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Using Neural Data to Test a Theory of Investor Behavior: An Application to Realization Utility

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ABSTRACT

We conduct a study in which subjects trade stocks in an experimental market while we measure their brain activity using functional magnetic resonance imaging. All of the subjects trade in a suboptimal way. We use the neural data to test a "realization utility" explanation for their behavior. We find that activity in two areas of the brain that are important for economic decision-making exhibit activity consistent with the predictions of realization utility. These results provide support for the realization utility model. More generally, they demonstrate that neural data can be helpful in testing models of investor behavior.

OVER THE PAST 20 years, economists have accumulated a large amount of evidence on how individual investors manage their financial portfolios over time. Some of this evidence is puzzling, in the sense that it is hard to reconcile with the simplest models of rational trading (Barberis and Thaler (2003), Campbell (2006)). Theorists have responded to this challenge by constructing new models of investor behavior. Empiricists, in turn, have started testing these newly developed models.

Most of the empirical work that tests theories of investor behavior uses field data (Barber and Odean (2000), Barber and Odean (2001), Choi et al. (2009), Grinblatt and Keloharju (2009)). A smaller set of studies uses data from laboratory experiments. The advantage of experiments is that they give researchers a large degree of control over the trading and information environment, which can make it easier to tease theories apart (Plott and Sunder (1988), Camerer

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and Weigelt (1991, 1993), Weber and Camerer (1998), Bossaerts and Plott (2004), Bossaerts, Plott, and Zame (2007)).

In this paper, we argue that another kind of data, namely, measures of *neural* activity taken using functional magnetic resonance imaging (fMRI) while subjects trade in an experimental stock market, can also be useful in testing theories of investor behavior. To demonstrate this, we use neural data to test the "realization utility" theory of trading, a theory that has been used to address several facts about investor trading behavior, including the so-called disposition effect.

The disposition effect is the robust empirical fact that individual investors have a greater propensity to sell stocks trading at a gain relative to purchase price than stocks trading at a loss. This fact has attracted considerable attention because it has proven hard to explain using simple rational models of trading. This impasse has motivated the development of competing alternative theories, both rational and behavioral (Shefrin and Statman (1985), Odean (1998), Barberis and Xiong (2009), Kaustia (2010)). One of these, the realization utility model (Shefrin and Statman (1985), Barberis and Xiong (2012), Ingersoll and Jin (2013)), is based on the assumption that, in addition to deriving utility from consumption, investors derive utility directly from *realizing* gains and losses on the sale of risky assets that they own. For example, if an investor realizes a gain (e.g., by buying a stock at $20 and selling it at $40), he receives a positive burst of utility proportional to the capital gain; in contrast, if he realizes a loss (e.g., by buying a stock at $20 and selling it at $10), he receives a negative burst of utility proportional to the realized loss. In combination with a sufficiently high time discount rate, realization utility will lead investors to exhibit a disposition effect (Barberis and Xiong (2012)).

Testing a theory such as realization utility is difficult because its predictions about investor behavior are similar, on many dimensions, to those of other theories (but see Weber and Camerer (1998)). Furthermore, using data on behavior alone, it is extremely difficult to carry out direct tests of the computations driving behavior (e.g., tests of whether, when thinking about selling, investors are tracking the capital gains they could potentially realize). However, as we show in this paper, a combination of neural measurement and careful experimental design does allow for direct tests of the extent to which the computations made by the brain at the time of decision-making are consistent with the mechanisms posited by different models.

Specifically, in this paper we describe the results of an fMRI study designed to test the hypothesis that, while trading in an experimental stock market, subjects are influenced by realization utility, and that this is associated with trading patterns consistent with the disposition effect. The experiment allows us to test several behavioral and neural predictions of the realization utility hypothesis.[1]

[1] We use the word "behavioral" in two different senses. Most of the time, as in the last sentence of this paragraph, we take it to mean "pertaining to behavior." Occasionally, we take it to mean

Behaviorally, we find that the average subject in our experiment exhibits a strong and significant disposition effect. This result stands in sharp contrast to the prediction of a simple rational trading model in which subjects maximize the expected value of final earnings. The reason is that our experimental design induces positive autocorrelation in stock price changes, which in turn implies that a risk-neutral rational trader would sell losing stocks more often than winning stocks, thereby exhibiting the opposite of the disposition effect. The strong disposition effect displayed by our subjects is, however, consistent with the realization utility model.

When taken literally as a description of the decision-making process, the realization utility model makes several predictions about the neural computations that should be observed at different points in time. We describe these predictions in detail in the main body of the paper, but summarize them briefly here.

