Attention and Effort in an Investment Decision under the Influence of Gains and Losses

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ATTENTION AND EFFORT IN AN INVESTMENT DECISION UNDER THE INFLUENCE OF GAINS AND LOSSES

By

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Dedicated to my son, Nicklas, for whom I find the inspiration to push boundaries; and my mother, Marie, whose path as an educator I humbly follow.
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ABSTRACT

I use multimodal physiological measurements to examine changes in investor behavior over a series of gains and losses. Specifically, I examine what information more- or less-sophisticated investors emphasize and characteristics of their associated effort over a series of decision rounds as they choose whether to take a long or short position in a stock. Using eye tracking, I measure where attention is directed. Using GSR, pupillometry, and EEG data, I measure characteristics of the effort expended by investors as they evaluate the information available to them. I find that investors emphasize information that trends in the same direction as the decision they ultimately make. Additionally, overall effort levels are greater when investors make investment decisions under the influence of prior losses. I also document evidence that suggests the magnitude of a participant's change in effort is greater when they go from experiencing gains to losses than from losses to gains.

I provide new insight into the process of investment decision-making and how framing and experience impact that process. This dissertation is one of the first examples in the accounting and finance literatures to make extensive use of eye tracking and introduces the use of GSR, pupillometry, and EEG measurements in investment decision-making research.
CHAPTER ONE

INTRODUCTION

1.1 Background, Research Problem, and Significance

This research examines investor propensity to attend to certain types of information and levels of effort expended while deciding to take a long or short position in a stock. Further, it examines how this acquisition and effort behavior changes when investors experience a series of gains and losses.

A large body of evidence from studies of market-wide stock price data suggests that accounting disclosures contain value-relevant information (see e.g. Ball and Brown 1968, Ohlson 1995, Feltham and Ohlson 1995), investors are influenced by analyst forecasts (see e.g. Bryan and Tiras 2007), analysts and investors are influenced by management forecasts (see e.g. Bartov et al. 2000; Healy and Palepu 2001; Atiase et al. 2005; Cotter et al. 2006; Rogers et al. 2009), and prior stock performance is a poor indicator of future performance (see e.g. Malkiel and Fama 1970, Fama 1991). Behaviorally-motivated research suggests that investors are prone to overconfidence, confirmation bias, and motivated reasoning (see e.g. Hirshleifer 2001). The asymmetry between how individuals perceive and experience gains and losses according to prospect theory has been well documented (Kahneman and Tversky 1979). How investment outcomes impact information acquisition and cognitive effort behavior in an investment decision, and specifically how this behavior interacts with a gain or loss frame, is of particular interest.

Rick (2011), when reviewing the neuro-methods literature highlights the potential value of incorporating multimodal measurements, which is a particular feature of this dissertation. The combination of eye tracking, EEG, GSR, and pupillometry allows for detailed insight into the
information individuals use to make an investment decision and how much effort they put into the use of that information to predict future stock prices.

1.2 Overview of Methodology

Eighty-eight graduate business students (investors) participated in an experiment that involved making a series of eleven investment decisions. Participants were drawn from a population of students in a Master of Science in Finance (MSF) degree program, a Master of Accounting (MAcc) degree program, and a Master of Business Administration (MBA) degree program at a large southeastern US public university. The MSF students, having received training and experience in investment decision techniques as part of their degree program, comprise the more-sophisticated investor group. Following prior research, MBA students proxy for less-sophisticated investors. The MAcc students form a middle group because they share characteristics of the other two groups. For instance, like the MSF group they possess a thorough understanding of financial disclosures, however they also have relatively little formal investment decision training or experience like the MBA group.

In each round of the experiment, investors had available to them (1) management guidance, (2) analyst guidance, (3) objective financial information and ratios, and (4) a stock chart. Investors were instructed to use this information to decide whether they believed the stock price would rise or fall in thirty days. After participants chose to take either a long or short position in the stock, they were given feedback telling them whether they experienced a gain or a loss each round. Two fixed series of gains and losses (counterbalanced between participants) ensured that they experienced either a multi-round series of gains followed by losses or losses followed by gains.
Eye tracking permits precise examination of what information is attended to, including the amount of time spent processing different types of information and the order in which the information is viewed. EEG (electroencephalography) measures small fluctuations in electrical activity associated with brain activity and provides information about how much effort an individual is expending on processing information. GSR (galvanic skin response) measures small changes in moisture from sweat glands under the skin that are associated with excitement, exertion, and stress. Pupillometry measures increases in the size of an individual’s pupils and is associated with effort in a decision-making task.

1.3 Overview of Results

I develop several hypotheses predicting investor behavior based on the sophistication level of the investor, the type of information investors will be likely to prefer and associated effort levels, and how these factors interact with whether decisions are being made under the influence of a prior loss frame or a prior gain frame.

There are several interesting findings to highlight from this research. I find that investors tend to emphasize information that trends in the same direction as their decision. If an investor chooses to take a long position on a stock, for example, he spends significantly more time viewing information that indicates a positive trend. This is in contrast to a theoretically rational approach which would involve the allocation of equal attention to positive or negative information. Next, I measure lower levels of effort during decision rounds when investors have experienced gains in the prior period. Conversely, investors seek to avoid losses after having experienced a prior period loss by increasing their effort levels. Finally, I also document evidence that suggests the magnitude of an investor’s change in effort is greater when they
switch from having experienced a long series of gains to a sudden loss compared to the magnitude of investor effort changes when transitioning from losses to a gain.

1.4 Contribution

The current study has the potential to inform standard setters and the investing public about tendencies in the use and evaluation of information as individuals experience repeated gains and losses. It also contributes to the literature on investor biases, providing a level of detail that is unavailable with traditional methodologies. Finally, it breaks new ground through the use of direct measurements of investor attention and corresponding multi-modal effort indicators to document how these factors change under the influence of gain and loss frames. To my knowledge, no prior study has incorporated these research tools in a single study in the accounting or finance literature.

Eye tracking (including pupillometry), GSR, and EEG measurements have a number of advantages over methods used traditionally in accounting research. In particular they allow direct, unbiased, and continuous parametric measurements of behavior without interrupting the task at hand. Eye tracking information provides insight into what information individuals use when making an investment decision and characteristics of this acquisition (time, order, and integration). Layered on top of this information is EEG data (a highly temporally precise physiological measurement) that provide information about cognitive effort synchronized to eye movements, permitting the examination of effort linked to specific types of information. Pupillometry is also temporally precise, although there is a slight lag between stimulus and response when compared to EEG which is instantaneous. Electrodermal Activity (EDA) as measured by the GSR sensor is a particularly useful and sensitive measure for longer-horizon physiological responses. It is highly effective at showing how general effort levels trend over a
series of gains and losses. EDA is slightly less temporally precise, with a typical lag between stimulus and response up to a few seconds.

To date, neuroeconomic research in the accounting, finance, and economic literature has focused heavily on Functional Magnetic Resonance Imaging (fMRI) studies and related imaging techniques that are very expensive. As a consequence of this focus, neuroeconomic research has been dominated by relatively few well-funded research centers. This study helps to demonstrate that there can be much to gain from the use of other lower cost neuro-method alternatives such as electroencephalography (EEG). Progressive neuro- and physiologically-based research can be accessible to a much larger set of researchers by looking beyond the fMRI (and related intra-cranial imaging techniques) paradigm.

Birnberg and Ganguly (2012) comment on recent research in neuroscience as it relates to accounting research. They highlight opportunities (and challenges) for the application of neuro techniques in behavioral accounting research. They comment that most neuroeconomic research to date has focused primarily on finding or confirming neural correlates for known behavioral tendencies. They suggest that the value of neuroeconomic research, particularly its ability to push decision-making research forward, has been difficult to demonstrate. They suggest that the types of neuro-based research with the most potential for meaningful impact in behavioral accounting research would be studies that focus on “a general understanding of (1) how people process information and stimuli (i.e., the cognitive domain); (2) how people exert control and react to favorable and unfavorable experiences (i.e., the affective domain); and (3) how people interact with others in an organization (i.e., the inter-personal domain)” (Birnberg and Ganguly 2012, 8) This study incorporates two of the three suggested topics for neuro-accounting research and helps pave a path for future studies using these powerful physiological measurements.
1.5 Organization of Dissertation

The dissertation is organized into five chapters. The current chapter introduced the dissertation, providing an overview of its background and motivation, the method employed, highlights of the results, and the study’s contribution. Chapter two provides a deeper discussion of the background and prior literature. I also develop six hypotheses in chapter two based on predictions that flow from theory and prior findings in related literature. In chapter three I detail the method employed in the study including a description of the participants, apparatus, materials, and experimental procedure. In chapter four I describe the data and variables used in the analysis and formally test the six hypotheses that were developed in chapter two. Finally, I provide a summary of the study, its findings, and future directions in the concluding section, chapter five.
CHAPTER TWO

BACKGROUND, RELATED LITERATURE, AND HYPOTHESIS DEVELOPMENT

2.1 Chapter Organization

In chapter two, I discuss background information and literature related to this study leading to the development of six hypotheses. Section 2.2 discusses the use of physiological measurements in experimental research with a focus on applications in financial or risk-related settings. In section 2.3, I discuss investment decision-making research, characteristics of information available to investors while making an investment decision, and how the behavior of sophisticated investors may be expected to differ from unsophisticated investors. Also in section 2.3, I make predictions about the likely role of information acquisition and effort in an investment decision leading to the development of hypotheses 1 through 3b. In section 2.4, I discuss the implications of a gain or loss frame on the investment decision setting employed in this experiment and develop hypotheses 4 through 6b. Section 2.5 summarizes the chapter.

2.2 Physiological Measures in Business and Decision-Making Research

In this dissertation, I employ technologies that precisely measure physiological signals with the goal of gaining better insight into what a participant is doing and experiencing while performing an investment decision-making task. For example, I use eye tracking to understand what an individual is attending to in an investment stimulus screen. Eye tracking also provides a measure of pupil size, which is linked to cognitive effort. I also use an electroencephalography (EEG) sensor that produces an algorithmically-driven summary engagement metric which provides a relative measure of instantaneous effort from electrical brain activity measured at the
scalp. Finally, I use a galvanic skin response (GSR) sensor that measures sympathetic nervous system response as an indicator of effort or general arousal. Electrodermal activity (EDA), which is measured via the GSR sensor is a highly stable measure of effort, but registers a response that is slightly lagged from the stimulus yielding less temporal resolution compared to EEG and pupillometry. I next describe each of these technologies with a particular focus on their use in business or risky decision-making settings.

The popularity of visual perception research is rising in part due to the maturation of techniques and increased accessibility of equipment (Holmqvist and Nystrom 2011; Duchowski 2007). However, there are only a couple of published examples of the use of eye tracking technology in accounting research: Hunton and McEwen (1997) and McEwen and Hunton (1999). The eye tracking technology that Hunton and McEwen used was an assistive device for individuals with motor impairments. It used eye position on the screen to direct a computer cursor in the same way that a mouse moves a cursor around the computer screen. Their work is similar to other studies that allowed individuals to use a mouse to interact with a computer program, tracking navigation to specific screens in a program via mouse clicks (see e.g., Ricchiute 2010; Kadous et al. 2008; Blay 2005; Cloyd and Spilker 1999). Hunton and McEwen (1999) presented results that relied primarily on navigation data – or tracking participant progression between different screens which presented discrete pieces of information rather than detailed eye position metrics. McEwen and Hunton (1999) discussed the idea of examining specific information that individuals directed their attention to on a single screen to a greater extent, but the analysis in the study ultimately depended very little on detailed eye tracking data.

To date, the most technical published use of eye tracking in a finance or accounting context comes from the field of behavioral finance. Shavit et al. (2010) used an eye tracker to
study mental accounting and loss aversion. They presented participants with gains and losses and measured time spent looking at different ways of representing value changes (absolute values, absolute change in value, and percentage change in value) and manipulated those changes as positive or negative. They found that individuals spent more time looking at percentage changes compared to absolute values, more time looking at gains compared to losses, and more time considering the changes in components of their portfolio rather than its overall value. Their study was not a judgment and decision-making (JDM) task; it presented only asset values and changes in values for participants to passively observe.

Eye tracking provides an opportunity to study disclosure usage at a more detailed level than alternative methodologies that have been previously used to determine information use and preference. For example, by reviewing web log information, Hodge and Pronk (2006) found that more experienced investors preferred to use a PDF version of the management discussion and analysis (MD&A) documentation from an investor-relations website rather than a HTML version with links to specific pieces of information. Due to the nature of a single file PDF document, they could not make any conclusions about what these individuals were looking at within the document, just that a single file was preferred by sophisticated users relative to unsophisticated users who preferred to navigate through a collection of html pages on the investment website to browse for various types of information.

Pupillometry involves measuring changes in pupil size associated with brain activity (Beatty and Jackson 1977). The technique has been used to measure mental activity when individuals are solving problems (Hess and Polt 1964), and under memory load (Kahneman and Beatty 1966). In a JDM context, pupillometry has been shown to be a sensitive measure of cognitive load (Beatty and Wagoner 1978, Ahern and Beatty 1979, Granholm et al. 1996). When
an individual is faced with increasingly difficult decisions, their pupil dilation size increases and the dilation is sustained until the decision is made (Beatty 1982).

EEG measures brain activity in the form of electrical fluctuations detected at the scalp. This technique is an alternative to other more expensive neuro-imaging and neural-activity detection techniques such as functional magnetic resonance imaging (fMRI) or positron emission tomography (PET), which has captured the interest of some accounting researchers. EEG offers unique benefits to these alternative techniques that make it a particularly good choice for certain applications. EEG equipment is far less expensive, requiring an initial purchase of hardware that can range from less than one thousand dollars to around fifty thousand dollars compared to the potential cost of multiple millions of dollars for more advanced imaging equipment such as fMRI. Also unlike fMRI, there are very low incremental costs associated with the use of the equipment whereas fMRI requires expensive consumables and a highly trained technical staff to run and maintain the equipment making imaging time an expensive (in the range of $500 to $1,000 per hour) and rare privilege.

There are also dramatic differences in the temporal precision associated with these techniques. EEG readings are measured anywhere from hundreds to thousands of times a second and record instantaneous responses in brain activity making direct stimulus-response examination a tractable endeavor. fMRI, by contrast, relies largely on the BOLD technique to localize brain activity. BOLD is an acronym that stands for “Blood Oxygen Level Diffusion” and essentially tracks the movement of blood to areas of the brain that have recently experienced increased levels of activity. When seeking the highest spatial resolution, the separation between neuron-firing and detected blood response can range anywhere from three to six seconds on average, making the link between stimulus and response much more difficult to isolate. The
fMRI technique, for instance, would be unable to achieve the kind of temporal precision I seek in this dissertation between visual attention (eye movements to specific types of information) and associated effort levels.

However, it should be noted that the spatial resolution of fMRI is far superior to EEG. Modern fMRI equipment is capable of measuring increased blood levels down to a 1 millimeter by 1 millimeter voxel within the brain. EEG, by contrast, is best used to detect activity in regions of the brain and is particularly good at distinguishing activity in the regions closest to the scalp. Advanced equipment and techniques are under development to improve the ability of EEG to make better spatial distinctions, but remain well behind the spatial resolution of fMRI.

Brain activity studies using the more expensive imaging technologies such as fMRI and PET have begun to appear in the business literature. As reported in a 2013 working paper, Yamaji et al. (2013) used fMRI data to examine brain activity in risky decision-making given varying completeness of information. Using PET, Smith et al. (2002) were able to determine that the evaluation of payoffs and outcomes are linked at an observable neurological level and not considered separately as economic theory predicts. Using fMRI data, Rustichini et al. (2005) showed that individuals approach a risky lottery choice by trying to estimate values, but that under ambiguity of risk, they rely less on frontal regions of the brain, and more on parietal areas that are related to gut or emotional decision-making. Dickhaut et al. (2009) and Dickhaut et al. (2010) described how neuro-imaging studies conducted in other disciplines have the potential to inform practice and evolution of institutions in accounting.

GSR has been employed in a wide variety of research due in part to its relatively low cost and high sensitivity to general arousal levels, but it has received very little attention in the business disciplines. A recent discussion by Lee et al. (2007) on the application of neuro-
techniques to the study of marketing suggests that a primary reason for the low number of studies in the area is a lack of awareness within the academic community of GSR and EEG and not for a lack of potentially valuable applications. Further, the knowledge of how to apply the measurements is not common among business researchers. (Lee et al. 2007) They suggest that lower-cost physiological measurements like GSR and EEG are poised to play a greater role in marketing-related research in the near future. Birnberg and Ganguly (2012), who discuss the potential application of neuro techniques to accounting research also cite cost and skillset as important obstacles to the proliferation of neuro research in the literature. In contrast to fMRI, which has both extremely high fixed costs and significant variable costs, eye tracking, EEG, and GSR require relatively modest fixed cost investments and negligible variable costs making them much better suited for mainstream academic research.

