Emotion regulation and trader expertise: heart rate variability on the trading floor

Journal Item

Emotion regulation and trader expertise: heart rate variability on the trading floor

Mark Fenton-O'Creevy[1], Jeffrey T. Lins[2], Shalini Vohra[3], Daniel W. Richards[4], Gareth Davies[5] ,

Kristina Schaaff[6]

Forthcoming in Journal of Neuroscience, Psychology and Economics

(http://www.apa.org/pubs/journals/npe)

Acknowledgements

We gratefully acknowledge the financial support of the European Commission under the 7th Framework Programme, Grant Nº231830, and practical advice and support from Saxo Bank and the traders and managers at the two banks who contributed to the research

---

[1] Corresponding author: Open University, Walton Hall, Milton Keynes, MK7 6AA, UK; email: m.p.fenton-ocreevy@open.ac.uk, Tel. +44 1908 655804.

[2] Saxo Bank, Philip Heymans Allé 15, 2900 Hellerup, Denmark.

[3] Open University, Walton Hall, Milton Keynes, MK7 6AA, UK . Present address: Sheffield Hallam University, Howard Street, Sheffield, S1 1WB, UK.

[4] Open University, Walton Hall, Milton Keynes, MK7 6AA, UK.

[5] Open University, Walton Hall, Milton Keynes, MK7 6AA, UK.

[6] FZI Forschungszentrum Informatik, Haid-und-Neu-Str. 10-14, D-76131 Karlsruhe, Germany.

Emotion regulation and trader expertise: heart rate variability on the trading floor

Abstract

We describe a psychophysiological study of the emotion regulation of investment bank traders. Building on work on the role of emotions in financial decision-making, we examine the relationship between market conditions, trader experience and emotion regulation whilst trading, as indexed by high frequency heart rate variability (HF HRV). We find a significant inverse relationship between HF HRV and market volatility and a positive relationship between HF HRV and trader experience. We argue that this suggests that emotion regulation may be an important facet of trader expertise and that learning effects demonstrated in financial markets may include improved emotion regulation as an important component of that learning. Our results also suggest the value of investigating the role of effective emotion regulation in a broader range of financial decision-making contexts.

Keywords: Emotion Regulation, Financial Decision-Making, Market Volatility, Trading, Heart Rate Variability

Emotion regulation and trader expertise: heart rate variability on the trading floor

Emotions move markets and market events have an emotional impact on traders. Contrary to financial economic accounts of traders as rational utility maximisers (with cognitive limits), evidence is building that the work of professional traders is intensely emotional and that those emotions have important effects on their decisions and behaviour.

Trading is a fast-paced decision environment with significant cognitive and emotional demands. Traders make judgements about risk and potential return under time pressure with potentially major financial consequences for the bank (and via bonus structures) for themselves.

A particular source of emotional pressure for traders is associated with market volatility. In volatile markets outcomes become more uncertain and risks greater. A commonly used measure of market volatility (the VIX) is colloquially known as the 'fear index'. High levels of the VIX are coincident with high degrees of market turmoil and spikes in this measure can be seen at times of stock market decline, the threat of war and other major events which create great economic uncertainty (Whaley, 2000).

Neo-classical financial economics treats traders as rational profit maximizers who act on price information which summarizes all available knowledge about asset values (Fama, 1991; Fama, 1998); making strong assumptions about the rational nature of investor behavior and the nature of investor preferences. More recent behavioral finance approaches draw upon insights from cognitive psychology to incorporate cognitive biases into models of financial decision-making (De Bondt, Palm, & Wolff, 2004; Thaler, 1993). However, within this field of study, until recently, the main role accorded to emotions has been that they are an interference with (normatively prescribed) rational cognition, or are an element of the utility of future outcomes rather than being central to deciding and acting (Shefrin, 2000). In contrast, advances in neuroscience are demonstrating, as Phelps (2006: 46) concludes, that the mechanisms of emotion and cognition are intertwined; from early perception to complex reasoning. There is also evidence from field research that highlights the pervasive role of emotion in traders working lives (Fenton-O'Creevy, Nicholson, Soane & Willman, 2005: 199).

As we explore below, research findings on the role of emotions in judgment and decision-making highlight both emotion effects which are detrimental to human performance, and the role of emotions in enhancing performance.

The biasing effect of emotion. Emotions can bias information retrieval (Meyer, Gayle, Meeham, & Harman, 1990), directly bias the cognitive processes engaged in decision-making (Shiv, Loewenstein, & Bechara, 2005), bias the value attached to outcomes (Gray, 1999) and significantly modify risk perceptions and behaviour (Lerner & Keltner, 2001). There is evidence specific to investment and trading decisions. For example, Lo, Repin and Steenbarger (2005) found some clear associations between day-traders' emotions (as measured by an emotional-state survey), their decision making, and performance (N=80). Investors who experienced more intense emotional reactions to gain and loss were poorer performers than those with more attenuated emotional responses. Schunk and Betsch (2006) found lower levels of emotional experience to be associated with higher levels of financial decision-making performance through greater risk neutrality.

