Trends in Cognitive Sciences

Feature Review

The Psychology and Neuroscience of Financial Decision Making

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Financial decisions are among the most important life-shaping decisions that people make. We review facts about financial decisions and what cognitive and neural processes influence them. Because of cognitive constraints and a low average level of financial literacy, many household decisions violate sound financial principles. Households typically have underdiversified stock holdings and low retirement savings rates. Investors overextrapolate from past returns and trade too often. Even top corporate managers, who are typically highly educated, make decisions that are affected by overconfidence and personal history. Many of these behaviors can be explained by well-known principles from cognitive science. A boom in high-quality accumulated evidence–especially how practical, low-cost 'nudges' can improve financial decisions–is already giving clear guidance for balanced government regulation.

Trends

A boom in accumulated evidence over the past several decades shows that financial decision-making at all levels in the economy often departs from the predictions of models of rational information-processing

New data from a variety of sources, including the human brain, corporate conference calls, genetics, and online trading activity, allow researchers to uncover new facts about the cognitive processes that influence financial decision-making

Evidence from these new data sources, and vigorous randomized field experiments, are already being used for prescriptive purposes to test out low cost practical "nudges" by governments around the world

Closer collaboration between behavioral economic theory and methodologies from cognitive science is likely to generate important new insights on financial decision-making from households to corporate managers

The Cognitive Basis of Financial Decisions

Many financial decisions have a big influence on people's lives and these decisions are made at many levels in the economy. For example, what mortgage a household chooses affects its finances substantially. The specifics of what mortgages are available, and how they can be described, are often constrained by government policy. The cumulative effect of millions of homeowner mortgage decisions, along with the government policy and corporate decisions about how mortgages are bundled and traded, influences mortgage rates and availability.

How well this financial ecosystem works is sensitive to cognition at all levels, ranging from homeowner confusion or gullibility to public sentiment that influences policy to whether large banks correctly understand (and 'price') the systemic risk inherent in our complicated modern financial network. The financial crisis of 2008, followed by the Great Recession, is an example of how mistakes and perverse incentives in this system can snowball to disaster. Until recently, there has been limited cognitive and neuroscientific evidence regarding the mechanisms that underlie financial decisions.

We describe some of this recent research at four levels of financial decision making in which cognitive principles play some role: (i) **household finance** (see Glossary) decisions about saving, borrowing, and spending; (ii) patterns in individual trading of financial assets; (iii) how the decisions of investors in the market aggregate to determine asset prices; and (iv) managerial decisions about raising and investing corporate funds.

A brief history of financial economics will set the stage. In the early 1950s, Modern Portfolio Theory (MPT) began to formalize ideas of how a rational investor would invest in a set of assets by accepting risk to earn higher 'returns' (which are percentage changes in asset prices). This

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theory formed the foundation of financial economics for several decades and made many surprising and sharp predictions; for example, about how investors choose which stocks to hold and what market prices would result from these decisions.

By the early 1980s, some researchers began to uncover facts about the aggregate stock market that were difficult to explain with this fully rational view of the world. For example, a classic paper that is often cited as the beginning of behavioral finance demonstrated that stock prices fluctuate too much to be justified by a rational theory of stock valuation [1]. This set of anomalous facts only grew stronger. More financial economists then began to create new mathematical models where investor behavior was governed by increasingly realistic psychological forces.

Over the past 30 years, researchers have made significant progress in rigorously testing these behavioral models of finance, often incorporating principles and methods from the cognitive psychology of judgment and choice [2,3]. Most recently, research in financial decision making has begun to use emerging sources of data such as fMRI, Google searches, and logins to online trading brokerages. In the rest of this review, we outline several of the advances that have been made in this research area and speculate on future directions where cognitive science can play a key role in advancing our understanding of financial decision making.

Household Finance

The study of household finance has recently boomed due to a combination of excellent data and an interest in helping households after the 2008 Great Recession. The general conclusion from this evidence is that many households do not save and invest according to normative models [4]. These mistakes occur despite the principles for optimal financial decision making being sometimes simple and intuitive and new technology sound decision making easier than ever.

The empirical facts about household finance do not vary much across eight developed countries in North America and Europe [4]. (Much less is known about developing countries, in which banking is often done informally through social relationships.) In those developed countries, most people (>92%) have checking accounts. One- to three-quarters have some retirement assets or life insurance but only about 15% hold stocks or bonds directly or hold mutual funds.

Looking at a household's balance sheet of assets and liabilities, the largest asset shares are lived-in housing (around 50% of wealth), with smaller shares of 10–20% in retirement assets, bank deposits, and vehicles. On the liability side, mortgage and vehicle debt are about 40% of what people owe. Credit card debt is substantial in the USA, Canada, and the UK (10–12%) and much lower (1–3%) in other European countries.

Almost all of the risky assets that US households own are now held through defined-contribution pension plans administered by employers. Before the 1970s, most plans had ‘defined benefits’, which guaranteed the amount of benefit paid on retirement (as does American Social Security). Then laws changed and now most workers and companies pay in contributions that are defined, but benefits are not guaranteed; depend on the investment success of the pension plans. This change in plan structure has reduced risk for companies and increased risk for workers.

The shift away from defined benefits makes saving for retirement more important in the USA than ever before. In the USA, many people retire with too little saved to maintain their level of spending [5]. Even professional National Football League (NFL) players, who earn millions of dollars per year on average, either save too little or invest too recklessly, so that 15% of them declare bankruptcy within 12 years after retirement [6].

