THE ACCOUNTING REVIEW
Vol. 89, No. 6
2014
pp. 1945–1977

American Accounting Association
DOI: 10.2308/accr-50841

The Neuroscience Behind the Stock Market's Reaction to Corporate Earnings News

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ABSTRACT: Using functional magnetic resonance imaging, we capture neural activity in the ventral striatum—a key area in the human brain's reward processing circuit—of 35 adult investors learning the earnings per share disclosed by 60 publicly traded companies. Before imaging, investors forecasted each company's earnings and took either a long or a short position in its stock. Consistent with prospect theory, we find strong neurobiological evidence of an asymmetric reaction to positive and negative earnings surprises. Moreover, investors' personality traits and investment positions, as well as firms' earnings predictability, modulate the brain's reaction to earnings news. We also find a strong association between the magnitude of the brain's reaction and risk-adjusted stock returns and abnormal share trading around earnings announcements for our sample firms; these findings evince the brain's reaction to earnings news as an alternative, biological measure of the information content of earnings.

Keywords: *earnings surprise; human brain; cognitive neuroscience; neuroaccounting; fMRI; reward prediction error; temporal difference reinforcement learning*.

Data Availability: *Data are available from the authors*.

I. INTRODUCTION

Dickhaut, Basu, McCabe, and Waymire (2010) argue that accounting institutions and principles evolved in consilience with the evolution of the human brain. They cite indirect neuroscientific evidence suggesting that basic accounting institutions, like double-entry bookkeeping, and accounting principles, like conservatism, objectivity, revenue recognition, and expense matching, have strong parallels with how the human brain evolved to process information

We appreciate the helpful comments of Donald V. Moser (editor), John Harry Evans III (senior editor), Monica Capra, John Hand, Bob Libby, Mark Nelson, Mike Prietula, Bill Tayler, Greg Waymire, members of Emory University's Center for Neuropolicy, the Goizueta Business School's behavioral brownbag group, and workshop participants at Cornell University and the 2012 Southeast Summer Accounting Research Colloquium. We also thank Kristina Blaine, Lisa Harris, Ron Harris, and Lisa LaViers for research assistance. This study was funded by a grant from the National Institutes of Health (R01-DA025045) through the American Recovery and Reinvestment Act of 2009.

Editor's note: Accepted by Donald V. Moser.

Submitted: August 2012
Accepted: June 2014
Published Online: June 2014

about economic exchange. Such parallels are consistent with the idea that accounting institutions and principles sustaining modern exchange economies did not just emerge fully developed, but rather evolved progressively as the human brain made sense of its environment (North 2005). Their argument is also consistent with archival and experimental evidence suggesting that record-keeping—the most basic of accounting functions—evolved to help the cognitively constrained human brain handle increasingly complex economic exchange (Basu and Waymire 2006; Basu, Dickhaut, Hecht, Towry, and Waymire 2009a; Basu, Kirk, and Waymire 2009b). Dickhaut and colleagues suggest that neuroscience and its methods can have profound implications for both accounting research and standard setting by framing the design of accounting institutions and principles in ways that are consistent with scientific theories of human behavior.

Our goal is to provide direct empirical evidence of the link between activity in the human brain and the disclosure of accounting information. We focus on corporate earnings announcements, arguably the most anticipated and watched-after recurring events for publicly traded firms. Reporting earnings that meet or beat Wall Street's expectations tend to be rewarded by an increase in the firm's stock price, lower cost of capital, and a boost to managers' reputations. However, missing expectations, even by as little as one cent per share, can lead to huge losses in shareholder and executive wealth. Not surprisingly, managers go to great lengths—some even illegal—to avoid disappointing Wall Street. A rich literature grounded in economics and psychology examines the role that earnings numbers play in contracting and valuation.[1] A fundamental question in this literature, going back to at least the seminal works of Ball and Brown (1968) and Beaver (1968), is how investors evaluate information contained in earnings.

We take a novel, radically different approach from the existing literature by relying on cognitive neuroscience and functional magnetic resonance imaging (fMRI) to explore how the human brain processes earnings news. We argue that earnings announcements convey information to investors akin to rewards and punishment.[2] The brain's ability to process rewards and punishment is critical to its ability to make competent decisions, whether the issue in question is as primal as searching for food or a mate or as modern as buying the newest iPad or selling Apple shares after a disappointing earnings announcement. Consistent with theories of reinforcement learning, neuroscientific evidence shows that dopamine neurons deep in the human brain—particularly in the ventral striatum—encode reward prediction errors (Montague, Dayan, and Sejnowski 1996; Schultz, Dayan, and Montague 1997; Niv 2009). Neurons in this region become more active when an individual learns that his estimates of the value of current or future events are too low, indicating a positive prediction error, such that events are better than expected. The neurons become less active when he learns that his estimates are too high, indicating a negative prediction error, such that events are worse than expected.

We test two hypotheses, one bearing on the relation between earnings news and the activity in investors' ventral striatum, and the other on the relation between this neural activity and the stock market's reaction to the earnings news. Our first hypothesis is that earnings surprises are processed in the brain's ventral striatum. Specifically, we expect that positive earnings surprises will be processed similarly to a positive reward prediction error, thus leading to increased activity in the ventral striatum. On the other hand, we expect negative earnings surprises to be processed as a negative reward prediction error, leading to decreased activity in the striatum. Because earnings

[1] For recent reviews, see Libby, Bloomfield, and Nelson (2002) and issues 1–3, Vol. 31 (2001) and 2–3, Vol. 50 (2010) of *Journal of Accounting and Economics*.

[2] Rewards are positive, appetitive stimuli that reinforce behavior, whereas punishments are negative, aversive stimuli that diminish it. Since less-than-expected or no punishment is a positively valenced event, one can think of it as a reward. Similarly, not getting a reward or getting less than expected can be viewed as punishment because of its negative valence.

meeting expectations convey no new information, we do not expect an effect on the striatum's activity in this case.[3] Of course, our predictions should hold only for individuals who view earnings as a good proxy for economic wealth—that is, when earnings news is a credible and reliable unconditioned stimulus. As is common in fMRI studies, we measure brain activation indirectly using blood oxygen level-dependent (BOLD) signals, which capture spatial changes in oxygenation around neurons processing and transmitting information.

Nontrivial factors work against us finding empirical support for our first hypothesis. Earnings announcements are infrequent, only quarterly in the case of publicly traded U.S. firms; mandatory, even if managers have no new substantial information to disclose; and backward-looking in that they only reflect partially, if at all, the future effects of historical transaction. Consequently, the average earnings announcement reveals only about 2–8 percent of the total information incorporated into a firm's share price over the year (Ball and Shivakumar 2008; Beyer, Cohen, Lys, and Walther 2010). Similarly, the changes in BOLD signals that our hypothesis predicts are even smaller, typically varying by less than 1 percent from baseline, a problem compounded by background physiological noise of similar magnitude (Huettel, Song, and McCarthy 2009).

It is also difficult to induce in an experimental setting the experience of economic loss of a meaningful magnitude. Even if institutional review boards would allow such experimental conditions, it is unlikely that a sufficiently large and representative group of investors would sign up voluntarily to participate in a study in which they can lose large amounts of money. Our study participants, while good proxies for nonprofessional investors, may not appreciate the value relevance of earnings. In this case, we would find striatal activation not at the earnings announcement period, but when participants learn the return on their investments. Finally, while existing evidence supports the hypothesis that the ventral striatum is the key brain nucleus processing positive reward prediction errors, the evidence is mixed when it comes to negative prediction errors. A hotly debated topic in the decision neuroscience literature is whether loss aversion results from a single system (e.g., Tom, Fox, Trepel, and Poldrack 2007) or multiple systems in the brain that include other structures like the amygdala (Yacubian et al. 2006) or the insula (Knutson, Rick, Wimmer, Prelec, and Loewenstein 2007).[4]

We test our first hypothesis by running an experiment in which an investor first forecasts a firm's current earnings per share (EPS), using historical actual EPS numbers and financial analysts' consensus forecasts. He then takes either a long or a short position in the firm's stock, depending on how his forecast compares to the consensus, our proxy for the stock market's expectation. In other words, we ask each investor to use his own EPS forecast as the reference point for taking a position in the stock, but the consensus analyst forecast as the reference point for estimating his expected investment gain or loss. The investor then undergoes fMRI scanning while he learns the actual EPS reported by the firm and the resulting market reaction to the announcement. Our study participants are 35 M.B.A. students with relevant accounting and investing experience to complete each task successfully. We use 60 real companies traded on the NYSE or NASDAQ during 2001–2009. Our choice of participants and trial firms is designed to increase statistical power and broaden the generalizability of our findings.

Strongly supporting our hypothesis, we find that earnings beating analysts' consensus forecasts lead to increased striatal BOLD signals, while earnings missing consensus forecasts lead to decreased activity. Earnings meeting analysts' expectations, as predicted, have no effect on the hemodynamic response in the striatum. Additional analyses reveal that the striatum also reacts to

[3] Whether an earnings surprise is positive or negative depends not only on whether the firm reports EPS that differs from the market's expectations, but also on whether the investor has a long or short position in the firm's stock.

[4] Activation of other brain areas due to the experience of loss may reflect emotions like regret and disappointment (Chua, Gonzalez, Taylor, Welsh, and Liberzon 2009).

the magnitude of an earnings surprise. Moreover, we find that BOLD signals are more strongly correlated with prediction errors based on the consensus forecast than on investors' own EPS forecasts. Finally, we find that the magnitude of the BOLD signal is almost twice as large when investors view a negative earnings surprise as when they view a positive one, consistent with Kahneman and Tversky's (1979, 2000) prospect theory and related empirical evidence suggesting that losses are about twice as "painful" as gains are rewarding. These results are also consistent with archival evidence showing an asymmetrically stronger market reaction to negative earnings surprises than to positive ones (Skinner and Sloan 2002).

To provide additional confidence that the ventral striatum indeed processes earnings surprises, we examine factors that should modulate the magnitude of the striatal reaction to the earnings surprises. If the ventral striatum processes earnings news, then we would expect the magnitude of the striatal BOLD signal to vary as a function of relevant investor characteristics and the predictability of firms' current-period earnings, after controlling for the magnitude and direction of the earnings surprise. Consistent with this prediction, we find that the magnitude of the BOLD signal is larger for investors with personality traits that identify them as more sensitive to either appetitive or aversive stimuli. As predicted by reinforcement learning theory, we also find that the magnitude of the BOLD signal is positively associated with the volatility of prior EPS, the volatility of analysts' prior forecast errors, and the dispersion in analysts' forecasts of current EPS, suggesting that forecast errors from more difficult-to-predict EPS tend to lead to stronger brain reactions.

Taken together, our fMRI analyses confirm our first hypothesis that the ventral striatum indeed processes earnings news. Therefore, the magnitude of the striatum's activation should serve as another measure—a biological one—of the information content of the earnings news. In the second part of our analyses, we examine the empirical implication of this claim. Consistent with a rich literature on the information content of earnings that dates back to Ball and Brown (1968) and Beaver (1968), we test our second hypothesis, which predicts an association between striatal BOLD signals and market reaction proxies like announcement-period stock returns and trading volume.

The analyses support our second hypothesis, as well. In fact, when we condition the BOLD signal by the sign of the earnings surprise, we find a positive association between actual market returns and the BOLD signal when earnings beat expectations, a negative association when earnings miss expectations, and no association when earnings meet expectations. With this conditional model, the ventral striatum's response explains about 36 percent of the variance in historical stock returns around the earnings announcement for the 60 firms in our sample, almost twice as much as the explanatory power of price-deflated earnings surprises common in the accounting literature. We also regress each firm's announcement-period abnormal trading on the average magnitude of the BOLD signal for that firm, conditional on the type of earnings surprise. As one would expect, we find greater turnover when firms beat or miss expectations than when they meet them, consistent with the magnitude of the earnings surprise conveying new information to the market. The BOLD signal explains about 44 percent of the variance in abnormal trading for the firms in our sample, also about twice the explanatory power of price-deflated earnings surprises. Supplemental analyses show that neural activity and earnings surprises each have incremental explanatory power for announcement-period stock returns and abnormal trading. Indeed, these analyses raise the question as to whether neurobiological measures of economic earnings surprises can add an extra, more nuanced dimension of insight into how investors and the overall market react to earnings news, in that brain signals incorporate investors' cognitive processing of the accounting information.

Of course, our market reaction findings must be interpreted with caution. Ideally, we would have liked to scan investors' brains at the same time as firms announced earnings. Yet, the logistics of scanning 35 people together and at the same time as 60 firms announce earnings are nearly impossible to carry out. Our only feasible option is to scan investors separately using a carefully selected set of historical earnings announcements and related market reactions. Even so, we have no reason *ex ante* to expect different results under these two alternative research design scenarios.

Our study shows that earnings news in the form of reward prediction errors are processed in the investor's ventral striatum, the same region of the brain that processes more primal and evolutionarily important stimuli like food and sex. We also show that even though the striatum seems to underreact to negative earnings news, its reaction is still almost twice as strong for negative earnings news than for positive news, consistent with Kahneman and Tversky's (1979, 2000) prospect theory and archival evidence of asymmetric market reaction to earnings news (Skinner and Sloan 2002). Our results hint at the possibility that market anomalies like the post-earnings announcement drift and the accrual anomaly may have a biological basis.

Section II next develops our two hypotheses, following a brief introduction to neuroanatomy, reward prediction errors, and functional brain imaging. Section III then describes our experimental paradigm, Sections IV and V present our analyses and results, and Section VI concludes.