The advantageous role of emotions in decision-making. However, there is also evidence that the use of emotional cues offers an important advantage in everyday decision-making. For example work on patients with damage to areas of the brain responsible for emotion processing suggests emotions are integral to effective every day decision-making and to effective processing of cues about risk (Bechara & Damasio, 2005; Brickner, 1932). There is also evidence which supports the idea that emotions may support effective decision-making in a financial context. For example Seo and Barrett (2007) carried out a study of investment club members (N=101), using an internet-based investment simulation accompanied by emotional-state surveys. They found that individuals who reported the experience of more intense emotions achieved higher decision-making performance.

There is thus some degree of support for two contrasting perspectives. The first suggests that emotions primarily interfere with rational assessment of information and risk. The second that emotions by representing experience gained across many relevant prior situations are an aid to navigation in complex information environments. A common distinction in studies of affect and emotion is between incidental emotions and integral emotions (see e.g. Lerner & Keltner, 2000). Incidental emotions are subjective emotional experiences which should be unrelated to present judgments and choices. Integral emotions, are those subjective emotional experiences which are relevant to present judgments and choices. Accounts of emotions as bias focus primarily on the role of incidental emotions. Studies of incidental emotion typically involve an experimental emotion manipulation followed by an unrelated decision-task (e.g. Lerner, Small & Lowenstein, 2004). By contrast, accounts of emotions as information focus primarily on the role of integral emotions in rapidly, often unconsciously, encapsulating the intersection of prior and current relevant experience (e.g. Bechara & Damsio, 2005). Such studies typically focus on the role of emotions which arise in consequence of characteristics of the studied decision task.

In principle, these two perspectives, emotions as bias and emotions as information, may not be in contradiction. Rather, the challenge for financial decision-makers, especially in fast-paced decision environments, may be to regulate emotions such that the impact of incidental emotions on decisions is ameliorated whilst retaining access to integral emotion cues which encapsulate genuine expertise.

Experienced traders do themselves make distinctions between incidental and integral emotions. In relation to integral emotions, it is common for traders to talk about the useful role of ‘gut feelings’ in trading decisions based on prior experience, whilst emphasizing the importance of subjecting such feelings to conscious monitoring and deliberation. The point here is not that integral emotions can never mislead, but that they can carry information relevant to the decision task. On the other hand, traders worry about incidental emotions biasing their decisions. For example, they typically talk about both the importance and emotional difficulty of ‘trading as if you have a flat book'; that is, that they should avoid any emotional influence on their trading decisions of emotions arising from prior gains and losses (Fenton-O'Creevy et al, 2005: 88-90; 2011). This suggests that a central challenge in this fast-paced decision work may to effectively monitor and regulate emotional responses to avoid the biasing impact of incidental emotions whilst retaining the information advantages conferred by integral emotions.

The Role of Emotion Regulation

There is some research support for the role of emotion regulation in the financial decision-making of finance professionals. In a large qualitative study (N=118) of financial traders, Fenton-O'Creevy et al (2011) found expert traders to engage in more effective forms of emotion regulation to novices and modest performers. In particular they conclude that expert traders are more inclined to regulate emotions through attentional deployment and cognitive change and may display a willingness to cope with negative feelings in the interests of maintaining objectivity and pursuing longer term goals. By contrast, less expert traders engaged either in avoidant behaviors, such as walking away from the desk, or invested significant cognitive effort in suppressing expression of emotional reactions. Further, expert traders experienced less intense emotions than novice traders. They also present evidence from traders' accounts that traders learn more effective emotion regulation strategies over the course of their careers. Seo and Barrett (2007) found investment club members who regulated emotions more effectively (as measured by greater discrimination between discrete emotions) to perform more effectively in a trading simulation. In a physiological study of 10 traders, Lo and Repin found evidence of emotion-related physiological reactions to trading events but less intense reactions among more experienced than less experienced traders(Lo & Repin, 2002).

Thus there is emerging evidence, that effective emotion regulation may be an important facet of traders' expertise.

A physiological measure of emotion regulation. The evidence to date on traders' emotion regulation (e.g. Fenton-O'Creevy et al., 2011 ; Seo & Barrett) relies on interview and self-report data.

However, much emotion regulation is inaccessible to self-report. First, people vary in their capacity to introspect and the affective system is focused on the present, rendering retrospective accounts of emotions and their regulation unreliable (Pham, 2004). Second, whilst some emotion regulation is conscious and explicit, much is unconscious and implicit (Koole & Rothermund, 2011). Thus physiological measures are highly desirable since they do not depend on accuracy of self-assessment and may encompass pre-conscious as well as conscious emotional states.

