# The Psychophysiology of Real-Time Financial Risk Processing

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## 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 decision-making 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 detected. In a sample of 10 traders, we find statistically significant differences in mean electrodermal responses during transient market events relative to no-event control periods, and statistically significant mean changes in cardiovascular variables during periods of heightened market volatility relative to normal-volatility control periods. We also observe significant differences in these physiological responses across the 10 traders that may be systematically related to the traders' levels of experience. ■

## INTRODUCTION

The spectacular rise of U.S. 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 (Barber & Odean, 2001; Gervais & Odean, 2001; Fischoff & Slovic, 1980), overreaction (DeBond & Thaler, 1986), loss aversion (Odean, 1998; Shefrin & Statman, 1985; Kahneman & Tversky, 1979), herding (Huberman & Regev, 2001), psychological accounting (Tversky & Kahneman, 1981), miscalibration of probabilities (Lichtenstein, Fischoff, & Phillips, 1982), and regret (Clarke, Krase, & Statman, 1994; Bell, 1982). 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 (Shefrin, 2001). The fact that the current value of the Nasdaq Composite Index, a bellwether indicator of the technology sector, is 1646.34 (October 17, 2001)—only 32.6% of its historical high of 5048.62 (March 10, 2000), reached less than 2 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 the U.S. 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 decision making and emotion (Loewenstein, 2000; Peters & Slovic 2000; Lo, 1999; Elster, 1998; Damasio, 1994; Grossberg & Gutowski, 1987), 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 (BVP), heart rate (HR), 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 their workflow while simultaneously capturing real-time financial pricing data from which market events can be defined. By matching these events with the traders' psychophysiological responses, we are able to determine the relation between

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financial risk measures and emotional states and dynamics. In a pilot sample of 10 traders, we find statistically significant differences in mean electrodermal responses during transient market events as compared with no-event control baselines, and statistically significant mean changes in cardiovascular variables during periods of heightened market volatility as compared with normal-volatility control baselines. We also observe significant differences in mean physiological responses among the 10 traders that may be systematically related to the amount of trading experience.

In studying the link between emotion and rational decision making 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, minimal 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 decision-making 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, namely, the fluctuations of market prices of the securities that they trade. With such real-time records, we are able to match 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 the 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 noninvasively 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 nonprofessional 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 decision-making processes (Damasio, 1994). In one of these experiments, skin conductance responses (SCRs) were measured in subjects involved in a gambling task (Bechara, Damasio, Tranel, & Damasio, 1997). The results indicated that the anticipation of the more risky outcomes led to more SCRs than of the less risky ones. The brain circuitry involved in anticipating monetary rewards has also been localized (Breiter, Aharon, Kahneman, Dale, & Shizgal, 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, Krase, & Statman, 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 (BVP and HR), electromyographic (EMG) data, respiration rate, and body temperature.

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 receive 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 response (on the scale of seconds) 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 task 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 in attention 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 BVP and 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, it has been shown to be related to information processing and decision making (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 an indication of extreme significance of the task or stimulus or, alternatively, simply indicate that some physical activity is being performed simultaneously (Boucsein, 1992).

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 et al., 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 HR through vascular receptors (Lorig & Schwartz, 1990), and although this variable is usually not of primary psychological importance, it is a reliable indicator of physically demanding activities undertaken by the subject, for example, 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, Zajonc, Vig, & Emerick, 1997). Another study reports that 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, MA. 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 1000- 1200 trades, with an average size of US$3- 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: SCR, 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

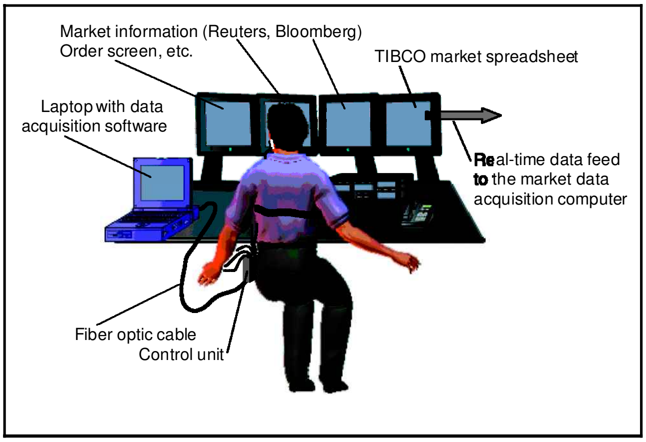


**Figure 1.** Typical set-up for the measurement of real-time physiological responses of financial traders during live trading sessions. Real-time market data used by the traders are recorded synchronously and subsequently analyzed together with the physiological response data.