II. HYPOTHESES

The human brain has more than 100 billion neurons, each connecting to anywhere from one to about 10,000 other neurons. Each neuron transfers information to another neuron by releasing chemicals like dopamine, serotonin, and glutamate that bind to receptors in the receiving neuron; the latter aggregates information from different sender neurons and relays it further downstream. There are approximately 100,000 dopamine neurons in the brain; these neurons encode reward prediction errors in a manner consistent with temporal difference models of reinforcement learning (Montague et al. 1996; Schultz et al. 1997; Niv 2009). Prediction errors are simply the difference between the actual rewards we receive and the ones we expected to receive. The experience of previous rewards and the expectation of future ones allow humans to make decisions and select appropriate behaviors to reach desired goals. Humans learn by taking actions that minimize prediction errors.

In reinforcement learning, the brain uses reward and punishment stimuli to learn appropriate behavior. The goal is to select a series of actions that will increase the probability of rewards and decrease the probability of punishment by optimizing the value of the actions over the long term. Indeed, reinforcement learning is typically viewed as "the most fundamental form of rational decision-making" (Niv 2009). Individual decision making can be represented as solving a reinforcement learning problem, usually beginning with a value function V of the expected total reward available in a state s at time t:

$$V(s_t) = E[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \gamma^4 r_{t+4} + \gamma^5 r_{t+5} + \ldots], \quad (1)$$

where $r_t, r_{t+1}, \ldots$, are future rewards (or, if negative, punishment) and γ is a discount factor $0 \leq \gamma \leq 1$ that accounts for the risk and the timing of the rewards. Equation (1) is identical to the discounted dividend, cash flow, or earnings models used in the finance and accounting literatures to value investments. If an investor could learn the expected value $V(s_t)$ perfectly for all states of the world at time t, then he would solve the learning problem by simply investing in firms with the greatest expected value $V(s_{t+1})$ for the next-period state s_{t+1}. In other words, his task would be reduced to forecasting a good approximation of $V(s_{t+1})$. Temporal difference models take into account the recursive nature of this task, so that:

$$V(s_t) = E[r_t + \gamma V(s_{t+1})]. \quad (2)$$

When the actual value of $V(s_t)$, which we denote $V^*(s_t)$, is revealed in state s_t, the prediction error δ_t becomes:

$$\delta_t = V^*(s_t) - V(s_t) = V^*(s_t) - r_t - \gamma V(s_{t+1}). \tag{3}$$

Thus, when $\delta_t > 0$, the forecast of V_t was too pessimistic, while when $\delta_t < 0$, this forecast was too optimistic.[5] Sutton and Barto (1998) show that the simple temporal-difference learning rule in Equation (3) leads to optimal behavior in a wide range of decision-making contexts.

When actions have long-term effects, the reinforcement problem is compounded by the need to assign credit to different actions—those actions that lead to reward or a positive prediction error should be repeated, while those that lead to punishment or a negative prediction error should be avoided. This problem is difficult to solve in decision contexts characterized by high levels of risk and ambiguity, as is the case of an investor trying to decide which firm's stock to invest in based on his expectations about the firm's future earnings. The reinforcement learning literature offers alternative methods for constructing algorithms that assign credit back in time to actions taken earlier that minimize prediction errors (Sutton and Barto 1998).

To maximize our ability to detect a reaction in the ventral striatum to earnings news, our experiment focuses on single-period investment decisions. Hence, the reward prediction error in Equation (3) simplifies in our case to $\delta_t = f(r_t)$, where r_t is the earnings surprise at time t and $f(\cdot)$ is an unspecified function mapping that surprise to the activity of neurons in the investor's ventral striatum.

The ventral part of the striatum, composed of the nucleus accumbens and the ventral regions of the caudate nucleus and the putamen, is richly innervated by dopamine neurons. Human imaging studies consistently identify the ventral striatum as the key brain region responsible for processing reward prediction errors (Montague et al. 1996; Schultz et al. 1997; Berns, McClure, Pagnoni, and Montague 2001; Knutson, Adams, Fong, and Hommer 2001; Pagnoni, Zink, Montague, and Berns 2002; O'Doherty, Dayan, Friston, Critchley, and Dolan 2003; O'Doherty et al. 2004; McClure, Berns, and Montague 2003; Bayer and Glimcher 2005).[6] The ventral striatum seems to encode information regarding prediction errors regardless of whether the outcome is "good" or "bad," or there is "more" or "less" of it (Brooks et al. 2010).[7]

We expect that corporate earnings surprises will be processed initially in the ventral striatum, where we measure activity indirectly using fMRI. Active neurons demand energy, leading to an increase in blood flow to the region of activation. fMRI relies on differences in the magnetic susceptibility of oxygenated and deoxygenated blood. Changes in oxygen concentration due to neural activity lead to a change in the blood oxygen level-dependent (BOLD) signal that we capture in the fMRI scanner. Increased neural activity leads to positive BOLD changes, while decreased activity leads to negative BOLD changes.

Assuming an investor has a long position in the stock, we predict that, at the time of an earnings announcement, actual earnings exceeding investors' expectations will result in increased striatal BOLD responses. On the other hand, actual earnings falling short of expectations will result in decreased striatal BOLD responses. Because earnings that meet expectations convey no new

[5] In the case of negative rewards, $\delta_t > 0$ is less-than-expected "bad," so one can view this positive prediction error as a reward.

[6] fMRI studies have found the reward system to react to a variety of stimuli: fruit juice and water (Berns et al. 2001; Pagnoni et al. 2002; McClure et al. 2003; O'Doherty et al. 2003), appetitive smells (Anderson et al. 2003), sex (Arnow et al. 2002; Komisaruk and Whipple 2005), money (Delgado, Nystrom, Fissell, Noll, and Fiez 2000; Knutson, Westdorp, Kaiser, and Hommer 2000; Knutson et al. 2001), beautiful faces (Aharon et al. 2001), social interactions (Rilling et al. 2002), and pleasant touch (Rolls et al. 2003).

[7] The ventral striatum also apparently processes other aspects of an economic choice, including risk (Preuschoff, Bossaerts, and Quartz 2006), expected rewards (Hsu, Bhatt, Adolphs, Tranel, and Camerer 2005; Preuschoff et al. 2006), and what the reward would have been had the investor made another choice (Lohrenz, McCabe, Camerer, and Montague 2007).

information, we expect no change in the striatal BOLD signal. Our first hypothesis, in alternative form, is:

H1: BOLD signals in the ventral striatum are positive, above baseline, when earnings surprises are positive; and negative, below baseline, when earnings surprises are negative. BOLD signals are zero, not different from baseline, when earnings meet the market's expectations.

If the ventral striatum indeed processes earnings news, then the magnitude of the striatum's activation should serve as a biological measure of the information content of the earnings news. Thus, we predict an association between striatal activity and market reaction proxies like announcement-period stock return and trading volume. While such a prediction is not controversial, we believe there are four potential reasons in our study to expect a credible null. First, investors' reaction to earnings news may be confounded with other factors, like management forecasts made concurrently with the earnings announcement. Second, our investors' reactions may be markedly different from the reactions that actual market participants had following the various earnings announcements. Market participants have a much richer information set about each company and hold greater financial stakes than our experiment's participants. Third, the noise inherent in the fMRI procedure that we use to capture striatal BOLD activity is sufficiently large to result in attenuation bias in our analyses. Fourth, the market mechanism likely aggregates investors' beliefs in a more complex process than the simple averaging of neural activity across investors that we use in our analyses. Our second hypothesis, in alternative form, is:

H2: Stock returns and abnormal trading volume around earnings announcements are associated with the sign and magnitude of announcement-period BOLD signals in the ventral striatum.

III. RESEARCH DESIGN

Investors

The tasks that we expect investors to complete require a basic knowledge of accounting and investing. M.B.A. students fit this criterion, as they are a good proxy for reasonably informed nonprofessional investors (Libby et al. 2002; Elliott, Hodge, Kennedy, and Pronk 2007). Moreover, this population is young and fairly homogenous, which should increase the fMRI signal-to-noise ratio in our study.[8]

We recruited 36 participants from a U.S. university's full-time M.B.A. program. All provided informed consent to experimental procedures approved by the university's Institutional Review Board. We developed a 25-question test to assess participants' task-related knowledge. We excluded one individual who did not meet our 80 percent correct response rate requirement for inclusion in the analyses.[9] Participants reported no psychiatric/neurological disorders or other characteristics that might preclude them from safely undergoing fMRI scanning.

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[8] fMRI-measured BOLD signals of older adults have much lower signal-to-noise ratios than those of younger adults (Huettel et al. 2001). While striatal activation during gain anticipation seems intact as people age, activation during loss anticipation tends to decrease (Samanez-Larkin et al. 2007).

[9] The number of participants scanned in an fMRI study is typically driven by practical considerations like scanning and data analysis costs, available scanning time, and access to qualified and willing participants. Murphy and Garavan (2004) and Thirion et al. (2007) suggest that at least 27 participants are required for internal validity in event-related fMRI studies; going beyond this number does not seem to translate into a marginal increase in power.

Table 1 summarizes demographic characteristics. The 35 participants (27 males, eight females) have an average age of 28, 74.3 percent report English as their first language, 8.6 percent are left-handed, and 57.1 percent participated in previous experimental studies. All had completed the core M.B.A. accounting and finance courses before participation, and at least 80 percent completed at least two courses in each of finance, accounting, economics, and statistics. Most participants reported frequently reading business news and following the stock market, having used financial analyst reports, and having invested directly in stocks. We believe our study participants are a good proxy for nonprofessional investors.

Experimental Task

Our experiment consists of three parts. In Part 1, investors completed a web-based questionnaire with demographic, financial literacy, personality, and risk-preference questions. The questionnaire included standardized behavioral inhibition system (BIS) and behavioral approach system (BAS) scales, well known and validated measures of affective responses to reward and punishment (Gray 1990; Carver and White 1994; Corr 2004). The BIS scale measures a person's sensitivity to punishment or absence of reward. An investor with high BIS would experience stronger negative feelings like anxiety and withdrawal when a firm he is invested in reports earnings that miss his expectations. In contrast, the BAS scale measures a person's sensitivity to rewards or escape from punishment. An investor with high BAS would experience stronger positive feelings like joy, elation, and happiness when a firm reports earnings that beat his expectations. There appears to be an interaction between these two scales in that investors with high BAS and low BIS tend to make riskier investment decisions than other investors (Kim and Lee 2011). We use investors' BIS/BAS scores later in our analyses.

In Part 2 of the experiment, investors forecasted EPS for 60 firms. In doing so, they could rely on the actual EPS and consensus analyst forecasts for the previous three years and the consensus forecast for the current year. Investors then took a long or short position in each firm's stock based on how their forecasts compared to the current consensus forecast. Investors were told that the 60 firms were real firms traded in the U.S. stock markets; we did not disclose the names of the companies or our process for selecting them since we wanted investors to focus only on the pattern of actual historical earnings and consensus forecasts when generating their own forecasts. Figure 1, Panel A depicts these tasks for one of the sample firms.

Finally, in Part 3, investors sequentially viewed three screens inside the fMRI scanner for each of the 60 firms. Panel B in Figure 1 depicts these screens. The "Event 1" screen reminded an investor of the firm's historical performance and his EPS forecast and investment position. "Event 2" reveals the actual EPS for the year forecasted, and the difference between this number and both his and the consensus analyst forecasts. "Event 2," thus, shows the earnings surprise relative to his and analysts' expectations. We provide investors both prediction errors because we have no evidence on which reference point investors use in "real-world" investment decisions. However, because investors are to act as price takers, we expect them to use the consensus analyst forecast as the reference point, and subsequent analyses confirm that they do. "Event 3" shows the firm's stock return around the earnings announcement and alerts the investor of the gain or loss he made from the investment. We built in a minimum delay of two seconds between screens, but we allowed investors to control movement from one screen to the next.[10]

Investors spent, on average, 49.8, 18.9, and 23.3 minutes completing Parts 1, 2, and 3, respectively. During Part 3, they spent, on average, 5.6, 4.3, and 3.6 seconds viewing the screens in

[10] Individuals can make comparisons between two single-digit numbers in less than 0.4 seconds (Milosavljevic, Madsen, Koch, and Rangel 2011). However, the hemodynamic response typically peaks around five seconds.

TABLE 1

Investors' Characteristics

Panel A: General

	Mean	SD
Male (%)	77.14	42.60
Age	28.11	1.94
First language is English (%)	74.29	44.34
Left-handed (%)	8.57	28.40
Participated in previous study (%)	57.14	50.21

Panel B: Academic Background

	Mean	SD
M.B.A. student in (%)		
First year	34.29	48.16
Second year	65.71	48.16
Concentration (%)		
Finance	54.29	50.54
Marketing	11.43	32.28
Consulting	17.14	38.24
Other business	14.29	35.50
Other degrees (%)		
Business undergraduate	60.00	49.71
Master's other than M.B.A.	11.43	32.28
Ph.D.	0.00	0.00
Two or more college-level courses in (%)		
Finance	80.00	40.00
Accounting	80.00	40.00
Economics	85.72	34.99
Statistics	82.86	37.69

Panel C: Practical Financial Experience

	Mean	SD
Frequently (%)		
Reads business news	74.29	44.34
Reads other news	74.29	44.34
Follows the stock market	68.57	47.10
Familiar with U.S. stock market (%)	94.29	23.55
Prior experience investing (%)		
Through a broker	37.14	49.02
Directly in stock	57.14	50.21
In short positions	20.00	40.58
In options	34.29	48.16
Used financial analyst reports (%)	51.43	50.71

(continued on next page)

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TABLE 1 (continued)

Panel D: Financial Literacy Test Scores

	Mean	SD
Accounting (%)	98.29	9.54
Investing (%)	88.00	6.82
Total (%)	92.11	5.70

Thirty-six adults initially participated in our study. We excluded one investor who did not meet our financial literacy requirement (i.e., this participant scored less than the minimum 80 percent we required in our financial literacy test). The summary statistics above are for the final set of 35 investors.