One important physiological measure which has recently been linked to emotion regulation is heart rate variability (HRV); which indexes moment by moment regulation of physiological arousal. The autonomic nervous system can be subdivided into the (excitatory) sympathetic and (inhibitory) parasympathetic sub-systems (SNS and PSNS respectively). These interact, often antagonistically, to produce variation in physiological arousal. During periods of stability and low stress the PSNS is dominant and maintains a lower degree of physiological arousal and lower heart rate. During periods of physical or psychological stress the SNS becomes dominant increasing physiological arousal and heart rate (fight – flight reactions). Effective emotion regulation requires the ability to adjust physiological arousal on a moment by moment basis (Gross & Thompson, 2007). The SNS triggers gross physiological reactions to internal and external events, fight/flight for example; while the PSNS effectively sculpts physiological reactions to be appropriately adaptive for the context (Appelhans & Luecken, 2006). Heart rate variability provides a measure of the moment by moment interaction of the SNS and PSNS yielding information about autonomic flexibility and thus regulated emotion responding. HRV can be considered a proxy for the central autonomic network's regulation, via inhibition, of the timing and intensity of an emotional response in response to environmental stimuli (Appelhans & Luecken, 2006; Geisler & Kubiak, 2009; Hansen, Johnsen, & Thayer, 2009; Moses, Luecken, & Eason, 2007; Utsey & Hook, 2007). Power spectral analysis of ECG can be used to separate out a high and low frequency band. The high frequency band (HF HRV) corresponds to the frequency of respiration (.15-.40 Hz) and primarily reflects the activity of the PSNS (due to respiratory sinus arrhythmia (RSA) - the gating on and off of PSNS effects on heart rate during the breathing cycle). The low frequency band (.04-.15 Hz) indexes a combination of SNS and PSNS activity. Thus HF HRV indexes moment by moment regulation of response to stimuli. Higher levels of HF HRV are associated with greater moment by moment regulation.

Higher levels of HF HRV have been associated with constructive coping in university students, less use of repressive coping strategies, lower anxiety, less depression and lower propensity to rigid attentional processing of threat (Appelhans & Luecken, 2006). Recent experimental studies also show higher HRV to predict lower propensity to framing effects and loss aversion via greater inhibitory control of emotion driven responses (Sütterlin, Herbert, Schmitt, Kübler, & Vögele, 2011).

While early studies focused on resting HRV as providing a global assessment of regulatory capacity, recent studies have demonstrated the utility of HRV in providing a task-related, moment by moment, assessment of regulation (Moses et al., 2007) and suited to field studies of task performance (Segerstrom & Nes, 2007). HF HRV typically declines during emotionally stressful tasks; for example marital disagreement discussions (Smith et al., 2011), consistent with greater difficulty in regulating emotional reactions and higher HF HRV is associated with greater emotion regulation effort (Butler, Wilhelm, & Gross, 2006) .

Fenton-O'Creevy et al (2011) suggest that traders learn to regulate their emotions during trading over time and that effective task related regulation of emotions is an aspect of trader expertise. If this is the case then we would expect this learning effect to show up in task-related emotion regulation as indexed by HF HRV during trading; rather than in relation to resting HRV which is a stable trait-related measure of global regulatory capacity. Thus we test:

H1: Moment by moment regulation of emotions during trading as indexed by HF HRV will be greater for greater trader experience.

There is existing physiological evidence that traders respond emotionally to market signals and that emotional reactions are stronger for greater market volatility. For example, a field study of 10 traders showed a significant relationship between volatility and skin conductance and heart rate (Lo & Repin, 2002); another study of real-time changes in traders hormones showed increases in market volatility to predict increases in levels of cortisol; a hormone related to fear response (Coates & Herbert, 2008). We would thus expect that traders will face greater difficulty in regulating emotions during periods of high market volatility. Thus we also test:

H2: Moment by moment regulation of emotions during trading as indexed by HF HRV will be lower during periods of higher market volatility.

Procedure

We negotiated access to two investment banks, one based in London and the other in Copenhagen. The research team spent time on each trading floor prior to commencing data collection. Members of the team were introduced by a senior manager in each bank and traders were recruited as volunteers to participate in the study following a presentation and discussion about the broad purpose and process of the research. Each participant was provided with an information sheet on the study including details of right to withdraw consent and how their data would be kept confidential. They signed an informed consent agreement to the use of their data. The informed consent process was subject to institutional review and fully compliant with APA ethical guidelines. Each participant was interviewed and provided detailed information on their background, experience, and current job.

Participants

We studied 28 traders over multiple trading days. All were market makers. Assets traded were foreign exchange, government bonds, stocks or their derivatives. Twenty-five were men and three women. Experience as a trader ranged from 1 month (at the start of the study) to 25 years. Age ranged from 27 to 47, mean age 31.9.

Traders took part in the study for between 2 and 9 days of trading. In total we collected 155 trader-days of data. We deliberately sought to include days on which there was a significant planned market news release (e.g. US non-farm employment statistics), to ensure we included periods of significant market activity. We also collected heart rate data overnight on each trader to establish a resting base line. Practical constraints including the time needed to wire up each trader, different shift patterns and operating constraints in the banks meant it was not practical to study all traders simultaneously. Data was collected on between 2 and 8 traders simultaneously on 38 separate days.