2.3 Investment Decision-Making, Information Characteristics, and Sophistication

Investment decisions have been a frequent topic of study in the accounting and finance literatures via three main approaches: archival, experimental, and survey-based research. A number of market-based economic and theoretical studies have established the importance of fundamental accounting information to firm valuation (see e.g. Ball and Brown 1968; Ohlson 1995; Feltham and Ohlson 1995), the important role that analysts play in securities pricing (see e.g. Bryan and Tiras 2007), the influence that management disclosures have on investors and analysts (see e.g. Bartov et al. 2000; Healy and Palepu 2001; Atiase et al. 2005; Cotter et al. 2006; Rogers et al. 2009). Survey and experimental work have also identified these types of information as important to investors as well (e.g. SRI International 1987). Additionally, it is generally believed that prior prices alone are not a good predictor of future asset value (see e.g.
Fama 1991 for a theoretical argument and discussion of evidence supporting the random walk model.

Bayesian rationality (and the rational actor model) predicts that individuals process all available information in their decision-making process independent of the influence of “exogenous factors” (Pitre 2012). Borrowing the approach suggested by Brown et al. (2009), the rational actor approach serves as the strong theoretical prediction providing the benchmark upon which competing behavioral theories are compared. Factors that should bear no influence to a rational actor include for example: affective responses, emotional reactions, or framing differences. A perfectly rational approach in an investment decision should result in no differences in information processing behavior from trial to trial or under gain/loss conditions or level of expertise.

However, a long history of empirical evidence shows that individuals fall far short of the Bayesian rational ideal. Focusing just on studies in an investment context, recent research on investors with differing levels of sophistication suggests that different groups of individuals emphasize different types of financial information (Victoravich 2010; Hunton and McEwen 1997). Elliott et al. (2008) showed that individuals with lower levels of sophistication earned higher returns when they used analyst information (filtered information) while higher sophistication investors performed better with raw financial data (unfiltered information). Others have either demonstrated the importance of, or called for, research focused on differences between investors of differing sophistication (e.g. Pinsker 2011). Based on prior findings, information acquisition and effort behavior is expected to vary across groups with different sophistication levels.
Another set of factors expected to play a role in behavior are characteristics of the information available to participants. Elliot et al. (2008) made a distinction between “filtered” and “unfiltered” information. Filtered information is that which is produced by a professional intermediary for consumption of the general investment public and is presented in a summarized or contextual way (an analyst report, MD&A, management press release, or conference call for example). Unfiltered information consists of factual (or independently verified) raw data or other types of observations that the user must interpret themselves (audited accounting information or stock price observations for example).

Textual (narrative) information, such as that contained in the management and analyst guidance, is generally preferred by unsophisticated investors in part because of its heightened accessibility (Hodge and Pronk 2006; Pinsker 2011). Factual financial information is considered to be relatively difficult to use as it requires attention to detail and an advanced understanding of the meaning and significance of its components to be most useful. A stock chart (historical security price graph) represents graphical information which is attractive, but also quite information rich. If an individual wishes to extract detailed information from the stock chart (such as price levels at specific periods of time), it can demand significantly more effort than the apparent simplicity of its presentation would suggest.

Management and analyst guidance (presented in narrative form) is largely stated in terms of opinions and contain forward-looking statements that cannot be validated until some future date. Financial information, however, primarily consists of independently audited historical information and also contains information that is directly observable in the market (such as outstanding shares, P/E ratio, etc.). Similarly, historical price information consists entirely of factual observations of closing stock prices.
A number of accounting studies have explored the concept of source credibility. The general finding has been that independent sources of information are favored in decision-making. For example, Hirst (1994) demonstrated that auditors were sensitive to income-decreasing earnings management incentives of management in a buy-out scenario (a situation where biasing earnings down is advantageous). Specifically, explanations for a high inventory estimate were discounted when the source was a member of management compared to a more independent source (an audit firm representative). Reimers and Fennema (1999) provided evidence that reviewers of audit workpapers were sensitive to the source of information when deciding whether to revise the allowance for doubtful accounts. They were significantly more likely to make revisions when the source of the collectability guidance was an independent third party than a member of management. Extending these prior findings to the context of this study, the entity that is independent of the firm (analysts) would have more credibility than management.

While management has better “insider” knowledge of the firm and its true opportunity set (Jensen and Meckling 1976), it also directly benefits from increases in the performance (or perceived performance) of the firm. This can manifest, for example, in career or reputation concerns (Harford and Schonlau 2003; Brickley et al. 1999) and compensation tied to bonus incentives (Healy 1985). The earnings management literature provides copious evidence of the role management plays to influence earnings, stock prices, and analysts. Management, then, represents the least independent and likely most biased source of information available to investors in this study.

Analysts have a complex relationship with investors and firm management. Analysts may be inclined to spur investors to purchase stock in order for the analysts to ingratiate themselves with the management of the firms they cover. Sell-side analysts can be compensated and
evaluated in part on the volume of trades they generate. Empirical evidence suggests that investors are aware of and respond to the incentives of analysts. Morgan and Stocken (2003), for example, found that the effect of analyst information was diluted to the extent that incentives were suspect to investors. Negative information from analysts carried more weight than positive information.\(^1\) However, ultimately analysts are evaluated on their accuracy, and error in their estimates can lead to career concerns in the labor market (reputation effects). Consistently biased and inaccurate guidance leads to a loss of credibility and influence. Therefore, analysts have good incentives to produce independent and accurate information about current and future company performance.

Financial information and stock chart data represent the least biased forms of information used in this experiment. Financial information is independently and professionally audited, and historical price data are simply direct observations of market behavior. This is a clear differentiation between unfiltered information and the filtered narrative management and analyst guidance in terms of opportunity to intentionally convey bias or misinformation.

The primary comparison of interest on the source credibility dimension is investor preferences between professionally-prepared narrative information in the form of management and analyst guidance and raw (unexplained) information in the form of financial information and stock price data. In this pairing, management and analyst guidance information is considered more biased compared to the raw financial and stock price data. A second possibility is that there may be perceived differences in credibility between the management- and analyst-derived information. In the absence of any other contextual cues, information originating from

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\(^1\) Note the tendency to place greater weight on losses as compared to gains is similar to findings with respect to prospect theory. (Kahneman and Tversky 1979)
management should be considered to be more biased than information originating from an analyst whose role in large part is to serve as an independent third party source of information.

More sophisticated investors are expected to be better focused on indicators of fundamental values and take a rational approach to their investment decisions. Hodge and Pronk (2006) found that more experienced investors preferred a comprehensive disclosure including raw financial data compared to less experienced investors that preferred the narrative firm performance discussions of management. Elliott et al. (2006) also found that less experienced investors preferred professionally packaged (filtered) information. Further, some of the most prevalent stock pricing techniques include P/E analysis, dividend growth models, and CAPM which focus on the evaluation of objective, factual information. Therefore, individuals who are trained to operate rationally in the markets should have a greater focus on factual versus unverifiable contextual information.

**H1:** More sophisticated investors will place greater emphasis throughout the trials on factual (unfiltered) information compared to less sophisticated investors.

While prior prices alone are a poor predictor of future returns, many market participants believe there is value in technical analysis (making investment decisions based on patterns in observed pricing trends). Brown and Jennings (1989) found that technical analysis can potentially be valuable when combined with information indicative of fundamental value. In other words, fundamental valuation techniques help to identify worthy investment targets, but technical analysis helps an investor to time their purchase. If an investor uses prior price information alone or significantly over-emphasizes it, this would be considered a suboptimal approach. However, if an investor integrates fundamental value information with historical stock
price information (refers back and forth between financial information/ratios and stock price data to try to generate new insight), this would be a sign of a relatively more sophisticated strategy.

**H2:** More sophisticated investors will perform more integrations of unfiltered financial information compared to less sophisticated investors.

A commonly identified behavioral bias in the accounting and finance literature is confirmation bias and the related concept of motivated reasoning (see e.g., Kunda (1990) for a useful overview). In many cases individuals tend to focus on information that confirms their position and de-emphasize information that is contrary to their position (Ditto and Lopez 1992). For example, Cloyd and Spilker (1999) showed that when a client’s tax position is known, tax accountants seek information that confirms the client’s position. Similarly, when evaluating a going-concern opinion, auditors with heightened sensitivity to the risk of litigation seek information that suggests the firm is not a viable going-concern while auditors facing heightened awareness of the potential for the loss of a client seek information that supports a determination that the firm is a viable going-concern (Blay 2005). Motivated reasoning incorporates higher-level influences such as emotions, pride, or strong convictions. Eames et al. (2006), for example, showed that analysts’ prior buy, sell, or hold recommendation influences their future recommendations presumably because they had made a prior commitment and prefer to stick to their position regardless of new evidence to the contrary.

If the investors in this study are susceptible to confirmation bias, it is likely that investors will prefer information that is consistent with their decisions at the expense of other information that may be disconfirming of their position. Specifically, if the prediction holds, then an investor that chooses to go long in the stock will prefer information in the stimulus that indicates a positive signal (optimistic management guidance for example). Conversely, if investors choose
to go short in the stock, they will prefer information in the stimulus that indicates a negative signal (pessimistic analyst guidance for example). Motivated reasoning is likely to influence behavior as well if investors experience an emotional/affective reaction to repeated series of gains or losses, potentially amplifying their selective search and processing behavior.

**H3a:** Investors will tend to focus more time on positive signals if they choose to take a long position than if they choose to take a short position.

**H3b:** Investors will tend to focus more time on negative signals if they choose to take a short position than if they choose to take a long position.

### 2.4 The Influence of a Gain or Loss Frame on Investment Decision-Making

Kida and Smith (1995) developed a model demonstrating the impact of affect on memory for financial information. They suggest that when individuals evaluate financial information, they make determinations from comparisons that have either a positive or negative valence. Further, the valence, rather than the underlying data itself, is the strongest and most influential memory trace during subsequent decision-making steps. Kida and Smith (1998) empirically test this model and find it to be descriptive of participant behavior in an investment decision. Stanton et al. (2014) showed that induced positive affect can make an individual more likely to display risk seeking behavior. Victoravich (2010) further demonstrated that investors affectively responded (positively or negatively) to earnings announcements and that this response related to subsequent stock price judgments. Hodder et al. (2001) linked large economic losses from derivatives to the negative valence affective response of dread. The sensitivity of decision making to positive and negative affective valence has been demonstrated in a number of key accounting settings (Hodder et al. 2001).
Given that prior research has demonstrated the presence of affective reactions to accounting information, it is important to then understand what the effect of a gain or loss frame has on investor process. Bonner (2008, 56) stated that “affect can influence initial choice of processing strategies; positive affect typically leads to the use of heuristic, or less effortful, processes, whereas negative affect tends to lead to more systematic, effortful processes.” This would suggest that as individuals experience negative affect in the face of losses, their effort should increase. Each subsequent decision is likely to be in some way impacted by prior decisions and outcome experiences. Einhorn and Hogarth (1981, 6) pointed out that decisions are often made in sequence and that “many biases reflect response tendencies which are functional in dynamic environments.” Thus, investor responses to an environmental factor, such as their changing affective frame over a series of experiences, is likely to influence their decision-making behavior.

In other disciplines, research using fMRI data provides direct evidence that individuals react more to a loss than a gain (Rick 2011) and that they expend proportionately greater cognitive effort when choosing between a sure loss or a risky loss compared to choosing between a sure gain or a risky gain (Gonzales et al. 2005). Kuhnen and Knutson (2005) showed that different areas of the brain are activated in anticipation of a positive or negative experience in an investment context and activation in either of these areas of the brain can influence subsequent decision behavior (risk preferences). Kuo et al. (2009) used pupillary dilation to obtain an alternative measure of cognitive effort in a risky decision-making task. Although my investment task differs from the decisions employed in the Gonzales et al. and Kuo et al. studies, I expect that the interaction between negative frame and effort to be directionally the same because an investment decision is a type of risk decision and the effect of frame should be similar.
Prospect theory describes an asymmetric utility response for positive versus negative movements from a reference point (Kahneman and Tversky 1979). Differences in behavior when a choice is framed as a gain or a loss have been well demonstrated. A choice that is in fact identical in terms of expected values can be manipulated to result in different outcomes based on the decision frame or wording (Kahneman and Tversky 1984; Thaler 1999). Research on affect shows that a negative frame has a bigger effect on a subsequent decision than a positive frame (Mittal and Ross 1998; Mittal et al. 1998). It has also been demonstrated that individuals prefer to avoid losses and negative affective states (Shavit et al. 2010, Kida et al. 2001). Therefore, when an individual has experienced a loss, he or she will seek strategies to avoid experiencing more losses, including expending greater effort.

H4: Effort levels measured during a series of investment losses will be higher than effort levels measured during a series of investment gains.

In an investment scenario, Pinsker (2007) showed that individuals adjusted price expectations more quickly, and to a greater magnitude, when presented with a series of ten negatively trending disclosures compared to individuals that saw ten positively trending disclosures. When this trend was reversed for another ten periods, the pattern repeated with negatively trending disclosures again evoking a greater price estimation reaction. Pinsker (2011) extended the prior study and used a much longer series of disclosures, demonstrating again a dramatic initial reaction to negative disclosures compared to positive disclosures. However, what becomes much more evident in the second study is the “contrast effect” as described by Einhorn and Hogarth (1992). When the direction of the disclosures (positive/negative) suddenly changed after 20 rounds, there was a very large price expectation reaction (in either direction) in the subsequent rounds. More specifically, after a series of bad news, price expectations increased.
very dramatically at the first mention of good news. Interestingly, the initial reactions to negative disclosures were greater in magnitude than the positive disclosures as predicted by prospect theory. The overall reactions to the entire series of negative disclosures was also greater than the total reaction to the series of positive disclosures whether the experiment began with a positive or negative series of disclosures.

**H5a:** When the direction of a series of gains or losses reverses, levels of effort will increase more quickly (in fewer rounds) for investors when they begin to experience losses compared to the speed of decreases in effort when they experience gains.

**H5b:** When the direction of a series of gains or losses reverses, levels of effort will increase with greater magnitude over the series of investment decisions for investors when they begin to experience losses compared to the magnitude of decreases in effort when they experience gains.

Under the influence of positive affect, individuals tend to use less effortful heuristic techniques, and under the influence of negative affect, individuals dedicate more effort to their decision-making process (Bonner 2008). As investors experience negative affect associated with a loss frame, they should tend to spend more time and effort on the more difficult to process information (the factual financial and historical price information – “unfiltered information”) compared to their behavior while experiencing a gain frame. Conversely, easier to process information (management and analyst narrative guidance – “filtered information”) should be preferred in a gain frame.

**H6a:** Investors will place a greater emphasis on unfiltered information when experiencing a loss frame compared to a gain frame.

**H6b:** Investors will place a greater emphasis on filtered information when experiencing a gain frame compared to a loss frame.
2.5 Chapter Summary

In this chapter I discussed the role and preferences of information usage in an investment decision given differing characteristics of individuals, primarily how their investment sophistication level should impact behavior. I also discussed the likely effect of a gain or loss frame on the subsequent behavior of an individual when making an investment decision. Further, I introduced the unique tools and methods employed in this study that are designed to capture, at a very precise level of detail, information preferences and effort levels during a series of investment decisions.

The introduction to the tools and methods in section 2.2 included a discussion of the use of eye tracking, pupillometry, galvanic skin response (GSR), electroencephalography (EEG) and associated neuro techniques in related literature. I suggest that the application of these techniques have particular promise in accounting and related business disciplines and that their rarity to date is not due to lack of utility, but primarily due to the inaccessibility of the tools and unfamiliarity with the techniques to most researchers in the discipline.

In section 2.3 I discussed how individuals are likely to use information in an investment decision. This included an examination of features and characteristics of the types of information available to participants in this dissertation in addition to the likely behavior of more- versus less-sophisticated investors in this study. I discussed the information content, accessibility, and relative source credibility of each information type to help make predictions about information preferences and effort behavior. Three hypotheses followed from this discussion: that more sophisticated investors would place a greater emphasis on unfiltered information, that they would display higher levels of integration of information between the two types of unfiltered
information, and that they would focus effort on positive (negative) signals if they choose to take a long (short) position.

Section 2.4 integrated the effect of a positive or negative valence on information preference and effort behavior. Based on a synthesis of prior literature and established theory, I developed a case for how prior period gains or losses would be expected to moderate investor behavior. The influence of gains should tend to decrease effort levels and shift attention to filtered information corresponding with simpler heuristic-based decision making while the influence of losses should increase general effort levels and tend to shift information acquisition toward factual unfiltered information as individuals seek to avoid further losses. This discussion led to three additional hypotheses that focused on the effects of prior gains or losses on investor behavior: I expect that effort levels would be higher during a series of losses compared to levels during a series of gains, that effort levels would respond more quickly when the series switches from gains to losses than when the series switches from losses to gains, that the magnitude of the change in effort would be greater when going from a series of gains to experiencing the first loss than going from a series of losses to a gain, and finally, that investors would place greater emphasis on unfiltered information when experiencing losses while placing greater emphasis on filtered information when experiencing gains.
CHAPTER THREE

RESEARCH METHOD AND EXPERIMENTAL DESIGN

3.1 Chapter Organization

Chapter three explains the research method and design. Section 3.2 discusses the participants in the experiment, including details about what populations they were drawn from, the method of recruitment, and summarizes some basic demographic information about the participants. Section 3.3 describes the apparatus used in the experiment which included an eye tracker, a GSR sensor, an EEG sensor, a webcam, a biometric data collection and experiment presentation software package, and a web-based survey tool. Section 3.4 describes the manner in which the experimental materials were generated including an explanation of design decisions and the rationale behind these decisions. Section 3.5 describes the experimental procedure in detail including steps taken to set up and calibrate the sensors, details about incentives and the experimental currency investment endowment determination, task practice, experiment instructions, the main experimental task, and post-experimental inquiry. Section 3.6 summarizes the chapter.