Events 1, 2, and 3. We told them at the beginning of the study that they would earn a fee of $50 for completing Part 1 and that, at the end of the study, they would be assigned randomly one of the 60 companies. Their total compensation equals $50 plus the gain or minus the loss from investing $50 in the selected company around its earnings announcement. Final payouts ranged from $33 to $67.

Trial Firms

The BOLD signals we are trying to detect are minuscule—typically about a 0.5 percent change and, at most, only 2 percent, from the baseline hemodynamic level in the brain (Huettel et al. 2009). As is common in event-related fMRI research designs (Amaro and Barker 2006), we attempted to increase the signal-to-noise ratio by including multiple trials, 60 firms in our case.[11]

Because to our knowledge, this is the first fMRI-based study in accounting, we are willing to sacrifice inferential generalizability to ensure internal validity. To this end, we impose fairly strict criteria for selecting trial firms. Table 2 summarizes these criteria and the number of firms meeting them.

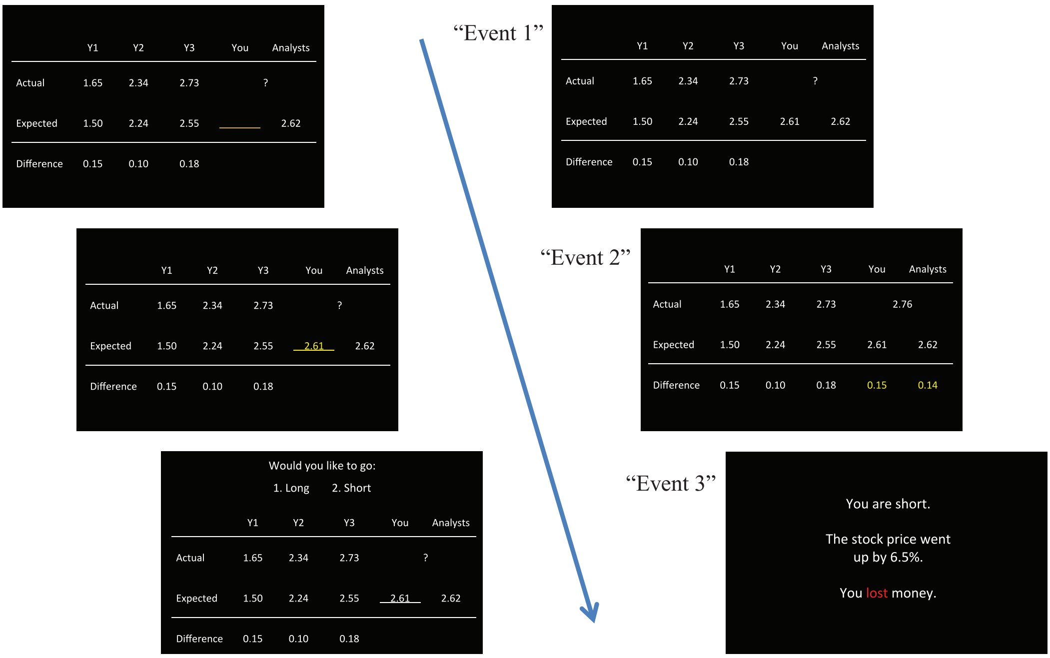
We restrict the sample period to 2000–2009 because of well-documented changes in the properties of reported earnings, earnings surprises, and earnings thresholds during the last half of the 20th century (Francis and Schipper 1999; Givoly and Hayn 2000; Brown 2001; Landsman and Maydew 2002; Brown and Caylor 2005). Sample firms must have not only data on CRSP and Compustat, but also financial analyst forecasts on I/B/E/S, our proxy for the market's expectations (Brown and Kim 1991; Bartov, Givoly, and Hayn 2002). These criteria yield an initial sample of 8,208 firms with 48,848 firm-years. We further restrict the sample to U.S. firms traded on a large exchange to ensure efficient price discovery around earnings announcements.

To help investors forecast EPS for each firm, we provide them with the consensus forecast for the "current" year, as well as actual EPS and consensus forecasts for the prior three years. We measure the consensus forecast as of two days before the earnings announcement. We limit historical data to three years to be consistent with Rule 3-02(a) of the Securities and Exchange Commission's (SEC) Regulation S-X, which requires income statements to present three years of earnings. This short time-series should mitigate investors' overreliance on old earnings numbers when predicting future earnings (Bloomfield, Libby, and Nelson 2003). Together, firms must have four years of consecutive actual EPS and consensus forecasts on I/B/E/S.

[11] Huettel and McCarthy (2001) show that in a typical fMRI study with 50 trials, about half of the voxels that eventually activate were first deemed insignificant at conventional levels. Their findings suggest that our study may still be limited by low power.

FIGURE 1
Experimental Tasks

Panel A: Outside fMRI Scanner **Panel B: Inside fMRI Scanner**



Each experimental trial consisted of two components. The first one, depicted in Panel A, took place outside the fMRI scanner and required investors to (1) view historical actual and expected EPS, (2) forecast current-period EPS, and (3) take a long or short position in the stock. The second component, depicted in Panel B, took place inside the fMRI scanner and required investors to (1) review the EPS data they viewed and predicted outside the scanner ("Event 1"), (2) view the actual EPS reported by the firm and the resulting earnings surprise ("Event 2"), and (3) view the change in the stock price as a result of the earnings announcement and whether investors won or lost money ("Event 3").

We keep the experimental task focused by limiting the information given to investors to only actual EPS and consensus analyst forecasts. The historical numbers are meant to provide information about earnings trends and earnings benchmark performance relative to analysts' forecasts. The current consensus forecast is meant to reflect new information since the previous reported EPS that analysts have been able to incorporate into their current forecasts.[12] This sample selection criterion is based on Koonce and Lipe's (2010) findings that investors rely on both earnings trends and benchmark performance when these measures are consistent over time; investors appear to use them additively when assessing firms' future prospects.

We further restrict the sample to firms with announcement-period returns that have the same sign as the earnings surprise. Since firms typically disclose other concurrent information during an earnings announcement (Francis, Schipper, and Vincent 2002), we expect this restriction to mitigate

[12] Engelmann, Capra, Noussair, and Berns (2009) showed that providing investors expert financial advice reduces the activation of brain regions associated with financial decision making under risk. The ventral striatum, however, showed no change in activation. If our investors view financial analysts' forecasts as expert advice, then we would not expect an effect on striatal activity; if there were one, then it would work against our hypothesis.

TABLE 2

Selection Criteria for Firms Used in Experiment

	Firms	Firm-Years
Included in I/B/E/S, CRSP, and Compustat databases over 2000–2009	8,208	48,848
Incorporated outside the USA	(977)	(5,071)
Without		
I/B/E/S data to compute earnings expectations and surprises	(1,590)	(16,037)
CRSP data to compute stock returns and trading volume	(126)	(638)
Compustat data to compute accounting variables	(4)	(29)
Not traded on NYSE or NASDAQ	(47)	(147)
	5,464	26,926
Without		
Four consecutive years of actual EPS and consensus forecasts	(2,531)	(13,257)
Three years of consistent EPS trends and benchmark performance	(1,948)	(11,851)
Earnings surprises and abnormal stock returns of same sign	(631)	(1,382)
Positive actual EPS in "current" year	(39)	(46)
Preliminary sample	315	390
Final random sample used in experiment	60	60

the effects of such disclosures on the valence of the announcement-period stock return. Finally, we only include firms with actual profits for the current year because analyst forecasts tend to be more optimistically biased and less accurate for firms reporting losses instead of profits (Das 1998). This pattern is consistent with fMRI evidence suggesting that adult brains process positive and negative numbers differently (Gullick, Wolford, and Temple 2012).

We randomly select 60 firm-years from those meeting our criteria. Of these, 45 percent beat the consensus forecast, 15 percent met it, and 40 percent missed it. Table 3 summarizes basic characteristics of these 60 firms. Compared with other publicly traded firms, our sample firms tend to be larger (Panel A), better performing (Panel B), and easier to forecast (Panel D). They have larger analyst followings, but similar actual EPS, consensus forecasts, and earnings surprises (Panel C). The market reactions to their earnings announcements do not differ significantly, either (Panel E).

Functional MRI Scanning Protocol and BOLD Capture[13]

We used a Siemens 3T Trio whole-body scanner to image investors' brains. Each investor received a structural scan to map the anatomical structure of his brain and two functional scans to capture the BOLD responses to the experimental stimuli.[14] We split the scanning session into two functional runs to give investors a small 5–10 minute break. We avoid order effects by assigning each trial firm randomly to one of the two functional runs.

[13] Huettel et al. (2009) provide an accessible introduction to functional MRI; Ashby (2011) to the statistical analysis of fMRI data. Ramsey, Hoogduin, and Jansma (2002) discuss fMRI-related experimental design.

[14] We ran one T1-weighted structural scan (TR = 2600 ms, TE = 3.02 ms, flip angle = 8°, 240 × 256 matrix, 176 sagittal interleaved slices, 1 mm^3 voxel size) and two T2*-weighted functional scans with an echo-planar imaging sequence (TR = 2000 ms, TE = 30 ms, flip angle = 90°, FOV = 192 mm, 64 × 64 matrix, 33 axial interleaved slices, 3 × 3 × 3.5 mm voxel size).

TABLE 3

Characteristics of Firms Used in Experiment

Panel A: Size and Exchange

	Trial Firms with Earnings Surprise					Other Publicly Traded Firms	
	> 0	= 0	< 0	F	All		t
n	27	9	24		60	Various	
Market capitalization ($ billion)	30.35	30.76	13.05	1.35	23.49	4.57	3.63***
Total assets ($ billion)	85.41	30.86	12.16	1.19	47.90	9.24	1.73*
Total revenues ($ billion)	31.66	8.22	11.62	1.45	20.13	3.48	2.69***
Net income ($ billion)	1.92	1.45	0.85	1.03	1.42	0.17	3.65***
Traded on NYSE (%)	66.67	44.44	75.00	1.37	66.67	45.32	3.47***
Dow Jones member (%)	14.81	11.11	12.50	0.05	13.33	2.54	2.44**

Panel B: Profitability and Valuation

	Trial Firms with Earnings Surprise					Other Publicly Traded Firms	
	> 0	= 0	< 0	F	All		t
n	27	9	24		60	Various	
Return on shareholders' equity (%)	20.40	13.94	22.14	0.46	20.13	−76.58	1.11
Net profit margin (%)	12.30	13.98	8.52	0.95	11.04	−461.90	3.46***
Total asset turnover	1.31	1.11	0.93	1.50	1.13	0.86	2.64**
Total debt/Total assets (%)	53.79	50.68	58.19	0.32	55.08	55.84	−0.22
P/B ratio	3.40	1.42	4.07	0.76	3.37	5.10	−0.91
P/E ratio	17.93	94.60	22.59	3.97**	31.29	4.05	1.83*

Panel C: Analyst Following and Earnings Surprise

	Trial Firms with Earnings Surprise					Other Publicly Traded Firms	
	> 0	= 0	< 0	F	All		t
n	27	9	24		60	Various	
Analyst following	15.70	15.56	12.42	1.63	14.37	7.44	7.77***
Consensus EPS forecast ($)	3.18	1.55	2.52	2.61*	2.67	2.39	0.52
Actual EPS ($)	3.36	1.55	2.32	3.31**	2.67	2.40	0.48
Earnings surprise ($)	0.18	0.00	−0.20	5.60***	0.00	0.01	−0.07
Earnings surprise (% of consensus)	5.04	0.00	−9.12	8.72***	−1.38	2.61	−1.29
Earnings surprise ≥ 0 (%)	100.00	100.00	0.00	—	60.00	63.76	−0.59
Earnings surprise < 0 (%)	0.00	0.00	100.00	—	40.00	36.24	0.59

(continued on next page)

TABLE 3 (continued)

Panel D: Forecasting Difficulty

	Trial Firms with Earnings Surprise					Other Publicly Traded Firms	t
	> 0	= 0	< 0	F	All		
n	27	9	24		60	Various	
Historical coefficient of variation in EPS (%)	27.15	31.03	30.00	0.07	28.87	62.14	–7.66***
Historical mean absolute forecast error (%)	3.94	4.34	18.93	1.41	9.99	19.94	–2.23**

Panel E: Market Reaction to Earnings Announcement

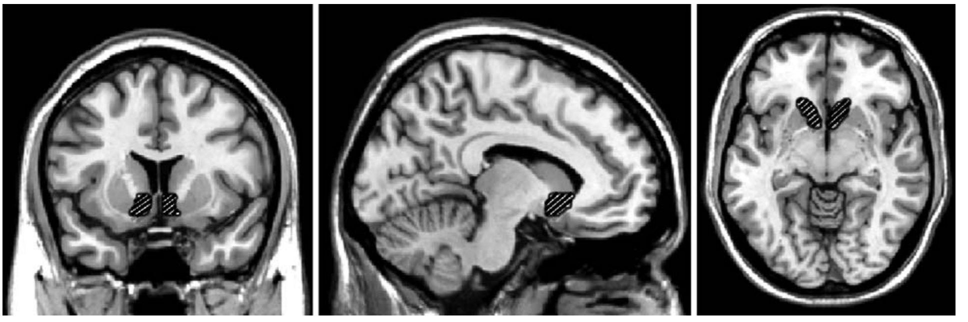
	Trial Firms with Earnings Surprise					Other Publicly Traded Firms	t
	> 0	= 0	< 0	F	All		
n	27	9	24		60	Various	
Cumulative raw return (*CRR*) (%)	8.52	1.09	−10.32	39.61***	−0.13	0.04	−0.11
Cumulative abnormal return (*CAR*) (%)	2.29	0.39	−1.87	13.34***	0.34	0.04	0.68
Abnormal trading volume	1.88	0.34	2.23	4.62**	1.78	0.95	3.80***