Data was not usable, for 14 trader-days of data out of 155, due to noisy signal or artifacts in heart beat patterns which compromised calculation of HRV. This included data from a trader who had been diagnosed with a tachycardia and data from a trader who logged very high levels of caffeine consumption while trading on several days. This left a usable sample of 141 trader days, including 55 trader-days on which there were planned news releases. Six traders either returned unusable overnight resting data or failed to cooperate in its collection. Rather than reduce the sample on account of a control variable we have used a multiple imputation approach to retain the data from these six traders in the analysis.

Measures

Heart rate variability (HRV). Each trader was equipped with a Camntech Actiwave Cardio ECG sensor, which was worn throughout the trading day. The sensor captures heart-beat information at 512 Hz. The sensor also contains a built in 3 axis accelerometer which captures data on physical movement. We used the frequency-based technique of power spectral analysis. The power spectrum of heart beats is separated into two bands the high frequency (HF) between .15-.40 Hz and low frequency (LF) between .04-.15 Hz. The HF primarily reflects PSNS influence. The LF reflects both SNS and PSNS activity. Thus higher HF scores indicate better moment by moment regulation (Appelhans & Luecken, 2006; Geisler & Kubiak, 2009; Taskforce). The power spectrum was analysed using a Lomb-Scargle transform (Saini, Singh, Uddin, & Kumar, 2009). Artifacts were removed using a threshold-based approach suggested by Clifford et al. (2002) so that if the inter beat interval (IBI) was 20% different to the previous IBI, it was not included in the HRV calculation. Data from the accelerometer was used to identify and drop periods of data with significant levels of physical activity (as for example when the trader left the desk or was jumping up and down) and to identify low activity periods overnight for calculation of resting HRV. ECG charts were also individually inspected to identify and drop a) data with identifiable arrhythmias; b) noisy data where the sensor had become partially detached. A moving five minute window was used to calculate HRV at one minute intervals for each trader. Some (e.g. Berntson et al, 1997) argue that HRV should always be measured in conjunction with respiration data since HRV may co-vary with respiration. However, more recent findings (Denver Reed and Porges, 2007) suggest that "the amplitude of RSA is not dependent on respiration frequency", further, a review of published research measuring both HRV and respiration frequency finds no evidence for controlling for respiration frequency making a significant difference to findings.

> "*No study contrasting corrected and uncorrected measures of RSA, using respiration frequency as a covariate, provides support for correction procedures. Furthermore, neither do studies evaluating tidal volume or respiration frequency and tidal volume as covariates*. (Denver Reed and Porges, 2007: 288).

In the light of these findings and the practical difficulties of measuring respiration on the trading floor we chose not to control for respiration frequency in this study.

HF HRV daily mean: We calculated HF HRV for each interval (discarding time periods compromised by noisy data; primarily at the start and end of recording periods and sometimes coincident with physical activity) and then calculated the mean for the whole trading day.

HF HRV resting: Psychological studies have often taken a baseline measure from a 10 minute resting period or period of neutral activity; primarily due to the convenience of capturing this data alongside the primary lab study. However, medical studies more typically take the baseline period from overnight resting data as a more reliable measure of regulative capacity. It is this approach we adopted. We collected data on each trader overnight to establish a resting baseline. The resting figure was calculated as an average over sleeping periods in which the subject was lying prone with minimal movement as shown by the three axis accelerometer.

Experience: Total tenure in any professional trading role (in years). In general, experience is not the same as expertise, since in most domains many highly experienced practitioners fail to achieve high levels of performance. However, in the trading context, we argue that experience is a reasonable proxy for expertise. Traders in investment banks are subject to stringent monitoring of performance and poor or mediocre performers tend to exit the job.

Market volatility: to assess the effect of market conditions on trader HRV we used the daily high value of the Chicago Board Options Exchange Market volatility index (VIX); which represents the market's current expectation of market volatility (in relation to the S&P 500) over the next 30 days. The index is quoted in percentage points which equate to the (annualized) expected percentage movement in the S&P 500 index over the next 30 days (Chicago Board Options Exchange, 2009). The VIX represents the degree of uncertainty in the market and is often known colloquially as the 'fear index'(Whaley, 2000). The period in which we captured data was particularly interesting in terms of market volatility, following shortly after the financial crisis and during a period of great uncertainty about sovereign debt in Europe. VIX values, on days we collected data, ranged from 17.42 to 42.15 (mean=26.08), representing large variation in expectations about market volatility relative to historic levels.