3.2 Participants

Eighty-nine students in masters-level business courses at a large southeastern US public university participated in this study. One participant’s data was lost due to a software conflict resulting in data from eighty-eight participants being available for the analysis portion of the dissertation. The remainder of the discussion and analysis will include only the eighty-eight participants with available data. Participants were divided into three groups based on sophistication level: More sophisticated (22 participants), a middle-group (35 participants), and
less sophisticated (31 participants). More sophisticated investors were proxied by individuals in the Masters of Science in Finance (MSF) degree program. As part of their degree requirements, MSF students at this university completed courses in which they made investment decisions for a university-managed investment fund under the supervision of a finance professor. They learned formal valuation techniques and were required to justify their investment decisions to the supervising professor prior to executing a trade. Although these MSF students were not professional investors insofar as they were not yet employed by a financial firm, they were trained to make professional-like investment decisions using financial and other market information and graduates from this program were frequently recruited for employment by brokerages and financial management firms.

The middle group, consisting of Masters of Accounting (MAcc) students, were highly familiar with financial accounting information. Their education also included training on making managerial decisions and interpretation of accounting principles and financial reporting. They were sophisticated producers and consumers of financial information, however their training on valuation strategies and investment decision-making was limited compared to the MSF students. The curriculum of the MAcc students by definition is focused on accounting whereas the other groups of students take more limited coursework in accounting.

Less sophisticated investors were proxied by MBA students whose management-focused curriculum was less technical. The curriculum of the MBA program included some courses in finance and accounting, but only a portion of these students pursued electives involving advanced training in finance. The use of MBA students as proxies for non-professional investors is common in academic research (e.g. Pitre 2012) and has been shown to be a valid approach.
(Elliott et al. 2007). Pinsker (2011) showed that students performed similarly to non-professional investors in a stock pricing task over a long series of disclosures.

Within each group, participants were assigned to one of two conditions: gains first (followed by losses), or losses first (followed by gains). Participants in the MAcc Group and MBA group were counterbalanced between the two sequences. There were fewer MSF students available to participate in the experiment due to the smaller size of the degree program, so a decision was made to concentrate these participants in a single sequence, the “gains followed by losses” sequence. Two MSF students were placed in the losses followed by gains sequence before this design decision was made. Table 3.1 tabulates the breakdown of groups and sequences.

Table 3.1
Groups and Sequences

<table>
<thead>
<tr>
<th>Group</th>
<th>Gains followed by Losses</th>
<th>Losses followed by Gains</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAcc</td>
<td>18</td>
<td>17</td>
<td>35</td>
</tr>
<tr>
<td>MBA</td>
<td>16</td>
<td>15</td>
<td>31</td>
</tr>
<tr>
<td>MSF</td>
<td>20</td>
<td>2</td>
<td>22</td>
</tr>
<tr>
<td>Total</td>
<td>54</td>
<td>34</td>
<td>88</td>
</tr>
</tbody>
</table>

Table 3.1 presents counts of participants by group that experienced each type of gain/loss sequence.

Participants were recruited from one MSF class, one MBA class, and one MAcc class. Professors were requested to provide students with course credit to participate in the experiment as a show-up incentive. At the beginning of one class period for each class, basic information about the experiment was shared with the students, a description of the incentives (course credit and entries into a lottery) was provided, students were invited to ask questions about the
experiment, and they were encouraged to sign up to participate. Students were provided with contact information and a website where they could sign up for a time to participate, and the professors posted a link on their course website and emailed occasional reminders to the students. Participants received an email confirmation of their signup, a reminder one to two days prior to their timeslot, and a reminder the morning of their participation date.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>MSF</th>
<th>MAcc</th>
<th>MBA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>19</td>
<td>15</td>
<td>21</td>
</tr>
<tr>
<td>Female</td>
<td>3</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>Age (average)</td>
<td>22.9</td>
<td>22.8</td>
<td>26.4</td>
</tr>
<tr>
<td>Risk Seeker (high)</td>
<td>11</td>
<td>19</td>
<td>15</td>
</tr>
<tr>
<td>Risk Seeker (low)</td>
<td>11</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>Personal Investments</td>
<td>7</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>High Professional Work Experience</td>
<td>3</td>
<td>7</td>
<td>18</td>
</tr>
<tr>
<td>University Investment Fund Experience</td>
<td>21</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 3.2 presents counts (or average where specified) for several demographic variables broken down by the degree program participants were a member of.

Basic demographic information was obtained through use of a web-based post-experimental questionnaire which was completed immediately following the experiment and prior to the participant leaving the lab. As shown in Table 3.2, the sample of participants from the MSF and MBA groups was more heavily male and the MAcc group more heavily female, similar to the populations of students enrolled in the degree programs from which the students were recruited. The average age observed in the MBA group was higher than the other two groups. This can be explained by the fact that the particular MBA class that was recruited from
was a combined traditional and part-time evening MBA class, which had a higher population of older working professionals. The “Risk Seeker”, “Personal Investments”, “High Professional Work Experience”, and “University Investment Fund Experience” variables were also generated from data collected in the post experimental questionnaire. The “Risk Seeker” variable was coded high if an individual chose the option involving risk in at least one of three scenarios selected from examples in Kahneman and Tversky (1979), participants that selected none of the options incorporating risk from these scenarios were coded as low risk seekers. If an individual indicated that they had personal investments, a significant amount of professional work experience, or had participated in managing the university’s student investment fund, they were included in the counts of the relevant variables. All participants reported normal or corrected-to-normal vision and wore corrective lenses if necessary.

3.3 Apparatus

The experiment utilized an eye tracker, an EEG sensor, a GSR sensor, a webcam, specialized experiment presentation and data collection software, and a web-based survey. All sensors were either wireless or remote, allowing the participant to move and interact with the experiment in a natural, unencumbered way.

The eye tracker employed was the Tobii T60 remote eye tracking device. This eye tracker is capable of utilizing either the bright or dark pupil tracking method which is automatically selected by the tracker to capture the highest level of accuracy for each participant. The Tobii T60 operates at a sampling rate of 60 Hz and is rated as typically accurate to within 0.5 degrees of visual angle (Tobii 2011). Individuals on average have a field of vision of approximately 160°, but the most detailed images occur at a very small area (approximately 2°) at the center of the visual field where light hits the most densely receptor-packed area of the retina (called the
fovea) adjacent to the optic nerve (Duchowski 2007). The Tobii T60 is accurate to within one quarter of that area. Drift, which refers to the change in accuracy attributable to the tendency for calibration to degrade over time is typically within 0.1 degree of visual angle. Spatial resolution, which refers to the ability of the eye tracker to detect eye movements, is detectable within 0.2 degrees of visual angle. Error due to head movement is typically within 0.2 degrees of visual angle. The head box, which refers to the three-dimensional area within which a participant may move their head while still maintaining eye tracking is approximately 44cm x 22cm at a distance of 70cm and tracking is possible at a range of distances between the tracker and the individual of 50cm to 80cm (Tobii 2011).
The generous head box and high level of accuracy of the eye tracker allowed for the experiment to be conducted without the aid of a chin rest or other equipment designed to restrict movement. Participants were able instead to sit comfortably in a stationary chair. The metrics of interest from the eye tracking device are the (x, y) coordinates of eye position on the screen and pupillary size. Position information is used to determine which area of interest (AOI) the participant directed their attention to. These data are time-stamped making it possible to calculate the amount of time spent on a given AOI and to count integrations of information types (the number of times an individual’s attention was directed back and forth between different information types). Pupillary size, specifically the maximal pupil size, is used to obtain an additional indication of effort. The Tobii T60 is an integrated eye tracker meaning that the eye tracking camera and infrared LED lighting necessary for tracking using the bright pupil method is integrated into the monitor. Images from the experiment were presented on the integrated 17” TFT monitor which had a native resolution of 1280x1024 pixels. (Tobii 2011)

The electroencephalography (EEG) device used was the Emotiv EEG Research Edition. This device is a light-weight, comfortable plastic headpiece that is placed over the participant’s hair and measures electrical fluctuations at the surface of the scalp that are associated with neuronal activity in the brain. A series of 14 felt-tipped sensors are positioned at specific locations in the EEG headset. Each felt sensor was saturated with saline solution to increase the sensitivity of the device to the electrical signals detected at the scalp. Internal measurements in the Emotiv EEG are taken at a rate of 2048 Hz, processed, and down-sampled to an output rate of 120 Hz before being transmitted via wireless RF connection to the host computer. The system outputs raw EEG data in addition to a number of automatically-generated metrics, the most important for this study being a continuous measure of engagement.
Figure 3.2 is an image of the Emotiv EEG wireless EEG headset used in this dissertation.

The galvanic skin response (GSR) sensor employed in the experiment was the Affectiva Curve Remote GSR sensor. GSR works by sending an imperceptible, very low voltage electrical current from one electrode to another across a participant’s skin. As a participant’s effort, engagement, excitement, or anxiety level changes, the sympathetic nervous system reacts by releasing small amounts of moisture in the skin. As this moisture level rises and falls, the skin’s ability to transfer electrical current between the electrodes fluctuates, providing a measure of general arousal. The Affectiva Curve is a watch-like device that is worn on the participant’s wrist and secured by a hook and loop fastener strap. The device operated at its maximum sample rate of 32 Hz. Skin conductance and temperature readings are transferred to the host computer via wireless Bluetooth connection.

Finally, a Microsoft LifeCam HD-5000 webcam was used to monitor the participant as they completed the experimental procedures. This webcam was used primarily to allow the
experimenter to record the steps that were taken with each participant and to discover, if necessary, any reasons for observed anomalies in the data.

Figure 3.3
Affectiva Curve Q-Sensor

Figure 3.3 is an image of the Affectiva Curve wireless GSR sensor used in this dissertation.

Recording multimodal physiological measurement data present a number of challenges beyond getting each individual signal to be properly prepared, initialized, and communicating with the computer. Syncing multiple data streams is a particular problem. Each device operates at a different frequency, depends on different methods and clocks to record the time-series data, and employs different (incompatible) native data file formats. A biometric data aggregation software platform, the iMotions Attention Tool version 5.0, was used to automatically manage, collect, and synchronize data from the eye tracker, EEG, and GSR sensors. Stimulus presentation and response variable capture during the main experiment were implemented using the built-in facilities of the iMotions Attention Tool software package. The post experimental questionnaire was administered using Qualtrics, a web-based survey tool. At the end of the experiment the iMotions Attention Tool was programmed to call Microsoft Internet Explorer and automatically
load the post experimental questionnaire using Qualtrics. The iMotions Attention Tool continued to record all physiological measurements during this time while syncing measurements to actions on the screen using its screen-capture facilities; although in general the EEG and GSR devices were removed from participants during the post-experimental questionnaire so preparations could begin for the next participant and to maximize the amount of time available to charge the wireless equipment.

3.4 Materials

The experiment presented participants with screens containing four equally-sized panels containing information intended for them to use while making an investment decision. An example of the stimulus screens can be seen in Figure 3.4. One panel included management guidance for the upcoming quarter. A second panel included analyst guidance for the same time period. A third panel included three years of financial statement information and key ratios patterned after the types of information available in Value Line Investment Survey Reports. A fourth panel included a three year stock chart. Participants were able to see all of this information on the screen simultaneously and had ample time to read and analyze the information. Additionally, due to the design of the stimuli, participants could freely direct their attention between the various types of information available to them without having to toggle between screens. The procedures for creating the four panels across trials are described next.

Eleven financial information and ratio panels were systematically generated based on random seeds and a jitter factor (which introduces a second-order randomization effect to help obscure patterns between rounds). Two templates were developed to create panels that indicated either positive or negative growth by reversing the direction of the formulas in the template. This had the effect of generating financial information that indicated either a positive trend or a
negative trend. Some ratios and values required share price information which was linked to the data underlying the stock chart to maintain a realistic correspondence between the information presented in the financial information and the stock chart portions of the stimulus.

Figure 3.4 provides an example of the stimulus screens available to participants when making their investment decisions. At the top left is “Analyst Guidance”, top right is the “Stock Chart”, bottom left is “Financial Information”, and at the bottom right is “Management Guidance”. The order in which these information types were presented on the screen was changed each decision round.
Stock charts were also generated using random data rather than actual historical stock returns to avoid any unintended connection between trends in prior returns and stock performance in the stimulus. Stock charts covered the same three year timeframe as the financial information. Stock charts were constructed with 144 data points (three years with 48 data points per year) that were determined as follows: I randomly determined the length of trends (between 1 and 10 periods) and the direction the trend should display (either a positive trend or negative trend). Within each positive or negative trend segment, the magnitude of the price change for each given period is also randomly determined. This method was intended to create a realistic-looking stock price series.

Management’s guidance was constructed in a way intended to convey expectations for either improvement or decline in EPS for the quarter while providing some tension allowing for the possibility that firm value may in fact achieve better or worse than expected results. For symmetry and greater control, analyst guidance was made to convey similar information in a slightly different order. Care was taken to keep analyst and management guidance at very similar lengths and to use plain (non-technical) terminology to minimize the potential for alternative explanations of behavioral differences between groups. Analyst forecasts were either in agreement with management, in disagreement with management, or neutral. To increase the salience of the sources of information, a header in the panel designates whether the guidance is from an analyst or management. Regardless of position on the screen, the header for analyst guidance was consistently colored garnet and the header for management guidance was consistently colored gold. Additionally, the text of the guidance starts with the source (either an
executive’s name with a CFO title for the management guidance, or an analyst firm’s name for the analyst guidance).

The structure and wording of the management and analyst guidance was kept very similar across the 10 rounds of investments. The decision to favor consistency was made specifically to eliminate unnecessary variation in the stimuli that may introduce additional noise when trying to understand differences in behavior between groups and for the same individual over multiple rounds. While similarity in disclosure wording is not mandated in practice, the information conveyed in management and analyst guidance is frequently disclosed in similar ways (i.e. through boilerplate statements that are recycled from period to period).

The order in which the four panels are presented was rotated in each stimulus such that conclusions made about the relative importance of various pieces of information are not dependent upon their fixed position on the screen (i.e. – that the information at the top left was not preferred simply because it was consistently at the most prominent location on the screen). Across the eleven rounds, participants were exposed to stimuli that presented all relevant combinations of positive and negative financial information trends, positive and negative management forecasts, and analyst forecasts that agree, disagree, or are neutral toward management’s forecast. The position of each type of information on the stimuli was counterbalanced. After the eleven stimuli were created, a single random drawing determined the order in which the stimuli would be presented for all participants so that the manipulation of these factors did not end up being systematically presented to participants.
3.5 Procedure

3.5.1 Beginning the Experiment and Calibrating the Sensors

Prior to each new participant, the wireless GSR and EEG sensors were charged and EEG sensors prepared with saline-hydrated felt sensors. Upon arrival, participants signed in to receive credit for their participation. Participants were provided with a stationary chair in front of a clean desk with the integrated eye tracker and monitor, a keyboard, mouse, and computer speakers. Before proceeding, participants were provided with a consent form (see Appendix D) and encouraged to ask questions.

When consent to participate was obtained, the experimenter explained each piece of equipment while helping the participant to correctly don the devices. Participants were shown how to wear the GSR sensor on their wrist and then invited to strap the sensor on the arm opposite the hand they preferred to use the mouse with. They were instructed to ensure the device was snug against their skin, but not so tight that it would become uncomfortable. Participants were supervised to ensure they correctly positioned and fastened the GSR sensor snugly. Next, the researcher explained the EEG sensor and obtained permission to put the EEG sensor on the participant’s head. The researcher then placed the EEG sensor on the participant’s head ensuring key sensors were located in the correct spots on the scalp. The EEG headset is made of flexible plastic which is spring-loaded to facilitate adequate contact between the sensors and the scalp. The Emotiv EEG Control Panel software includes a sensor status diagnostic aid which was displayed to the participant during setup to assist in obtaining solid contact for each sensor. This allowed the participant an opportunity to understand the process of setting up the EEG sensor and to assist with sensor placement as necessary. Sensor contact quality could also
be monitored by the experimenter through the iMotions Attention Tool while the experiment was in progress.

The final step in the equipment setup process involved ensuring that the eye tracker was correctly configured for each participant. Adjustments were made by tilting the eye tracking unit to adjust for the height of the participant and by sliding the eye tracker on the desk until the participant was located in the ideal location in the tracker’s usable head box. When all sensors were confirmed to be operating correctly and successfully communicating to the iMotions Attention Tool software, the eye tracking calibration routine was initiated. This involved participants following a pulsating dot with their eyes across the computer screen, stopping temporarily at five fixed points. The eye tracker takes eye measurements at each of the five calibration points and then interpolates the measurements at all other locations on the screen. Following an acceptable calibration, the experiment presentation began.

First participants viewed, while hearing the experimenter read to them, a consent screen that reiterated important information from the consent form including the option to quit or temporarily pause the experiment for any reason. As part of this orientation, the general nature of the experiment was discussed, the equipment being used was listed, and the experimental incentives available to the participants were explained. Participants were invited again to ask questions. Their consent to proceed, which was obtained in written form earlier, was received again orally before moving on.