*, **, *** Denote significance at the 0.10, 0.05, and 0.01 levels, respectively.
The F-statistics are for one-way ANOVA tests of difference in means across the three sets of firms used in the experiment—those that met, beat, or missed the consensus EPS forecast. The t-statistics are for two-tailed tests of difference in means (allowing for unequal variances) between firms used in the experiment and other publicly traded firms.
The table shows the means of various characteristics for the 60 firms included in the experiment, and a comparison set of all other U.S. publicly traded firms with data available on Compustat, CRSP, or I/B/E/S over 2000–2009. The sample sizes used to compute the means for the comparison set average 23,866 firm-years. Earnings surprise is actual annual EPS minus consensus EPS forecast; the latter is calculated as the mean analyst forecast issued after the announcement of last-year EPS and before the announcement of current-year EPS. Analyst following is the number of analysts issuing annual EPS forecasts for the firm. The historical coefficient of variation in EPS and mean absolute forecast error are computed using data for the three-year period preceding the year that investors had to forecast in the experimental task. *CRR* is the raw stock return accumulated over the three trading days centered on the earnings announcement date. *CAR* is *CRR* less the Fama and French (1993) three-factor cumulative expected return during the same period, obtained from Prof. Ken French's Dartmouth University faculty website. Abnormal trading volume is the trading volume over the three trading days centered on the earnings announcement date, minus the mean volume during the previous 200 trading days, divided by the standard deviation of volume during those 200 days.

We process much more data than a typical empirical accounting study. During functional imaging, the scanner captures an entire 3D volume of the brain every two seconds; each volume consists of 33 slices with a total of 135,168 spatial data points or 3D "voxels" (33 slices × 64 × 64 voxels). Investors spent, on average, 13.5 minutes in the scanner while viewing stimuli, so we collected, on average, about 54.7 million observations per session (135,168 observations/volume × 30 volumes/minute × 13.5 minutes) or over two billion observations in total. The data are both spatially and sequentially correlated, which we consider when estimating each investor's striatal BOLD.

Before statistical analysis, we preprocessed the fMRI data using SPM8 (Wellcome Department of Imaging Neuroscience, University College London) to correct for slice acquisition timing and head motion, to normalize each brain to a common brain template, and to reduce noise by smoothing the data spatially. We then construct three indicator variables—*EVENT1*, *EVENT2*, and *EVENT3*—taking on the value 1 (0 otherwise) during the time when the investor is viewing each of the three screens per trial. Because the BOLD signal is delayed following these stimuli, we then

FIGURE 2
Ventral Striatum in the Human Brain



The three images are from a structural MRI scan of the human brain. The first image shows a frontal or coronal view of the brain (the face of the person is to the front, facing the reader), the second image shows a side or sagittal view (the face is to the right), and the third image is a horizontal or axial view (the face is to the top of the image). The areas highlighted in stripes show the ventral striatum, the region in the brain that we predict will process investors' reactions to earnings news.

convolve the indicator variables with a double gamma function $h_{(t)}$ that is a proxy for the brain's hemodynamic response function at time t.[15] These convolved variables capture the expected level of the BOLD signal in each brain location if, as predicted by H1, that location indeed responds to our stimuli. In our model below, we denote the convolved variables using the operator $\boxtimes$, so that the term $EVENT1_t \boxtimes h_{(t)}$, for example, denotes the convolved indicator for Event 1. We then estimated the following generalized linear model per investor i:

$$B_{vit} = \beta_{0vi} + \textstyle\sum_j \beta_{1vij}[EVENT1_{it} \boxtimes h_{(t)}] + \sum_j \beta_{2vij}[EVENT2_{it} \boxtimes h_{(t)}] + \sum_j \beta_{3vij}[EVENT3_{it} \boxtimes h_{(t)}] \\ + \boldsymbol{\beta_{vi}}'\boldsymbol{CONTROLS_{it}} + \varepsilon_{vit}, \tag{4}$$

where B is the adjusted BOLD signal in voxel v at time t, j denotes trial firm, and ***CONTROLS*** is a vector of variables controlling for run and head motion corrections. We allow the residuals to follow an AR(1) process.

We estimate Equation (4) using only observations for voxels mapping to the investor's ventral striatum, our region of interest. By doing so, we avoid potential reverse inference problems and Type I error (Poldrack 2011; Poldrack, Mumford, and Nichols 2011). Figure 2 shows this region in a standard anatomical scan. The coefficient β_0 in Equation (4) captures the investor's baseline BOLD signal, while the coefficients β_1, β_2, and β_3 capture experimental stimuli-induced changes in brain activation. For instance, $\beta_2 > 0$ suggest an increase in striatal activity when earnings surprises are revealed to the investor.

To carry out the remaining analyses, we combine the estimated coefficients β_1, β_2, and β_3 (which we call *BOLD*) with data from investor questionnaires, Compustat, CRSP, and I/B/E/S. The

15 The concept of convolution can be thought of as the combination of two functions. It plays a key role in the detection and analysis of neural signals. Specifically, to enhance the detection of neural signals, actual brain activity is compared to expected brain activity under the stimulus; the expected activity is the combination or convolution between the stimulus function and the hemodynamic response function (Poldrack et al. 2011).

merged database consists of 2,100 investor-firm observations (35 investors × 60 firms). We delete 11 observations with corrupted scanner data.

IV. ASSOCIATION BETWEEN BRAIN ACTIVITY AND EARNINGS ANNOUNCEMENTS

Investors' Behavior

Table 4 summarizes initial analyses bearing on the quality of investors' earnings forecasts and investment decisions. The consensus forecast is the mean EPS forecast, the forecast dispersion is the standard deviation of within-firm EPS forecasts, and the earnings surprise is the actual EPS minus the consensus forecast. Panel A shows descriptive statistics for these variables computed separately, using investors' forecasts in the first two numeric columns and financial analysts' forecasts obtained from I/B/E/S in the next two columns. The last column shows t-tests indicating that investors' forecasts are slightly more optimistic than analysts' forecasts. The mean forecast dispersion is almost three times bigger for investors, suggesting greater disagreement among investors than among financial analysts.

Investors made a total of 2,100 EPS forecasts and investment choices for the 60 trial firms. We split investors into those with high and low task-related forecasting ability, based on the median value of the proportional mean absolute forecast error across all investors (Clement, Koonce, and Lopez 2007). Table 4, Panel B shows that high- and low-ability investors are fairly homogenous when it comes to demographics, experience, and financial literacy. Of the 2,100 investment decisions, 72 were inconsistent given investors' forecasts relative to the analyst consensus. For example, if an investor forecasted EPS to be \$3.50 and the consensus was \$3.00, then we deduce that he is more optimistic than the market and, therefore, should take a long position in the stock if his goal is to maximize his payout at the end of the experiment. Taking a short position would be incorrect, so we exclude from further analysis the 72 observations relating to these positions. Fifteen investors made at least one of these errors; two investors made the majority, 62.5 percent.[16]

Brain Activity during Earnings Announcements

Table 5 presents descriptive statistics in Panel A and significance tests in Panels B through D for striatal BOLD signals, by event and earnings surprise type. Where investors took short positions, we reverse the sign of the *BOLD* coefficients.

H1 predicts $BOLD > 0$ when $SURPRISE > 0$, $BOLD = 0$ when $SURPRISE = 0$, and $BOLD < 0$ when $SURPRISE < 0$. The investors' reference point for the earnings surprise should be the consensus analyst forecast because investors' investment returns are based on the consensus forecast; hence, *SURPRISE* is actual EPS minus the consensus analyst forecast. We test H1 using striatal activation during Event 2, when investors learn the firm's actual EPS and the resulting earnings surprise, both relative to the consensus forecast and investors' own forecasts.

Our analyses and test statistics are based on the following regression model:

$$BOLD_{ijk} = \varphi_{k1}BEAT_{ijk} + \varphi_{k2}MEET_{ijk} + \varphi_{k3}MISS_{ijk} + \varepsilon_{ijk}, \tag{5}$$

where *BOLD* is the striatal *BOLD* coefficient of investor $i \in \{1, 2,\ldots,35\}$ while viewing event $k \in \{1, 2, 3\}$ for firm $j \in \{1, 2,\ldots,60\}$; *BEAT* is 1 if $SURPRISE > 0$, and 0 otherwise; *MEET* is 1 if $SURPRISE = 0$, and 0 otherwise; *MISS* is 1 if $SURPRISE < 0$, and 0 otherwise; and *SURPRISE* is actual annual EPS minus the consensus analyst forecast immediately before the earnings announcement. To mitigate cross-sectional residual dependent, we calculate both t- and F-statistics

[16] Excluding the data of these two investors from our analyses does not materially affect our results.

TABLE 4

Investors' Earnings Forecasts and Investment Positions

Panel A: Study Investors' versus Financial Analysts' EPS Forecasts (n = 60)

	Investors		Financial Analysts		
	Mean	**SD**	**Mean**	**SD**	**t**
Consensus forecast	2.69	1.95	2.67	1.95	2.10**
Forecast dispersion	0.20	0.25	0.08	0.27	2.76***
Earnings surprise	−0.02	0.48	0.00	0.44	−2.10**

Panel B: Mean Differences between Investors with High versus Low Forecasting Ability and between Investors Taking Correct versus Wrong Investment (i.e., Long or Short) Positions

	Forecasting Ability			Investment Positions		
Investor's Characteristic	**High**	**Low**	**t**	**Correct**	**Wrong**	**t**
n	18	17		2,028	72	
Male (%)	77.8	76.4	0.09	78.7	33.3	2.92***
Age	28.4	27.8	0.85	28.1	27.9	0.43
First language is English (%)	72.2	76.5	−0.28	74.6	65.3	0.43
Business undergraduate (%)	66.7	52.9	0.81	61.1	29.2	2.19**
First-year M.B.A. student (%)	33.3	35.3	−0.12	34.9	16.7	1.82*
M.B.A. focusing in finance (%)	44.4	64.7	−1.19	55.4	23.6	2.56**
Familiar with U.S. stock market (%)	94.4	94.1	0.04	94.1	98.6	−1.35
Follows the stock market (%)	66.7	70.6	−0.24	70.2	23.6	3.85***
Invested directly in stock (%)	55.6	58.8	−0.19	58.1	29.2	1.98*
Invested in short positions (%)	27.8	11.8	1.18	20.6	2.8	2.71**
Used financial analyst reports (%)	66.7	35.3	1.90*	52.4	25.0	2.04**
Accounting literacy score (%)	98.3	98.2	0.03	98.6	90.7	2.45**
Investing literacy score (%)	88.5	87.5	0.46	88.2	83.1	3.09***
Total financial literacy score (%)	92.4	91.8	0.35	92.3	86.1	3.13***

*, **, *** Denote significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests for difference in means/proportions.
The sample in Panel A consists of 60 observations, one for each firm in the experimental task. The sample in Panel B consists of 2,100 investor-firm observations. The consensus forecast is the mean annual forecast of EPS for firm *j,* calculated using either investors' or financial analysts' forecasts. Forecast dispersion is the standard deviation of EPS forecasts for firm *j,* using either investors' or analysts' forecasts. Earnings surprise is actual EPS less the consensus forecast, using either investors' or analysts' consensus forecasts. Investor *i*'s forecasting ability is the mean absolute forecast error for all the 60 forecasts he made, one for each firm included in the experiment. We classify an individual as having high (low) forecasting ability if his mean absolute forecast error is below (above) the median. Investment position is the position taken by the investor in the firm's stock after forecasting its earnings. A correct (wrong) position, for example, is one where the investor took a long (short) position if he forecasted higher EPS for the firm than the analyst consensus forecast, or a short (long) position if he forecasted lower EPS than the consensus. The 72 wrong positions were taken by 15 investors; two investors made the majority (62.5 percent) of these errors.

by double-clustering observations by investor and firm (Cameron, Gelbach, and Miller 2011). Basing the test statistics on mixed-effects models commonly estimated in the neuroscientific literature (Poldrack et al. 2011), with investors treated as random effects and firms as fixed effects, leads to similar inferences.

