	Latin American, major currencies	3	72'12"	11:02
B39	M	high	derivatives	S&P500 futures, eurodollar futures	9	62'03"	08:19
B310	M	low	retail	major currencies	7	60'08"	09:47
B311	M	moderate	retail	major currencies	7	54'25"	11:32
B312	M	low	retail	major currencies	7	59'00"	09:10

Table 5. Summary statistics for all subjects: individual trader's characteristics, specialty, type and number of market time-series collected during the session, session duration, and absolute time (Eastern standard time) of the start of the session.

Trader ID	EUR			JPY			Other Major Currencies*			Latin American Currencies**			Derivatives***		
	DEV	TRV	VOL	DEV	TRV	VOL	DEV	TRV	VOL	DEV	TRV	VOL	DEV	TRV	VOL
B32	21	16	15	25	17	15	-	-	-	-	-	-	-	-	-
B34	18	10	14	17	17	14	-	-	-	-	-	-	-	-	-
B35	20	16	14	13	17	15	21	9	15	24	16	13	-	-	-
B36	-	-	-	-	-	-	-	-	-	-	-	-	28	23	31
B37	19	19	14	18	18	12	18	18	14	105	86	63	-	-	-
B38	21	20	12	22	18	13	23	20	15	96	61	56	-	-	-
B39	-	-	-	-	-	-	-	-	-	-	-	-	40	37	23
B310	10	17	10	18	16	14	116	59	61	-	-	-	-	-	-
B311	17	15	15	17	16	15	94	61	67	-	-	-	-	-	-
B312	19	17	15	16	19	13	107	83	71	-	-	-	-	-	-

*   GBP, CAD, CHF, AUD, NZD
** MXP, BRL, ARS, COP, VEB, CLP
*** EDU, SPU

Table 6. Number of deviation (DEV), trend-reversal (TRV), and volatility (VOL) events detected in real-time market data for each trader over the course of each trading session.

Security Identifier	Mean k for Price	Mean k for Spread	Mean k for Return	Mean δ for Price	Mean δ for Spread	Mean δ for return	Mean η for Maximum Volatility	Mean η for Average Price Volatility	Mean η for Average Return Volatility
ARS	0.10	0.10	0.01	0.10000	0.100	-	0.10	0.10	0.10
AUD	1.38	1.47	10.14	0.00090	0.475	-	0.58	0.43	0.58
BRL	0.10	0.10	0.50	0.00010	0.005	-	20.00	10.00	20.00
CAD	1.02	0.84	10.83	0.00058	0.250	-	0.72	0.72	0.63
CHF	1.75	2.12	9.17	0.00053	0.610	-	0.38	0.42	0.38
CLP	0.40	1.00	12.00	0.00020	0.200	-	0.60	0.50	0.50
COP	0.50	0.50	15.00	0.00070	0.200	-	5.00	3.00	3.00
EDU	1.40	2.50	11.00	0.00155	1.575	-	0.75	0.70	0.43
EUR	2.03	2.43	7.06	0.00066	1.274	-	0.45	0.45	0.36
GBP	1.54	2.85	9.24	0.00039	0.472	-	0.46	0.51	0.42
JPY	1.18	1.86	8.56	0.00089	0.803	-	0.54	0.54	0.41
MXP	1.00	0.10	15.00	0.00040	0.010	-	1.00	1.05	0.85
NZD	1.58	1.30	10.00	0.00085	0.288	-	0.73	0.65	0.73
SPU	0.63	0.25	14.09	0.00004	0.002	-	0.68	0.07	0.03
VEB	1.90	2.50	11.00	0.00060	0.500	-	0.30	0.40	0.40

Table 7. Average values of the parameters used to define market events: deviations (*k*), trend-reversals (δ), and volatility events (η); see equations (1)–(3) in the text.

Market information (Reuters, Bloomberg)
Order screen, etc.