Analysis

Since HRV and volatility were measured at the trading day level, while experience and resting HRV were measured at the trader level we adopted a multilevel modeling approach using the SPSS mixed models procedure (Heck, Thomas, & Tabata, 2010). Using OLS regression at the trader level would throw away information and using OLS regression at the trading episode level would underestimate standard errors. We used the SPSS mixed models procedure to estimate a multilevel model such that:

$$HFHRV_{ij} = \beta_{0j} + \beta_1 VIX_{ij} + + \varepsilon_{ij} \qquad \text{(level 1)}$$

$$\text{Where } \beta_{0j} = \gamma_{00} + \gamma_{01} Experience_j + \gamma_{01} resting\_HFHRV_j + \mu_{0j} \qquad \text{(level 2)}$$

VIX and Experience were grand mean centered to aid interpretation of results. HF HRV and resting HF HRV were standardized to zero mean and unit standard deviation (since their measurement units have less relevant meaning for our purposes than their distribution across traders and trading episodes).

Resting HRV values were missing for six traders. We used a multiple imputation approach to impute these values from the other variables in the model, adjusting standard errors for the error of imputation (Allison, 2001; King, Honaker, Joseph, & Scheve, 2001). As a check we also repeated the analysis using listwise deletion of missing data (all results remained significant and with the same sign).

Results

Table 1 gives (level 1) correlations between all variables. Correlations between level 1 and level 2 variables should be interpreted with caution given the level 2 clustering of data. Results of the hierarchical (two level) linear modeling analysis are reported in table 2.We first estimated the null model (with only intercepts and random variables) then the full model. We report one-tailed significance for the variance components since they are constrained to be non-negative. We also report one-tailed significance for the two independent variables since the hypotheses are directional.

Both trader experience and market volatility have significant coefficients. As hypothesized greater experience is associated with higher HF HRV and greater market volatility is associated with lower HF HRV. The coefficient for Resting HF HRV is positive but does not achieve significance at the 0.95 level. The model explains 31% of variance in HF HRV between traders. Both hypotheses are supported; suggesting that traders have greater difficulty regulating their emotions in volatile markets and that more effective emotion regulation is associated with greater experience. (Because of concerns about potential non-stationarity in the heart rate data on which the analysis was based (Berntson, 1996) we also repeated the analysis using normalized HRV measures and controlling for heart rate. The sign and significance of VIX and Experience parameters remained unchanged).

The results also suggest that, if this is a learning effect, that learning takes place slowly. A standard deviation difference in daily average HF HRV is associated with a difference of about 15 years in experience. This is consistent with the development of expertise over a career.

Discussion

This study, as with all field research has a number of necessary limitations. Examining traders' moment by moment physiological reactions to trading in the context of their real work has the great advantage of ecological validity. In particular, we are concerned with the development of trader expertise; learning effects which accumulate across a career. Such effects are typically highly domain specific (Ericsson, 2006). However, unlike the experimental setting we cannot ensure a standard stimulus across traders and times. This is especially important since, in our study, operating constraints within the banks meant we were unable to carry out simultaneous measurements on all traders. Different market conditions are likely to place different emotion regulation demands on traders. While we include market volatility in our model of traders' responses, the demands on traders of different market conditions vary significantly with factors other than expertise; not least with the current assets they hold and the asset classes that they are concerned with in their trading.

The relatively small sample of traders also imposed limitations on the study. In particular, it is of great interest to consider whether more experienced traders cope more effectively with volatile trading conditions than inexperienced traders. However, the sample is really insufficient to support a test of the interactive effect of market volatility and experience. In standard moderated regression it is well established that for a given sample there is generally less power to test for interactions than for main effects. This is a particular problem where, as in most field research, variables are measured with less than perfect reliability (Aguinis & Stone-Romero, 1997). In multi-level modeling the situation is more complex, particularly as in this case, where interactions are cross-level (Sherbaum & Ferreter, 2009). The level 2 clustering of values further increases standard error and reduces power. In this particular case, with a high ICC implying greater variance in the dependent variable between than within traders, little can be done to increase power by increasing the number of level 1 observations (trading periods), as power is dominated by the level 2 degrees of freedom. Greater power to detect cross-level interactions would primarily depend on increasing the number of traders studied.

Experience is almost completely confounded with age in this sample, so it is possible that the relationship we have shown between experience and HRV is due to the relationship of age with both variables. However, we believe this to be implausible. It is well established that HRV declines significantly with age (e.g. Antelmi et al, 2004); the inverse correlation we find between experience and resting HRV (a proxy for regulative capacity) is consistent with this. In contrast to this inverse relationship between age and HRV we have found that (task-related) HRV increases with experience. Unfortunately more direct performance measures were not readily available to us. The banks were unwilling to disclose profit performance data to us on grounds of individual and commercial sensitivity. It is also the case that direct measures of profit performance are highly noisy performance measures for traders, especially over the relatively short period during which we monitored them. Whilst trading outcomes are to some extent contingent on trader skill, there are many other factors at play and any element of individual skill in short term profit performance is likely to be masked by the impact of unpredictable market movements, except for very large samples.