TABLE 5

***BOLD* Coefficients in Ventral Striatum across Events by Earnings Surprise Type**

Panel A: Descriptive Statistics for Striatal BOLD by Event (n = 2,017)

Event	Mean	SD	Min.	Median	Max.
1. "Reminder"	0.00	1.16	−5.48	−0.02	12.18
2. "Earnings announcement"	−0.04	1.26	−5.06	−0.07	12.85
3. "Return announcement"	−0.02	1.48	−16.09	−0.06	11.83

Panel B: *BOLD* Coefficients for Event 1, "Reminder"

Variable	Expected Sign	Coefficient	t
BEAT	n.s.	−0.03	−0.94✓
MEET	n.s.	0.01	0.22✓
MISS	n.s.	0.04	1.11✓
R^2			0.00
F test			
BEAT = *MEET* = *MISS* = 0			0.80

Panel C: *BOLD* Coefficients for Event 2, "Earnings Announcement"

Variable	Expected Sign	Coefficient	t
BEAT	+	0.12	2.24**
MEET	n.s.	0.06	0.95✓
MISS	−	−0.25	−5.39***
R^2			0.02
F tests			
BEAT = *MEET* = *MISS* = 0			20.79***
BEAT = −*MISS*			4.71**
2 × *BEAT* = −*MISS*			0.01

Panel D: *BOLD* Coefficients for Event 3, "Return Announcement"

Variable	Expected Sign	Coefficient	t
BEAT	n.s.	0.04	0.56✓
MEET	n.s.	0.07	0.66✓
MISS	n.s.	−0.12	−1.92•
R^2			0.003
F tests			
BEAT = *MEET* = *MISS* = 0			2.92*

*, **, *** Denote significance at the 0.10, 0.05, and 0.01 levels, respectively, based on one-tailed tests for signed predictions, and two-tailed otherwise.
✓ Denotes not significant ("n.s.") at the 0.10 level or better, as expected.
• Denotes significance at the 0.10 level or better, inconsistent with our predictions.
The initial sample consists of 35 investor observations for each of the 60 firms used in the experiment. We exclude 72 observations for which investors took incorrect investment positions based on their EPS forecasts, and 11 observations that were corrupted during the image acquisition stage of the study. The final estimation sample consists of the resulting 2,017 observations. In Event 1 ("Reminder"), investors reviewed their EPS forecasts and the firm's history of actual and forecasted EPS. In Event 2 ("Earnings announcement"), investors learned about the actual EPS reported by the firm, along with the earnings surprise relative to the consensus forecast and the investor's own forecast. In Event 3 ("Return

(continued on next page)

TABLE 5 (continued)

announcement"), investors learned the stock market reaction to the earnings announcement and whether they won or lost money. The coefficients, t-, and F-statistics in Panels B though D are obtained from estimating the model:

$$BOLD_{kij} = \varphi_{k1}BEAT_{kij} + \varphi_{k2}MEET_{kij} + \varphi_{k3}MISS_{kij} + e_{kij},$$

where *BOLD* measures the blood oxygen level-dependent activation in the ventral striatum during an event in the scanner; $BEAT = 1$ if $SURPRISE > 0$, and 0 otherwise; $MEET = 1$ if $SURPRISE = 0$, and 0 otherwise; and $MISS = 1$ if $SURPRISE < 0$, and 0 otherwise. *SURPRISE* is actual annual EPS minus the consensus analyst forecast immediately before the earnings announcement. We use investor's *i* striatal *BOLD* coefficient while he views firm *j*'s data during event *k*. We mitigate cross-sectional residual dependence by double-clustering the observations by investor *i* and firm *j* and using the resulting coefficient standard errors to calculate test statistics (Cameron et al. 2011). Basing the test statistics on mixed-effects models commonly estimated in the neuroscientific literature (Poldrack et al. 2011) leads to similar inferences.

One would not expect significant striatal activity during Event 1, when investors are reminded of their forecasts and investment positions, because there is no new information revealed to investors during this period. Consistent with this view, Panel B of Table 5 shows the coefficients are not statistically significant, either individually or jointly ($F_{(2,2014)} = 0.80$, two-tailed $p = 0.449$), at conventional levels.

In contrast, Panel C of Table 5 shows that during the Event 2 earnings announcement period, *BOLD* is positive when $SURPRISE > 0$ ($\varphi_{21} = 0.12$, $t = 2.24$, one-tailed $p = 0.013$), not significant when $SURPRISE = 0$ ($\varphi_{22} = 0.06$, $t = 0.95$, two-tailed $p = 0.342$), and negative when $SURPRISE < 0$ ($\varphi_{23} = -0.25$, $t = -5.39$, one-tailed $p < 0.001$). These results support H1, showing that investors process information about earnings surprises in the ventral striatum. Specifically, earnings that beat the consensus forecast lead to striatal activation, while earnings that miss the forecast lead to deactivation. The effects are sufficiently large to be detectable through functional brain imaging.

In Panel C of Table 5, the *BOLD* coefficient is about twice as large, in absolute terms, when investors view a negative surprise than when they view a positive one. These findings are consistent with Kahneman and Tversky's (1979, 2000) prospect theory and supporting empirical evidence suggesting that losses are about twice as "painful" as gains are rewarding. They are also consistent with archival evidence showing a stronger market reaction when earnings miss expectations than when they beat them (Skinner and Sloan 2002).

Panel D of Table 5 shows that the *BOLD* coefficients during Event 3, when participants learn about their investment gains or losses, are not statistically significant in the case of positive earnings surprises ($\varphi_{31} = 0.04$, $t = 0.56$, two-tailed $p = 0.576$) or earnings that meet expectations ($\varphi_{32} = 0.07$, $t = 0.66$, two-tailed $p = 0.509$), but marginally negative in the case of negative surprises ($\varphi_{33} = -0.12$, $t = -1.92$, two-tailed $p = 0.055$). We are unable to distinguish between the significant negative coefficient reflecting a reactivation of the ventral striatum versus the persistence of the striatum's activation in Event 2.[17]

To determine whether the ventral striatum processes not only the sign, but also the magnitude of an earnings surprise, we estimate the following model using *BOLD* coefficients for Event 2:

$$BOLD_{ij} = \psi_1 BEAT_{ij} + \psi_2 MEET_{ij} + \psi_3 MISS_{ij} + \psi_4 (SURPRISE \times BEAT)_{ij} + \psi_5 (SURPRISE \times MISS)_{ij} + \varepsilon_{ij}. \quad (6)$$

As before, the results reported in Table 6, Panel B show that the ventral striatum reacts to whether the firm reports earnings that beat or miss expectations. An F-test also rejects the null that $\psi_4 = \psi_5 =$

[17] Because the ventral striatum does not process emotional responses to stimuli, the striatal deactivation we find during Event 3 does not indicate that investors "felt bad" when reminded of losses they incurred earlier during Event 2.

TABLE 6

Association between *BOLD* Coefficients in Ventral Striatum and Earnings Surprise Type and Magnitude

Panel A: Descriptive Statistics (n = 2,017)

Variable	Mean	SD	Min.	Median	Max.
BOLD	−0.04	1.26	−5.06	−0.07	12.85
BEAT	0.45	0.50	0.00	0.00	1.00
MEET	0.15	0.36	0.00	0.00	1.00
MISS	0.40	0.49	0.00	0.00	1.00
SURPRISE	0.00	0.43	−2.75	0.00	1.41
SURPRISE × *BEAT*	0.08	0.22	0.00	0.00	1.41
SURPRISE × *MISS*	−0.08	0.36	−2.75	0.00	0.00

Panel B: Regression Results (n = 2,017)

$$BOLD_{ij} = \psi_1 BEAT_{ij} + \psi_2 MEET_{ij} + \psi_3 MISS_{ij} + \psi_4 (SURPRISE \times BEAT)_{ij} + \psi_5 (SURPRISE \times MISS)_{ij} + \varepsilon_{ij}.$$

Variable	Expected Sign	Coefficient	t
BEAT	+	0.12	1.90**
MEET	n.s.	0.06	0.95✓
MISS	−	−0.28	−6.03***
SURPRISE × *BEAT*	+	0.07	1.73*
SURPRISE × *MISS*	−	−0.15	−5.44***
R^2			0.02
F tests			
BEAT = *MEET* = *MISS* = 0			14.87***
SURPRISE × *BEAT* = *SURPRISE* × *MISS* = 0			3.48**

*, **, *** Denote significance at the 0.10, 0.05, and 0.01 levels, respectively, based on one-tailed tests for signed predictions, and two-tailed otherwise.
✓ Denotes not significant ("n.s.") at the 0.10 level or better, as predicted.
The initial sample consists of 35 investor observations for each of the 60 firms used in the experiment. We exclude 72 observations for which investors took incorrect investment positions based on their EPS forecasts, and 11 observations that were corrupted during the image acquisition stage of the study. The final estimation sample consists of the resulting 2,017 observations. We mitigate cross-sectional residual dependence by double-clustering the observations by investor *i* and firm *j* and using the resulting coefficient standard errors to calculate test statistics (Cameron et al. 2011). Basing the test statistics on mixed-effects models commonly estimated in the neuroscientific literature (Poldrack et al. 2011) leads to similar inferences.

Variable Definitions:
BOLD = blood oxygen level-dependent activation in investor *i*'s ventral striatum while viewing Event 2, the actual EPS announced by firm *j*;
BEAT = 1 if *SURPRISE* > 0, and 0 otherwise;
MEET = 1 if *SURPRISE* = 0, and 0 otherwise;
MISS = 1 if *SURPRISE* < 0, and 0 otherwise; and
SURPRISE = actual annual EPS minus the consensus analyst forecast immediately before the earnings announcement.

0 ($F_{(2,2014)} = 3.48$, two-tailed $p = 0.031$), suggesting that the striatum also processes the magnitude of the earnings surprise—striatal BOLD signals are increasing in the magnitude of positive earnings surprises ($\psi_4 = 0.07$, $t = 1.73$, one-tailed $p = 0.042$) and decreasing in the magnitude of negative earnings surprises ($\psi_5 = -0.15$, $t = -0.15$, one-tailed $p < 0.001$).

Do Investors React to Earnings Surprises Relative to Their Own or the Market's Expectations?

It is not clear whether actual stock market participants use their own earnings forecasts or a proxy, such as the consensus analyst forecast, when reacting to actual earnings disclosures. We instructed investors to use their own EPS forecasts only when choosing either a long or a short position in a firm's stock. We also explained that their investment return would be based on the firm's actual EPS relative to the consensus analyst forecast, not relative to their own forecast. Three questions in our financial literacy test explicitly tested investors' ability to appropriately select the consensus analyst forecast instead of investors' own forecasts when estimating investment returns; the correct response rate for these questions was 83.8 percent. Nevertheless, because our experiment does not distinguish which reference point investors actually react to, it could still be the case that striatal BOLD signals reflect investors' own EPS forecasts as the reference point.

Table 7, Panel A presents descriptive statistics for *SURPRISE, SURPRISE_OWN* (i.e., actual earnings minus the investor's own earnings forecast), and *BOLD,* while Panel B cross-tabulates the distribution of earnings surprise types by reference point. Consistent with the strong correlation between *SURPRISE* and *SURPRISE_OWN* (Pearson $\rho = 0.84$, $p < 0.001$), Panel B shows that about 72 percent of earnings news would be classified as beating, meeting, or missing expectations regardless of whether those expectations were based on the consensus analyst forecast or the investors' own forecasts. The remaining 28 percent of the earnings news should lead to opposite striatal activity depending on whether investors anchored on the consensus or their own forecasts. To parse out the effects of different forecast baselines, we estimate the following model:

$$\begin{aligned} BOLD_{ij} = {} & \lambda_0 + \lambda_1 BEAT_{ij} + \lambda_2 MISS_{ij} + \lambda_3 (SURPRISE \times BEAT)_{ij} + \lambda_4 (SURPRISE \times MISS)_{ij} \\ & + \lambda_5 BEAT\_OWN_{ij} + \lambda_6 MISS\_OWN_{ij} + \lambda_7 (SURPRISE\_OWN \times BEAT\_OWN)_{ij} \\ & + \lambda_8 (SURPRISE\_OWN \times MISS\_OWN)_{ij} + \varepsilon_{ij}, \end{aligned} \tag{7}$$

using *BOLD* coefficients for Event 2, the earnings announcement. The coefficients on the earnings surprise variables calculated using the consensus analyst forecast are all significant at conventional levels, as predicted. A joint test of $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ rejects the null hypothesis ($F_{(4,561)} = 3.50$, $p = 0.008$). In contrast, the only statistically significant coefficient on the earnings surprise variables based on investors' own forecasts is that on *BEAT_OWN* ($\lambda_5 = 0.46$, $t = 2.53$, one-tailed $p = 0.006$). A joint test of $\lambda_5 = \lambda_6 = \lambda_7 = \lambda_8 = 0$ fails to reject the null ($F_{(4,561)} = 1.95$, $p = 0.101$). We interpret these findings as suggesting that investors seem to primarily use as reference point the consensus analyst forecast; however, the overall fit of the model is low ($R^2 = 0.03$), so we interpret these results cautiously.

Modulation of Brain Activity during Earnings Announcements

To provide additional confidence that the ventral striatum indeed processes earnings surprises, we examine factors that modulate the magnitude of striatal reaction to earnings surprises. Specifically, we expect the magnitude of the striatal BOLD signal to vary as a function of relevant investor characteristics, the investment position, and the predictability of the firm's current-period earnings, after controlling for the magnitude and direction of the earnings surprise.