Glossary

Actively managed fund: a portfolio of assets that are traded by a fund manager with the objective of outperforming a benchmark, usually charging higher fees (1–2%/year) than an index fund.

Disposition effect: the tendency to sell assets with accumulated capital gains (‘winners’) more often than assets with capital losses.

Efficient markets hypothesis: if a market is efficient, prices reflect all publicly available information. An important implication is that, if markets are efficient, buying stocks based on publicly information will not lead to excess returns on average.

Financial literacy: the knowledge of basic facts of how asset and credit markets work that is necessary for good household finance decisions.

Household finance: decisions by households about the use of financial instruments–credit, mortgages, stock and bond ownership, and retirement savings.

Index fund: a mutual fund that buys a large, diversified portfolio of stocks in an effort to match the performance of an index basket (e.g., the Standard and Poor's 500), saving on trading fees compared with active management.

Price bubble: an episode in which asset prices are persistently above an intrinsic or fundamental asset value and eventually crash.

Reinforcement learning (RL): a learning algorithm where an agent uses feedback from previous experience to update the representation of a stimulus or environment.

Theory of mind: the capacity to mentalize about the desires, beliefs, and intentions of other goal-driven agents.

Households tend to make several distinct types of mistakes and many households have low **financial literacy** (Box 1). It is often difficult to show that a specific financial decision is necessarily good or bad because that judgment might depend on a household's patience toward the future or willingness to bear risk. However, some decisions are clearly mistakes. For example, many employees fail to invest in a company retirement plan that matches the employee's contribution. Since employees can potentially gain from the company's matching contribution and then withdraw such funds without a fee when they are old enough, failing to contribute to gain the company's match is a mistake [7]. People also hold bonds on which interest is taxed, although those taxable assets could be easily moved to a tax-free retirement account to avoid taxes [8]. Homeowners also fail to refinance mortgages, which would save thousands of dollars on future interest charges, even when firms make it easy to do so [9,10]. Allocations between *N* different mutual funds, for the purpose of spreading risk, is biased toward simply 1/*N* into each, which can be a mistake [11] (and is susceptible to 'framing' effects like those seen in many psychological laboratory experiments [12]).

Another pattern of household investment that appears to be a mistake on average is the household preference for investing in **actively managed funds** (which try to pick outperforming stocks, usually holding them for months or years). Typical fees charged by such funds are 1–2% per year but almost all studies show that the universe of actively managed funds does not beat the overall market, especially net of fees [13]. Most households in developed countries can easily choose **index funds**. These funds charge much lower fees (often as low as 0.1% per year) and simply try to match the performance of a large index such as the Standard and Poor's 500 stock index. These funds have grown over the years but still represent only a small fraction of total

Box 1. Financial Illiteracy

Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? (Possible answers: more than $102; exactly $102; less than $102; do not know; no answer).

In a 2004 survey, only 67% of households chose the correct answer [5].

Four other simple questions were given on the survey. Financial literacy is defined as getting at least two of those five questions right. In the USA, financial literacy is disconcertingly low among people aged 18–24 years, at 43% and 32% for men and women, respectively. Those rates rise steadily to 86% and 73% for ages 65–69 years then decrease again at older ages. Financial literacy is similar in other countries.

People who are aware of their financial illiteracy should shop around or seek financial advice. However, large variations in fees and interest rates, even for standard products such as credit cards [96], mean that households are not shopping around enough (otherwise high-cost products would be squeezed out of the market). Financial advisors also do not always help their clients, often pushing high-fee products [97]. Households are also strategically naïve about their advisors' intentions [98], consistent with laboratory experiments on strategic naïveté [99,100].

Financial literacy can be increased, but doing so with simple education is more difficult than one might imagine [5,10]. Fortunately, some social and psychological influences have been shown to help. University employees were more likely to sign up for tax-deferred retirement accounts if they received an invitation (offering $20 to attend); employees who did not receive an invitation but whose colleague received an invitation were also more likely to sign up [101]. Planning for retirement also seems to be accelerated by personal experience, such as seeing the financial condition of older siblings and parents [5,102].

The psychological 'status quo bias' [103] led behavioral economists to advise companies to 'default' employees into investing some of their pay into 401(k) stock accounts (i.e., they are auto-enrolled but can easily opt out). Making opt-in the default increased employee saving. A 2006 US law then required companies to auto-enroll their workers [104].

Standardized disclosures required by law have also made it easier to compare products. Disclosures that made high-cost fees salient reduced payday loans [30]. Requiring credit card disclosures in a 'Schumer box' (in 12-point font) saved consumers US$11.9 billion [105].

investment (about 10%). There is no consensus on why active management is so popular. A plausible psychological principle is that households misunderstand the roles of luck and skill. They expect a fund to perform poorly after a short streak of high returns. When the fund then does well (perhaps luckily), they become mistakenly convinced that the fund's managers are skilled [14].

An important question for policy analysis is whether competition among firms helps or hurts borrowers who make bad credit decisions. Economic analysis is excellent for answering this type of question, but good psychological evidence is also necessary to understand what mistakes are made and by which types of borrowers. It can be shown mathematically [15] that even when credit card companies compete for profits, naïve borrowers who underestimate how much they will borrow and how quickly they can repay will accumulate large fees and interest charges. Imposing restrictions such as interest-rate caps helps naïve borrowers. Many new studies extend this type of general analysis.