TIBCO market spreadsheet

Laptop with data
acquisition software

Real-time data feed
to the market data
acquisition computer
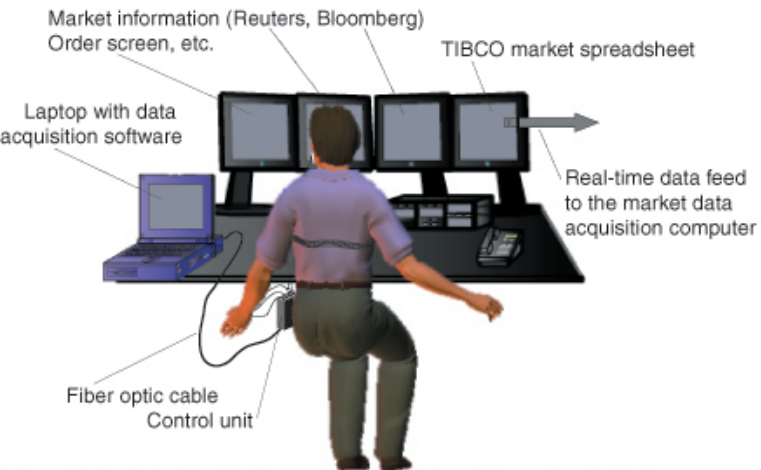
Fiber optic cable
Control unit

Figure 1. Typical set-up for the measurement of real-time physiological responses of financial traders during live trading sessions. Real-time market data used by the traders are recorded synchronously and subsequently analyzed together with the physiological response data.
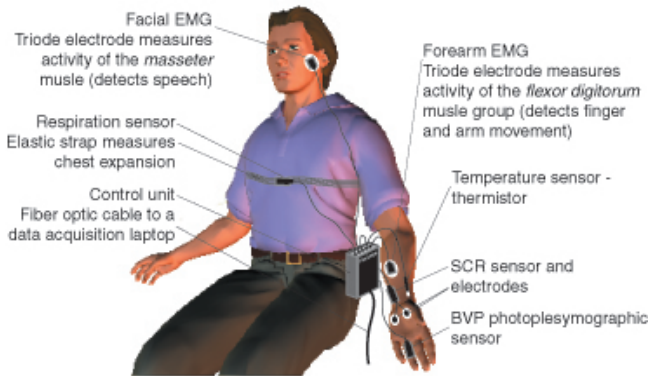
Facial EMG
Triode electrode measures activity of the *masseter* musle (detects speech)

Forearm EMG
Triode electrode measures activity of the *flexor digitorum* musle group (detects finger and arm movement)

Respiration sensor
Elastic strap measures chest expansion

Control unit
Fiber optic cable to a data acquisition laptop

Temperature sensor - thermistor

SCR sensor and electrodes

BVP photoplesymographic sensor

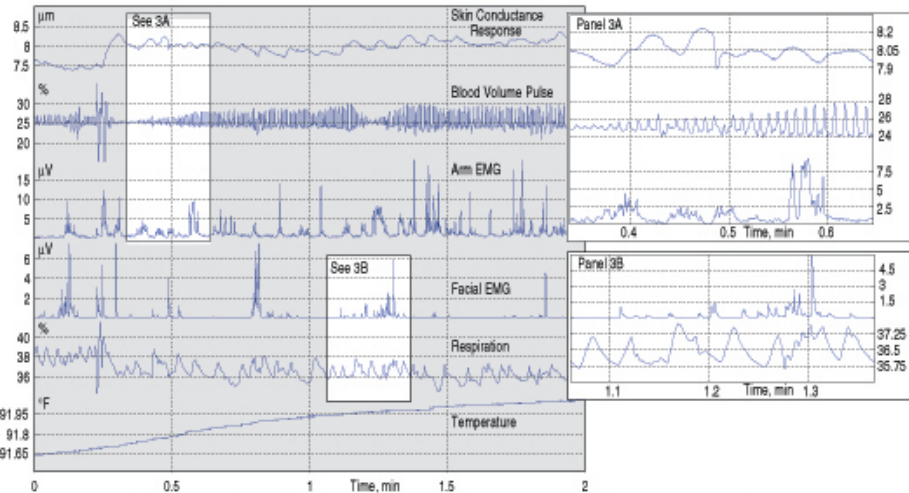Figure 2. Placement of sensors for measuring physiological responses.

Figure 3. Typical physiological response data recorded by six sensors for a single subject over a two-minute time interval.
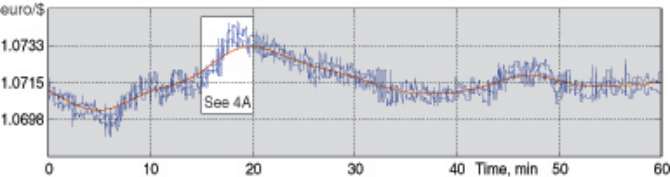
Figure 4. Typical real-time market data (euro/US dollar exchange rate) recorded during a 60-minute time interval, and corresponding five-minute moving-average.