TABLE 7

Associations among Surprises Based on Analysts' Consensus Forecasts, Surprises Based on Investors' Own Forecasts, and Striatal BOLD

Panel A: Descriptive Statistics for Full Sample (n = 2,017)

Variable	Mean	SD	Min.	Median	Max.
SURPRISE	0.00	0.43	−2.75	0.00	1.41
SURPRISE_OWN	−0.02	0.57	−7.25	−0.10	4.40
BOLD	−0.04	1.26	−5.06	−0.07	12.85

Panel B: Percentage Frequency and Concordance of Surprise Types (n = 2,017)

		SURPRISE			
		< 0	**= 0**	**> 0**	**Total**
SURPRISE_OWN	< 0	34.2%	8.4%	7.7%	50.3%
	= 0	1.1	2.8	2.4	6.3
	> 0	4.7	4.0	34.7	43.4
Total		40.0%	15.2%	44.8%	100.0%
Pearson $\chi^2_{(4)}$		937.30***			

Panel C: Regression Results using Observations with *SURPRISE* ≠ *SURPRISE_OWN* (n = 570)

$$\begin{aligned} BOLD_{ij} = {} & \lambda_0 + \lambda_1 BEAT_{ij} + \lambda_2 MISS_{ij} + \lambda_3 (SURPRISE \times BEAT)_{ij} + \lambda_4 (SURPRISE \times MISS)_{ij} \\ & + \lambda_5 BEAT\_OWN_{ij} + \lambda_6 MISS\_OWN_{ij} + \lambda_7 (SURPRISE\_OWN \times BEAT\_OWN)_{ij} \\ & + \lambda_8 (SURPRISE\_OWN \times MISS\_OWN)_{ij} + \varepsilon_{ij}. \end{aligned}$$

Variable	Expected Sign	Coefficient	t
Intercept	n.s.	−0.13	−1.19✓
BEAT	+	0.27	2.13**
MISS	−	−0.64	−3.26***
SURPRISE × *BEAT*	+	0.57	0.39
SURPRISE × *MISS*	−	−8.22	−2.71***
BEAT_OWN	+	0.46	2.53***
MISS_OWN	−	0.03	0.25
SURPRISE_OWN × *BEAT_OWN*	+	−0.07	−0.27
SURPRISE_OWN × *MISS_OWN*	−	−0.10	−1.27
R^2			0.03
F tests			
BEAT = *MISS* = *SURPRISE* × *BEAT* = *SURPRISE* × *MISS* = 0			3.50***
BEAT_OWN = *MISS_OWN* = *SURPRISE_OWN* × *BEAT_OWN* = *SURPRISE_OWN* × *MISS_OWN* = 0			1.95

, * Denote significance at the 0.05 and 0.01 levels, respectively, based on one-tailed tests for signed predictions, and two-tailed otherwise.
✓ Denotes not significant ("n.s.") at the 0.10 level or better, as predicted.
The initial sample consists of 35 investor observations for each of the 60 firms used in the experiment. We exclude 72 observations for which investors took incorrect investment positions based on their EPS forecasts, and 11 observations that were corrupted during the image acquisition stage of the study. The final estimation sample consists of the resulting

(continued on next page)

TABLE 7 (continued)

2,017 observations. We mitigate cross-sectional residual dependence by double-clustering the observations by investor *i* and firm *j* and using the resulting coefficient standard errors to calculate test statistics (Cameron et al. 2011). Basing the test statistics on mixed-effects models commonly estimated in the neuroscientific literature (Poldrack et al. 2011) leads to similar inferences.

Variable Definitions:
BOLD = blood oxygen level-dependent activation in investor *i*'s ventral striatum while viewing Event 2, the actual EPS announced by firm *j;*
BEAT = 1 if *SURPRISE* > 0, and 0 otherwise;
MISS = 1 if *SURPRISE* < 0, and 0 otherwise;
SURPRISE = actual annual EPS minus the consensus analyst forecast immediately before the earnings announcement;
BEAT_OWN = 1 if *SURPRISE_OWN* > 0, and 0 otherwise;
MISS_OWN = 1 if *SURPRISE_OWN* < 0, and 0 otherwise; and
SURPRISE_OWN = actual annual EPS minus investor *i*'s forecast immediately before the earnings announcement.

Males are more sensitive to monetary reward prediction errors (Spreckelmeyer et al. 2009), so we expect the absolute value of the *BOLD* coefficient, $|BOLD|$, to be larger for males. We also expect $|BOLD|$ to vary positively with investors' BIS/BAS scale scores (Gray 1990; Carver and White 1994; Corr 2004), but negatively with their interaction, $BAS \times BIS$ (Kim and Lee 2011). Investors with stronger financial backgrounds, forecasting ability, and confidence in their forecasts should react more strongly to earnings surprises, assuming that their priors are more compact in the Bayesian sense. We measure financial literacy (*FIN_LITERACY*) by the score investors obtained in our financial literacy test, forecasting ability (*ABILITY*) as the investor's mean absolute forecast error over all 60 forecasts he made, and forecasting confidence (*CONFIDENCE*) as the absolute value of the difference between his forecast and the consensus analyst forecast of firm *j*'s EPS, expressed as a percentage of the consensus forecast. We expect these variables to be positively associated with $|BOLD|$. Consistent with Bayesian updating and temporal difference models of reinforcement learning, we also expect a negative relation between $|BOLD|$ and earnings predictability. We include three proxies for the latter: the historical earnings volatility, *EPS_VOLATILITY,* measured as the coefficient of variation in actual EPS over the preceding three years; the historical earnings surprise volatility, *SURPRISE_VOLATILITY,* measured as the coefficient of variation in *SURPRISE* over those same preceding three years; and *DISPERSION,* the standard deviation in analysts' forecasts of current-period EPS. Because a short position in a stock carries more risk than a long one, we expect short positions (*SHORT* = 1, and 0 otherwise) to lead to increased striatal activation in the case of positive earnings surprises and increased deactivation in the case of negative surprises. Finally, we also control for the magnitude and direction of *SURPRISE,* but make no predictions for their signs.

Table 8 presents descriptive statistics (Panel A) and regression results (Panel B) from estimating the following model:

$$\begin{aligned}|BOLD|_{ij} = {} & \omega_0 + \omega_1 MALE_{ij} + \omega_2 BAS_{ij} + \omega_3 BIS_{ij} + \omega_4 (BAS \times BIS)_{ij} + \omega_5 FIN\_LITERACY_{ij} \\ & + \omega_6 ABILITY_{ij} + \omega_7 CONFIDENCE_{ij} + \omega_8 EPS\_VOLATILITY_{ij} \\ & + \omega_9 SURPRISE\_VOLATILITY_{ij} + \omega_{10} DISPERSION_{ij} + \omega_{11} SHORT_{ij} \\ & + \omega_{12} BEAT_{ij} + \omega_{13} MISS_{ij} + \omega_{14} (SURPRISE \times BEAT)_{ij} \\ & + \omega_{15} (SURPRISE \times MISS)_{ij} + \varepsilon_{ij}. \end{aligned} \tag{8}$$

As before, our test statistics are based on double-clustered standard errors to mitigate cross-sectional dependence among multiple observations for the same investor and firm.

As predicted, the coefficients on *MALE, BAS, BIS,* and the $BAS \times BIS$ interaction are significant at the 0.05 level or better, suggesting that gender and personality traits modulate the striatal reaction

TABLE 8

Factors Associated with Magnitude of Striatal BOLD

Panel A: Descriptive Statistics (n = 2,017)

Variable	Mean	SD	Min.	Median	Max.
|BOLD|	0.92	0.87	0.00	0.69	12.85
MALE	0.79	0.41	0.00	1.00	1.00
BAS	8.43	1.85	5.00	9.00	12.00
BIS	14.91	2.64	9.00	15.00	20.00
FIN_LITERACY	23.08	1.37	20.00	23.00	25.00
ABILITY	0.00	0.55	−0.43	−0.19	2.41
CONFIDENCE	4.89	12.49	0.00	1.35	88.68
EPS_VOLATILITY	0.29	0.32	0.06	0.18	1.56
SURPRISE_VOLATILITY	0.58	0.33	0.12	0.51	1.41
DISPERSION	0.08	0.27	0.00	0.02	2.06
SHORT	0.33	0.47	0.00	0.00	1.00
BEAT	0.45	0.50	0.00	0.00	1.00
MISS	0.40	0.49	0.00	0.00	1.00
SURPRISE	0.00	0.43	−2.75	0.00	1.41

Panel B: Regression Results (n = 2,017)

$$\begin{aligned}|BOLD|_{ij} = {} & \omega_0 + \omega_1 MALE_{ij} + \omega_2 BAS_{ij} + \omega_3 BIS_{ij} + \omega_4 (BAS \times BIS)_{ij} + \omega_5 FIN\_LITERACY_{ij} \\ & + \omega_6 ABILITY_{ij} + \omega_7 CONFIDENCE_{ij} + \omega_8 EPS\_VOLATILITY_{ij} \\ & + \omega_9 SURPRISE\_VOLATILITY_{ij} + \omega_{10} DISPERSION_{ij} + \omega_{11} SHORT_{ij} \\ & + \omega_{12} BEAT_{ij} + \omega_{13} MISS_{ij} + \omega_{14} (SURPRISE \times BEAT)_{ij} \\ & + \omega_{15} (SURPRISE \times MISS)_{ij} + \varepsilon_{ij}.\end{aligned}$$

Variable	Expected Sign	Coefficient	t
Intercept	?	−1.49	−2.28*
MALE	+	0.19	1.73**
BAS	+	0.38	3.71***
BIS	+	0.19	4.88***
BAS × *BIS*	−	−0.03	−4.00***
FIN_LITERACY	+	−0.03	−0.80
ABILITY	+	−0.06	−1.03
CONFIDENCE	+	0.00	−0.10
EPS_VOLATILITY	+	0.14	2.16**
SURPRISE_VOLATILITY	+	−0.06	−0.93
DISPERSION	+	0.19	2.41***
SHORT	+	0.08	1.74**
BEAT	?	−0.09	−2.06**
MISS	?	−0.08	−1.69*
SURPRISE × *BEAT*	?	−0.26	−1.93*
SURPRISE × *MISS*	?	0.08	3.53***
R^2			0.04
F-tests			
MALE = *BAS* = *BIS* = (*BAS* × *BIS*) = *FIN_LITERACY* = *ABILITY* = *CONFIDENCE* = 0			11.30***
EPS_VOLATILITY = *ERROR_VOLATILITY* = *DISPERSION* = 0			2.23*

(continued on next page)

TABLE 8 (continued)

*, **, *** Denote significance at the 0.10, 0.05, and 0.01 levels, respectively, based on one-tailed tests for signed predictions, and two-tailed otherwise.

The initial sample consists of 35 investor observations for each of the 60 firms used in the experiment. We exclude 72 observations for which investors took incorrect investment positions based on their EPS forecasts, and 11 observations that were corrupted during the image acquisition stage of the study. The final estimation sample consists of the resulting 2,017 observations. We mitigate cross-sectional residual dependence by double-clustering the observations by investor *i* and firm *j* and using the resulting coefficient standard errors to calculate test statistics (Cameron et al. 2011).

Variable Definitions:

|BOLD| = absolute value of the blood oxygen level-dependent activation in investor *i*'s ventral striatum while viewing the actual EPS announced by firm *j* (i.e., during Event 2);

MALE = 1 if the investor is male, and 0 if she is female;

BIS and *BAS* = investor's scores in the seven-item BIS and 13-item BAS scales in Carver and White's (1994) version of the self-reported BIS/BAS scale;

FIN_LITERACY = score in our financial literacy test;

ABILITY = investor's forecasting ability, measured as the mean absolute forecast error over all 60 forecasts he made, one for each firm included in the experiment;

CONFIDENCE = absolute value of the difference between investor's forecast and the consensus analyst forecast of firm *j*'s EPS, expressed as a percentage of the consensus forecast;

EPS_VOLATILITY = coefficient of variation in actual EPS over the preceding three years;

SURPRISE_VOLATILITY = coefficient of variation in *SURPRISE* over the preceding three years;

DISPERSION = the standard deviation in analysts' forecasts of current-period EPS for firm *j*;

SHORT = 1 if the investor took a short position in the stock, and 0 otherwise;

BEAT = 1 if *SURPRISE* > 0, and 0 otherwise;

MISS = 1 if *SURPRISE* < 0, and 0 otherwise; and

SURPRISE = actual annual EPS minus the consensus analyst forecast immediately before the earnings announcement.

to earnings news. The coefficients on *FIN_LITERACY, ABILITY,* and *CONFIDENCE,* however, are not statistically significant. Finally, the coefficients on *SHORT, EPS_VOLATILITY,* and *DISPERSION,* but not on *SURPRISE_VOLATILITY,* are statistically significant at the 0.05 level or better, suggesting that investment position and earnings predictability affect the way investors' brains react to earnings news. Because the overall fit of the model is low ($R^2 = 0.04$), we interpret these results cautiously.

Taken together, the findings we report so far strongly support H1, showing that investors process information about earnings surprises in the ventral striatum. Indeed, the striatum appears to process both the magnitude and sign of an earnings surprise. The striatal reaction is consistent with Kahneman and Tversky's (1979, 2000) prospect theory, and is modulated by personality traits, earnings predictability, and investment position.

V. ASSOCIATION BETWEEN BRAIN ACTIVITY AND THE MARKET'S REACTION TO EARNINGS ANNOUNCEMENTS

Our last set of analyses is aimed at testing H2, which predicts an association between striatal BOLD signals and proxies for the market's reaction to earnings news. The analyses we report in Section IV suggest that the striatal BOLD signal that we capture essentially behaves as a neurobiological measure of earnings surprise. Therefore, we expect it to be associated with announcement-period stock returns and trading volume for the 60 firms we used in the first part of our study testing H1.