Next, participants listened to two and a half minutes of classical music (Adagio from Dvorak’s New World Symphony). Prior to starting the classical music, participants were encouraged to relax and clear their minds so that baseline measurements could be obtained under low effort load. Immediately following the classical music, participants received instructions
about a math problem-solving task. During the math problem-solving task, participants could use a pencil and scratch paper, but were not allowed to use a calculator. When they were ready, participants initiated the math problem-solving exercise themselves by pressing the spacebar. This task served two purposes. First, participants were able to earn a larger initial experimental currency endowment by correctly solving as many math problems as possible (of ten maximum problems) in two and a half minutes. Second, high effort load baseline measurements were obtained. After the timed exercise completed, participants were informed how many math problems they correctly answered.2

3.5.2 Incentives and Investment Endowment

To increase participant involvement in and engagement with the experimental task, participants were provided with a performance-based incentive. To operationalize the performance incentive, participants were provided with experimental dollars which were converted into lottery entries for five $100 cash prizes. Lottery entries were awarded at the end of the experiment at the rate of 1 lottery entry for every $10,000 in experimental currency. The more experimental dollars earned by a participant in a pre-determined portion of the experiment, the more lottery entries they received. All participants began the experiment with $100,000 in experimental currency, each correct answer to the math problems earned the participant an additional $10,000 in experimental currency up to a maximum of an additional $100,000 in experimental currency. The incentive was designed to encourage participants to engage with and seek to maximize their performance in the experimental task. The portion of the experiment selected to determine lottery entries, which was never revealed to participants, was immediately

---

2 No participant completed all ten math problems in the allotted time indicating that, as intended, the task was sufficiently challenging.
after the math problem exercise and prior to the investment decision-making portion of the experiment.

3.5.3 Practice

After participants learned their initial experimental currency balance, they were given an opportunity to practice making an investment decision. Participants were provided with instructions about the experimental task and the investment decision they had to make. When participants indicated they understood the task and were ready for the practice round, an investment stimulus screen was presented and participants were given an extended period of time to review the investment-related information. When participants were finished reviewing the information and ready to make their decision, they pressed the spacebar to proceed to the practice decision screen where they indicated whether they would prefer to take a long or short position in the stock and their confidence level in that decision. The practice round was intended primarily to familiarize participants with the investment decision stimulus screens. Participants did not receive feedback about the result of their decision in the practice round so as to not begin the experiment with a prior gain or loss valence. Participants were asked whether they had any questions and were comfortable with the experimental task prior to proceeding to the main experiment.

3.5.4 Experiment Instructions

As part of the instructions, participants were told that the investment decisions they were making were for a short one month (thirty day) time horizon and that they must decide whether the stock price would be higher or lower in thirty days. Participants received instruction about what taking a long or short position in a stock meant (i.e. a long position should be taken when the investor believes the stock price will go up, so they purchase shares anticipating that they can
sell them later at a higher price; a short position should be taken when the investor believes the stock price will go down, so they borrow shares from somebody to sell now, expecting that they will be able to repurchase the shares later at a lower price to return to the lender.) Participants were told to assume that there were no obstacles, advantages, or disadvantages to taking either a short or long position in the stock so they should base their experimental decisions solely on their expectation of whether the stock price would be higher or lower in thirty days. To ensure that participants were not confused by the use of unfamiliar terminology, the screen where participants indicate their investment choices clearly explained which type of position (long or short) they should take if they expected the stock price to increase or decrease (see Appendix A).

3.5.5 Series of investments

In each of the eleven main experiment decision rounds, participants were presented with a screen containing the four panels of information that they were to base their investment decision on. To ensure the experiment concluded in a timely manner, participants had a maximum of three minutes to view each screen prior to deciding whether they will take a short or long position in the stock. When participants finished reviewing the experimental materials for that round, they pressed the spacebar to continue to a screen where they would indicate their preferred investment position by using a computer mouse to click a radio button choosing either a long or short position. There was also a text entry dialog box where participants entered their confidence level in their decision on a percentage scale (from 0-100% confident). When participants completed this step, they advanced to a new screen where they were provided with feedback that indicated the percentage amount of gains or losses on their investment (see Appendix A to see all experimental materials including an example of a gain feedback screen and a loss feedback screen).
Participants were assigned to one of two conditions: either they experienced a series of outcomes that included four gains followed by four losses in sequence, or they experienced four losses first followed by four gains in sequence. A pilot study where participants were presented with a series of five gains followed by five losses revealed that several participants were able to pick up on the non-random nature of the sequence. To combat this, buffer rounds were added to the beginning and end of the series for the dissertation study. Therefore, while the focus of the study was primarily on the four gains and four losses portion of the sequences, the actual sequence experienced by participants was either: [gain – loss – gain – gain – gain – loss – loss – loss – loss – gain], or [loss – gain – loss – loss – loss – loss – gain – gain – gain – loss].

3.5.6 Post-Experimental Inquiry

At the end of the sequence of investment decisions, participants were asked a number of questions to help explain their performance, their choices, and to provide some context in which to frame the experimental results. Prior risk-related research has shown that in some cases demographic variables can be a factor in observed experimental behavior (Barber and O’Dean 2001; Elliott 2006). The demographic information collected included age, gender, right/left handedness, educational background, professional experience, finance-specific coursework, accounting-specific coursework, and investment experience. As part of the post-experimental questionnaire, questions were asked to classify individuals as either risk-seeking or risk-avoiding. Specifically, I used three classic examples from Khaneman and Tversky’s (1979) risk preference literature. If two or more of the participant’s answers indicate a preference to seek higher rewards in exchange for accepting risk, that individual was classified as a risk seeker.
Appendix B provides an example of the post experimental questionnaire including all questions that were asked.

3.6 Chapter Summary

In chapter 3, I provided a detailed description of the participants, apparatus, and materials that were employed in this study. I also outlined the experimental procedures that were followed. In section 3.2 I highlighted that the eighty-eight participants used in the analysis were drawn from three distinct populations of graduate business students enrolled in different degree programs. I described the differences in each group and what advantages or disadvantages each possess in order to allow them to perform the investment decision task with higher or lower levels of sophistication. A case was made for the assertion that the Masters of Science in Finance (MSF) group are likely to display the most sophisticated behavior when making investment decisions.

In section 3.3, I described the apparatus, which included several key pieces of research equipment and two software programs. The Tobii T60 eye tracker provided eye location information and pupil size measurements, the Emotiv EEG headset provided an algorithmic measure of engagement driven by brain electrical activity observed at the scalp, the Affectiva Curve Q Sensor provided measurements of electrodermal activity via a device worn like a wrist-watch, and a webcam recorded the entire procedure. The experimental stimuli presentation and biometric information aggregation and recording was handled by the iMotions Attention Tool 5.0 software suite. Finally, the post experimental questionnaire was constructed administered through Qualtrics, a web-based survey tool.

The design and construction of the investment stimuli were the primary focus of section 3.4. Each investment decision stimulus was divided into four equally-sized sections with a
distinct type of information appearing in each quadrant of the stimulus. The types of information that appeared on each stimulus were analyst guidance, management guidance, financial information, and stock charts. Information in the financial information and stock chart portions of the screens were randomly determined, but presented within a structure to achieve desired experimental manipulations and greater apparent realism. The position of the information was presented in a non-systematic way so that inferences about the relevant importance of each type of information would not be influenced by the prominence of their position on the screen. The content of the management and analyst guidance was carefully controlled to yield similar lengths and content between information sources and between rounds.

Finally, I described the experimental procedure in section 3.5 beginning with the start-up, equipment configuration, and calibration process. Participant experimental currency endowment was determined through the number of correctly answered questions on a timed math exercise. The experimental currency balances drove the number of lottery entries participants received for one of five $100 cash prizes. Participants were told that their experimental currency balance at a pre-determined, but undisclosed time determined their lottery entries. Therefore, the lottery was used to encourage participant involvement in the experimental tasks. Participants were given a practice round where they were able to familiarize themselves with the investment-decision-related information available to them and the decision that they must make, but they did not receive feedback on the outcome of the practice investment. After all instructions and practice were complete, participants began the main experiment where they made a series of eleven investment decisions. One group experienced a gain, loss, then four gains, followed by four losses, ending with a final gain. A second group experienced a loss, then gain, then four losses, followed by four gains, ending with a loss. When the main experiment was completed,
participants were directed to a web-based post experimental questionnaire that included
demographic information, questions that gauged risk preferences, and sentiment towards the
various types of information available to them in the experiment.
CHAPTER FOUR

EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Chapter Organization

Chapter 4 describes the data analysis and presents the experimental results for the study. In section 4.2 I describe the experimental data including the steps taken to collect, prepare, and clean the data. In section 4.2, I present descriptions and summary statistics for the key variables used in the analyses to follow. In sections 4.4 through 4.9, I present and discuss the formal tests of the hypotheses developed in Chapter 3: H1, H2, H3a, H3b, H4, H5a, H5b, H6a, and H6b. Section 4.10 provides a chapter summary including an overview of the results from the testing of each hypothesis.

4.2 Data

Eighty-eight participants completed eleven rounds of investment decisions for a total of 880 trials. Several methods were employed to check the validity of the data from the various data streams and to eliminate, when necessary, invalid data from the analysis. Eye tracking was the most stable data stream. No participants or participant-rounds needed to be removed from the analysis due to errors in eye tracking measurements. Electrodermal Activity (EDA) was the next most stable measurement. A total of 103 participant-rounds for the EDA stream of data were removed from the analysis (approximately 11.7% of EDA rounds). Engagement was the most challenging metric to capture because the EEG sensors required nearly perfect and continuous contact to generate the metric. A total of 115 participant-rounds for the engagement stream of data were removed from the analysis (approximately 13.1% of engagement rounds). Two criteria were used to identify rounds for removal. First, if rounds showed no or very little variation (i.e.
they contained primarily or exclusively repeating values at each observation) the round was identified for removal. Second, a z-score was generated for each observation, essentially using the sample mean and standard deviation to generate a distance score for each observation based on the sample’s distribution. If the average z-score for a given data stream was greater than 3 for multiple rounds, that participant’s data was identified for removal from the analysis. Due to participant error, 15 rounds were identified for removal of all data streams. In these cases, participants erroneously advanced the experiment screens too quickly and did not have an opportunity to review the information in the stimulus or make an informed decision. In the end, 865 trials were available for analysis with the eye tracking data stream (including pupil measurements), 762 trials were available for analysis with the EDA stream, and 750 trials were available for analysis with the engagement metric stream.

Each of the data streams (from the eye tracker, the EEG sensor, and the GSR sensor) were captured at a different sampling rate. The eye tracker operates at 60 Hz (60 samples per second), the EEG at 128 Hz, and the GSR sensor at 32 Hz. The most detailed temporal level of interest in this study was corresponding gaze location with other measurements, therefore the EDA measurements were up-sampled from 32 Hz to 60 Hz and the EEG signals downsampled from 128 Hz to 60 Hz to sync with the eye tracking measurements. The average time spent across all participants per decision-round was 74.2 seconds. A one-way ANOVA comparing trial times by group showed that the difference in time (measured in milliseconds) spent per round between groups was significant at the p<.05 level $F(2, 1,029) = 3.86, \ p = 0.0213$. A post-hoc comparison of means using the Bonferroni-adjusted criterion for significance revealed that the mean time for the MAcc group ($M = 78,098.53 ms, SD = 39,302.9$) was significantly higher than
the MSF group ($M = 70,304.05ms$, $SD = 35,174.48$), however the mean time spent by the MBA group ($M = 72,382.23ms$, $SD = 39,194.23$) was not statistically different from either other group.

### 4.3 Key Variables

In this section I briefly describe the key variables used in the analysis. I will discuss the dependent variables first. “Sum of time on AOI” is an aggregate measure of the amount of time (measured in milliseconds) that a participant spent on a particular area of interest (“AOI”) during a decision round. The areas of interest were defined as 1, analyst forecast; 2, management forecast; 3, financial information; and 4, stock chart. The number of times a participant's gaze bounced between financial information and the stock chart in a given decision round constitutes the variable “Count of Integrations of Unfiltered Info”. “EDA” refers to electrodermal activity and is the measure that comes from the GSR sensor. “Engagement” was an algorithmically-determined summary measure ranging from 0 to 1 produced directly by the Emotiv Cognitiv Suite software. Emotiv’s engagement metric measures cognitive activity associated with performing cognitively challenging tasks such as puzzle- or problem-solving. “Pupil Size” is measured through the Tobii T60 by fitting an ellipse to the area observed as the pupil. The width of the pupil is estimated using this ellipse rather than via a pixel-counting method due to the relatively low resolution of the eye tracking camera in a remote configuration.

The key independent variables used in the analysis are primarily binary or categorical variables. “Loss Series First” was coded 1 when the participant was shown the version of the experiment that included a series of four losses followed by four gains. If the participant experienced four gains followed by four losses, this variable was coded 0. If a participant’s answers to questions in the post-experimental questionnaire indicated that they were comfortable accepting risk in a financial decision, he or she was coded 1 in the “Risk Seeker” variable. If the
Table 4.1
Variable Descriptions

**Dependent Variables:**

**Sum of Time on AOI** = Sum of the time (in milliseconds) a participant spent on each type of information (Areas Of Interest: Analyst Forecast, Management Forecast, Financial Information, and Stock Chart) by decision round.

**Integrations of Unfiltered Information** = A count of the number of times that consecutive fixations were observed between unfiltered information (Financial Information and Stock Charts).

**EDA** = Electro-dermal Activity (Skin Conductance) (effort measurement, higher values = higher arousal)

**Engagement** = Summary metric from EEG, generated directly by Emotiv algorithms. (relative values that range from 0 to 1, higher values = higher engagement)

**Pupil Size** = the fitted-ellipse-method approximated pupil size for the right pupil. Note that the Tobii T60 reports a left and right pupil measurement. However, these measurements are highly correlated r(4,903,847) = 0.887, p < 0.001. Given the high correlation, only on the right pupil measurement is used for simplicity of presentation and discussion. In tables and narrative discussion I refer to the right pupil size as simply “pupil size”.

**Independent Variables:**

**Loss Series First** = Indicates the order in which participants experienced gains and losses. Coded: (0) series of gains followed by losses (1) series of losses followed by gains.

**Risk Seeker** = Participant’s comfort with financial decisions involving risk. Coded: (0) for participants that prefer to avoid risk (1) for participants that are more willing to accept risk in financial decisions.

**Group** = Classification of the degree program the participant belongs to. Coded: (0) for Master of Science in Finance [MSF] (1) for Master of Accounting [MAcc] (2) for Master of Business Administration [MBA]. The sophisticated investor group is the MSF group, who receive specific training in investments. In the regression results, the MSF group is absorbed into the intercept, so the coefficients for the MAcc and MBA groups indicate their difference from the MSF group. In some analyses, interactions are presented as contrasts between these groups as if each group was coded as a 0/1 variable. This is the case for the group variable and the AOI variable.

**AOI** = Area of Interest. Coded: (1) Analyst Forecast (2) Management Forecast (3) Financial Information (4) Stock Chart.

*Note*: Management and Analyst forecasts are classified as “filtered” information while financial information and stock charts are “unfiltered” information.

**Decision Round** = Numbered rounds of decisions in the series (1-11).

**Chose a Long Position** = The participant’s investment decision for the round. Coded: (0) chose a short position indicating that the participant expected the stock price to go down (1) chose a long position indicating that the participant expected the stock price to go up.

**AOI Trend is Positive** = Whether the information in the AOI trends positive or negative. Coded: (0) the information in the AOI is negative (1) the information in the AOI is positive.

Table 4.1 presents descriptions of key variables used in the following analyses.
Table 4.2
Summary Statistics on Key Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>25th %</th>
<th>75th %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of Time on Analyst Forecast</td>
<td>20,815.17</td>
<td>13,427.59</td>
<td>10,806</td>
<td>28,262</td>
</tr>
<tr>
<td>Sum of Time on Management Forecast</td>
<td>17,469.33</td>
<td>11,155.38</td>
<td>8,926</td>
<td>24,082</td>
</tr>
<tr>
<td>Sum of Time on Financial Info</td>
<td>22,335.00</td>
<td>16,900.37</td>
<td>9,430</td>
<td>31,610</td>
</tr>
<tr>
<td>Sum of Time on Stock Chart</td>
<td>6,478.79</td>
<td>6,372.30</td>
<td>2,231</td>
<td>8,662</td>
</tr>
<tr>
<td>Integrations of Unfiltered Information</td>
<td>18.94</td>
<td>31.99</td>
<td>2</td>
<td>21</td>
</tr>
<tr>
<td>EDA</td>
<td>1.3964</td>
<td>2.4676</td>
<td>0.1540</td>
<td>1.4430</td>
</tr>
<tr>
<td>Engagement</td>
<td>0.6079</td>
<td>0.1145</td>
<td>0.5481</td>
<td>0.6749</td>
</tr>
<tr>
<td>Pupil Size</td>
<td>3.0059</td>
<td>0.3629</td>
<td>2.7497</td>
<td>3.2162</td>
</tr>
</tbody>
</table>

Counts by Group

<table>
<thead>
<tr>
<th></th>
<th>MSF</th>
<th>MAcc</th>
<th>MBA</th>
</tr>
</thead>
<tbody>
<tr>
<td>N (Total)</td>
<td>22</td>
<td>35</td>
<td>31</td>
</tr>
<tr>
<td>Gain Series First</td>
<td>20</td>
<td>18</td>
<td>16</td>
</tr>
<tr>
<td>Risk Seeker</td>
<td>11</td>
<td>19</td>
<td>15</td>
</tr>
<tr>
<td>Chose a Long Position</td>
<td>114</td>
<td>184</td>
<td>186</td>
</tr>
<tr>
<td>Chose a Short Position</td>
<td>146</td>
<td>218</td>
<td>168</td>
</tr>
</tbody>
</table>

Table 4.2 presents summary statistics on key variables that are described in Table 4.1 and in the text of the chapter.