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 preprocessing, the following seven features were extracted from SCR, BVP, temperature, and respiration signals:

1. times of onset of SCR responses
2. amplitudes of SCR responses
3. average HR (every 3 sec)
4. BVP signal amplitudes
5. respiration rates (every 5 sec)
6. respiration amplitudes
7. temperature changes (from the 10-sec lag)

These features were selected to reflect the different properties and different information contained in the raw physiological variables. SCRs 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. Intervals of 3 and 5 sec 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 3-sec interval and approximately three breaths per 5-sec interval. Temperature was the slowest-varying physiological signal, and the 10-sec 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 $P_t^{\mathrm{b}}$; (2) the ask price $P_t^{\mathrm{a}}$; (3) the bid/ask spread $X_t \equiv P_t^{\mathrm{b}} - P_t^{\mathrm{a}}$; and (4) the net return $R_t \equiv (P_t - P_{t-1}) / P_{t-1}$, where $P_t$ denotes the mid-spread price at time $t$, and all 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 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 was constructed for deviation and trend-reversal events (10-sec intervals), and a second set was constructed for volatility-type events (5-min intervals). A two-sided $t$ test was applied to each component of 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 5-min intervals (event windows), we constructed feature vectors containing the following information for the duration of the event window:

1. number of SCR responses
2. average SCR amplitude
3. average HR
4. average ratio of the BVP amplitude to local baseline
5. average ratio of the BVP amplitude to global baseline
6. number of temperature changes exceeding 0.1°F
7. average respiration rate
8. average 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-min windows containing no events of any

**Table 1.** 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

| | *EUR* | | | *JPY* | | | *Other Major Currencies*[a] | | | *Latin American Currencies*[b] | | | *Derivatives*[c] | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Trader ID* | *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 | - | - | - | - | - | - |

[a]GBP, CAD, CHF, AUD, NZD.

[b]MXP, BRL, ARS, COP, VEB, CLP.

[c]EDU, SPU.

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-sec 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 a time scale of 1 to 10 sec (see Cacioppo et al., 2000), hence, 10-sec 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-sec 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-sec interval, except, of course, under extreme conditions, for example, the stock market crash of October 19, 1987 (no such conditions prevailed during any of our sessions).

The statistical analysis of the physiological and market data was motivated by four objectives: (1) to identify particular classes of events with statistically significant differences in mean 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 mean autonomic responses during market events; (3) to identify particular financial instruments or groups of instruments that are associated with significant mean autonomic responses; and (4) to identify particular physiological variables that demonstrate significant mean 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 in which mean autonomic responses during event periods were compared to mean autonomic responses during no-event control periods.

The $t$ statistics corresponding to the two-sided hypothesis test are given in the left subpanel of Table 2, labelled "All Traders." Statistics that are significant at the 5% level—based on the $t$ distribution with the appropriate degrees of freedom for each entry—are highlighted. For

**Table 2.** *t* Statistics for Two-Sided Hypothesis Tests of the Difference in Mean Autonomic Responses During Market Events Versus No-Event Controls for Each of the Eight Components of the Physiology Feature Vectors (Rows) for Each Type of Market Event (Columns)

| | *Market Events* | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *All Traders* | | | | | | *High Experience* | | | | | | *Low or Moderate Experience* | | | | | |
| *Physiology Features* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* |
| Number of SCR responses | **2.872** | 0.604 | **2.088** | **1.664** | 0.636 | 0.579 | 0.561 | 1.228 | −0.221 | −1.261 | 0.184 | **2.081** | **2.696** | 0.123 | **2.752** | **2.170** | −0.665 | −0.688 |
| Average SCR amplitude | −0.695 | 0.887 | 0.186 | −2.478 | 1.136 | 0.880 | 0.030 | 0.344 | 0.744 | −1.340 | 1.149 | 0.904 | 0.756 | 1.578 | −1.265 | −1.947 | −0.012 | −0.615 |
| Average HR | 0.905 | −0.588 | −0.596 | −0.617 | 1.032 | −0.270 | 0.449 | **1.886** | −1.797 | −1.635 | **1.836** | −2.018 | 1.310 | 0.051 | −0.382 | −1.106 | −0.311 | 1.283 |
| Average BVP amplitude relative to local baseline | 0.128 | −0.855 | 0.688 | 1.408 | −0.523 | **3.619** | −0.061 | −0.747 | 0.334 | 0.015 | 0.164 | **2.623** | −0.204 | −1.775 | 0.875 | **1.796** | −1.289 | **2.708** |
| Average BVP amplitude relative to global baseline | 1.417 | −2.726 | **2.324** | 1.417 | −2.211 | **2.886** | −2.529 | −1.367 | 1.590 | 1.110 | −1.165 | **2.301** | **1.917** | −2.664 | **1.884** | **2.082** | −1.759 | **2.758** |
| Number of temperature jumps | 0.988 | **2.820** | 0.650 | **1.777** | **4.868** | −2.482 | −1.010 | −1.435 | NA | NA | NA | 1.644 | 0.837 | **2.902** | 1.145 | **2.445** | **2.633** | −3.213 |
| Average respiration rate | 0.729 | −1.173 | 0.671 | 1.155 | −1.628 | −0.064 | −1.556 | 1.109 | 0.121 | 0.866 | −0.102 | 0.093 | 0.079 | −0.552 | 0.323 | −0.631 | −2.170 | −1.528 |
| Average respiration amplitude | −1.646 | −0.250 | 0.136 | 0.034 | −1.487 | −3.499 | 1.087 | 0.265 | −1.777 | −0.657 | 0.121 | −0.607 | −2.749 | −1.319 | **2.142** | 0.055 | −2.832 | −4.533 |