As people are living longer in most parts of the world, how aging affects financial decisions becomes increasingly important. Older people appear to make poorer decisions in novel financial environments but often use crystallized intelligence and expertise to compensate [16,17]. The scarce neuroscientific evidence that is most relevant to household financial decisions concerns aging and patience. There is tentative evidence that people become more patient as they age [18]. Consistent with this behavioral evidence, in older adults the reduction in neural activity in the ventral striatum (VSt) is smaller [17]; that is, early and delayed rewards generate more similar activity in older adults. (The VSt encodes a wide variety of anticipated rewards, including primary rewards such as liquid, learned rewards such as money, and social rewards, and reward-prediction errors [19].)

Newer studies are showing the interaction between neural circuitry involved in memory and valuation [20,21]. Thinking about future rewards that are timed to personally important events increases patience (probably because it makes the future more salient) [22]. This enhanced-imagination effect is linked to increased connectivity between the hippocampus and cingulate cortex, two brain areas involved in memory consolidation and retrieval and conflict monitoring. At the behavioral level, imagining one's future self through age-progressed facial renderings increased savings behavior in an experiment [23]. Important work remains to be done extrapolating from understanding how memory affects patience to natural decisions that households face (such as tempting credit-card spending).

Owing to the fire hose of financial information available to households, it is hard to pay attention to everything. It follows that the financial information that receives disproportionate attention is likely to have a larger impact on household decisions and, potentially, on market prices [24]. Over the past decade, economists have begun to generate clever measures that can be used to understand what variables are proxies for investor attention. For example, Google searches of individual stock ticker symbols as a measure of attention [25] can be used to measure attention to a specific stock. This real-time measure of attention has been shown to predict stock prices over the subsequent 2 weeks. Investors are also likely to pay less attention to financial news on certain days of the week. Stock prices adjust less to corporate earnings announcements that are delivered on Fridays compared with other weekdays [26].

Recent research has used data on online brokerage logins to directly measure attention to a household's portfolio. Investors tend to allocate more attention to their portfolio when markets are rising [27] and when there is less market volatility [28]. Once investors allocate attention to their portfolio, investors must choose what part of the financial statement or online trading platform to attend to [29]. The salience of certain attributes on financial statements and contracts has been shown to affect payday-loan borrowing [30], trading behavior [31,32], and bank-account overdrafts [33].

Individual Investor Trading

Normative theories based on a risk–reward tradeoff predict that individuals will invest a positive fraction of their wealth in the stock market and will hold a large, diversified portfolio of stocks. However, a large body of empirical evidence shows that investor behavior often deviates from this normative benchmark. These deviations are systematic and give rise to a set of stylized facts that characterize the trading patterns of individual investors [2]. For example, one robust and well-known trading pattern among individual investors is the **disposition effect**–the greater tendency to sell stocks that have gone up in price after they were bought ('winners') compared with stocks that have gone down ('losers'). The disposition effect is evident in individual trading records from retail brokerages [34,35], professional money managers' trades [36], and laboratory experiments that carefully control the statistical process of price movements [37] (Figure 1). While the disposition effect is now a solid empirical fact, its cause is still debated (Box 2).

Individual investors also tend to invest in stocks that are headquartered close to their home, a pattern called 'home bias'. For example, investors disproportionately invest in local stocks–in their home countries and home states–which generates an undiversified portfolio and concentrates risk rather than spreading it out [38,39]. Worse yet, investors often invest in their own company stock, exposing them to a dangerous scenario of losing both labor income and stock market wealth if their company suffers financial distress. The psychological mechanisms that generate home bias are not precisely known. Three likely mechanisms are a direct preference for familiar stocks [39], an aversion to ambiguity [40], and a desire to 'keep up with the neighbors" stock returns [41].

Another prediction of normative models is that individual investors should trade infrequently, mostly to rebalance the risk in their portfolio or to liquidate assets (e.g., to pay for college).

Box 2. Using Neuroimaging to Understand the Cognitive Mechanisms of Trading Biases

Economists have documented many patterns regarding how individual investors trade stocks but less is known about the cognitive mechanisms that generate these patterns. For example, there are various competing theories that can potentially explain the disposition effect (i.e., the tendency to sell winning stocks more often than losing stocks) [35,106,107]. One recent hypothesis is that investors derive utility directly from the act of selling a winning stock and derive disutility from selling a losing stock [108,109]. This 'realization utility' hypothesis is difficult to test using behavioral data alone but methods from cognitive neuroscience have proved useful in testing the theory.

In a recent experiment [110], human subjects traded stocks while inside an fMRI scanner (Figure 1A). The average subject exhibited a large disposition effect, although it was a costly mistake. Figure 1B shows a spike in neural activity in the striatum on selling a winning stock. By contrast, there was no spike in activity when the subject chose not to sell the winning stock. This neural signal provides evidence that is consistent with the realization utility hypothesis of the disposition effect.

Some investors also exhibit a 'repurchase effect' whereby they are more likely to repurchase stocks previously sold that have gone down in price than those that have increased in price since the last sale [111]. Using the same data and design as above, a combination of neural data and trading data could be exploited to test the regret devaluation mechanism of the repurchase effect [92]. This theory states that after experiencing regret over 'missing out' on a purchase, or from selling too early, the stock under consideration is subsequently devalued.

The average subject exhibits a significant repurchase effect. When a subject receives news about a price increase for a stock he does not own but had the chance to previously purchase, activity in the VSt decreases (Figure 1C). This decrease in VSt activity is interpreted as a regret signal and the strength of this regret signal explains variation in the severity of the repurchase effect across subjects. There is also evidence that the disposition effect and repurchase effects are highly correlated within subjects (Figure 1D), suggesting that a common cognitive mechanism may generate both trading biases. We speculate that there may exist similar correlations among other well-known trading biases generated by common mechanisms.