Participant indicated aversion to risk, this variable was coded 0. A “Group” variable tracked which degree program the participant was recruited from. This variable was coded 0 for MSF, 1 for MAcc, and 2 for MBA. The “Decision Round” variable ranged was from 0 to 11 and indicated the order of the decisions that were made by the participant. Decision round 0 was the practice decision round and is generally excluded from analyses. Decision rounds 1 through 11 correspond to a participant’s progression through the experimental decision rounds. Decision round 1 was the first investment decision, 2 the second, and so on with 11 being the last.
<table>
<thead>
<tr>
<th></th>
<th>Sum of Time on AOI</th>
<th>Count of Integrations</th>
<th>EDA</th>
<th>Engagement</th>
<th>Pupil Size</th>
<th>Loss Series First</th>
<th>Risk Seeker Group</th>
<th>Decision Round</th>
<th>Chose Long</th>
<th>AOI Trend Positive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of Time on AOI</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count of Integrations</td>
<td>0.1676</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EDA</td>
<td></td>
<td>0.025</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Engagement</td>
<td>0.0243</td>
<td>0.0075</td>
<td>-0.0201</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pupil Size</td>
<td>0.1578</td>
<td>-0.1429</td>
<td>0.0864</td>
<td>-0.1309</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Loss Series First</td>
<td>0.0609</td>
<td>0.018</td>
<td>0.0906</td>
<td>0.018</td>
<td>0.0893</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk Seeker Group</td>
<td></td>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group</td>
<td>-0.0166</td>
<td>0.0139</td>
<td>0.0619</td>
<td>0.0895</td>
<td>-0.0101</td>
<td>0.2915</td>
<td>-0.0122</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision Round</td>
<td></td>
<td>0.2883</td>
<td>0.3781</td>
<td>0.0002</td>
<td>0.0000</td>
<td>0.5196</td>
<td>0.0000</td>
<td>0.4364</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chose Long</td>
<td></td>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.1011</td>
<td>0.0088</td>
<td>0.9516</td>
<td>0.6625</td>
<td>0.9076</td>
<td></td>
</tr>
<tr>
<td>AOI Trend Positive</td>
<td>-0.0198</td>
<td></td>
<td>0.0608</td>
<td>0.0102</td>
<td>-0.0065</td>
<td>-0.0251</td>
<td>0.0071</td>
<td>-0.0013</td>
<td>0.0739</td>
<td>0.0662</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.2079</td>
<td>0.0001</td>
<td>0.5459</td>
<td>0.7055</td>
<td>0.1095</td>
<td>0.6506</td>
<td>0.9323</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.0606</td>
<td>0.0506</td>
<td>-0.0032</td>
<td>-0.0248</td>
<td>-0.0041</td>
<td>-0.0015</td>
<td>0.0001</td>
<td>0.0008</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.0017</td>
<td>0.8516</td>
<td>0.157</td>
<td>0.7958</td>
<td>0.9232</td>
<td>0.9975</td>
<td>0.9619</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Table 4.3 presents correlations between key variables used in the analysis. Bolded coefficients indicate correlations that are significant at the p<.01 level. The second line indicates p-values.
investment decision for all participants regardless of the gain or loss sequence condition they
were in. If a participant chose a long position in a given round (i.e. they believed the stock price
would rise in 30 days), the “Chose a Long Position” variable was coded 1. If the participant
chose a short position instead (indicating they believed the stock price would be lower in 30
days), the “Chose a Long Position” variable was coded 0. Finally, for each decision round
stimulus, every AOI was individually indicated for either displaying a positive or negative trend.
If the AOI indicated a positive trend (e.g. the EPS was expected to increase), the “AOI Trend is
Positive” variable was coded 1. If the AOI instead indicates a negative trend, this variable was
coded 0. Descriptions of the key variables used in the analysis can be found in Table 4.1.
Summary statistics are available in table 4.2, and a correlation matrix is presented in table 4.3.

There are several control variables included in every regression analysis presented in this
chapter. The first is “Loss Series First”. This variable captures the average difference between
participants who experienced losses first compared to those who experienced gains first. In
Tables 4.4 and 4.6, the coefficients on this variable are positive and significant indicating that the
overall average time spent was greater for participants that began the experiment while
experiencing a series of losses. Next, the variable “Risk Seeker” captures the difference in
average performance for participants that code high on the risk seeking dimension. In every
regression model to follow, the coefficients on this variable are negative and significant
indicating that individuals who are more comfortable accepting risk in a financial decision spend
less time or effort making their decisions in this setting. Finally, every regression analysis
includes decision round fixed effects, which is a series of dummy variables that account for the
variation associated with each individual decision round. The importance of this control is
apparent when viewing the virtually monotonically-increasing negative and significant
coefficients on each of these terms. Participants tend to spend less time on their decisions as rounds progress and the round fixed-effects control, then, is an important tool to isolate this variation so that the effects in the variables of primary interest are not obscured.

4.4 Test of Hypothesis 1

H1 requires investigating whether more sophisticated investors place greater emphasis throughout the trials on factual (unfiltered) information. Unfiltered information is that which has not been processed and packaged by professionals, rather it presents facts in a straightforward way. The “Financial Information” and the “Stock Chart” are the unfiltered information types. Filtered information, by contrast, has been professionally prepared and summarizes information in a narrative format. “Management Guidance” and “Analyst Guidance” are the filtered information types. Table 4.4 presents the results of a regression model with the primary goal of determining whether there are significant differences between groups on the use of the different information types. I control for the sequence of gains and losses the participant experienced, whether participants are risk seeking or risk avoiding in a financial setting, and decision-round fixed effects which help to capture changes in time spent on decisions as the experiment progresses. I find no main effects for group (including no difference between MAcc and MSF $F(1, 3412) = 0.10, p > 0.05$), but I do find that on average individuals spend more time on financial information $b = 2,993.763, t(3,429) = 2.70, p < 0.01$, less time on management guidance $b = -2,960.819, t(3,429) = -2.66, p < 0.01$, and much less time on the stock chart $b = -13,624.94, t(3,429) = -12.21, p < 0.001$ compared to analyst guidance.

Of primary interest in the examination of this hypothesis is to identify any instances where a group of participants spent more or less time on a type of information compared to the
Table 4.4
Attention on Specific AOI’s During Decision-making Process

<table>
<thead>
<tr>
<th>DV = Sum of Time on AOI</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>23,587.65</td>
<td>***</td>
</tr>
<tr>
<td>Loss Series First</td>
<td>2,307.28</td>
<td>***</td>
</tr>
<tr>
<td>Risk Seeker</td>
<td>-1,847.49</td>
<td>***</td>
</tr>
<tr>
<td>Group:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAcc Participant</td>
<td>-1,411.85</td>
<td>(-1.38)</td>
</tr>
<tr>
<td>MBA Participant</td>
<td>-1,704.02</td>
<td>(-1.64)</td>
</tr>
<tr>
<td>AOI:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Management Guidance</td>
<td>-2,960.82</td>
<td>**</td>
</tr>
<tr>
<td>Financial Information</td>
<td>2,993.76</td>
<td>**</td>
</tr>
<tr>
<td>Stock Chart</td>
<td>-13,624.94</td>
<td>***</td>
</tr>
<tr>
<td>Group x AOI:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAcc x Management Guidance</td>
<td>699.66</td>
<td>(0.49)</td>
</tr>
<tr>
<td>MAcc x Financial Info</td>
<td>-387.59</td>
<td>(-0.27)</td>
</tr>
<tr>
<td>MAcc x Stock Chart</td>
<td>1,944.94</td>
<td>(1.36)</td>
</tr>
<tr>
<td>MBA x Management Guidance</td>
<td>748.37</td>
<td>(0.52)</td>
</tr>
<tr>
<td>MBA x Financial Info</td>
<td>-3,285.56</td>
<td>*</td>
</tr>
<tr>
<td>MBA x Stock Chart</td>
<td>1,158.80</td>
<td>(0.80)</td>
</tr>
<tr>
<td>Decision Round Dummy Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision 3</td>
<td>-140.27</td>
<td>(-0.16)</td>
</tr>
<tr>
<td>Decision 4</td>
<td>-2,334.43</td>
<td>**</td>
</tr>
<tr>
<td>Decision 5</td>
<td>-2,500.76</td>
<td>**</td>
</tr>
<tr>
<td>Decision 6</td>
<td>-4,510.07</td>
<td>***</td>
</tr>
<tr>
<td>Decision 7</td>
<td>-2,367.16</td>
<td>**</td>
</tr>
<tr>
<td>Decision 8</td>
<td>-4,158.74</td>
<td>***</td>
</tr>
<tr>
<td>Decision 9</td>
<td>-5,327.53</td>
<td>***</td>
</tr>
<tr>
<td>Decision 10</td>
<td>-6,230.77</td>
<td>***</td>
</tr>
<tr>
<td>Decision 11</td>
<td>-7,706.85</td>
<td>***</td>
</tr>
</tbody>
</table>

N = 3,453
R^2 (adjusted) = 0.220

Table 4.4 reports the coefficients (with t-statistics) for regressions using the DV Time (in milliseconds) spent on an AOI by trial. Decision round 1 (buffer) was excluded.

\[ \text{Sum of Time on AOI} = \alpha + \beta_1 \text{Group} + \beta_2 \text{AOI} + \beta_3 \text{Group} \times \text{AOI} + \beta_4 \text{Loss Series First} + \beta_5 \text{Risk Seeker} + \beta_6 \text{Round Fixed Effects} + \varepsilon \]

Significance is indicated via the convention (***, **, *) corresponding to two-tailed p-values of (p<0.001, p<.01, and p<.05), respectively.
sophisticated group. This is tested by interacting the “Group” and “AOI” variables. The results of this interaction indicate that the MBA group spends significantly less time on financial information compared to the MSF group $b = -3.285.561$, $t(3,429) = -2.27$, $p < 0.05$. Financial information is an unfiltered information type and as such, the hypothesis is partially supported by the evidence. However, I do not find differences in time spent on AOI’s between the MSF group and the MAcc group, nor do I find differences between the MSF group and the MBA group for the other type of unfiltered information, the stock chart. While the hypothesis is only partially supported, it should be noted that the most value-relevant type of unfiltered information, the financial information, received more attention by the two more-sophisticated groups.

4.5 Test of Hypothesis 2

The test of H2 is focused on whether more sophisticated investors integrate unfiltered financial information more than the other groups. Integrating information refers to the act of going back and forth between two pieces of information in order to gain additional insight that each individual piece of information cannot provide alone. This analysis uses a count of the number of times a participant’s attention went from financial information to the stock chart or from the stock chart to the financial information as the dependent variable. The regression results in Table 4.5 again control for the order in which the participant saw gains or losses and their risk-seeking tendencies in addition to decision round fixed effects. I find that compared to the MSF group, the MAcc group performs more integrations of unfiltered information $b = 7.529$, $t(3,389) = 6.06$, $p < 0.001$, however the MBA group does not perform more or less integrations than the MSF group. An F test shows that the MAcc group also performs more integrations than the MBA group $F(1, 3,389) = 38.37$, $p < 0.001$. I do not find evidence to support hypothesis two.
Instead, I find that the MAcc group, who are highly trained on financial information but not on making investment decisions, perform more integrations of unfiltered information.

4.6 Test of Hypotheses 3a and 3b

The test of H3a and H3b involves examining whether participants spend more time on information that agrees with the investment decision that they ultimately indicate. More

<table>
<thead>
<tr>
<th>DV = Count of Integrations of Unfiltered Info</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>8.201 ***</td>
<td>(4.75)</td>
</tr>
<tr>
<td>Loss Series First</td>
<td>1.030</td>
<td>(1.02)</td>
</tr>
<tr>
<td>Risk Seeker</td>
<td>-7.576 ***</td>
<td>(-8.20)</td>
</tr>
<tr>
<td>Group:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAcc Participant</td>
<td>7.529 ***</td>
<td>(6.06)</td>
</tr>
<tr>
<td>MBA Participant</td>
<td>0.927</td>
<td>(0.74)</td>
</tr>
</tbody>
</table>

Decision Round Dummy Variables

| Decision 3                                  | 12.414 ***  | (6.01)|
| Decision 4                                  | 32.248 ***  | (15.62)|
| Decision 5                                  | 8.611 ***   | (4.18)|
| Decision 6                                  | 23.520 ***  | (11.34)|
| Decision 7                                  | -7.009 ***  | (-3.40)|
| Decision 8                                  | -0.316      | (-0.15)|
| Decision 9                                  | 0.151       | (0.07)|
| Decision 10                                 | 4.441 *     | (2.16)|
| Decision 11                                 | 28.134 ***  | (13.55)|

N                                        3,403
R²(adjusted)                                0.204

Table 4.5 reports the coefficients (with t-statistics) for regressions using the DV Time (in milliseconds) spent on an AOI by trial. The equation is displayed below:

\[
\text{Sum of Time on AOI} = \alpha + \beta_1 \text{Loss Series First} + \beta_2 \text{Risk Seeker} + \beta_3 \text{Group} + \beta_{4-11} \text{Decision Round(2-11)}
\]

Significance is indicated via the convention (***, **, *) corresponding to two-tailed p-values of (p<0.001, p<.01, and p<.05), respectively.
specifically, if participants choose a long position indicating that they believe the stock price will rise, do they spend more time on AOI’s that trend in a positive direction? Similarly, if participants choose a short position indicating that they believe the stock price will go down, do they spend more time on AOI’s that trend in a negative direction? Recall from the procedure description in chapter three that participants indicated this decision on a separate screen after they were finished viewing the investment information stimulus.

The results of the regression model in Table 4.6 shows the incremental time response at the AOI (area of interest) level based on participant investment choices. The regression includes variables controlling for the order in which the participant saw gains or losses, their risk-seeking tendencies, and decision round fixed effects. The results show that in general when an individual chooses a long position (predicting the stock price will go up) they spend a bit less time on the decision \( b = -2,776.201, t(3,849) = -4.07, p < 0.001 \). Additionally, MBA students spend, on average, less time on their decisions \( b = -1,453.942, t(3,849) = -2.49, p < 0.05 \). An F-test reveals that the MAcc students also spend significantly more time on the decision than the MBA students \( F(1, 3849) = 4.44, p < 0.05 \). Of primary importance, however, is the interaction between investment choice and the trend of the AOI \( b = 4,951.601, t(3,849) = 5.60, p < 0.001 \). The coefficient on the interaction is positive and highly significant indicating that higher levels of time are associated with AOI information that trends in the same direction as the investment decision the participant made. This provides direct evidence in support of hypothesis 3a. By extension, the coefficient on the interaction can be further interpreted as indicating that when AOI information trends in the opposite direction of the participant’s investment decision, less
Table 4.6
Time and Attention on Specific AOI's Given the Individual's Choice

<table>
<thead>
<tr>
<th>DV = Sum of Time on AOI</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>26,486.08</td>
<td>***</td>
</tr>
<tr>
<td>Loss Series First</td>
<td>2,185.54</td>
<td>***</td>
</tr>
<tr>
<td>Risk Seeker</td>
<td>-1,680.67</td>
<td>***</td>
</tr>
<tr>
<td>Group:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAcc Participant</td>
<td>-411.23</td>
<td></td>
</tr>
<tr>
<td>MBA Participant</td>
<td>-1,453.94</td>
<td>*</td>
</tr>
<tr>
<td>Chose a Long Position</td>
<td>-2,776.20</td>
<td>***</td>
</tr>
<tr>
<td>AOI Trend is Positive</td>
<td>168.40</td>
<td></td>
</tr>
<tr>
<td>Chose a Long Position x AOI Trend is Positive</td>
<td>4,951.60</td>
<td>***</td>
</tr>
</tbody>
</table>

Decision Round Dummy Variables

<table>
<thead>
<tr>
<th>Decision Round Dummy Variables</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision 1</td>
<td>-4,175.88</td>
<td>***</td>
</tr>
<tr>
<td>Decision 2</td>
<td>-7,777.05</td>
<td>***</td>
</tr>
<tr>
<td>Decision 3</td>
<td>-7,479.33</td>
<td>***</td>
</tr>
<tr>
<td>Decision 4</td>
<td>-8,697.62</td>
<td>***</td>
</tr>
<tr>
<td>Decision 5</td>
<td>-9,273.53</td>
<td>***</td>
</tr>
<tr>
<td>Decision 6</td>
<td>-11,014.06</td>
<td>***</td>
</tr>
<tr>
<td>Decision 7</td>
<td>-13,136.32</td>
<td>***</td>
</tr>
<tr>
<td>Decision 8</td>
<td>-10,839.92</td>
<td>***</td>
</tr>
<tr>
<td>Decision 9</td>
<td>-11,927.95</td>
<td>***</td>
</tr>
<tr>
<td>Decision 10</td>
<td>-14,070.82</td>
<td>***</td>
</tr>
<tr>
<td>Decision 11</td>
<td>-15,294.14</td>
<td>***</td>
</tr>
</tbody>
</table>

N 3,868
R²(adjusted) 0.102

Table 4.6 reports the coefficients (with t-statistics) for regressions using the DV Time (in milliseconds) spent on an AOI by trial. The equation is displayed below:

\[
\text{Sum of Time on AOI} = \alpha + \beta_1\text{Loss Series First} + \beta_2\text{Risk Seeker} + \beta_3\text{Group} + \beta_4\text{Chose a Long Position} + \beta_5\text{AOI Trend is Positive} + \beta_6\text{Chose Long x Positive Trend} + \beta_{7:18}\text{Decision Round(0-11)}
\]

Significance is indicated via the convention (***, **, *) corresponding to one-tailed p-values of (p<0.001, p<.01, and p<.05), respectively.
time is spent on the AOI, providing evidence in support of hypothesis 3b as well. Individuals, then, emphasized information that supported their decision rather than equally weighting information that was positive or negative, providing evidence of the influence of confirmation bias in their decision-making process.