**Bolded** statistics are significant at the 5% level.

The left panel gives aggregate results for all traders. Similar *t* tests for traders with high experience and low or moderate experience are shown in the middle and right panels, respectively. Entries marked "NA" indicate that no valid data were present in either the event or control feature vector for the particular market-event type.

DEV = deviation; TRV = trend-reversal; VOL = volatility; SCR = skin conductance responses; HR = heart rate; BVP = blood volume pulse.

deviations and trend-reversals, both the number of SCRs and the number of temperature jumps reached statistically significant levels for three out of the five event types. BVP amplitude-related features were highly significant for volatility events—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 report the results only for maximum volatility 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-sec windows, while volatility events, defined in 5-min windows, elicited a tonic response in BVP.

To explore potential differences between experienced and less experienced traders, a 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, where the levels of experience were determined through interviews with the traders' supervisors. 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 high-experience traders generally exhibited low responses for deviations and trend-reversal events, with only two types of market events (spread deviations and spread trend-reversals) eliciting significant mean autonomic responses (average HR). However, even for high-experience traders, volatility events induced statistically significant mean responses for both SCR and BVP amplitude. Less experienced traders showed a much higher number of significant mean responses in the number of SCRs, BVP amplitude, and number of temperature increases for deviations and trend-reversal events. Table 2 shows that sessions with low- and moderate-experience traders yielded 13 $t$ statistics significant at the 5% level, while sessions with high-experience traders yielded only five $t$ statistics significant at the 5% level. For both sets of traders, volatility events were associated with significant BVP amplitude. The differences in response patterns for deviations and trend-reversals observed in this case 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-sec 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 the three types of deviations and two types of trend-reversals. Because the objective was 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 were 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 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)

Group 1 is, by far, the most actively traded set of financial instruments and accounts for most of the trading activities of our sample of 10 traders, hence, it is not surprising that the pattern of statistical significance for Group 1 in Table 4 is almost identical to the pattern for all traders in Table 2 (the left panel). SCR is significant for price and return deviations, temperature jumps are significant for spread and price deviations, and both measures of BVP are significant for volatility events. For Group 2, none of the eight physiological variables were significant for price or spread deviations, although temperature changes and respiration rates were significant for return deviations, and both BVP measures were significant for price trend-reversals and volatility events. The financial instruments in Group 2 were not the primary focus of any of the traders in our sample, which may explain the different patterns of significance as compared with Group 1. Group 4 contains the fewest significant responses, and this is consistent with the fact that these securities were traded by two of the most experienced traders in our sample. Derivative securities are considerably more complex instruments than the spot currencies, requiring more skill and training than the other groups of securities. However, SCR was

**Table 3.** *t* Statistics for Two-Sided Hypothesis Tests of the Difference in Mean Autonomic Responses During Pre- and Post-event Time Intervals Versus No-Event Controls for Each of the Eight Components of the Physiology Feature Vectors (Rows) for Each Type of Market Event (Columns)

| | *Market Events* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Pre-event Interval* | | | | | | *Post-event Interval* | | | | | |
| *Physiology Features* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* |
| Number of SCR responses | **3.756** | 1.543 | **2.540** | **2.118** | **2.401** | 0.579 | **2.872** | 0.604 | **2.088** | **1.664** | 0.636 | 0.579 |
| Average SCR amplitude | 0.700 | −0.454 | −1.793 | 0.511 | 1.068 | 0.880 | −0.695 | 0.887 | 0.186 | −2.478 | 1.136 | 0.880 |
| Average HR | 0.968 | −0.205 | −0.552 | −0.663 | −0.386 | −0.270 | 0.905 | −0.588 | −0.596 | −0.617 | 1.032 | −0.270 |
| Average BVP amplitude relative to local baseline | 0.043 | −0.895 | 0.060 | 0.814 | −0.045 | **3.619** | 0.128 | −0.855 | 0.688 | 1.408 | −0.523 | **3.619** |
| Average BVP amplitude relative to global baseline | 1.183 | −2.794 | **2.397** | 1.317 | −2.256 | **2.886** | 1.417 | −2.726 | **2.324** | 1.417 | −2.211 | **2.886** |
| Number of temperature jumps | 1.110 | **2.767** | 0.505 | **2.158** | **3.925** | −2.482 | 0.988 | **2.820** | 0.650 | **1.777** | **4.868** | −2.482 |
| Average respiration rate | 1.261 | −1.650 | −0.254 | 1.303 | −1.999 | −0.064 | 0.729 | −1.173 | 0.671 | 1.155 | −1.628 | −0.064 |
| Average respiration amplitude | −1.620 | −0.067 | 0.561 | 0.068 | −1.807 | −3.499 | −1.646 | −0.250 | 0.136 | 0.034 | −1.487 | −3.499 |

**Bolded** statistics are significant at the 5% level.

The left panel contains *t* statistics for pre-event feature vectors and the right panel contains *t* statistics for post-event feature vectors, both tested against the same set of controls.