However, the data indicate that most individual investors who trade at all trade too much and lose money by doing so [42]. Such 'overtrading' may be driven by overconfidence, in the sense that investors mistakenly believe they have better information than they actually do. Another explanation for the high volume of trade is that investors derive entertainment from doing so. One interesting study shows that speeding tickets (a proxy for sensation seeking) and perceiving one's intellect to be above actual intellect (a proxy for overconfidence) are associated with higher trading frequency [43].

Trading biases can also be generated by deviations from Bayesian learning. For example, investors use **reinforcement learning** (RL) [44,45], learn asymmetrically from good and bad news [46], are overconfident when interpreting new information [47,48], underweight non-events that are actually informative [49], and overextrapolate from past returns [50].

Given the robustness of extrapolative beliefs across a wide variety of investor classes, this bias offers a promising ingredient that can explain key facts about the overall stock market such as its historical high rate of return over bonds and the excessive movement of prices [51]. The origin of these extrapolative beliefs is still not fully understood, although some research suggests that they may stem from a mistaken belief in mean reversion [14] or from lower-level perceptual processes proposed in cognitive science [52].

There is also a great deal of heterogeneity in trading behavior among individual investors. One important source of this heterogeneity is likely to be genetic. Twin studies have shown strong genetic effects on financial behavior, including risk taking [53], underdiversification, and over-trading [54]. Women born with male twins, who are exposed to elevated testosterone *in utero* via the fetal membranes, take more financial risks (and the size of that effect accounts for almost half of the well-established gender difference in risk taking) [55].

Because the central focus in both behavioral and rational theories of financial decision making is on the tradeoff between risk and return, early work in neurofinance began by investigating the neural correlates of these two key variables. This research documented that greater neural activity in the VSt was associated with higher investment in risky assets and that neural activity in the anterior insula was associated with investing in safer assets [56]. The latter finding is consistent with a role for the anterior insula in interoception of bodily states and emotions, including uncomfortable sensations such as uncertainty and pain [57]. Contemporaneous work showed that expected-reward signals are found in the VSt and so-called 'risk-prediction errors'– a computational signal tracking changes in the amount of variability (risk)–are found in the anterior insula [58,59]. There is also evidence that priming subjects with positive stimuli increases risk taking and that this effect is mediated by increased activity in the VSt [60].

More recent work using neuroimaging during stock trading has examined the psychological underpinnings of trading biases such as the disposition effect and the repurchase effect (Box 2, Figure 1). In addition, advances in fMRI technology have allowed 'hyperscanning', where multiple subjects can be scanned simultaneously allowing researchers to probe the neural activity generated in a market setting where prices are set by aggregating the decisions of all subjects. This ability to collect data during market trading is useful because of the impact that social forces have on trading behavior [3]. Moreover, the ability to scan multiple subjects at the same time can be exploited to study interesting aggregate phenomena such as stock market bubbles and crashes, which we discuss in the next section.

Asset Pricing

For decades, a central focus in financial economics has been how asset prices are set and what makes prices move up and down as a result of collective activity. (Empirically, this means analyzing market-level data rather than data from individuals.) One of the key conceptual innovations early in the study of asset pricing was the **efficient markets hypothesis**. Essentially, this hypothesis states that if markets are efficient, then prices should reflect all available information [61]. For example, in an efficient market once a company announces an earnings report this new information should be quickly and accurately incorporated into the stock price.

However, evidence challenging the efficient market hypothesis has accumulated over the past few decades. In the mid-1980s, economists found that investors tended to 'overreact' to bad news: after a series of poor-earnings years, investors overreacted to the bad news and became excessively pessimistic [62]. Other studies showed an opposite pattern of 'under-reaction': investors tended to bid up the price of a stock after good news was released, but by too little [63].

The efficient market hypothesis also implies that prices should not respond to information that does not change a company's value. For example, advertising of a company's products tends to spill over to temporary gains in the company's stock price and firms appear to choose advertising strategically (to some extent) to boost their stock price [64].

One way to explain these kinds of empirical facts is to create models of investor behavior that are informed by cognitive science and are then combined with important constraints on institutional practices. (For example, a practical constraint is that even sophisticated traders who know prices are too low may be unable to buy aggressively to correct the mispricing if they are evaluated by short-term performance.) One important ingredient in this behavioral finance approach to asset pricing is the type of 'preferences' that investors have. The standard rational model typically uses preferences based on the expected utility (EU) hypothesis, while behavioral finance has made progress using other preferences, most notably based on prospect theory (PT) (Box 3).

Stock prices are also likely to be influenced by an investor's (time-varying) mood. When investors are in a good mood, they may be more prone to taking risk. Economists have investigated this link by measuring the impact of weather and sporting events on stock returns. For example, stock returns are higher on sunnier days, even controlling for rain and snow levels [65] (indicating that bad weather, which may decrease labor productivity, does not fully account for the effect). Winter months are associated with lower stock returns, which is consistent with investors experiencing seasonal affective disorder [66]. On the day after a country loses a World Cup soccer match, that country's stock market tends to fall [67]. The hypothesized mechanism is that the loss induces a bad mood, thus increasing risk aversion and in turn decreasing demand for risky stocks.

However, studies with field data are not able to pin down the precise cognitive mechanisms that generate the pricing effects. For example, does an increase in mood causally change an investor's taste for risk or does it instead lead to higher expectations of returns (or both)? Recent experimental evidence suggests that mood affects financial decision making through both a preference [68] and a beliefs [69] channel and future work could help investigate a potential interaction between these two causes.