We estimate the following regression models to examine the association between announcement-period market reactions and the striatal BOLD signal, conditional on earnings surprise:

$$RETURN_j = \phi_1|\$SURPRISE|_j \times BEAT_j + \phi_2|\$SURPRISE|_j \times MEET_j + \phi_3|\$SURPRISE|_j \times MISS_j + \phi_4|AvgBOLD|_j \times BEAT_j + \phi_5|AvgBOLD|_j \times MEET_j + \phi_6|AvgBOLD|_j \times MISS_j + \varepsilon_j, \quad (9)$$

and:

$$VOLUME_j = \theta_1|\$SURPRISE|_j \times BEAT_j + \theta_2|\$SURPRISE|_j \times MEET_j + \theta_3|\$SURPRISE|_j \times MISS_j + \theta_4|AvgBOLD|_j \times BEAT_j + \theta_5|AvgBOLD|_j \times MEET_j + \theta_6|AvgBOLD|_j \times MISS_j + \varepsilon_j, \quad (10)$$

where *RETURN* is the three-factor adjusted (Fama and French 1993) cumulative abnormal return over the three-day period centered on the earnings announcement date; *VOLUME* is the standardized abnormal trading volume, calculated as the trading volume over the three trading days centered on the earnings announcement date, minus the mean volume during the previous 200 trading days, divided by the standard deviation of volume during those 200 days; $|AvgBOLD|$ is the absolute value of the mean *BOLD* coefficients in the ventral striatum of all 35 investors while viewing the actual EPS of firm *j* (i.e., during Event 2);[18] *\$SURPRISE* is *SURPRISE* scaled by beginning-of-period stock price; and *BEAT, MEET,* and *MISS* are as defined earlier—relative to the consensus analyst forecast.

Consistent with an extensive accounting literature documenting an increasing association between announcement-period returns and earnings surprises (e.g., Ball and Brown 1968; Kothari 2001; Skinner and Sloan 2002; Bartov et al. 2002), we expect $\varphi_1 > 0$, $\varphi_2 = 0$, $\varphi_3 < 0$, $\varphi_4 > 0$, $\varphi_5 = 0$, and $\varphi_6 < 0$ in Equation (9). We expect $\theta_1 > 0$, $\theta_2 = 0$, $\theta_3 > 0$, $\theta_4 > 0$, $\theta_5 = 0$, and $\theta_6 > 0$ in Equation (10), consistent with larger earnings surprises leading to greater belief revision and subsequent trading (Beaver 1968; Bamber, Barron, and Stevens 2011).

Table 9, Panel A presents descriptive statistics, while Panels B and C present regression results for Equations (9) and (10). We compare Model 1 including only earnings surprises, in the spirit of basic models of market reaction reported in the archival accounting literature (Kothari 2001; Bartov et al. 2002); Model 2 including only striatal BOLD signals; and Model 3 including both sets of variables. We report standardized coefficients to help assess the relative importance of the independent variables both within and across models.

As expected, Table 9, Panel B shows that announcement-period abnormal returns are increasing in positive earnings surprises, decreasing in negative earnings surprises, and unaffected by zero earnings surprises (Models 1 and 3). Abnormal returns show a similar pattern for striatal BOLD signals conditioned on the type of earnings surprise (Models 2 and 3). For our sample firms, the magnitude of the earnings surprise, conditioned on earnings benchmark performance as in Model 1, explains about 21 percent of the variance in stock returns around the earnings announcement. In contrast, Model 2 shows that the magnitude of the BOLD signal, conditioned on the type of earnings surprise, explains about 36 percent of the variance. Model 3 shows that, together, these two sets of variables explain about 39 percent of the variance in announcement-period returns. An F-test of the joint significance of the $|AvgBOLD|$ variables in Model 3 (i.e., Equation (9)) reveals that the striatal BOLD signals have incremental explanatory power to that of the earnings surprise alone ($F_{(3,55)} = 7.14$, $p < 0.001$). The relative R^2s of Models 1 and 2 and the standardized coefficients of Model 3 suggest that the brain activity following an earnings surprise does a better job of explaining the stock price reaction to the earnings announcement than the

[18] Averaging BOLD signals across investors is consistent with how the archival literature examining the market reaction to earnings surprises calculates the consensus analyst forecasts (as a simple average of financial analysts' individual forecasts) as a proxy for the market's earnings expectation.

TABLE 9

Association between Striatal BOLD and Market Reaction to Earnings News

Panel A: Descriptive Statistics (n = 60)

Variable	Mean	SD	Min.	Median	Max.
RETURN	0.00	0.03	−0.05	0.00	0.21
VOLUME	1.78	1.70	−0.68	1.38	8.73
AvgBOLD	−0.04	0.27	−0.65	0.01	0.49
\$SURPRISE	0.00	0.01	−0.03	0.00	0.01
BEAT	0.45	0.50	0.00	0.00	1.00
MEET	0.15	0.36	0.00	0.00	1.00
MISS	0.40	0.49	0.00	0.00	1.00

Panel B: Regression Results for Abnormal Return Models (n = 60)

$$RETURN_j = \phi_1|\$SURPRISE|_j \times BEAT_j + \phi_2|\$SURPRISE|_j \times MEET_j + \phi_3|\$SURPRISE|_j \times MISS_j + \phi_4|AvgBOLD|_j \times BEAT_j + \phi_5|AvgBOLD|_j \times MEET_j + \phi_6|AvgBOLD|_j \times MISS_j + \varepsilon_j.$$

		Model 1		Model 2		Model 3	
Variable	Exp. Sign	Std. Coeff.	t	Std. Coeff.	t	Std. Coeff.	t
|*\$SURPRISE*| × *BEAT*	+	0.36	2.15**			0.12	1.49*
|*\$SURPRISE*| × *MEET*	n.s.	0.00	—✓			0.00	—✓
|*\$SURPRISE*| × *MISS*	−	−0.21	−3.72***			−0.13	−3.60***
|*AvgBOLD*| × *BEAT*	+			0.44	2.49***	0.37	2.14**
|*AvgBOLD*| × *MEET*	n.s.			0.05	0.87✓	0.05	0.85✓
|*AvgBOLD*| × *MISS*	−			−0.24	−4.83***	−0.20	−4.02***
R^2			0.21		0.36		0.39
F tests							
|*\$SURPRISE*| × *BEAT* = |*\$SURPRISE*| × *MEET* = |*\$SURPRISE*| × *MISS* = 0							7.57***
|*AvgBOLD*| × *BEAT* = |*AvgBOLD*| × *MEET* = |*AvgBOLD*| × *MISS* = 0							7.14***

(continued on next page)

magnitude of the earnings surprise itself. However, as a joint F-test of the significance of the |*\$SURPRISE*| variables in Model 3 shows ($F_{(2,55)} = 7.57$, $p = 0.001$), the explanatory power of earnings surprises is not completely subsumed by that of the related brain activity. This incremental explanatory power might reflect, for example, additional information about the firm's prospects disclosed by management at the time of the earnings announcement.[19]

A similar pattern emerges in Table 9, Panel C for the abnormal trading volume surrounding an earnings announcement. Specifically, abnormal trading volume is increasing in the magnitude of the earnings surprise (Models 1 and 3) and the related striatal activity (Models 2 and 3). For our sample firms, the magnitude of the earnings surprise, conditioned on earnings benchmark

[19] These findings suggest that some features of the earnings surprise not directly processed in the ventral striatum appear to affect the market's reaction to the earnings surprise. Identifying what these features are is a task we leave for future research.

TABLE 9 (continued)

Panel C: Regression Results for Abnormal Trading Volume Models (n = 60)

$$\begin{aligned} VOLUME_j = {} & \phi_1|\$SURPRISE|_j \times BEAT_j + \phi_2|\$SURPRISE|_j \times MEET_j \\ & + \phi_3|\$SURPRISE|_j \times MISS_j + \phi_4|AvgBOLD|_j \times BEAT_j \\ & + \phi_5|AvgBOLD|_j \times MEET_j + \phi_6|AvgBOLD|_j \times MISS_j + \varepsilon_j. \end{aligned}$$

		Model 1		Model 2		Model 3	
Variable	**Exp. Sign**	**Std. Coeff.**	**t**	**Std. Coeff.**	**t**	**Std. Coeff.**	**t**
$\|\$SURPRISE\| \times BEAT$	+	0.56	4.12***			0.33	2.54**
$\|\$SURPRISE\| \times MEET$	n.s.	0.00	—✓			0.00	—✓
$\|\$SURPRISE\| \times MISS$	+	0.37	2.01**			0.16	1.63*
$\|AvgBOLD\| \times BEAT$	+			0.54	5.57***	0.35	3.91***
$\|AvgBOLD\| \times MEET$	n.s.			0.06	1.69•	0.06	1.66✓
$\|AvgBOLD\| \times MISS$	+			0.60	3.52***	0.55	3.13***
R^2			0.26		0.44		0.50
F tests							
$\|\$SURPRISE\| \times BEAT = \|\$SURPRISE\| \times MEET = \|\$SURPRISE\| \times MISS = 0$							4.56**
$\|AvgBOLD\| \times BEAT = \|AvgBOLD\| \times MEET = \|AvgBOLD\| \times MISS = 0$							9.28***

*, **, *** Denote significance at the 0.10, 0.05, and 0.01 levels, respectively, based on one-tailed tests for signed predictions, and two-tailed otherwise. All tests are based on robust standard errors.
✓ Denotes not significant at the 0.10 level or better, as predicted.
• Denotes significant at the 0.10 level or better, inconsistent with our predictions.
The estimation sample consists of one observation for each of the 60 firms used in the experiment.

Variable Definitions:
$|AvgBOLD|$ = absolute value of the mean blood oxygen level-dependent activation in the ventral striatum of all 35 investors viewing the actual EPS (i.e., Event 2) of firm *j;*
$|\$SURPRISE|$ = absolute value of firm *j*'s *SURPRISE,* scaled by its beginning-of-fiscal-year share price;
SURPRISE = actual annual EPS minus the consensus analyst forecast immediately before the earnings announcement;
RETURN = three-factor adjusted (Fama and French 1993) cumulative abnormal return over the three-day period centered on the earnings announcement date. We obtain the three-factor adjusted expected return from Prof. Ken French's Dartmouth University faculty website;
VOLUME = standardized abnormal trading volume, calculated as the trading volume over the three trading days centered on the earnings announcement date, minus the mean volume during the previous 200 trading days, divided by the standard deviation of volume during those 200 days;
BEAT = 1 if *SURPRISE* > 0, and 0 otherwise;
MEET = 1 if *SURPRISE* = 0, and 0 otherwise; and
MISS is 1 if *SURPRISE* < 0, and 0 otherwise.

performance as in Model 1, explains about 26 percent of the variance in abnormal trading around the earnings announcement. On the other hand, Model 2 shows that the magnitude of the BOLD signal, conditioned on the type of earnings surprise, explains about 44 percent of the variance. Model 3 shows that these variables together account for 50 percent of the variance in abnormal trading. An F-test of the joint significance of the $|AvgBOLD|$ variables in Model 3 (i.e., Equation (10)) reveals that the striatal BOLD signals have incremental explanatory power to that of the earnings surprise alone ($F_{(3,55)} = 9.28$, $p < 0.001$). The relative R^2s of Models 1 and 2 and the standardized coefficients of Model 3 suggest that activity in the ventral striatum following an earnings surprise does a better job of explaining abnormal trading around the earnings announcement than the magnitude of the earnings surprise itself. A joint F-test of the significance of the |*\$SURPRISE*| variables in Model 3 ($F_{(2,55)} = 4.56$, $p = 0.015$) suggests that the explanatory power of earnings surprises is not completely subsumed by that of the related brain activity.

Consistent with H2, the results in Table 9 suggest that the striatal BOLD signal that we capture through functional brain imaging is sufficiently precise to show a strong association with common proxies for the market's reaction to earnings news. Indeed, the association and explanatory power of these signals is almost twice that of the earnings surprises giving rise to the signals. Of course, we instituted a fairly strict set of criteria for selecting the firms we used in the experiment, so our results may not generalize to the broader population of publicly traded firms. As Table 3 shows, our sample firms are larger, more profitable, and easier to forecast than other publicly traded firms, even though they have similar earnings surprises and market reactions. We cannot rule out low external validity, especially when the regression R^2s in Table 9 are about one order of magnitude larger than those typically reported in the literature for return-earnings models (Kothari 2001; Bartov et al. 2002; Ball and Shivakumar 2008).

VI. CONCLUSION

We take a different approach from the existing literature on the information content of earnings news by relying on the tools of cognitive neuroscience to explore how the human brain processes earnings surprises. Because earnings announcements convey information to investors akin to rewards and punishment, we test the hypothesis that earnings surprises are processed in the human brain's ventral striatum, an area rich in dopamine neurons. These neurons encode reward prediction errors that serve a key role in the brain's learning mechanism, leading to goal-directed behavior critical for survival.

We measure brain activation indirectly using blood oxygen level-dependent (BOLD) signals, which capture metabolic changes around neurons processing and transmitting information. We test our hypothesis through an experiment in which 35 adult investors forecast the earnings per share of 60 firms traded on the NYSE or NASDAQ exchange and take either long or short positions in the firms' stocks. Investors then undergo fMRI scanning while they learn the actual EPS reported by the firms and the resulting market reaction to the earnings announcements. Our results show that earnings beating the consensus analyst forecast are associated with increased striatal BOLD activity, while earnings missing the consensus forecast lead to decreased activity. Earnings meeting expectations, as expected, have no effect on the baseline hemodynamic level in the striatum. We also find that, at the time of the earnings news, investors' brains fully anticipate the eventual stock return for firms beating the consensus forecast, but tend to underreact to earnings missing the forecast.

We also predict and find a significant association between the magnitude of the striatal BOLD signal and investors' personality traits, investment positions, and the predictability of corporate earnings. Finally, our analysis also shows a strong association between the BOLD signal—a biological measure of the information content of earnings—and two measures of the market's reaction to earnings news: abnormal stock returns and abnormal trading volume around the earnings announcement. The BOLD signal has incremental explanatory power beyond the earnings surprise giving rise to the signal.