DEV = deviation; TRV = trend-reversal; VOL = volatility; SCR = skin conductance responses; HR = heart rate; BVP = blood volume pulse.

**Table 4.** *t* Statistics for Two-Sided Hypothesis Tests of the Difference in Mean Autonomic Responses During Market Events Versus No-Event Controls for Each of the Eight Components of the Physiology Feature Vectors (Rows) for Each Type of Market Event (Columns), Grouped Into Four Distinct Sets of Financial Instruments

| | *Market Events* | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Group 1: EUR and JPY* | | | | | | *Group 2: Other Major Currencies*[a] | | | | | | *Group 3: Latin American Currencies*[b] | | | | | | *Group 4: Derivatives*[c] | | | | | |
| *Physiology Features* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* | *DEV, Price* | *DEV, Spread* | *DEV, Return* | *TRV, Price* | *TRV, Spread* | *VOL, Maximum* |
| Number of SCR responses | **1.653** | −1.902 | **1.964** | −0.554 | −2.286 | −0.940 | 0.332 | 0.112 | 0.544 | −1.795 | −2.417 | −1.108 | **2.498** | **2.188** | −0.397 | **2.995** | −0.405 | 0.898 | **2.682** | 1.094 | **1.669** | 1.594 | −0.239 | **2.236** |
| Average SCR amplitude | −1.639 | 0.623 | 0.279 | −1.756 | 1.098 | −1.112 | −0.503 | 0.540 | 1.138 | −2.190 | −0.106 | 0.896 | 1.116 | 1.279 | −1.525 | −1.802 | **2.220** | −0.986 | −0.610 | 1.236 | 0.930 | −1.513 | 0.242 | −1.510 |
| Average HR | 0.731 | −0.004 | −1.268 | −1.815 | −0.698 | −1.612 | −0.991 | −1.452 | −1.034 | −1.326 | −0.308 | −1.089 | **2.921** | −1.432 | −1.070 | −1.002 | −1.416 | 1.183 | 0.816 | −0.322 | 0.577 | 0.492 | 0.515 | −0.169 |
| Average BVP amplitude relative to local baseline | 0.562 | −1.368 | −0.805 | 1.273 | 0.885 | **2.587** | −0.922 | 0.220 | 1.457 | **2.323** | −1.275 | **2.308** | −0.982 | −0.001 | **2.828** | 1.454 | 0.598 | **2.192** | −0.592 | −3.032 | −3.953 | −0.894 | −1.904 | −1.433 |
| Average BVP amplitude relative to local baseline | 0.597 | −3.010 | **1.714** | 0.375 | −0.252 | **2.592** | 0.521 | 1.448 | 0.972 | **3.087** | −1.499 | **2.633** | −1.925 | −0.849 | 1.482 | 0.259 | −0.351 | −0.129 | −0.660 | −1.501 | −3.274 | −1.626 | −2.004 | −2.411 |
| Number of temperature jumps | 0.688 | **4.141** | −1.444 | **2.283** | 0.295 | −2.043 | 1.073 | −1.557 | **2.404** | 1.248 | **3.726** | −1.564 | −1.603 | −1.275 | −1.922 | −0.512 | −1.128 | −1.540 | −1.367 | −1.349 | −1.362 | −1.367 | −1.053 | NA |
| Average respiration rate | 0.525 | −1.741 | −0.797 | 0.163 | −1.884 | −0.004 | 0.756 | −0.560 | **2.023** | −1.095 | −1.784 | −0.116 | 0.037 | 0.446 | −1.124 | 0.643 | −1.392 | 0.125 | −1.946 | −0.291 | 0.361 | 0.416 | −1.105 | −1.725 |
| Average respiration amplitude | −2.120 | −0.692 | 0.345 | −0.509 | −0.935 | −2.079 | −0.746 | 0.560 | 0.470 | 0.905 | 0.893 | −3.839 | 0.280 | −0.207 | 1.426 | −0.360 | −0.534 | −0.437 | 0.920 | −0.955 | −1.915 | 1.257 | 1.593 | −0.039 |

**Bolded** statistics are significant at the 5% level.

[a]MXP, BRL, ARS, COP, VEB, CLP.

[b]MXP, BRL, ARS, COP, VEB, CLP.

[c]EDU, SPU.

Entries marked ''NA'' indicate that no valid data was present in either the event or control feature vector for the particular market-event type.