As in the study of individual trading, there is very little neuroscientific evidence related to aggregate asset pricing. One study measured neural activity as experimental traders tried to infer whether artificial stock prices moved because other traders had inside information about stock values [70]. There was more activity in the dorsomedial prefrontal cortex, a region that is well known for its role in **theory of mind**. Subjects who made the most money scored more highly on the 'eyes of the mind' test, a measure known to correlate with the capacity to infer intentions of others.

Box 3. Risky Choice and PT

Theories of financial decision making describe how people perceive, weigh, and integrate risks and rewards. One prominent theory is that people weigh the value (or 'utility') of all possible consequences, $u(x_i)$, from taking a risk by the subjective probability of each consequence, p_i. This integrated number is the EU of a risk: $\sum_i p_i\, u(x_i)$ [112].

While EU is normatively appealing, a large amount of laboratory and field data is inconsistent with this theory. An alternative theory of decision making under risk, PT, fits many data better [113]. PT is popular in biology and social sciences but is particularly useful in finance because of the fundamental role that risk plays.

Four features distinguish PT from EU. First, reference dependence assumes that individuals value outcomes relative to a reference point. Second, the hedonic intensity of differences from the reference point has diminishing sensitivity. Third, decision makers are more sensitive to a subjective loss (from the reference point) than they are to an equally sized gain ('loss aversion'). Finally, decision makers apply a decision weight, $\pi(p_i)$, subjectively overweighting small probabilities and underweighting large ones.

These features of PT can explain a wide variety of financial phenomena ranging from puzzles about the aggregate stock market to systematic trading biases exhibited by individual investors [114]. For example, the tendency of investors to overweight small probabilities predicts that stocks with returns that are positively skewed ('lottery stocks') will be attractive to PT investors and become overpriced [115].

Another empirical fact is that the average return on US stocks is about 3–5% larger than returns on safer assets such as corporate bonds [116] (although this number may be inflated by the unusual success of the US market). Mathematically, it is difficult to explain the size of this 'equity premium' difference in stock and bond returns unless investors are very averse to financial risk. The explanation from PT is that investors are loss averse and they 'narrowly frame' stock market risk, worrying about returns each year rather than taking a longer view [117].

Ongoing research in PT goes in two directions. One direction is specifying which reference points are most natural: candidates include status quo states, averages of historical outcomes, and expectations of future outcomes. Attention to a reference point is probably also important. The second direction is establishing the psychological mechanisms that generate nonlinear probability weighting. These are likely to include psychophysics of perception, salience of extreme-value outcomes, and emotional response to risk.

Two studies investigated **price bubbles**. Price bubbles are said to exist when asset prices increase far above an intrinsic value based on economic fundamentals and eventually 'crash' back to the intrinsic value. Their existence and causes are controversial in academic finance [61,71]. Bubbles can be studied in laboratory experiments by creating a known intrinsic value that comes from monetary payments to subjects holding an asset that lives for 15 trading periods, declining in value at each step. In experiments, prices tend to rise and peak well above the intrinsic value, although bubbles are smaller and shorter lived when subjects participate repeatedly [72,73] and when subjects are highly cognitively skilled.

One fMRI study using this paradigm found that in market sequences that exhibited bubbles, activity in the ventral and dorsomedial prefrontal cortex (PFC) was more responsive to a trader's portfolio value, and those regions were more strongly coactivated during bubbles. The strength of that activity in the ventromedial PFC (vmPFC) was also correlated with the tendency to participate in the bubble. These results suggest that a coordination of valuation and mentalizing in the ventral and dorsal prefrontal regions are associated with bubbles [74].

A more ambitious fMRI study created experimental assets that had a fixed intrinsic value over 50 trading periods [75]. Prices were entirely determined by 20 subjects trading among themselves (two subjects were being scanned). Bubbles were common and activity in the nucleus accumbens tracked prices (Figure 2). Differential activity in the insula cortex between successful and unsuccessful traders typically peaked several periods before the bubble crash, suggesting a neural 'early-warning signal' associated with uncertainty or discomfort.

There is also some evidence of how asset prices in naturally occurring markets are associated with physiological responses among traders. Professional traders showed psychophysiological