Finally, on the basis of the data in this study we cannot rule out that differences in emotion regulation are not a product of learning but of a selection effect, with poor regulators exiting the job more readily, perhaps due to lower stress resilience. This alternative explanation is plausible, but is a poor fit with qualitative evidence (Fenton-O'Creevy et al., 2011 ; Vohra & Fenton-O'Creevy, 2011) that experienced traders commonly describe themselves as having learned to regulate their emotions over the course of their career and typically describe early career difficulties with their regulation of emotions.

Previous work has offered physiological evidence of traders' emotional responses to market events (Lo et al., 2005; Lo & Repin, 2002) and qualitative evidence of the role of emotion regulation in traders decision-making (Fenton O'Creevy et al, 2011). The novel contribution of this study is to offer evidence, first, that traders find it more difficult to regulate their emotions in volatile market conditions and second psychophysiological evidence that emotion regulation may be an important element of trader expertise. Not only are emotions implicated in traders moment by moment financial decision-making (Lo et al., 2005; Lo, 2004; Lo & Repin, 2002), but, this study suggests, effective emotion regulation in the context of financial decision-making may be an important part of what traders learn over the course of a career.

While HRV has been proposed as indexing emotion regulation, there is some support for such regulation being cognitively mediated (León, Hernández, Rodríguez, & Vila); suggesting that high HF-HRV may be most strongly associated with intentional cognitive emotion regulation, a conclusion also supported by Denson et al (2011). While much attention has been paid to the nature of cognition in expert performance, the expertise literature hardly considers the role of emotion. For example, examining the index of the Cambridge Handbook of Expertise and Expert Performance (Ericsson et al, 2006) reveals very few references to emotion or affect; and these are all peripheral to the main arguments of the chapters which contain them. Our research supports the view that effective emotion regulation may, at least in the case of traders, be an important facet of expert performance.

This study does not offer direct evidence on the relationship between emotion regulation and decision quality or performance of traders; and those studies which do consider trader performance in relation to physiological measures (e.g. Coates & Herbert, 2008) need to be treated with caution, as most of the variance in traders' daily profit and loss figures is due to factors beyond the traders' control; identification of performance effects thus is likely to need large samples over substantial periods of varied market conditions. Nonetheless there is some qualitative evidence from traders' own accounts (Fenton-O'Creevy et al, 2011) that high performing traders show more effective regulation of emotions than equivalently experienced moderate performers. A relationship between level of trader experience and emotion regulation is at the very least consistent with evidence for the performance advantages of more effective emotion regulation. Two principle and probably related paths for such a relationship between emotion regulation and performance suggest themselves. First, there is evidence for more effective emotion regulation reducing the impact of incidental emotions and hence reducing susceptibility to key biases (e.g. Gross, 2007; Heilman Crisan, Houser, Miclea, & Miu, 2010; Sokol-Hessner et al., 2010; Sütterlin et al, 2011). Second, emotions play a key role in the allocation of attention and low HF HRV is associated with reduced capacity to generate or alter emotional responses in synchrony with the environment, rigid attentional processing such that attentional resources are diverted to internal states, and poor moment by moment adaptation to environmental signals (Appelhans & Luecken, 2006). Thus it seems likely that, for traders, low HF HRV is associated with both greater susceptibility to incidental emotions and greater difficulty in using integral emotions as a guide to attention which enables adaptive responses to environmental signals.

Many studies of market anomalies consequent on behavioral biases limit themselves to noting the existence of a bias in a population. However, the variability in susceptibility to such biases within populations is also important and interesting. Our results may suggest, for example, an important possible category of explanation for the learning effects that have been demonstrated in financial markets. One large study of the trading records of Finnish investors (Seru, Shumway, & Stoffman, 2010) shows susceptibility to bias to decrease and performance to increase over the course of large numbers of trades. Our study, in conjunction with other work showing effective emotion regulation to diminish susceptibility to cognitive biases (e.g. Heilman, et al, 2010; Sokol-Hessner et al., 2010) suggests that an important component of such learning effects may be learning to more effectively regulate the emotions that are both incidental and integral to high stakes financial decision-making. We recommend further investigation of the role of emotion-regulation in high stakes financial decision-making tasks.

References

Allison, P. D. (2001). *Missing data*: Sage Publications, Inc.

Aguinis, H., & Stone-Romero, E. F. (1997). Methodological artifacts in moderated multiple regression and their effects on statistical power. *Journal of Applied Psychology*, *82*(1), 192.

Appelhans, B. & Luecken, L. (2006). Heart rate variability as an index of regulated emotional responding. *Review of General Psychology*, 10(3), 229.

Antelmi, I., De Paula, R. S., Shinzato, A. R., Peres, C. A., Mansur, A. J., & Grupi, C. J. (2004). Influence of age, gender, body mass index, and functional capacity on heart rate variability in a cohort of subjects without heart disease. *The American Journal of Cardiology, 93*(3), 381-385.

Bechara, A. & Damasio, A. (2005). The somatic marker hypothesis: a neural theory of economic decision. *Games and Economic Behavior*, 52, 336-372.