DEV = deviation; TRV = trend-reversal; VOL = volatility; SCR = skin conductance responses; HR = heart rate; BVP = blood volume pulse.

significant for both price and return deviations in Group 4, which was not the case for the sample of high-experience traders in Table 2. SCR was also significant for volatility events in Group 4, which is consistent with the central role that volatility plays in the pricing and hedging derivative securities (Black & Scholes, 1973; Merton, 1973). Volatility is a more sophisticated aspect of the trading milieu, requiring a higher degree of training to fully appreciate its implications for market trends and profit-and-loss probabilities. This may explain the fact that SCR is significant for volatility events only among the high-experience traders in Table 2 and the derivatives traders in Table 4.

## 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 decision-making processes, physiological variables associated with the ANS exhibit significant changes during market events even for highly experienced professional traders. Moreover, the response patterns among variables and events differed in important ways for less experienced traders—mean autonomic responses were significantly higher—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 decision making 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 decision-making processes. In particular, there is considerable anecdotal evidence that subjects involved in professional trading activities perform very differently depending on whether real financial capital is at risk or if they are trading with ''play'' money. Such distinctions have been documented in other contexts; e.g., 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 decision-making 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 broadly 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, Hamm, Grassia, & Pearson, 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 (Niederhoffer, 1997; Schwager, 1989, 1992). 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 decision-making process.

Our results 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, Chap. 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; an analysis of the psychophysiological responses of traders in a laboratory environment; a more direct analysis of the correlation between autonomic responses and trading performance; 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, Chap. 4.4- 4.5); and a direct mapping of the neural centers for trading activity through functional magnetic resonance imaging (Breiter et al., 2001).

There are a number of caveats that must be kept in mind in interpreting our findings. First, because of the small sample size of 10 subjects, our results are, at best, suggestive and promising, not conclusive. A more comprehensive study with a larger and more diverse sample of traders, a more refined set of market events, and a broader set of controls are necessary before coming to any firm conclusions regarding the precise mechanisms of the psychophysiology of financial risk processing and the role of emotion in market efficiency.

Second, while we have documented the statistical significance of autonomic responses during market events relative to control baselines, we have not established specific causal factors for such responses. Many cognitive tasks generate autonomic effects, hence, a marked change in any one psychophysiological index may be due to changes in cognitive processing, for example, complex numerical computations, rather than more fundamental affective responses. For example, more experienced traders in our sample may have displayed lower autonomic response levels because they required less cognitive effort to perform the same functions as less experienced traders, which may have nothing to do with emotion. Without a more targeted set of tasks or additional data on the characteristics of the subjects, it is difficult to distinguish between the two. One way to address this issue is to correlate a subject's autonomic responses with his or her trading performance, so as to develop a more complete profile of the relation between psychophysiological indices and the dynamics of the trading process. However, because trading performance is generally summarized by multiple characteristics—total profit-and-loss, volatility, maximum drawdown, Sharpe ratio, and so on—estimating a relation between autonomic responses and such characteristics may require significantly larger sample sizes and longer observation windows due to the "curse of dimensionality." It may be possible to overcome this challenge to some degree through a more carefully crafted experimental design in which specific emotional responses are paired with specific trading performance measures, namely, anxiety levels during consecutive sequences of losing trades. With a larger sample size, we can also begin to track groups of traders over a period of time and through varying market conditions. By measuring their autonomic response profiles at different stages of their careers, it may be possible to determine more directly the role of emotion in financial risk processing.

Finally, a much larger set of controls should accompany a larger sample of traders. These controls should include psychophysiological measurements for professional traders taken outside their natural trading environment—ideally in a laboratory setting that is identical for all traders—as well as corresponding measurements for subjects with little or no trading experience, in both trading and nontrading environments. Along with psychophysiological data, more traditional personality inventory data, for example, MMPI or Myers- Briggs, may provide additional insights into the psychology of trading.

We hope to address each of these issues in our ongoing research program to better understand the cognitive processes underlying 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 to 83 min, and all sessions were held during live trading hours, typically between 8 a.m. and 5 p.m., eastern daylight time.

### Physiological Data Collection

A ProComp+ data-acquisition unit and Biograph (Version 1.2) biofeedback software from Thought Technology 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 nondominant 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

**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 | 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&P 500 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 |

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 2-min 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 5 min and was often performed either before the trading day began or during relatively calm trading periods. Subjects indicated that the 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 subjects 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.