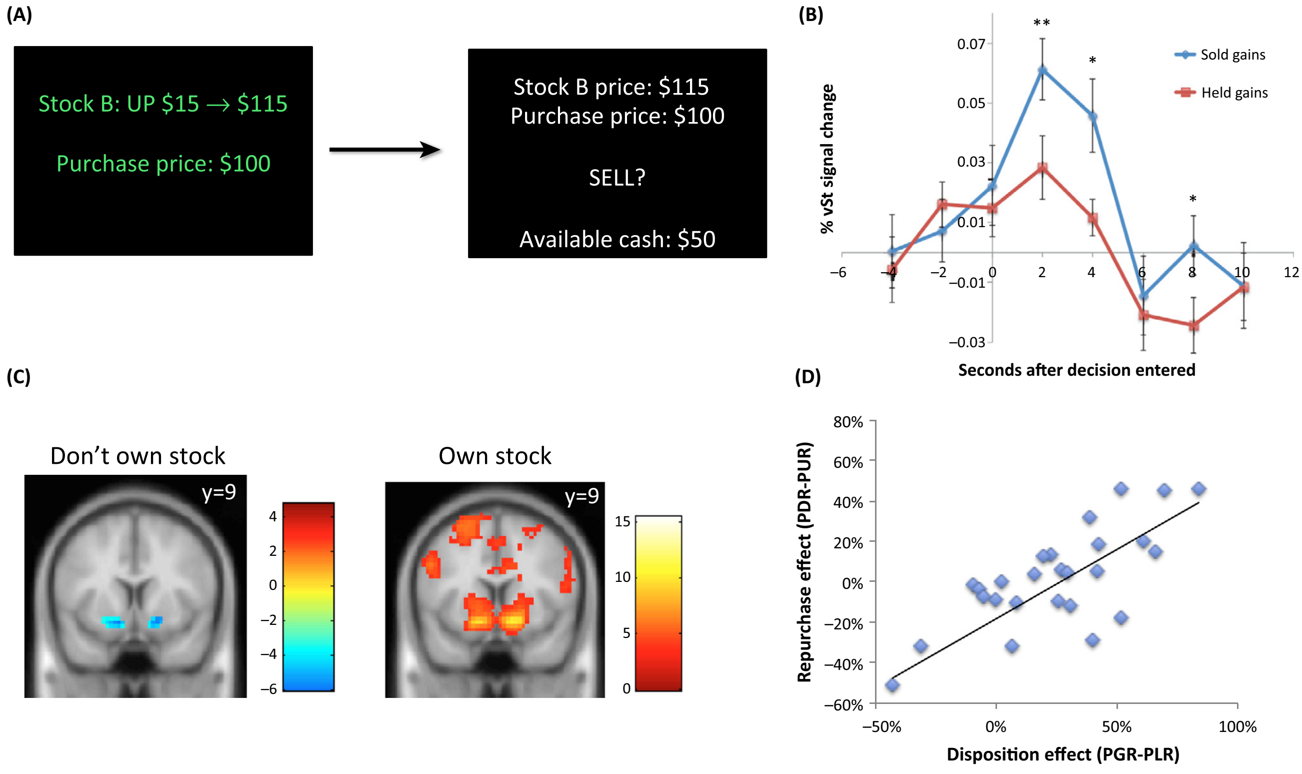

Figure 1. An Experiment to Understand the Cognitive Mechanisms of Trading Biases. (A) The experiment comprises two screens: a price update screen, where subjects see news about price changes, and a trading screen, where subjects can trade stocks. (B) Ventral striatum (VSt) activity time locked to selling decision when given opportunity to sell a winning stock. (C) Areas of the brain where activity correlates with stock price change at moment when price change is revealed. (D) Selling mistakes and purchasing mistakes are highly correlated within subjects. (A,B) reproduced, with permission, from [110]. (C,D) reproduced, with permission, from [92].

responses to price changes and trend reversals and more experienced traders showed lower responses [76]. In another study with experienced traders, testosterone was positively associated with daily trading profit [77], consistent with pre-game 'androgen priming' observed in athletes [78]. Those experts' cortisol levels also correlated with profit variance across days and with volatility in market prices. Other work shows that declines in the stock market are associated with an increase in hospital admissions, particularly for psychological conditions such as panic disorder and anxiety [79].

Managerial Decisions

Complex large corporations have thousands of employees. However, the most important corporate decisions are often made by small numbers of individuals; typically, by the chief executive officer (CEO) and other top executives, overseen by the board of directors. Thus, while it might seem odd to speak of how cognition influences the behavior of Intel or Apple, the decisions of those corporations are likely to be strongly influenced by psychological propensities of their top executives. For publicly traded companies, government reporting requirements also mean that much is known about both the personal histories and the important managerial decisions of CEOs [e.g., they must reports trades in their own company's stock to the Securities and Exchange Commission (SEC)].

Large modern companies have gone through booms of merger and acquisition (M&A). Despite the popularity of growth by acquisition, most studies indicate that acquisition is profitable for the