Berntson, G., Bigger Jr, J., Eckberg, D., Grossman, P., Kaufmann, P., Malik, M., . . . Stone, P. (1997). Heart rate variability: origins, methods, and interpretive caveats. *Psychophysiology, 34*(6), 623.

Brickner, R. M. (1932). An interpretation of frontal lobe function based upon the study of a case of partial bilateral frontal lobectomy: localization of function in the cerebral cortex. *Proceedings of the Association for Research in Nervous and Mental Diseases*, 13, 259.

Butler, E. A., Wilhelm, F. H., & Gross, J. J. (2006). Respiratory sinus arrhythmia, emotion, and emotion regulation during social interaction. *Psychophysiology*, 43(6), 612-622.

Chicago Board Options Exchange. (2009). The CBOE volatility index - VIX: Chicago Board Options Exchange.

Clifford, G. D., McSharry, P. E., & Tarassenko, L. (2002). Characterizing artefacts in the normal human 24-Hour RR time series to aid identification and artificial replication of circadian variations in human beat to beat heart rate using a simple threshold. *Computers in Cardiology*, 29, 129-132.

Coates, J. M. & Herbert, J. (2008). Endogenous steroids and financial risk taking on a London trading floor. *Proceedings of the National Academy of Sciences*, 105(16), 6167.

De Bondt, W., Palm, F., & Wolff, C. (2004). Introduction to the special issue on behavioral finance. *Journal of Empirical Finance*, 11(4), 423-427.

Denson, T. F., Grisham, J. R., & Moulds, M. L. 2011. Cognitive reappraisal increases heart rate variability in response to an anger provocation. ***Motivation And Emotion***: 1-9.

Denver, J. W., Reed, S. F., & Porges, S. W. (2007). Methodological issues in the quantification of respiratory sinus arrhythmia. *Biological Psychology, 74*(2), 286-294.

Ericsson, K. A. (2006). An introduction to the Cambridge Handbook of Expertise and Expert Performance, its development organization and content. In K. A. Ericsson & N. Charness & P. J. Feltovich & R. R. Hoffman (Eds.), *The Cambridge Handbook of Expertise and Expert Performance*, 1st ed.: 3-20. Cambridge: Cambridge University Press.

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance*, 46(5), 1575-1617.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics*, 49, 283-306 224 pages.

Fenton-O'Creevy, M., Nicholson, N., Soane, E., & Willman, P. (2005). *Traders: Risks, decisions and management in financial markets*. Oxford: Oxford University Press.

Fenton-O'Creevy, M., Soane, E., Nicholson, N., & Willman, P. (2011) Thinking, feeling and deciding: The influence of emotions on the decision making and performance of traders. *Journal of Organizational Behavior*, 32(8), 1044-1061.

Geisler, F. & Kubiak, T. (2009). Heart rate variability predicts self-control in goal pursuit. *European Journal of Personality*, 23(8), 623-633.

Gray, J. R. (1999). A bias toward short-term thinking in threat-related negative emotional state. *Personalityand Social Psychology Bulletin*, 25, 65-75.

Gross, J. J. & Thompson, R. A. (2007). Emotion regulation: Conceptual foundations. In J. J. Gross (Ed.), *Handbook of emotion regulation*. New York, NY: Guilford Press.

Hansen, A., Johnsen, B., & Thayer, J. (2009). Relationship between heart rate variability and cognitive function during threat of shock. *Anxiety, Stress and Coping*, 22(1), 77-89.

Heck, R., Thomas, S. L., & Tabata, L. (2010). *Multilevel and longitudinal modeling with IBM SPSS*: Routledge.

Heilman, R. M., Cri an, L. G., Houser, D., Miclea, M., & Miu, A. C. (2010). Emotion regulation and decision making under risk and uncertainty. *Emotion,* 10(2), 257.

King, G., Honaker, J., Joseph, A., & Scheve, K. (2001). Analyzing incomplete political science data: An alternative algorithm for multiple imputation. *American Political Science Review*, 95(1), 49-70.

Koole, S. L. & Rothermund, K. (2011). 'I feel better but I don't know why': The psychology of implicit emotion regulation. *Cognition & Emotion*, 25(3), 389-399.

León, I., Hernández, J. A., Rodríguez, S., & Vila, J. 2009. When head is tempered by heart: Heart rate variability modulates perception of other-blame reducing anger. ***Motivation And Emotion***, 33(1): 1-9.

Lerner, J., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & Emotion, 14*(4), 473-493.

Lerner, J. & Keltner, D. (2001). Fear, Anger, and Risk. *Journal of Personality and Social Psychology*, 81(1), 146-159.

Lerner, J. S., Small, D. A., & Loewenstein, G. (2004). Heart strings and purse strings: Carryover effects of emotions on economic decisions. *Psychological Science*, *15*(5), 337-341. doi: 10.1111/j.0956-7976.2004.00679.x

Lo, A., Repin, D., & Steenbarger, B. (2005). Fear and greed in financial markets: A clinical study of day traders. *American Economic Review*, 95(2), 352-359.