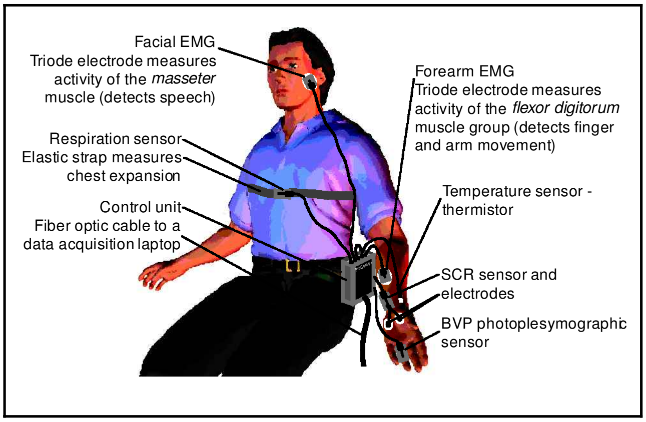


**Figure 2.** Placement of sensors for measuring physiological responses.

## 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 0.75 mV, both SCR and BVP readings at this time were discarded because of the high probability of artifacts, for example, typing, grasping telephone handsets, or inadvertent physical disturbances to the sensors. Similarly, if the level of the filtered facial EMG signal exceeded 0.75 mV, 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- 20 standard deviations within $\frac{1}{32}$ 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

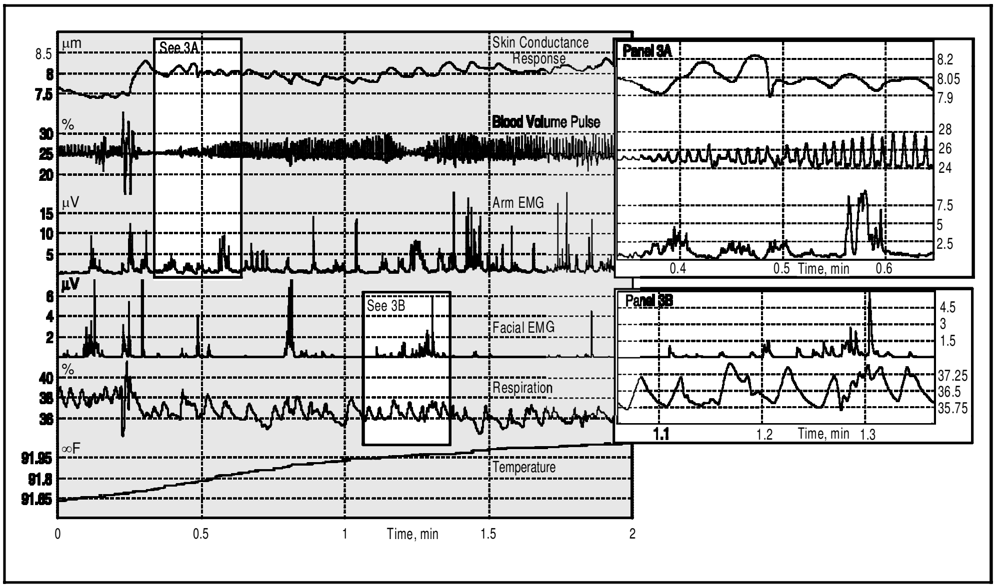


**Figure 3.** Typical physiological response data recorded by six sensors for a single subject over a 2-min time interval.

differed by more than 10 standard deviations from a local average (with both standard deviation and local average computed over the most recent 30 sec 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 preprocessing, 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) stored all market data for the key financial instruments in an Excel spreadsheet, time-stamped to the nearest second. The initial time-markers and time-stamped spreadsheets allowed us to align the market and

**Table 6.** Summary Statistics of Physiological Response Data for All Traders: Means and *SD* for Each of the Six Sensors

| | *Facial EMG* ($\mu V$) | | *Forearm EMG* ($\mu V$) | | *SCR* ($\mu m$) | | *TMP* ($^\circ C$) | | *BVP (%)* | | *RSP (%)* | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Trader ID* | *Mean* | *SD* | *Mean* | *SD* | *Mean* | *SD* | *Mean* | *SD* | *Mean* | *SD* | *Mean* | *SD* |
| 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 |

EMG = electromyographic data; SCR = skin conductance responses; TMP = body temperature; BVP = blood volume pulse; RSP = respiration rate.

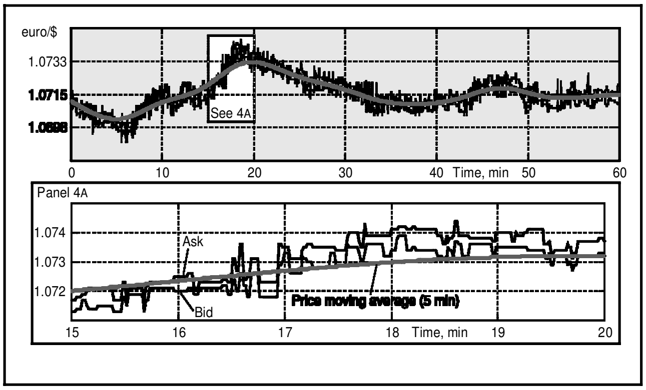


**Figure 4.** Typical real-time market data (euro/US dollar exchange rate) recorded during a 60-min time interval and the corresponding 5-min moving-average.

physiological data to within 0.5 sec of accuracy. Figure 4 displays an example of the real-time financial data—the euro/US dollar exchange rate—collected over a 60-min 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 $\sigma_z$ 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 it was calibrated to yield approximately 5- 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 5-min moving-average, $MA_{5\ \min}(Z_t)$ (see, e.g., Figure 4, Panel 4A). Positive and negative trend-reversals were defined as those observations $Z_t$ such that $Z_t > (1 + \delta)MA_{5\ \min}(Z_t)$ and $Z_t < (1 - \delta)MA_{5\ \min}(Z_t)$, respectively. The parameter $\delta$ 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 (1 sec), 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-reversals only for prices and spreads, excluding returns from this event category.