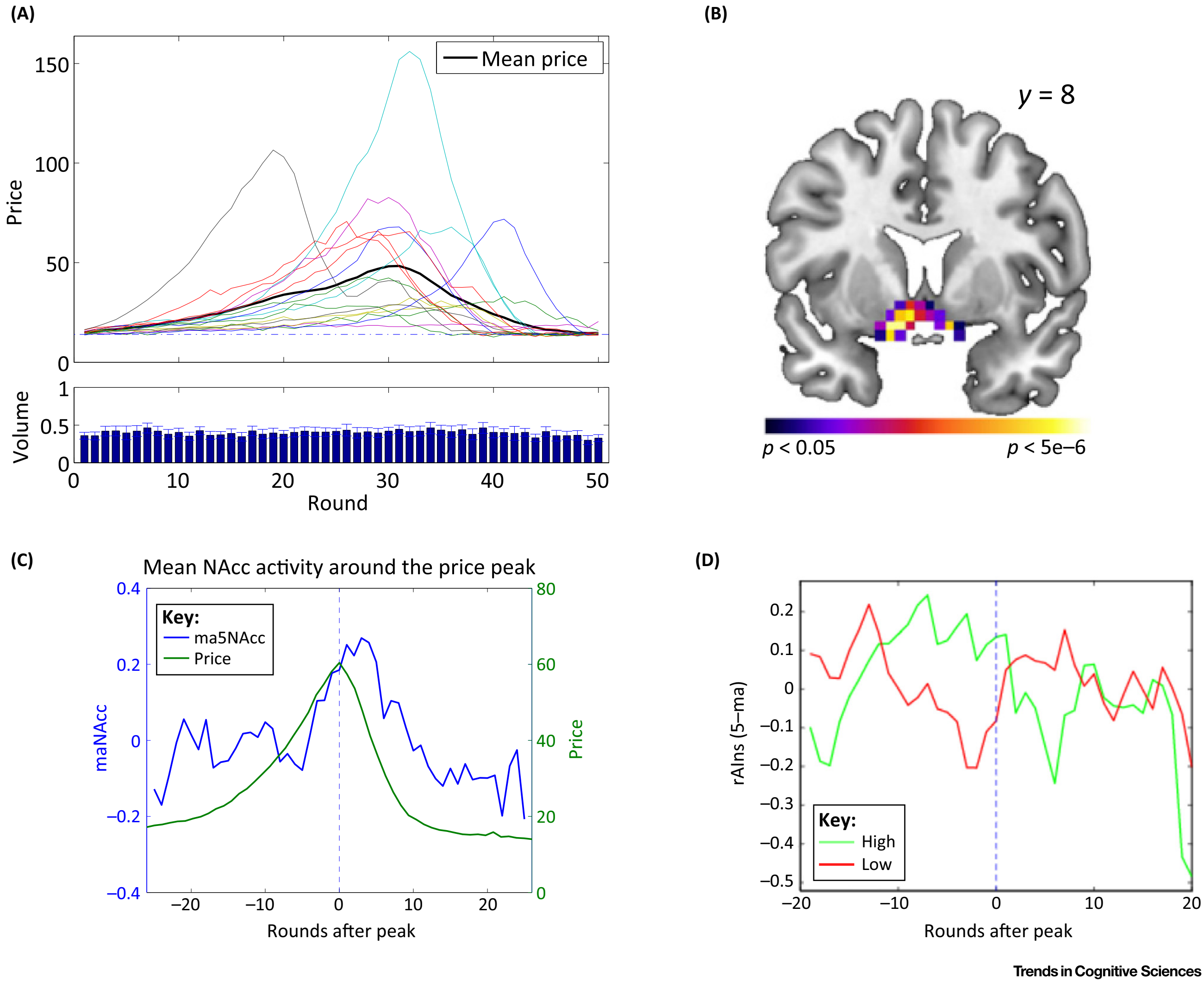

Figure 2. Bubble Price Paths and Associated Neural Activity. (A) Price paths of 16 experimental market sessions where prices are set by the aggregate decisions of subjects. The heavy black line is the average price over the 16 sessions. The fundamental value is constant throughout the sessions and equal to US$14 (dotted line). Plotted below are normalized per-subject number of shares traded during each period. (B) Areas of the ventral striatum (VSt) where activity increased significantly at revelation of information that a trade was executed. This signal is consistent with the VSt encoding a prediction error in a call-market mechanism, since there is uncertainty about whether a trade is executed after a subject enters an order. The color bar denotes the *P* values from the hypothesis test that there is no differential activity between trials where subjects trade and trials where they do not trade. (C) Five-period moving average of the blood oxygen level-dependent (BOLD) signal in an area of the VSt (nucleus accumbens) tracks peak-centered prices averaged across the 16 experimental sessions. (D) Insula activity diverges between high-performing (green) and low-performing (red) traders from period −10 to −5 (before the eventual price peak). This insula signal is a candidate early-warning signal predicting a price peak and crash several periods later.All panels are reproduced, with permission, from [75].

takeover target but not always profitable for the (typically) larger firm making the acquisition [80]. This led to the proposal that managerial 'hubris' or overconfidence fuels mergers [81].

Managerial hubris is one form of overconfidence exhibited in executive decision making. Overconfidence among executives has been measured in various ways. One method used a psychometric approach (asking executives to complete surveys over a 10-year period) [82] while others have inferred overconfidence from whether executives forecast earnings too optimistically [83] (compared with ex-post, actual earnings). Others methods look at how CEOs are described in the press [84] or whether they hold on to stock options too long because they expect their stock to rise [85]. All of these measures of overconfidence are correlated with the business choices made by CEOs and more overconfidence is generally associated with poor corporate decision making [83].

Personal experiences affect CEO behavior just as they do for regular households and investors (Box 4). 'Depression baby' American CEOs–those who grew up in the Great Depression–are also less likely to use corporate debt than their peers and those with military service take more financial risk in their companies [86]. There is tentative new evidence of gender effects among top managers: female chief financial officers (CFOs) were less aggressive about pursuing tax-savings policies that might draw legal scrutiny [87].

The examples above provide evidence of psychological biases among managers. There is also an extensive literature on how rational managers make decisions to 'exploit' investors with psychological biases [88]. For example, managers seem to realize that investors have a preference for low-price stocks and often issue more stock when this preference is strongest [89]. There are now interesting new data that can be used to document the interactions between managers and investors.

A fascinating source of psychological data is recorded 'earnings calls'. These are large-scale conference calls that CEOs and CFOs make several times each year to discuss with security analysts what their company's upcoming accounting earnings per share are likely to be. These calls are used to preempt bad news and talk up good news. One study analyzed the words that

Box 4. Experience Effects of Financial Outcomes and Behavior

Emerging studies are now showing that personal experiences systematically change large-scale financial decision making. For example, people living through the Great Depression in the 1930s suffered through years of massive unemployment (25–30%) and economic dislocation. Their tendency to invest in the stock market was much lower than for later generations, a pattern that has persisted for decades after the Depression [118]. People who lived through periods of high inflation have higher expectations of future inflation than those who lived through periods of more moderate inflation [119]. There is also evidence that adults from lower socioeconomic backgrounds have more pessimistic beliefs about future stock returns [120].