4.7 Test of Hypothesis 4

H4 requires testing whether observed effort levels are higher during a series of losses compared to effort levels measured during a series of gains. Table 4.7 presents a series of t-tests that compare mean effort levels in trials when participants were under the influence of gains to effort levels when participants were under the influence of losses. The primary metric used in the comparison across all effort measure types (EDA, pupil size, and engagement) is the average high measurement. This metric is constructed by taking the weighted average of the highest effort readings across all rounds by participant. Two additional measures, average low and overall average, are sensitive in the EDA measurement. Like the average high metric, the average low metric is similarly constructed of the weighted average of the lowest effort readings across all rounds by participant. The overall average metric does not apply any filters, and instead uses all measurements to calculate the average rather than just the high or low measurements.

Prior literature has shown that larger pupil dilation size is associated with higher levels of effort making the average high pupil size metric the most relevant. Table 4.7 tabulates a series of two-sample t-tests with Welch’s adjustment for degrees of freedom allowing for unequal variances between groups. As shown in this table, pupil size measurements indicate greater effort levels under the influence of prior losses $M = 3.7069$ compared to gains $M = 3.6684$ $[t(3,478,814) = 76.902, p < 0.001]$. 60
Table 4.7 presents means and unmatched two-sample t-tests allowing for unequal variances between groups and using Welch’s adjustment for degrees of freedom for the calculation of significance.

<table>
<thead>
<tr>
<th></th>
<th>Loss Influence</th>
<th>Gain Influence</th>
<th>t</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engagement (average high measurements)</td>
<td>0.8353</td>
<td>0.8291</td>
<td>57.81</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Pupil Size (average high measurements)</td>
<td>3.7069</td>
<td>3.6684</td>
<td>76.90</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>EDA (average high measurements)</td>
<td>1.8503</td>
<td>1.5971</td>
<td>80.59</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>EDA (average of all measurements)</td>
<td>1.5413</td>
<td>1.3383</td>
<td>70.60</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>EDA (average low measurements)</td>
<td>1.1621</td>
<td>1.0542</td>
<td>42.88</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

EDA is a sensitive measure of general arousal at all thresholds (average high, overall mean, and average low) making it a particularly information rich effort measurement. All levels of EDA show the same trend with higher levels of effort indicated during times when the participant is under the influence of prior losses and lower levels of effort during times when the participant is under the influence of prior gains. Specifically, average high EDA (under loss influence \( M = 1.8503 \), under gain influence \( M = 1.5971 \)) \( t(3,112,678)=80.593, p<0.001 \), overall average EDA (under loss influence \( M = 1.5413 \), under gain influence \( M = 1.3383 \)) \( t(3,081,498)=70.598, p<0.001 \), and average low EDA (under loss influence \( M =1.1621 \), under gain influence \( M = 1.0542 \)) \( t(3,112,678)=42.8844, p<0.001 \) are all higher under the influence of losses.

Engagement only exhibits the expected relationship for the average high engagement measurements statistic (under loss influence \( M = 0.8353 \), under gain influence \( M = 0.8291 \)) \( t(3,070,630)=57.807, p<0.001 \). It should be noted that the engagement metric is a relative measure that is intended to measure instantaneous changes in engagement, and not a long-run measure. The most useful feature of the engagement measurement may indeed be the maximum
engagement, however additional testing in other contexts will be necessary to bear this out. For nearly all relevant effort measures, H4 is supported by the evidence.

4.8 Test of Hypotheses 5a and 5b

H5a suggests that the amount of time it takes for effort levels to respond to changes in a gain or loss series will be less when participants begin to experience losses after a series of gains. Conversely, effort levels of participants will be slower to respond when they have previously encountered a series of losses and begin to experience gains. This test is operationalized by comparing the mean of effort levels in all rounds of the gain or loss series that the participant begins with to the mean effort levels observed in the subsequent rounds after the shift from losses to gains or from gains to losses. The goal of the test to discover how many post gain/loss switch rounds it takes for the mean effort levels of the individual rounds to exceed the threshold of the mean effort levels of the combined pre-switch rounds.

Table 4.8 presents this test. The first column presents the overall mean of each effort measure in the combined pre-switch rounds. Subsequent columns present the individual round effort level means until the mean exceeds the threshold in the first column. When going from a series of gains to a series of losses, I seek the first post-switch round in which the mean effort levels are higher than the combined pre-switch mean. When going from a series of losses to a series of gains, I seek the first post-switch round in which the mean effort levels are lower than the combined pre-switch mean. If the gains first cases exceeded the threshold in fewer rounds than the losses first cases, hypothesis 5a would be supported. However, in all cases but one the effort level adjustment is instantaneous and passes the pre-switch mean threshold in the first round. The exception is that the engagement effort measure did not appear to adjust higher than
the pre-switch average in any round when gains were experienced first. Taken together, I find no evidence to support H5a.

Table 4.8 presents the test of H5a, seeking the first post gain/loss switch round in which the average effort levels exceed the average effort levels of the pre-switch rounds.

Table 4.8 Speed of Effort Reversal

<table>
<thead>
<tr>
<th>EDA</th>
<th>Average Before Switch (combined rounds)</th>
<th>Average After Switch in Direction (by round)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gain First 0.9908593</td>
<td>1 1.129063</td>
</tr>
<tr>
<td></td>
<td>Loss First 2.032005</td>
<td>2 1.793536</td>
</tr>
<tr>
<td>Engagement (Average High)</td>
<td>1 0.8318475</td>
<td>1 0.825166</td>
</tr>
<tr>
<td></td>
<td>Gain First 0.8473883</td>
<td>2 0.826760</td>
</tr>
<tr>
<td></td>
<td>Loss First 0.8473883</td>
<td>3 0.819033</td>
</tr>
<tr>
<td>Pupil Size (Average High)</td>
<td>1 3.566805</td>
<td>4 0.82505</td>
</tr>
<tr>
<td></td>
<td>Gain First 3.857437</td>
<td>2 3.608819</td>
</tr>
<tr>
<td></td>
<td>Loss First 3.857437</td>
<td>3 3.844459</td>
</tr>
</tbody>
</table>

Table 4.8 presents the test of H5a, seeking the first post gain/loss switch round in which the average effort levels exceed the average effort levels of the pre-switch rounds.

H5b focuses on the magnitude of the change in effort levels when the direction of a series of gains or losses reverses. More specifically, the question is whether participant levels of effort will increase with greater magnitude when they begin to experience losses after having experienced a series of gains compared to the magnitude of decreases in effort levels when they begin to experience gains after a series of losses.

Table 4.9 shows that this appears to be the case for the EDA measurement only. In the first and third columns, this table compares the average effort levels in the last decision round that was under the influence
of a prior loss. The second and fourth columns compare the average levels in the last decision round that was under the influence of prior losses to the first decision round that was under the influence of a prior gain. Note that in the case of EDA, the magnitude of the change in effort from the round just before a frame change to the round just after a frame change was much greater coming from a gain frame to a loss frame compared to that of the switch from a loss frame to a gain frame. The magnitude changes in the other measures are much lower making them more difficult to interpret.

<table>
<thead>
<tr>
<th></th>
<th>Gain to Loss Round Averages</th>
<th>Loss to Gain Round Averages</th>
<th>Gain to Loss %Δ</th>
<th>Loss to Gain %Δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDA</td>
<td>1.2000</td>
<td>2.4878</td>
<td>22.97%</td>
<td>-16.68%</td>
</tr>
<tr>
<td>Engagement</td>
<td>0.8328</td>
<td>0.8528</td>
<td>-0.91%</td>
<td>-3.05%</td>
</tr>
<tr>
<td>Pupil Size</td>
<td>3.5654</td>
<td>3.9011</td>
<td>1.22%</td>
<td>-1.51%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>EDA % Δ by group</th>
<th>Gain to Loss</th>
<th>Loss to Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSF</td>
<td>7.52%</td>
<td>-12.55%</td>
</tr>
<tr>
<td>MBA</td>
<td>41.69%</td>
<td>-13.05%</td>
</tr>
<tr>
<td>MAcc</td>
<td>25.63%</td>
<td>-20.70%</td>
</tr>
</tbody>
</table>

Table 4.9 presents the average effort levels in the rounds immediately prior to and immediately following a switch from gains to losses including the percentage change in effort levels. A supplemental analysis breaks down the EDA percentage change from the last gain round to the first loss round and the last loss round to the first gain round by participant group.

A supplemental analysis also presented in Table 4.9, which breaks the EDA measurement response down by group, reveals an interesting pattern. The MBA group, which represents the
least sophisticated investor group, appears to be the most sensitive to changes in the gain or loss sequence. The magnitude of changes in their effort levels is dramatic for the gains to losses transition in particular. The MAcc group has a relatively high, but balanced response to changes in fortune. The magnitude of their effort level adjustments is relatively high, but nearly equivalent for gains to losses and losses to gains. The MSF group, which is the highest trained group for making investment decisions displays adjustments in effort levels that are lower, on average, than the other groups. This is particularly true for the increase in effort levels in the transition from experiencing gains to experiencing losses. In these cases the MSF group increases effort levels by a mean of only 7.52% compared to 41.69% for the MBA group and 25.63% for the MAcc group. This may be explained by the training that the MSF group has that the other groups do not possess. The MSF group has a set of strategies they can draw upon to help them make subsequent decisions while the other groups do not. They know how to approach the next investment decision in a rational manner using the information at their disposal through valuation models that they have previously studied and applied.

I find partial evidence to support H5b in that for the EDA measurement, the magnitude of changes in effort levels when a participant transitioned from making decisions under the influence of a prior gain to making decisions under the influence of a prior loss was greater than the magnitude of changes in effort levels when a participant transitioned from making decisions under the influence of a prior loss to making decisions under the influence of a prior gain.

4.9 Test of Hypotheses 6a and 6b

The last hypotheses, H6a and H6b, focus on examining information preferences when a participant is making a decision under the influence of a prior gain or a prior loss. Specifically, the prediction is that participants will place a greater emphasis on unfiltered information when
Table 4.10
Attention on Specific AOI’s When Under the Influence of Gains or Losses

<table>
<thead>
<tr>
<th>DV = Sum of Time on AOI</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>23,283.58***</td>
<td>(25.33)</td>
</tr>
<tr>
<td>Risk Seeker</td>
<td>-1,842.33***</td>
<td>(-4.66)</td>
</tr>
<tr>
<td>Loss Series First</td>
<td>2,307.28***</td>
<td>(5.33)</td>
</tr>
<tr>
<td>Group:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAcc Participant</td>
<td>-861.72</td>
<td>(-1.62)</td>
</tr>
<tr>
<td>MBA Participant</td>
<td>-2,057.43***</td>
<td>(-3.80)</td>
</tr>
<tr>
<td>AOI:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Management Guidance</td>
<td>-2,014.79*</td>
<td>(-2.56)</td>
</tr>
<tr>
<td>Financial Information</td>
<td>1,384.13</td>
<td>(1.76)</td>
</tr>
<tr>
<td>Stock Chart</td>
<td>-12,125.21***</td>
<td>(-15.35)</td>
</tr>
<tr>
<td>Under Gain Influence x AOI:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gain infl x Management Guidance</td>
<td>-802.52</td>
<td>(-0.72)</td>
</tr>
<tr>
<td>Gain infl x Financial Info</td>
<td>582.30</td>
<td>(0.52)</td>
</tr>
<tr>
<td>Gain infl x Stock Chart</td>
<td>-634.92</td>
<td>(-0.57)</td>
</tr>
<tr>
<td>Decision Round Dummy Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decision 3</td>
<td>-106.21</td>
<td>(-0.12)</td>
</tr>
<tr>
<td>Decision 4</td>
<td>-2,328.06**</td>
<td>(-2.64)</td>
</tr>
<tr>
<td>Decision 5</td>
<td>-2,498.09**</td>
<td>(-2.84)</td>
</tr>
<tr>
<td>Decision 6</td>
<td>-4,511.42***</td>
<td>(-5.09)</td>
</tr>
<tr>
<td>Decision 7</td>
<td>-2,369.95**</td>
<td>(-2.67)</td>
</tr>
<tr>
<td>Decision 8</td>
<td>-4,121.02***</td>
<td>(-4.61)</td>
</tr>
<tr>
<td>Decision 9</td>
<td>-5,290.60***</td>
<td>(-5.95)</td>
</tr>
<tr>
<td>Decision 10</td>
<td>-6,192.22***</td>
<td>(-6.97)</td>
</tr>
<tr>
<td>Decision 11</td>
<td>-7,671.80***</td>
<td>(-8.62)</td>
</tr>
</tbody>
</table>

N 3,435
R²(adjusted) 0.218

Table 4.10 reports the coefficients (with t-statistics) for regressions using the DV Time (in milliseconds) spent on an AOI by trial. Decision round 1 (buffer) was excluded.

Sum of Time on AOI = α + β₁Under Gain Influence + β₂Risk Seeker + β₃Group + β₄AOI + β₅Under Gain Influence x AOI + β₆Losses First + β₇-15Round Fixed Effects + ε

Significance is indicated via the convention (***, **, *) corresponding to two-tailed p-values of (p<0.001, p<.01, and p<.05).
experiencing a loss frame and that they will place greater emphasis on filtered information when experiencing a gain frame. The regression model in Table 4.10 is presented as the test of hypotheses 6a and 6b.

The results of this regression indicate that all participants, on average, spend less time on management guidance $b = -2,014.789, t(3,414) = -2.56, p < 0.05$ and stock charts $b = -12,125.21, t(3,414) = -15.35, p < 0.001$ while the main effect for the most value-relevant type of unfiltered information, the financial information, is insignificant $b = 1,384.134, t(3,414) = 1.76, p > 0.05$. Additionally, it is apparent that MBA participants spend less time on the decision than the MSF group $b = 1,384.134, t(3,414) = 1.76, p > 0.05$. An F-test also reveals that the MBA group spends less time than the MAcc group $F(1, 3,414) = 6.89, p < 0.01$.

The test of H6a and H6b, however, involves the two-way interaction between “Under Gain Influence” and “AOI”. The interaction of these variables reveals no significant differences between the use of the various information types under the influence of gains or losses. The coefficients on management guidance $b = -802.7216, t(3,414) = -0.72, p > 0.05$, financial information $b = 582.2979, t(3,414) = 0.52, p > 0.05$, and stock charts $b = -634.9248, t(3,414) = -0.57, p > 0.05$ indicate that the amount of time spent on these AOI’s under the influence of prior gains is not statistically distinguishable from the time spent on these AOI’s when a participant is under a loss influence. Given these results, I do not find evidence to support H6a or H6b.

4.10 Chapter Summary

In chapter four I presented the experimental results including a discussion of the data, variables, and the analyses employed to test the six hypotheses that were developed in chapter three. I found at least partial support for most of the hypotheses, however in three cases I did not
find sufficient evidence to support a tested hypothesis or a portion of the hypothesis. The results of the hypothesis testing are summarized later in this section.

In section 4.2 I discussed the data that was used in the analysis. As part of this discussion, I outlined how data was identified to be removed either due to inadvertent actions by the participants themselves, or issues with a particular data stream. No participant rounds required removal of eye tracking data. The EDA signal, which was generated by the GSR sensor, was removed from 11.7% of trials and the engagement metric, which was generated by the EEG sensor, was removed from 13.1% of trials. These signals were identified for removal either because their average z-score exceeded 3 for multiple rounds in which case all rounds of that particular measurement were excluded for that participant, or because the signal quality was so low that the recorded values showed little or no variation. 1.7% of trials were removed due to participant error. At the end of section 4.2, the process of combining the data streams for analysis was described. Section 4.3 provided definitions of the key variables used in the analyses and summary statistics describing these variables and their univariate relationships.

In section 4.4 I found partial evidence to support H1, in particular, I found that the MBA group (the less sophisticated investors) spent significantly less time on financial information, an unfiltered information type. While this finding was not repeated for the other unfiltered information type, the stock chart, financial information is the more value-relevant of the two and thus the fact that participants from the MSF group (the more sophisticated investors) spent more time on financial information is consistent with the goal of the test which was to detect whether the more sophisticated group gravitates incrementally more than the other groups toward factual and value relevant information.
In section 4.5, I did not find adequate evidence to support H2. Specifically, the MAcc group, rather than the MSF group, performed more integrations of unfiltered information. There were at least two plausible explanations for this finding that cannot be fully resolved with this experimental design. The first is that the MSF group may have been more efficient at integrating data between the two AOIs and required fewer fixations to obtain the same level of information. Secondly, the MSF group, having knowledge of the lower value relevance of the stock chart information, may have intentionally suppressed fixations on stock charts. Either of these explanations are consistent with sophisticated investment decision-making behavior, however there was insufficient evidence to make conclusions about these alternative explanations in the current study.