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

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

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

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

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

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

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

for $l = 1, 2, 3$. The parameter $\eta$ 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.

## Test Statistics

For each of the eight types of events, a sample mean $\hat{\mu}_j$ was computed for that component $X_{jt}$ of the feature vector $[X_{1t}\, X_{2t} \ldots X_{8t}]$ and compared to the sample mean $\hat{\mu}_j^c$ of the corresponding component of the control feature vector $[Y_{1t}\, Y_{2t} \ldots Y_{8t}]$ according to the test statistic:

$$z_j = \frac{\hat{\mu}_j - \hat{\mu}_j^c}{\sqrt{2\hat{\sigma}_j^2/n_j}} \tag{6}$$

where

$$\hat{\mu}_j = \frac{1}{n_j}\sum_{t=1}^{n_j} X_{jt}, \quad \hat{\mu}_j^c = \frac{1}{n_j}\sum_{t=1}^{n_j} Y_{jt} \tag{7}$$

**Table 7.** Average Values of the Parameters Used to Define Market Events: Deviations ($k$), Trend-Reversals ($\delta$), and Volatility Events ($\eta$)

| *Security Identifier* | *Mean $k$ for Price* | *Mean $k$ for Spread* | *Mean $k$ for Return* | *Mean $\delta$ for Price* | *Mean $\delta$ for Spread* | *Mean $\delta$ for Return* | *Mean $\eta$ for Maximum Volatility* | *Mean $\eta$ for Average Price Volatility* | *Mean $\eta$ 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 |

See Equations 1-3 in the text.

$$\hat{\sigma}_j^2 = \frac{1}{2n_j - 2}\left(\sum_{t=1}^{n_j}(X_{jt} - \hat{\mu}_j)^2 + \sum_{t=1}^{n_j}(Y_{jt} - \hat{\mu}_j^c)^2\right) \quad (8)$$

Under the null hypothesis that $X_{jt}$ and $Y_{jt}$ are independently and identically distributed normal random variables with mean $\mu$ and variance $\sigma^2$, the test statistic $z_j$ has a $t$ distribution with $2n_j{-}2$ degrees of freedom. In the absence of normality (Riniolo & Porges, 2000), the Central Limit Theorem implies that under certain regularity conditions, $z_j$ is approximately standard normal in large samples (Bickel & Doksum, 1977, Chap. 4.4.B), in which case the 95% critical region is defined by the complement of the interval $[-1.96, 1.96]$.


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## REFERENCES


Barber, B., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics, 116,* 261-292.

Bechara, A., Damasio, H., Tranel, D., & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science, 275,* 1293-1294.

Bell, D. (1982). Risk premiums for decision regret. *Management Science, 29,* 1156-1166.

Bickel, P., & Doksum, K. (1977). *Mathematical statistics: Basic ideas and selected topics.* San Francisco: Holden-Day.

Black, F., & Scholes, M. (1973). Pricing of options and corporate liabilities. *Journal of Political Economy, 81,* 637-654.

Boucsein, W. (1992). *Electrodermal activity.* New York: Plenum.

Breiter, H., Aharon, I., Kahneman, D., Dale, A., & Shizgal, P. (2001). Functional imaging of neural responses to expectancy and experience of monetary gains and losses. *Neuron, 30,* 619-639.

Brown, J. D., & Huffman, W. J. (1972). Psychophysiological measures of drivers under the actual driving conditions. *Journal of Safety Research, 4,* 172-178.

Cacioppo, J. T., Tassinary, L. G., & Bernt, G. (Eds.) (2000). *Handbook of psychophysiology.* Cambridge, UK: Cambridge University Press.

Cacioppo, J. T., Tassinary, L. G., & Fridlund, A. J. (1990). The skeletomotor system. In J. T. Cacioppo & L. G. Tassinary (Eds.), *Principles of psychophysiology: Physical, social, and inferential elements* (pp. 325-384). Cambridge, UK: Cambridge University Press.

Clarke, R., Krase, S., & Statman, M. (1994). Tracking errors, regret, and tactical asset allocation. *Journal of Portfolio Management, 20,* 16-24.

Critchley, H. D., Elliot, R., Mathias, C. J., & Dolan, R. (1999). Central correlates of peripheral arousal during a gambling task. *Abstracts of the 21st International Summer School of Brain Research,* Amsterdam.

Damasio, A. R. (1994). *Descartes' error: Emotion, reason and the human brain.* New York: Avon Books.