Many studies have shown that traumatic experiences, such as exposure to violent civil war [121] or natural disasters [122,123], change behavior in the next couple of years, sometimes increasing aversion to risk, although results are inconsistent [124]. A remarkable survey of Korean War survivors [121] found that those who were children of 4–8 years old during that war were more averse to financial risk 50 years later (although there were no effects on children who were either younger or older during wartime, consistent with 'childhood amnesia' in younger children).

These facts are consistent with a workhorse model of learning in decision neuroscience, reinforcement learning (RL), which is a descendent of much older models in cognitive psychology. In RL, an agent updates the value of taking an action (e.g., investing in a stock) based on the outcome received from taking that action [125]. This contrasts with Bayesian learning, where the agent updates a subjective probability distribution of value after receiving new information. Under a RL model, after experiencing a bad outcome from taking the 'action' of investing in the stock market during the Depression, the value of this action is updated downward because of the negative outcome, thus decreasing the probability of selecting the action again.

A simple RL-like 'forgetting' model, cumulating past experiences, is able to account rather accurately for US inter-generational differences in buying stocks and bonds and guessing future stock returns. For a 50-year-old, the estimated degree of forgetting implies that experiences 18 years ago are still about half as influential as the last year's experience [118].

This type of extended learning from natural experience can be informed by emerging evidence that during economic decision making that depends on associative memory, areas of the brain that store memory (hippocampus) exhibit activation that correlates with activity in areas responsible for valuation (vmPFC) [21]. More generally, many economic decisions are thought to draw on memory stored in the hippocampus [20], and heterogeneity across investors in these stored memories (e.g., from the Great Depression or other traumatic experiences) may provide the neural basis for the effects of experience on financial decisions.

CEOs used to predict implicit deception, as defined by the difference between optimism during the call and later accounting problems. Text analysis could predict deception about 10% better than random [90]. Deceptive CEOs spoke more vaguely, used more extreme positive emotion words, and used fewer anxiety words. Other research used the voice pitch of the CEO on these conference calls to document vocal emotion markers, which were associated with contemporaneous changes in stock prices [91].

Concluding Remarks and Future Directions

We have surveyed a large set of empirical facts about the ways in which financial decision making is influenced by cognitive processes. These departures occur at all levels in the economy (from households to CEOs). The literature in behavioral finance has forcefully demonstrated that these robust decision anomalies have important consequences for individual investor wealth, stock market prices, and regulatory policy. What is less clear, from a cognitive science perspective, is the psychology that generates the observed patterns of saving, investing, and trading behavior.

Some progress is already being made on rigorously understanding the cognitive operations that give rise to the pattern of observed financial decisions (Box 2). This progress has come from fruitful collaboration between behavioral economic theory (i.e., mathematical models of decision making that incorporate psychological assumptions) and new data sources. For example, we surveyed studies that use data on fMRI, computer logins to brokerage accounts, hormones, genetics, and Google searches. We believe this newer set of data sources will be crucial in measuring variables that are traditionally unobservable but integral to theories of realistic financial decision making.

One area where this newer data combined with principles from cognitive science can contribute to behavioral finance is by determining how a very long list of behavioral effects can be explained by a small number of principles. As we have described throughout, there is a large number of trading patterns that are inconsistent with the rational use of information and the ideal balance of risk and return. A useful next step in organizing this set of facts is to understand the correlation structure among the various biases (see Outstanding Questions). We speculate that many of these seemingly distinct biases could be generated by a common neural and psychological mechanism. Some emerging evidence for this conjecture has already been found, as the same brain areas encode signals that generate the disposition effect and repurchase effect [92]. This neural overlap fits with a strong correlation between these effects at the behavioral level (Figure 1D).

Newer data can also help discipline behavioral theories of finance and will allow policymakers to more accurately forecast the impact of new laws on human behavior. One successful program that has already been effective in applying principles from cognitive science to regulation is based on the notion of soft, paternalistic 'nudges'. These nudges are simple changes that help people to avoid what they themselves would consider mistakes but are not onerous for firms or for people who already make excellent decisions [93,94].

The formal policy program began with the UK Behavioral Insights Team in 2010. There are now dozens of units all over the world, in both governments and companies [95]. Hundreds of randomized trials have been conducted to test which nudges improve financial decisions, as well as decisions about health and education.

Most of the research we described (and many nudge designs) use longstanding folk psychological constructs such as limited attention, emotion, salience, and the value of simplicity that psychological limits imply. Frontier cognitive science has played a limited role in this booming nexus of research and policy. For example, none of the studies of financial attention that we

Outstanding Questions

What is the reference point that investors use when tracking gains and losses? How do investors update their reference point over time?

How are the trading biases discussed in this review correlated statistically? Is there a small set of core psychological mechanisms that generate many of these biases?

What are the neural computations underlying the effects of social contagion and media reporting on stock price movements?

What psychological and neural principles can explain an investor's preference for stocks with low nominal prices?

Where does overconfidence exhibited in financial markets come from (e.g., from personal traits or from experience) and is it selected by, or limited by, organizational design?

Can psychological theories of strategic naivete, which were developed to fit controlled laboratory experiments based on game theory, also help explain naivete in financial decisions?

Why do average household investors pay substantial fees for actively managed mutual funds, despite the evidence that actively managed funds do not generally outperform lower cost index funds, especially after fees?

mentioned measured attention directly (as a vision scientist would, using eye tracking). Emotions are also rarely measured directly. Perhaps our review will alert *TICS* readers to the exciting interdisciplinary study of financial decision making and promote broader, better collaboration using the ideal combination of mathematical modeling, cognitive and neural measures, and observed behavior.

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