Our study demonstrates that cognitive neuroscience and its methods can cast new light on the relation between the human brain, accounting numbers, and economic exchange. We echo Dickhaut, Basu, McCabe, and Waymire's (2010) conclusion that neuroscience and its methods can have profound implications for both accounting research and standard setting by framing the design of accounting institutions and principles in ways that are consistent with scientific theories of human behavior.

REFERENCES

Aharon, I., N. Etcoff, D. Ariely, C. F. Chabris, E. O'Donner, and H. C. Breiter. 2001. Beautiful faces have variable reward value: fMRI and behavioral evidence. *Neuron* 32: 527–551.

Amaro, E., Jr., and G. J. Barker. 2006. Study design in fMRI: Basic principles. *Brain and Cognition* 60: 220–232.

Anderson, A. K., K. Christoff, I. Stappen, D. Panitz, D. G. Ghahremani, G. Glover, J. D. Gabrieli, and N. Sobel. 2003. Dissociated neural representations of intensity and valence in human olfaction. *Nature Neuroscience* 6: 196–202.

Arnow, B. A., J. E. Desmond, L. L. Banner, G. H. Glover, A. Solomon, M. L. Polan, T. F. Lue, and S. W. Atlas. 2002. Brain activation and sexual arousal in healthy, heterosexual males. *Brain* 125: 1014–1023.

Ashby, F. G. 2011. *Statistical Analysis of fMRI Data*. Cambridge, MA: The MIT Press.

Ball, R., and P. Brown. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6: 159–178.

Ball, R., and L. Shivakumar. 2008. How much new information is there in earnings? *Journal of Accounting Research* 46: 975–1016.

Bamber, L. S., O. E. Barron, and D. E. Stevens. 2011. Trading volume around earnings announcements and other financial reports: Theory, research design, empirical evidence, and directions for future research. *Contemporary Accounting Research* 28: 431–471.

Bartov, E., D. Givoly, and C. Hayn. 2002. The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics* 33: 173–204.

Basu, S., and G. Waymire. 2006. Recordkeeping and human evolution. *Accounting Horizons* 20: 1–29.

Basu, S., J. Dickhaut, G. Hecht, K. Towry, and G. Waymire. 2009a. Recordkeeping alters economic history by promoting reciprocity. *Proceedings of the National Academy of Sciences of the United States of America*, 106, 1009–1014.

Basu, S., M. Kirk, and G. Waymire. 2009b. Memory, transaction records, and *The Wealth of Nations*. *Accounting, Organizations and Society* 34: 985–917.

Bayer, H. M., and P. W. Glimcher. 2005. Midbrain dopamine neurons encode a quantitative reward prediction error signal. *Neuron* 47: 129–141.

Beaver, W. 1968. The information content of annual earnings announcements. *Journal of Accounting Research* 6: 67–92.

Berns, G. S., S. M. McClure, G. Pagnoni, and P. R. Montague. 2001. Predictability modulates human brain response to reward. *The Journal of Neuroscience* 21: 2793–2798.

Beyer, A., D. A. Cohen, T. Z. Lys, and B. R. Walther. 2010. The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics* 50: 296–343.

Bloomfield, R. J., R. Libby, and M. W. Nelson. 2003. Do investors over-rely on old elements of the earnings time series? *Contemporary Accounting Research* 20: 1–31.

Brooks, A. M., V. S. C. Pammi, C. Noussair, C. M. Capra, J. B. Engelman, and G. S. Berns. 2010. From bad to worse: Striatal coding of the relative value of painful decisions. *Frontiers in Neuroscience* 4: 1–7.

Brown, L. D., and K-J. Kim. 1991. Timely aggregate analyst forecasts as better proxies for market earnings expectations. *Journal of Accounting Research* 29: 382–385.

Brown, L. D. 2001. A temporal analysis of earnings surprises: Profits versus losses. *Journal of Accounting Research* 39: 221–241.

Brown, L. D., and M. L. Caylor. 2005. A temporal analysis of quarterly earnings thresholds: Propensities and valuation consequences. *The Accounting Review* 80: 423–440.

Cameron, A. C., J. B. Gelbach, and D. L. Miller. 2011. Robust inference with multi-way clustering. *Journal of Business and Economic Statistics* 29: 238–249.

Carver, C. S., and T. L. White. 1994. Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS scales. *Journal of Personality and Social Psychology* 67: 319–333.

Chua, H. F., R. Gonzalez, S. F. Taylor, R. C. Welsh, and I. Liberzon. 2009. Decision-related loss: Regret and disappointment. *Neuroimage* 47: 2031–2040.

Clement, M. B., L. Koonce, and T. J. Lopez. 2007. The roles of task-specific forecasting experience and innate ability in understanding analyst forecasting performance. *Journal of Accounting and Economics* 44: 378–398.

Corr, P. J. 2004. Reinforcement sensitivity theory and personality. *Neuroscience and Behavioral Reviews* 28: 317–332.

Das, S. 1998. Financial analysts' earnings forecasts for loss firms. *Managerial Finance* 24: 39–50.

Delgado, M. R., L. E. Nystrom, C. Fissell, D. C. Noll, and J. A. Fiez. 2000. Tracking the hemodynamic responses to reward and punishment in the striatum. *Journal of Neurophysiology* 84: 3072–3077.

Dickhaut, J., S. Basu, K. McCabe, and G. Waymire. 2010. Neuroaccounting: Consilience between the biologically evolved brain and culturally evolved accounting principles. *Accounting Horizons* 24: 221–255.

Elliott, W. B., F. D. Hodge, J. J. Kennedy, and M. Pronk. 2007. Are M.B.A. students a good proxy for nonprofessional investors? *The Accounting Review* 82: 139–168.

Engelmann, J. B., C. M. Capra, C. Noussair, and G. S. Berns. 2009. Expert financial advice neurobiologically "offloads" financial decision-making under risk. *PLoS ONE* 4: 1–14.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33: 3–56.

Francis, J., and K. Schipper. 1999. Have financial statements lost their relevance? *Journal of Accounting Research* 37: 319–352.

Francis, J., K. Schipper, and L. Vincent. 2002. Expanded disclosure and the increased usefulness of earnings announcements. *The Accounting Review* 77: 515–546.

Givoly, D., and C. Hayn. 2000. The changing time-series properties of earnings, cash flows and accruals: Has financial reporting become more conservative? *Journal of Accounting and Economics* 29: 287–320.

Gray, J. A. 1990. Brain systems that mediate both emotion and cognition. *Cognition and Emotion* 4: 269–288.

Gullick, M. M., G. Wolford, and E. Temple. 2012. Understanding less than nothing: Neural distance effects for negative numbers. *Neuroimage* 62: 542–554.

Hsu, M., M. Bhatt, R. Adolphs, D. Tranel, and C. F. Camerer. 2005. Neural systems responding to degrees of uncertainty in human decision-making. *Science* 310: 1680–1683.

Huettel, S. A., A. W. Song, and G. McCarthy. 2009. *Functional Magnetic Resonance Imaging*. 2nd Edition. Sunderland, MA: Sinauer Associates Inc.

Huettel, S. A., J. D. Singerman, and G. McCarthy. 2001. The effects of aging upon the hemodynamic response measured by functional MRI. *Neuroimage* 13: 161–175.

Huettel, S. A., and G. McCarthy. 2001. The effects of single-trial averaging upon the spatial extent of fMRI activation. *Neuroreport* 12: 2411–2416.

Kahneman, D., and A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* 47: 263–292.

Kahneman, D., and A. Tversky. 2000. *Choices, Values, and Frames*. Cambridge, MA: Cambridge University Press.

Kim, D-Y., and J-H. Lee. 2011. Effects of the BAS and BIS on decision making in a gambling task. *Personality and Individual Differences* 50: 1131–1135.

Knutson, B., A. Westdorp, E. Kaiser, and D. Hommer. 2000. fMRI visualization of brain activity during a monetary incentive delay task. *Neuroimage* 12: 20–27.

Knutson, B., C. M. Adams, G. W. Fong, and D. Hommer. 2001. Anticipation of increasing monetary reward selectively recruits nucleus accumbens. *The Journal of Neuroscience* 21 (16): RC159.

Knutson, B., S. Rick, G. E. Wimmer, D. Prelec, and G. Loewenstein. 2007. Neural predictors of purchases. *Neuron* 53: 147–156.

Komisaruk, B. R., and B. Whipple. 2005. Functional MRI of the brain during orgasm in women. *Annual Review of Sex Research* 16: 62–86.

Koonce, L., and M. G. Lipe. 2010. Earnings trends and performance relative to benchmarks: How consistency influences their joint use. *Journal of Accounting Research* 48: 859–884.

Kothari, S. P. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31: 105–231.

Landsman, W. R., and E. L. Maydew. 2002. Has the information content of quarterly earnings announcements declined in the past three decades? *Journal of Accounting Research* 40: 797–808.

Libby, R., R. Bloomfield, and M. W. Nelson. 2002. Experimental research in financial accounting. *Accounting, Organizations and Society* 27: 775–810.

Lohrenz, T., K. McCabe, C. F. Camerer, and P. R. Montague. 2007. Neural signature of fictive learning signals in a sequential investment task. *Proceedings of the National Academy of Sciences of the United States of America* 104: 9493–9498.

McClure, S. M., G. S. Berns, and P. R. Montague. 2003. Temporal prediction errors in a passive learning task activate human striatum. *Neuron* 38: 339–346.

Milosavljevic, M., E. Madsen, C. Koch, and A. Rangel. 2011. Fast saccades toward numbers: Simple number comparisons can be made in as little as 230 ms. *Journal of Vision* 11: 1–12.

Montague, P. R., P. Dayan, and T. J. Sejnowski. 1996. A framework for mesencephalic dopamine systems based on predictive Hebbian learning. *The Journal of Neuroscience* 16: 1936–1947.

Murphy, K., and H. Garavan. 2004. An empirical investigation into the number of subjects required for an event-related fMRI study. *Neuroimage* 22: 879–885.

North, D. C. 2005. *Understanding the Process of Economic Change*. Cambridge, U.K.: Cambridge University Press.

Niv, Y. 2009. Reinforcement learning in the brain. *Journal of Mathematical Psychology* 53: 139–154.

O'Doherty, J. P., P. Dayan, K. J. Friston, H. D. Critchley, and R. J. Dolan. 2003. Temporal difference models and reward-related learning in the human brain. *Neuron* 38: 329–337.

O'Doherty, J. P., P. Dayan, J. Schultz, R. Deichmann, K. Friston, and R. J. Dolan. 2004. Dissociable roles of ventral and dorsal striatum in instrumental conditioning. *Science* 304: 452–454.

Pagnoni, G., C. F. Zink, P. R. Montague, and G. S. Berns. 2002. Activity in human ventral striatum locked to errors of reward prediction. *Nature Neuroscience* 5: 97–98.

Poldrack, R. A. 2011. Inferring mental states from neuroimaging data: From reverse inference to large-scale decoding. *Neuron* 72: 692–697.

Poldrack, R. A., J. A. Mumford, and T. E. Nichols. 2011. *Handbook of Functional MRI Data Analysis*. New York, NY: Cambridge University Press.

Preuschoff, K., P. Bossaerts, and S. R. Quartz. 2006. Neural differentiation of expected reward and risk in human subcortical structures. *Neuron* 51: 381–390.

Ramsey, N. F., H. Hoogduin, and J. M. Jansma. 2002. Functional MRI experiments: Acquisition, analysis and interpretation of data. *European Neuropsychopharmacology* 12: 517–526.

Rilling, J., D. Gutman, T. Zeh, G. Pagnoni, G. Berns, and C. Kilts. 2002. A neural basis for social cooperation. *Neuron* 35: 395–405.

Rolls, E. T., J. O'Doherty, M. L. Kringelbach, S. Francis, R. Bowtell, and F. McGlone. 2003. Representations of pleasant and painful touch in the human orbitofrontal and cingulate cortices. *Cerebral Cortex* 13: 308–317.

Samanez-Larkin, G. R., S. E. B. Gibbs, K. Khanna, L. Nielsen, L. L. Carstensen, and B. Knutson. 2007. Anticipation of monetary gain but not loss in healthy older adults. *Nature Neuroscience* 10: 787–791.

Schultz, W., P. Dayan, and P. R. Montague. 1997. A neural substrate of prediction and reward. *Science* 275: 1593–1599.

Skinner, D. J., and R. G. Sloan. 2002. Earnings surprises, growth expectations, and stock returns, or, don't let an earnings torpedo sink your portfolio. *Review of Accounting Studies* 7: 289–312.

Spreckelmeyer, K. N., S. Krach, G. Kohls, L. Rademacher, A. Irmak, K. Konrad, T. Kircher, and G. Gründer. 2009. Anticipation of monetary and social reward differently activates mesolimbic brain structures in men and women. *Social Cognitive and Affective Neuroscience* 4: 158–165.

Sutton, R. S., and A. G. Barto. 1998. *Reinforcement Learning: An Introduction*. Cambridge, MA: The MIT Press.

Thirion, B., P. Pinel, S. Mériaux, A. Roche, S. Dehaene, and J-B. Poline. 2007. Analysis of a large fMRI cohort: Statistical and methodological issues for group analyses. *Neuroimage* 35: 105–120.

Tom, S. M., C. R. Fox, C. Trepel, and R. A. Poldrack. 2007. The neural basis of loss aversion in decision-making under risk. *Science* 315: 515–518.

Yacubian, J., J. Glascher, K. Schroeder, T. Sommer, D. F. Braus, and C. Buchel. 2006. Dissociable systems for gain- and loss-related value predictions and errors of prediction in the human brain. *Journal of Neuroscience* 23: 8092–8097.