In section 4.6 I found evidence to support H3a and H3b. The test focused on the interaction between the variables “Chose a Long Position” and “AOI Trend is Positive”. The positive and highly significant coefficient on this interaction term indicated that participants spent significantly more time on information that agreed with their ultimate investment decision rather than equally weighting all evidence (either for or against their decision).

In section 4.7 I presented evidence that supports H4. Using multiple methods of measuring effort and the most relevant metrics for each signal type, I found that effort levels were significantly higher when participants were under the influence of a prior loss. Conversely, effort levels were lower when participants were under the influence of a prior gain.

In section 4.8 I did not find sufficient evidence to support H5a, but I did find partial evidence to support H5b. The test of H5a involved measuring the number of post gain/loss series rounds it took for effort levels to exceed the average effort levels observed in the pre-switch rounds. There was no evidence to support the suggestion that effort levels passed the pre-switch
effort levels more quickly when a participant was coming from a series of gains to losses compared to when a participant was coming from a series of losses to gains. In nearly all cases, the adjustment was instantaneous and dramatic enough to exceed the pre-switch thresholds in the first post-switch round. The test of H5b provided partial support for the suggestion that the magnitude of effort changes was greater when transitioning from a gain series to a loss series compared to the magnitude of effort changes when transitioning from a loss series to a gain series. This test compared effort levels in the period immediately prior to the gain/loss series switch to effort levels in the period immediately following the switch. The engagement and pupil size metrics did not display a high degree of sensitivity and are more difficult to interpret, however the EDA measurements displayed a dramatic adjustment which was greater in absolute terms for the transition from gains to losses than the transition from losses to gains.

Finally, H6a and H6b could not be supported by the evidence presented in section 4.9. The key tests of these hypotheses were the interaction of the variables “Under Gain Influence” and “AOI”. For H6a and H6b to be supported, there should have been positive and significant coefficients on the “Under Gain Influence” x “AOI” interaction for the unfiltered information variables (financial information and stock chart), or a negative and significant coefficient on analyst guidance, a filtered information type. However, all information types yielded small coefficients that were not statistically significant. Therefore, I failed to find evidence for an incremental effect of the influence of prior gains on the amount of time spent on filtered or unfiltered information.
CHAPTER FIVE

SUMMARY AND DISCUSSION

5.1 Introduction

I conclude the dissertation by providing a summary of what was achieved in this study, what it means, and how it can impact future research. In section 5.2, I provide a recap of the purpose of the study including a brief reiteration of the hypotheses. Section 5.3 provides a review of the method employed. Section 5.4 provides a summary of the results from the formal test of the hypotheses. Section 5.5 includes a discussion of what was learned from this study. Finally, section 5.6 suggests directions for research that may follow from this dissertation.

5.2 Research Problem

This study examines investment decision-making behavior at a level of detail which has previously been unavailable. I address several key questions in this dissertation. First, what information do investors prefer when making an investment decision? Second, does this preference for information vary between investor sophistication levels? Third, how do information preferences and investor sophistication interact with whether individuals are making decisions under a prior gain or loss frame? Finally, how do effort levels vary across these same dimensions? Investor behavior is a subject that has received significant attention in the accounting and finance literatures. This study contributes to our existing understanding of investor decision making and the investor experience. Using eye tracking, I objectively observe what information is preferred by investors when making an investment decision. Using EEG and GSR data, I gain unique insight into levels of effort associated with the overall investment decision and that associated with processing specific pieces of information. Together, this builds...
a richly detailed picture of how individuals make investment decisions and how this behavior changes under the manipulated conditions.

Based on relevant theory and findings from prior literature, I developed six hypotheses predicting investor behavior. The first three focused on expected information acquisition and effort behavior across all trials, the last three suggested how behavior will interact with a prior gain or loss frame. I predicted that more sophisticated investors would place greater emphasis on unfiltered information and integrate unfiltered information to a greater extent when making their investment decisions. I also suggested that individuals would tend to pay more attention to information that supported their investment decisions rather than equally weighting the information available to them. When individuals were making decisions under the influence of a prior period loss, I suggested that their observed effort levels would be higher compared to effort levels observed after a prior period gain. I also predicted that effort behavior would change more quickly and with greater magnitude when investors transitioned from having experienced a series of gains to losses. Finally, I predicted that investors would place greater emphasis on unfiltered information under the influence of losses and filtered information under the influence of gains.

5.3 Review of Methodology

Eighty-eight graduate business students from three degree programs participated in an experiment that required them to make a series of eleven investment decisions. Participants were drawn from a population of students in a Master of Science in Finance (MSF) degree program, a Master of Accounting (MAcc) degree program, and a Master of Business Administration (MBA) graduate business degree program at a large southeastern US university. One group, the students from the MSF degree program, received training in rational investment decision-making strategies and experience making professional investment decisions through a student investment
fund under the supervision of a finance professor as part of their coursework. This specialized training and experience is the primary justification for considering this group to be more-sophisticated investors, while MBA students who received comparatively little specialized training in finance and accounting were considered less-sophisticated investors. A third group, MAcc students, had extensive training in the details of financial information and preparation of disclosures but little specialized investment knowledge, particularly in the evaluation of securities investments. This set of participants formed a middle group.

Participants began the experiment with a calibration and instruction routine followed by a practice round in which they were able to familiarize themselves with the types of information available to them and the decision they were asked to make. In each round, participants had available to them (1) management guidance, (2) analyst guidance, (3) objective financial information and ratios, and (4) a stock chart. Participants used this information to decide whether the stock price would rise or fall in thirty days. After indicating their choice to either take a long or short position in the stock, they were given feedback telling them whether they experienced a gain or a loss each round. Two fixed series of gains and losses were employed that presented either a series of gains followed by a series of losses or a series of losses followed by a series of gains with buffer rounds before and after the primary gain-loss series. These conditions were counterbalanced between subjects except that the MSF group was primarily given the gains followed by losses sequence due to the limited population of this type student from which to recruit participants. Following the series of eleven investment decisions, participants completed a post-experimental questionnaire that included demographic questions, questions designed to gauge risk preferences in a financial decision, and questions on participant perceptions of the different types of information used in the study and their sources.
The experiment used a Tobii T60 remote eye tracker, an Affectiva Curve Q-sensor wireless GSR device, and an Emotiv wireless EEG headset to capture multimodal physiological data during the participants’ decision rounds. A specialized biometric software platform, the iMotions Attention Tool, was used to present the stimuli and to collect and manage the multimodal physiological data. Qualtrics web-based survey software was used to administer the post-experimental questionnaire. Eye tracking permitted precise examination of what information was acquired by participants, including the amount of time spent processing different types of information and the order in which the information was viewed. Data from the eye tracker also made possible the use of pupil size measurements (pupillometry) as a measure of effort. EEG and GSR data provided information about how much effort an individual was expending while making a decision and processing specific types of information.

5.4 Summary of Results

The test of H1 involved examining whether more sophisticated investors place greater emphasis throughout the trials on unfiltered information compared to less sophisticated investors. The results partially supported this hypothesis. Participants in the MBA group (less sophisticated investors) spent significantly less time on financial information compared to the MSF group (more sophisticated investors). However, there was no difference in the time spent on unfiltered information when compared to the MAcc group.

I did not find adequate evidence to support H2, which suggested that the more sophisticated investor group would integrate unfiltered information more frequently. Instead, I found that the MAcc group (the middle sophistication group) integrates unfiltered information most frequently.
H3 was supported by the evidence. The test of this hypothesis examined whether individuals emphasized information that agreed with the position they took on the stock and focused on the interaction between the variables “Chose a Long Position” and “AOI Trend is Positive.” The positive and highly significant coefficient on this interaction term indicated that participants deviated from the rational actor model by not allocating their time consistently between all information. Instead, participants spent significantly more time on information that agreed with their ultimate investment decision.

Consistent with H4, I found that effort levels were significantly higher when participants were under the influence of a prior period loss. Conversely, effort levels were lower when participants were under the influence of a prior period gain.

I did not find sufficient evidence to support H5a which examined the speed of the effort response after a switch in direction of the gain or loss series. The adjustment in effort levels was instantaneous and dramatic enough to exceed the pre-switch thresholds in the first post-switch round. The test of H5b provided partial support for the suggestion that the magnitude of effort changes was greater when participants experienced a loss after having experienced a series of gains compared to experiencing a gain after a series of losses. The only signal that appeared to have adequate sensitivity in this analysis, however, was EDA which results in a conclusion that the hypothesis was only partially supported by the data.

H6a and H6b, which predict differences in information type preferences under the influence of prior period gains or losses, could not be supported by the evidence. The key tests of these hypotheses were the interaction of the variables “Under Gain Influence” and “AOI”. The analysis revealed no incremental differences in information type usage given the gain or loss influence.
5.5 Discussion of Results

Several findings from this study have the potential to be particularly impactful from a research and practice perspective. I highlight conditions under which behavior in an investment decision-making task can be affected by prior gains or losses and characteristics of how the decision-making process differs between groups with varying levels of investor sophistication. These results have potential relevance to a relatively wide audience. For instance, professional investors or brokerages may benefit from awareness that information acquisition and effort behavior can be affected by recent gains or losses. They may, for instance, be able to develop training or decision-aids that help individuals adapt to changes in market conditions or prior gain or loss experiences. Individual investors similarly can benefit by being aware of how their approach to investing in terms of information preferences and effort responses differ from more sophisticated investors. Consumer advocacy groups and educators can adapt the knowledge gained from this (and follow-on) research to help current or future investors to better understand behavioral tendencies. This research may also help policymakers identify ways to help reduce market inefficiencies at the micro- or macro-level and encourage more rational, less biased, behavior by individual actors or groups of investors.

The findings also have the potential to advance academic research in the investment decision-making and investor bias literature. The level of detail about what information investors prefer and how their behavior is modified by gains and losses provides insight at the process level that is difficult to collect and rarely obtained in any accounting or finance-related study. This research represents a step forward into the black box of financial decision-making and adds, in a unique way, to the evidence that at the individual level (and in groups of individuals) investors do not behave as rational actors. I demonstrate in my setting that although all
participants have a common goal of maximizing investment income, different types of individuals prefer different types of information. Further, while each investment opportunity is unique and not linked in any way to others, investors exert more or less effort on their current decision based on the outcome of a prior decision.

Additionally, investors display behavior consistent with confirmation bias during the process of making discrete investment decisions. Rather than allocating attention consistently between the positive and negative information available to them as they make their decision, participants display a clear preference for viewing information that corresponds with their investment decision. This serves as a powerful example of how this study is truly unique compared to other related research. Prior decision-making research examining investor biases has typically been limited to making conclusions based on outcome information or at best may incorporate data obtained at the end of discrete steps in a multi-step decision. By contrast, this study offers the opportunity to continuously observe a bias in action for a decision type that does not involve multiple observable steps. This is achieved through the use of multimodal physiological measurements without interrupting participants’ natural behavior or prompting them for any additional information than they would naturally produce if they were performing a similar task outside of the experimental setting.

Several hypotheses were not supported by the evidence collected in this study. The most sophisticated group of investors, the MSF group, did not perform more integrations of unfiltered information. Rather, the MAcc group investors, who are thoroughly trained on financial disclosures, but not on investment decision making, perform the most integrations. Another unexpected finding was that after a switch in a series of gains to losses (or losses to gains) effort levels respond immediately and dramatically enough to exceed the pre-switch average effort.
levels in the first post-switch round. This did not differ between switching from gains to losses or losses to gains as predicted. I also found no evidence that participants favored unfiltered information when under the influence of a prior loss or filtered information after having experienced gains.

5.6 Future Research

This dissertation provides many opportunities to advance future research. An important contribution of this study is the method (more specifically, the tools employed to examine investor decision-making behavior at a highly detailed level through physiological measurements). Future behavioral research in finance and accounting should leverage this example to incorporate physiological measurements when a deeper understanding of process and the reasons behind the outcome of participant behavior is of particular interest or has the potential to advance theory or practice in a unique and powerful way. Experimental research that incorporates physiological measurements can yield fascinating data, but it comes at a significant cost in terms of time and complexity.

The costs of incorporating physiological measurements in experimental research include several considerations. While much experimental work can be done in relatively large groups or by leveraging surveys to reach many individuals with minimal researcher involvement, participation in experiments leveraging physiological measurements is limited by the availability of equipment. This results in a significantly more time consuming process of gathering data one participant at a time. The amount of data involved in a physiological experiment is staggering and requires altogether different skills to manage, analyze, and interpret compared to traditional outcome-based behavioral research. Finally, many researchers will find the cost associated with
acquiring and maintaining the necessary software and equipment to be non-trivial, although likely not prohibitive.

In the interest of efficient use of scarce research resources, however, care should be taken to evaluate the planned study for simpler methods that do not require as costly an approach. In cases where a determination is made that the incorporation of physiological measurements offers value that is likely to exceed the associated costs, researchers should challenge themselves to maximize the value they can extract from the study. For example, a careful evaluation of the experimental design and concerted thought around the efficient use of researcher, participant, and equipment time may yield opportunities to test multiple theories, settings, or tasks in a single session to the extent they are unlikely to interfere with one another. This can help offset the overhead associated with employing the more complex methodology.

There are opportunities to follow-up on questions raised by this study. While in general the effort measurements appeared to converge well, in a few cases they did not. Further research should seek to resolve under what conditions each type of effort measurement is likely to be most sensitive in a financial decision-making task. A logical next step would be to employ principal components factor analysis to gain a better understanding of how these multimodal measurements work together and potentially reveal a cleaner, more sensitive effort measure. Further, there is an opportunity to explore the use of raw EEG signals as an additional effort measure to compare against or incorporate with the existing measurements employed in this study.

Another opportunity for follow-up based on an unexpected result from the current study is exploring whether MSF students, who have acquired expertise in investment decision-making, are more efficient at integrating information between sources. In addition to examining the
influence of investment decision expertise on the ability to integrate investment information, this
could be extended to other groups who have exceptional knowledge in other domains such as
auditor efficiency at integrating audit information.

There are several opportunities to extend the current study such as substituting different
disclosures or allowing participants access to a greater variety of information. It may be
particularly interesting to incorporate proposed disclosures or alternative disclosure formats to
see how information acquisition and effort behavior changes for experienced/knowledgeable
individuals and inexperienced/untrained users under these different conditions.

Discovering ways to enhance the performance of experts and to improve the accessibility
of financial information to non-experts on both the visual design and cognitive processing
dimensions can be useful at a theory and practice level. The multimodal physiological
measurement approach used in this study allows for the examination of usage characteristics at a
highly detailed level with improved insight into how experimental manipulations differentially
impact individual participants or groups of participants.

Finally, these methods can and should be applied in areas other than investment decision-
making research. They may have particular value in audit and management accounting topics
where contextually rich settings dominate and could in many cases benefit from tools that bring
greater levels of precision to the investigation of information utilization and the process of
completing a task.
APPENDIX A

EXAMPLE EXPERIMENTAL MATERIALS

Please be sure you have read and signed the consent form.

Ask the experimenter any questions you have now or any time before, during, or after the experiment. Proceed only when you are comfortable with the task. Your participation is completely voluntary and you may choose to stop at any time for any reason without penalty.

This experiment uses an eye tracker, a GSR sensor, an EEG sensor array, and a webcam to capture physiological measurements as you perform tasks. We interested both in your decisions and the process leading up to your decisions.

Please be cautious with the equipment as it can be fragile. When properly configured, you should not need to do anything with the equipment until the end of the experiment. As a reminder, should you become uncomfortable, you are free to terminate the experiment or to temporarily halt the experiment so adjustments can be made. Please allow the experimenter to assist you with the equipment at all times.

In this experiment you will be performing a number of tasks including making investment decisions. You will begin the experiment with $100,000 in experimental currency and you will have an opportunity to earn more currency before the investment decisions begin. Experimental currency will be converted into lottery entries at the rate of 1 entry for every $10,000 in experimental currency. One part of this experiment (that is known only to the experimenters) has been selected where your currency balance will determine the number of lottery tickets you receive in a drawing for a large cash prize. Because you can not be sure which part of the experiment determines your lottery entries, the best strategy is to do your very best throughout the entire experiment to maximize your chances of winning the prize. The optional lottery drawing for 1 of 3 $100 cash prizes will take place after all participants have completed the study.