Lo, A. W. & Repin, D. V. (2002). The Psychophysiology of Real-Time Financial Risk Processing. *Journal of Cognitive Neuroscience*, 14(3), 323-339.

Lo, A. W. (2004). The Adaptive Markets Hypothesis. *The Journal of Portfolio Management*, 30(5), 15-29.

Meyer, J. D., Gayle, M., Meeham, M. E., & Harman, A. K. (1990). Toward a better specification of the mood congruency effect in recall. *Journal of Experimental Psychology*, 26, 465-480.

Moses, Z., Luecken, L., & Eason, J. (2007). *Measuring task-related changes in heart rate variability*. Paper presented at the Engineering in Medicine and Biology Society: 29th Annual International Conference of the IEEE, Lyon, 644-647.

Pham, M. T. (2004). The Logic of Feeling. *Journal of Consumer Psychology*, 14(4), 360-369.

Phelps, E. A. (2006). Emotion and cognition: Insights from Studies of the Human Amygdala. *Annual Review of Psychology*, 57(1), 27-53.

Saini, B., Singh, D., Uddin, M., & Kumar, V. (2009). Improved Power Spectrum Estimation for RR-Interval Time Series. *International Journal of Computer Science*.

Schunk, D. & Betsch, C. (2006). Explaining the heterogeneity in utility functions by individual differences in decision modes. *Journal of Economic Psychology*, 27(3), 386-401.

Segerstrom, S. & Nes, L. (2007). Heart rate variability reflects self-regulatory strength, effort, and fatigue. *Psychological Science-Cambridge-*, 18(3), 275.

Seo, M. G. & Barrett, L. F. (2007). Being Emotional During Decision Making—Good or Bad? An Empirical Investigation. *The Academy of Management Journal*, 50(4), 923-940.

Scherbaum, C. A., & Ferreter, J. M. (2009). Estimating Statistical Power and Required Sample Sizes for Organizational Research Using Multilevel Modeling. *Organizational Research Methods, 12*(2), 347-367. doi: 10.1177/1094428107308906

Seru, A., Shumway, T., & Stoffman, N. 2010. Learning by trading. *Review of Financial Studies*, 23(2): 705-739.

Shefrin, H. (2000). *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*. Boston, MA: Harvard Business School Press.

Shiv, B., Loewenstein, G., & Bechara, A. (2005). The dark side of emotion in decision-making: When individuals with decreased emotional reactions make more advantageous decisions. *Cognitive Brain Research*, 23(1), 85-92.

Smith, T. W., Cribbet, M. R., Nealey-Moore, J. B., Uchino, B. N., Williams, P. G., MacKenzie, J., & Thayer, J. F. (2011). Matters of the variable heart: Respiratory sinus arrhythmia response to marital interaction and associations with marital quality. *Journal of Personality and Social Psychology*, 100(1), 103-119.

Sokol-Hessner, P., Hsu, M., Curley, N., Delgado, M., Camerer, C., & Phelps, E. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *Proceedings of the National Academy of Sciences*, 106(13), 5035.

Sütterlin, S., Herbert, C., Schmitt, M., Kübler, A., & Vögele, C. (2011). Frames, decisions, and cardiac–autonomic control. *Social Neuroscience*, 6(2), 169-177.

Taskforce. (1996). Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. *European Heart Journal*, 17, 254-381.

Thaler, R. H. (1993). Advance in Behavioral Finance. New York: Russel Sage Foundation.

Utsey, S. & Hook, J. (2007). Heart rate variability as a physiological moderator of the relationship between race-related stress and psychological distress in African Americans. *Cultural Diversity and Ethnic Minority Psychology*, 13(3), 250.

Vohra, S. & Fenton-O'Creevy, M. (2011). Managing the heart of finance: Domain specific emotion regulation in the work of financial traders, *Academy of Management Conference*. San Antonio.

Whaley, R. E. 2000. The investor fear gauge. ***The Journal of Portfolio Management***, 26(3): 12-17.

Table 1: Level 1 Pearson Correlations

	1	2	3	4
1. High frequency HRV (daily mean)				
2. Resting HF HRV	.153			
3. Trader Experience (years)	.526**	-.277**		
4. Volatility (VIX)	-.058	-.046	.102	

**. Correlation is significant at the 0.01 level (2-tailed).

Table 2: Two-level hierarchical linear regression on daily mean HF HRV

Model	**Null**			**Full**		
	parameter	S.E.	Sig.	parameter	S.E.	Sig.
Intercept	-.154	.149	.302	-.132	.127	.300
Resting high frequency HRV				.177	.110	.057
Experience (years)				.065	.024	.004 [a]
Market volatility (VIX)				-.016	.008	.023 [a]
Intercept variance component	.535	.031	.000[a]	.370	.143	.006 [a]
Residual variance component	.236	.167	.001 [a]	.235	.032	.000 [a]
Intra-class correlation	0.69					
Level 1 R^2				.01		
Level 2 R^2				.31		

a. 1-tailed