DeBond, W., & Thaler, R. (1986). Does the stock market overreact? *Journal of Finance, 40,* 793-807.

Ekman, P. (1982). Methods for measuring facial action. In K. Scherer & P. Ekman (Eds.), *Handbook of methods in nonverbal behavior research.* Cambridge, UK: Cambridge University Press.

Elster, J. (1998). Emotions and economic theory. *Journal of Economic Literature, 36,* 47-74.

Fischoff, B., & Slovic, P. (1980). A little learning . . .: Confidence in multicue judgment tasks. In R. Nickerson (Ed.), *Attention and performance, VIII.* Hillsdale, NJ: Erlbaum.

Frederikson, M., Furmark, T., Olsson, M. T., Fischer, H., Andersson, J., & Langstrom, B. (1998). Functional neuroanatomical correlates of electrodermal activity: A positron emission tomographic study. *Psychophysiology, 35,* 179-185.

Gervais, S., & Odean, T. (2001). Learning to be overconfident. *Review of Financial Studies, 14,* 1-27.

Grossberg, S., & Gutowski, W. (1987). Neural dynamics of decision making under risk: Affective balance and cognitive-emotional interactions. *Psychological Review, 94,* 300-318.

Hammond, K. R., Hamm, R. M., Grassia, J., & Pearson, T. (1987). Direct comparison of the efficacy of intuitive and analytical cognition in expert judgment. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-17,* 753-770.

Huberman, G., & Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *Journal of Finance, 56,* 387-396.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision making under risk. *Econometrica, 47,* 263-291.

Lichtenstein, S., Fischoff, B., & Phillips, L. D. (1982). Calibration of probabilities: The state of the art to 1980. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases* (pp. 306-334). Cambridge, UK: Cambridge University Press.

Lindholm, E., & Cheatham, C. M. (1983). Autonomic activity and workload during learning of a simulated aircraft carrier landing task. *Aviation, Space, and Environmental Medicine, 54,* 435-439.

Lo, A. W. (1999). The three P's of total risk management. *Financial Analysts Journal, 55,* 12-20.

Loewenstein, G. (2000). Emotions in economic theory and economic behavior. *American Economic Review, 90,* 426-432.

Lorig, T. S., & Schwartz, G. E. (1990). The pulmonary system. In J. T. Cacioppo & L. G. Tassinary (Eds.), *Principles of psychophysiology: Physical, social, and inferential elements* (pp. 580-598). Cambridge, UK: Cambridge University Press

McIntosh, D. N., Zajonc, R. B., Vig, P. S., & Emerick, S. W. (1997). Facial movement, breathing, temperature, and affect: Implication of the vascular theory of emotional efference. *Cognition and Emotion, 11,* 171-195.

Merton, R. (1973). Theory of rational option pricing. *Bell Journal of Economics and Management Science, 4,* 141-183.

Niederhoffer, V. (1997). *Education of a speculator.* New York: Wiley.

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance, 53,* 1775-1798.

Papillo, J. F., & Shapiro, D. (1990). The cardiovascular system. In J. T. Cacioppo & L. G. Tassinary (Eds.), *Principles of psychophysiology: Physical, social, and inferential* *elements* (pp. 456- 512). Cambridge, UK: Cambridge University Press.

Peters, E. & Slovic, P. (2000). The springs of action: Affective and analytical information processing in choice. *Personality and Social Psychology Bulletin, 26,* 1465- 1475.

Rimm-Kaufman, S. E., & Kagan, J. (1996). The psychological significance of changes in skin temperature. *Motivation and Emotion, 20,* 63- 78.

Riniolo, T., & Porges, S. (2000). Evaluating group distributional characteristics: Why psychophysiologists should be interested in qualitative departures from the normal distribution. *Psychophysiology, 37,* 21- 28.

Rolls, E. (1990). A theory of emotion, and its application to understanding the neural basis of emotion. *Cognition and Emotion, 4,* 161- 190.

Rolls, E. (1992). Neurophysiology and functions of the primate amygdala. In J. P. Aggelton (Ed.), *The amygdala: Neurobiological aspects of emotion, memory, and mental dysfunction* (pp. 143- 166). New York: Wiley-Liss.

Rolls, E. (1994). A theory of emotion and consciousness, and its application to understanding the neural basis of emotion. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences* (pp. 1091- 1106). Cambridge: MIT Press.

Rolls, E. (1999). *The brain and emotion.* Oxford, UK: Oxford University Press.

Samuelson, P. A. S. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review, 6,* 41- 49.

Schwager, J. D. (1989). *Market wizards: Interviews with top traders.* New York: New York Institute of Finance.

Schwager, J. D. (1992). *The new market wizards: Conversations with America's top traders.* New York: HarperBusiness.

Shefrin, H. (2001). *Behavioral finance.* Cheltenham, UK: Edward Elgar Publishing.

Shefrin, M., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance, 40,* 777- 790.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211,* 453- 458.