To be in the lottery, you must provide basic contact information so you can be notified if you win. This information will be kept separate from the data in this study so that no association between your personal information and the results of this study can be made. Additionally, contact information will be destroyed after the prizes have been awarded.
First, we will get baseline measurements when you are relatively relaxed. Please sit comfortably, clear your mind, and enjoy the relaxing classical music for 2.5 minutes.
Next we will get baseline measurements when you are solving the following math problems. You may use scratch paper if you wish, but no calculators. You will earn an additional $10,000 experimental currency for each correct answer (up to an additional $100,000). You have a maximum of 2.5 minutes.
The experimenter will now tell you how many math problems you got correct and what your beginning experimental currency balance is for the investment decision rounds.
You will now have an opportunity to practice making an investment decision. You will first be presented with a screen showing four pieces of information that investors often have available to them when making investment decisions: 1. Management Guidance, 2. Analyst Guidance, 3. Financial Information and Ratios, and 4. Stock Charts.
Your investment horizon is exactly 30 days and you must decide whether you think the stock price is going to go up or down in that time period. You may use scratch paper if you wish to take notes or make calculations. When you are finished reviewing and thinking about the information on the screen, press the spacebar on the keyboard.
Analyst Guidance

*Analyze Intuition, LLC* forecasts that the company’s EPS is expected to increase from 0.42 to 0.43 for the quarter due to stronger than normal sales and a forecasted increase in demand across the industry. The company’s management is investing to capitalize on these opportunities, but we anticipate that increases in capital spending and higher costs will partially offset the gains expected from the increased quarterly revenue. We believe these expectations have been largely incorporated in the current share price and that dividends and share repurchase plans should be unaffected for the foreseeable future, however the industry is dynamic and share prices are likely to fluctuate.

Management Guidance

*Michael Smith, CFO:* Overall industry trends will heavily influence the company’s EPS projections for this quarter. We currently forecast an increase in EPS from 0.42 to 0.44 due to stronger than normal sales and an increase in demand affecting the entire industry. To capitalize on this trend, our management team is accelerating planned capital spending. Additionally, expenses associated with additional revenue will increase. However, these costs will only partially offset increases in quarterly revenue. We are not certain how long these favorable conditions will be sustained – the industry is dynamic and share prices are likely to fluctuate with changes in the business environment.

Financial Performance and Ratios

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<thead>
<tr>
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<tbody>
<tr>
<td>Sales per sh</td>
<td>1.31</td>
<td>1.31</td>
<td>1.31</td>
<td>Sales (mil)</td>
<td>3089.4</td>
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<td>“Cash Flow” per sh</td>
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<td>0.52</td>
<td>0.52</td>
<td>Operating Margin</td>
<td>31.9%</td>
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<td>Earnings per sh</td>
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<td>0.42</td>
<td>0.41</td>
<td>Depreciation (mil)</td>
<td>331.0</td>
<td>322.2</td>
<td>309.8</td>
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<tr>
<td>Div/Div if per sh</td>
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<td>-</td>
<td>-</td>
<td>Net Profit (mil)</td>
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<td>980.3</td>
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<tr>
<td>Cap/Spending per sh</td>
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<td>0.01</td>
<td>0.01</td>
<td>Income Tax Rate</td>
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</tr>
<tr>
<td>Book Value per sh</td>
<td>0.26</td>
<td>0.26</td>
<td>0.26</td>
<td>Net Profit Margin</td>
<td>27.4%</td>
<td>26.6%</td>
<td>26.0%</td>
</tr>
<tr>
<td>Common/1k Outst</td>
<td>2359</td>
<td>2358</td>
<td>2356</td>
<td>Beta</td>
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<tr>
<td>Avg Anv PE Ratio</td>
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<td>238.2</td>
<td>224.8</td>
<td>Beta</td>
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<td>1.18</td>
<td>Ending Stock Price</td>
<td>79.35</td>
<td>90.79</td>
<td>92.48</td>
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<tr>
<td>Avg Anv DivYld</td>
<td>-</td>
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<td>-</td>
<td>Ending Stock Price</td>
<td>79.35</td>
<td>90.79</td>
<td>92.48</td>
</tr>
</tbody>
</table>

Stock Chart

Press the Spacebar when ready to make investment decision.
On the next screen you will indicate your investment decision. If you think the stock price will be higher in 30 days, you should choose what investors call a “long” position. If you think the stock price will be lower in 30 days, you should choose what investors call a “short” position.

Assume there are no barriers to or cost differences between the two choices - base your decision only on whether you believe the price will be higher or lower in 30 days.
The practice round is complete. Ask the experimenter any questions you have now before proceeding.

In each round you will have a maximum of 3 minutes to view the information related to the investment decision, but you can proceed at your own pace if you do not need that much time.

There will be 11 rounds of investment decisions. You will receive feedback after each round indicating how your experimental currency investment fund is changing.

Press the spacebar when ready to continue.
**Analyst Guidance**

*Wavelength Analysts, LLC* forecasts that the company’s EPS is expected to decrease from 0.84 to 0.83 for the quarter due to weaker than normal sales and a forecasted decrease in demand across the industry. The company’s management has been proactive when dealing with these issues, but we anticipate that a planned reduction in capital spending and cost cutting initiatives will not fully compensate for the reduced quarterly revenue. We believe these expectations have been largely incorporated in the current share price and that dividends and share repurchase plans should be unaffected for the foreseeable future, however the industry is dynamic and share prices are likely to fluctuate.

**Management Guidance**

*Richard Wilson, CFO*:

Overall industry trends will heavily influence the company’s EPS projections this quarter. We currently forecast a decrease in EPS from 0.84 to 0.83 due to weaker than normal sales and a decrease in demand affecting the entire industry. To combat this trend, our management team is instituting cost cutting initiatives and deferring planned capital spending. However, these countermeasures may not fully compensate for the reduced quarterly revenue. We believe these conditions will be temporary, although we are not yet willing to predict the timing of the turnaround - the industry is dynamic and share prices are likely to fluctuate with changes in the business environment.

---

**Financial Performance and Ratios**

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<tbody>
<tr>
<td>Sales per sh</td>
<td>2.35</td>
<td>2.42</td>
<td>2.61</td>
<td>625.8</td>
<td>660.8</td>
<td>712.7</td>
</tr>
<tr>
<td>&quot;Cash Flow&quot; per sh</td>
<td>0.33</td>
<td>0.34</td>
<td>0.37</td>
<td>35.8%</td>
<td>37.1%</td>
<td>38.3%</td>
</tr>
<tr>
<td>Earnings per sh</td>
<td>0.84</td>
<td>0.90</td>
<td>1.00</td>
<td>547.4</td>
<td>577.4</td>
<td>640.9</td>
</tr>
<tr>
<td>Div./Dil per sh</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>2240.4</td>
<td>2452.0</td>
<td>2796.2</td>
</tr>
<tr>
<td>Cap/Spend per sh</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>23.8%</td>
<td>26.1%</td>
<td>25.8%</td>
</tr>
<tr>
<td>Book Value per sh</td>
<td>0.28</td>
<td>0.35</td>
<td>0.45</td>
<td>20.0%</td>
<td>20.0%</td>
<td>20.0%</td>
</tr>
<tr>
<td>Common Sts Outst'd</td>
<td>2803</td>
<td>2733</td>
<td>2960</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Avg Ann P/E Ratio</td>
<td>22.5</td>
<td>17.3</td>
<td>13.6</td>
<td>Beta</td>
<td>0.95</td>
<td>1.04</td>
</tr>
<tr>
<td>Relative P/E Ratio</td>
<td>0.82</td>
<td>0.87</td>
<td>0.92</td>
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<tr>
<td>Avg Ann Div/Yld</td>
<td>0.17%</td>
<td>0.23%</td>
<td>0.36%</td>
<td>Ending Stock Price</td>
<td>18.96</td>
<td>15.54</td>
</tr>
</tbody>
</table>

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**Stock Chart**

- Press the Spacebar when ready to make investment decision.
Choose from one of the two options:

- I expect the stock price to be higher in 30 days and choose to take a long position.
- I expect the stock price to be lower in 30 days and choose to take a short position.

I am [ ] % confident in my decision
Excellent!

You gained

4%

on your investment.
Too bad!

You lost

4%

on your investment.
The investment decision portion of the experiment is complete. You will now answer a number of questions including basic demographic information, some information about your academic and investment-related experience, and your feedback and perceptions on some key issues related to this experiment.

While you are completing these questions, the experimenter will determine your lottery entries and prepare the paperwork to finish out the study.
APPENDIX B

POST EXPERIMENTAL QUESTIONS

3/23/2014

Default Block

This page is to be filled out by the experimenter.

Respondent Number

Experiment Code

Please answer the following questions to the best of your ability. This survey should take approximately 10-15 minutes to complete.

Gender

- Male
- Female

Age

Current Degree Program

- MBA
- MAcc
- MSF

Are you predominantly right or left-handed?

- Right
- Left

Do you require corrective lenses?

- Yes, glasses
- Yes, contacts
- No

Did you wear the corrective lenses?

Do you have investment experience actively controlling (making individual investments for) your own personal investment portfolio?

- No
- Yes, portfolio less than $10,000
- Yes, portfolio greater than $10,000

Concerning your personal investment portfolio, is it:

- A 401K or other managed investment fund that you let professionals primarily control.
- A private brokerage account that you let a professional investor manage.
- A private brokerage account that you manage personally.

Do you have investing experience through the FSU finance department's student investment fund?

- Yes
- No

Please describe your approach to making investment decisions in this experiment in approximately 3-5 sentences.
Please rank the following in terms of how biased the information is likely to be: (1 - most biased; 4 - least biased)

<table>
<thead>
<tr>
<th>Information</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Audited financial information</td>
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<tr>
<td>Management guidance</td>
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<td>Stock chart (historical price) information</td>
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<td>Analyst Guidance</td>
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Please rank the following in terms of how useful you think the information is when making an investment decision: (1 - most useful; 4 - least useful)

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<th>Information</th>
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How would you rate your level of trust in the following pieces of information? (0 - low, 100 - high)

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How would you rate your level of reliance on the following pieces of information in an investment decision? (0 - low, 100 - high)

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<td>How knowledgeable about market-wide performance trends are management?</td>
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Which of the following would you prefer?

○ 50% chance to win $1,000 and 50% chance to win $0
○ $450 for sure

Choose between:

○ $2,500 with probability .33, $2,400 with probability .66, and $0 with probability .01
○ $2,400 with certainty

Choose between:

○ $4,000 with probability .80, $0 with probability .20
○ $3,000 with certainty

What do you think this experiment was about?

Thank you for your participation. The experiment is complete. If you chose to participate in the raffle, you will be contacted if you win. Bear in mind that this was a laboratory experiment with carefully controlled variables and limited information about fictional companies. Your performance here should not be construed as indicative of how you would perform when investing real money in real securities.

Please let the experimenter know that you have completed the experiment and read the debriefing statement below.

This experiment was about studying how individuals make investment decisions—particularly how their behavior changes after experiencing gains and losses. Theory says that on average and over the long run, stock prices reflect underlying fundamental value (rational prices). However, stock prices often fluctuate from day to day with little bearing on the underlying fundamentals like firm financial performance, news, market-wide trends, other influences, and individual investor behavior can cause short-term price movement. In this experiment, you were forced to make investment decisions on a specific day (30 days after the earnings release and guidance). Therefore, it is possible that the price on that specific day could be higher or lower regardless of the fundamental value. Depending on the particular experiment form you were assigned to, you had a 6/11 chance of experiencing a gain or a 9/11 chance of experiencing a loss. Gains and losses were programmed to enable specific analyses and behavioral observations. Once again, bear in mind that this was a laboratory experiment with carefully controlled variables and limited information about fictional companies. Your performance here should not be construed as indicative of how you would perform when investing real money in real securities. Thank you again for your time and participation. Please contact Bachman Fulmer if you have any questions or would like to discuss the experiment.
APPENDIX C

IRB APPROVAL

Office of the Vice President for Research
Human Subjects Committee
Tallahassee, Florida 32306-2742
(850) 644-8673  FAX (850) 644-4392

APPROVAL MEMORANDUM

Date: 02/13/2014

To: Buchanan Fulmer  Redacted

Address: Accounting Department, College of Business

Dept.: ACCOUNTING

From: Thomas L. Jacobson, Chair

Re: Use of Human Subjects in Research

Information Acquisition and Cognitive Effect in an Investment Gain or Loss Frame

The application that you submitted to this office in regard to the use of human subjects in the proposal referenced above have been reviewed by the Secretary, the Chair, and two members of the Human Subjects Committee. Your project is determined to be Expedited per 45 CFR § 46.110(C) and has been approved by an expedited review process.

The Human Subjects Committee has not evaluated your proposal for scientific merit, except to weigh the risk to the human participants and the aspects of the proposal related to potential risk and benefit. This approval does not replace any departmental or other approvals, which may be required.

If you submitted a proposed consent form with your application, the approved stamped consent form is attached to this approval notice. Only the stamped version of the consent form may be used in recruiting research subjects.

If the project has not been completed by 06/14/2014 you must request a renewal of approval for continuation of the project. As a courtesy, a renewal notice will be sent to you prior to your expiration date; however, it is your responsibility as the Principal Investigator to timely request renewal of your approval from the Committee.

You are advised that any change in protocol for this project must be reviewed and approved by the Committee prior to implementation of the proposed change in the protocol. A protocol change/amendment form is required to be submitted for approval by the Committee. In addition, federal regulations require that the Principal Investigator promptly report, in writing, any unanticipated problems or adverse events involving risks to research subjects or others.

By copy of this memorandum, the chairman of your department and/or your major professor is reminded that he/she is responsible for being informed concerning research projects involving human subjects in the department, and should review protocols as often as needed to assure that the project is being conducted in compliance with our institution and with DHHS regulations.

This institution has an Assurance on file with the Office for Human Research Protection. The Assurance Number is IRB00000446.

Cc: Gregory Gerard  Redacted  Advisor

HSC No  2013.10215  Redacted

100
APPENDIX D

EXAMPLE CONSENT FORM

FSU Behavioral Consent Form
Investment Decision Making

You are invited to be in a research study examining how people make investment decisions. This study is being conducted by Bachman Fulmer under the supervision of Dr. Gregory Gerard, Ph.D. from the Accounting Department at Florida State University. We ask that you read this form and ask any questions you may have before agreeing to be in the study.

Background Information:
The purpose of this study is to learn about how people use financial information to make investment decisions.

Procedures:
If you agree to be in this study, you will first view financial statements and other disclosures on a computer monitor and answer comprehension questions for which correct answers will earn you experimental dollars. Next, you will make a series of investment decisions over several rounds based on information that is given to you about various stocks. The information provided is generally considered to be relevant to investment decisions. When you have decided how to invest your experimental dollars, you will press a key on the keyboard to indicate your choice.

Of primary interest in this study are certain physiological measurements that will be taken as you consider the information available to you and make your investment decision. An eye tracking device will be on the desk in front of you and will record your eye movements, an EEG headset will be placed on your head and measure small electrical fluctuations associated with brain activity, a GSR sensor will be placed on your wrist and/or fingers that measures skin temperature and conductivity associated with effort or excitement, and a webcam will record a video to help with assessing data anomalies and emotional response. At the beginning of the experiment you will experience a period of relaxing music to obtain baseline measurements. All of the equipment is wireless and you are free to move around, take a break, or terminate the experiment at any time for any reason. The entire experiment should last between 20 and 40 minutes.

Risks and Benefits of Being in the Study:
There are no anticipated risks beyond those of normal everyday computer-based activity. The sensors employed are research grade and have been used in numerous other studies. There are no direct benefits to you by participating in this study. However, your participation will serve to enhance our understanding of the use of financial information in investment decision making.

Compensation:
Your professor has offered to provide course credit as compensation for your participation in this experiment. If you are uncomfortable performing the task and decide to withdraw from the study you will not be penalized (you will still receive credit). If you complete the study, the experimental dollars you earn will be converted into lottery tickets that will allow you a chance to win one of (five available) $100 cash prizes.

Confidentiality and Voluntary Nature of the Study:
The records of this study will be kept private and confidential to the extent permitted by law. In any sort of report we might publish, we will not include any information that will make it possible to identify a subject. Research records will be stored securely and only researchers who have access to the records. Participation in this study is voluntary. Your decision whether or not to participate will not affect your current or future relations with the University. If you decide to participate, you are free to not answer any question or withdraw at any time without affecting those relationships.

Contacts and Questions:
You may ask any questions you have now. If you have a question later, you are encouraged to contact Bachman Fulmer at the Business Building or Dr. Gregory Gerard at

If you have any questions or concerns regarding this study and would like to talk to someone other than the researcher(s), you are encouraged to contact the FSU IRB at 2010 Levy Street, Research Building B, Suite 276, Tallahassee, FL 32306-2742, or 850-644-8633, or by email at humanresearch@magnet.fsu.edu.

You will be given a copy of this information to keep for your records.

Statement of Consent:
I have read the above information. I have received answers to my questions. I consent to participate in the study.

Signature __________________________ Date ______________ Signature of Investigator __________________________ Date ______________

REFERENCES


BIOGRAPHICAL SKETCH

Son of Marie Fulmer, an award-winning math teacher, and BP Fulmer, JR, a healthcare administration executive and entrepreneur, Bachman P. Fulmer, III was born in South Carolina. The majority of his childhood years, however, were spent in the suburbs of Atlanta, GA. While attending high school, Mr. Fulmer played bass trombone in a nationally-recognized symphonic band and national championship marching band. Mr. Fulmer attended the University of Georgia, where he received a bachelor’s degree in International Business with a focus on real estate and minor in German. Mr. Fulmer later pursued an MBA with a focus in Management Information Systems from Florida State University before joining Ernst & Young, LLP as an IT auditor. Later, he returned to Florida State to pursue a PhD in Accounting where he has focused primarily on the application of innovative tools and techniques used in cognitive psychology to the applied field of Accounting. Mr. Fulmer will graduate at the conclusion of the spring semester, 2014, after which he will join the faculty at California State University, Fullerton as an Assistant Professor of Accounting.