First, the realization utility model predicts that, at the moment when a subject is making a decision as to whether to sell a stock, neural activity in areas of the brain associated with encoding the value of potential actions at the time of a decision should be proportional to the capital gain that would be realized by the trade (i.e., to the difference between the sale price and the purchase price). In particular, the model implies that, at the time of decision, activity in the ventromedial prefrontal cortex (vmPFC), an area of the brain that has been reliably shown to be involved in the computation of the value of the available options, should be positively correlated with the capital gain or loss associated with selling a stock.

Second, the realization utility model predicts that a subject whose vmPFC activity at the time of a sell decision is particularly correlated with the potential capital gain or loss—in other words, a subject who is particularly influenced by realization utility—will exhibit a stronger disposition effect. Across individuals, then, the strength of the disposition effect should be correlated with the strength of the realization utility signal in the vmPFC.

Third, the realization utility hypothesis posits that realizing a capital gain generates a positive burst of utility, while realizing a capital loss generates a negative one. This predicts that, controlling for the size of the capital gain or loss, and regardless of the precise timing of the utility burst, realizing a capital gain should increase activity in certain areas of the ventral striatum (vSt), while realizing a capital loss should decrease activity in these areas. This is because the vSt is known to encode so-called reward prediction errors, which measure the change in the expected net present value of lifetime utility induced by new information or changes in the environment. Since selling a stock at a gain generates a utility burst, it also generates a change in the expected net present value of utility, one that should be reflected in the striatum at the moment of sale.

"less than fully rational" or "psychological," as is common in the social sciences. It will be clear from the context which of the two meanings is intended.

Our fMRI measurements reveal patterns of neural activity that are largely consistent with the three neural predictions. These results provide novel and strong support for the mechanisms at work in the realization utility model. Furthermore, to our knowledge, they also provide the first example of how neural evidence can be used to test economic models of financial decision-making. We emphasize that the results do not imply that realization utility is the only force driving investor behavior, even in the context of our experiment. However, the fact that activity in the decision-making circuitry corresponds to some of the computations hypothesized by the realization utility model provides novel evidence in support of the model. It also suggests that computations of this kind may, in part, be driving the real-world transactions of individual investors.

Using neural data to test an economic model is an unusual exercise in the field of economics. A common view in the field is that models make "as if" predictions about behavior, and should not be taken as literal descriptions of how decisions are actually made (Gul and Pesendorfer (2008), Bernheim (2009)). In contrast to this view, we adopt a neuroeconomic approach. According to this approach, knowledge about the computational processes that the brain uses to make decisions should be of central interest to economists because, since these processes describe the actual determinants of observed behavior, they provide valuable insights into the drivers of economic activity (Camerer, Loewenstein, and Prelec (2005), Camerer (2007), Rustichini (2009), Glimcher (2010), Fehr and Rangel (2011)).

Our study contributes to the nascent field of neurofinance, which seeks to characterize the computations undertaken by the brain to make financial decisions, and to understand how these computations map to behavior. Several early contributions are worth highlighting. Lo and Repin (2002) investigate the extent to which professional experience affects the emotional arousal of traders in stressful situations, where arousal is measured using skin conductance responses and changes in blood pressure. Kuhnen and Knutson (2005) use fMRI to measure neural responses during a simple investment task and find that activity in brain regions associated with emotional processing, such as the nucleus accumbens and the insula, predicts subjects' willingness to take risks. Knutson et al. (2008) take these ideas further by showing that exogenous emotional cues (e.g., erotic pictures) can affect investment behavior, and that these cues increase activity in the same brain regions as in their previous study. More recently, Bruguier, Quartz, and Bossaerts (2010) show that fMRI measures of the extent to which subjects activate brain areas associated with concrete cognitive skills, such as the ability to predict another person's state of mind, might be useful in identifying which subjects would be successful traders, while Wunderlich et al. (2011) look at how the brain tracks correlation during an attempt to optimally hedge two sources of risk. Finally, De Martino et al. (2013) show that fMRI measures of activity in valuation and mentalizing (theory of mind) regions of the brain are associated with the propensity to buy during experimental price bubbles. Our paper contributes to this literature by showing that a combination of fMRI neural measurements and careful experimental design can be used to test specific economic theories of financial decision-making. More broadly, our work also contributes to the rapidly growing field of neuroeconomics, which seeks to characterize the computations made by the brain in different types of decisions, ranging from simple choices to choices involving risk, self-control, and complex social interactions.[2]

The paper is organized as follows. Section I presents background information on the disposition effect and realization utility. Section II describes the experimental design and the predictions of the realization utility hypothesis. Section III provides a detailed description of how fMRI can be used to test the neural predictions. Section IV presents the results. Section V concludes.

I. Background: The Disposition Effect and the Realization Utility Model

Using an argument based on Kahneman and Tversky's (1979) prospect theory, Shefrin and Statman (1985) predict that individual investors will have a greater propensity to sell stocks trading at a gain relative to purchase price, rather than stocks trading at a loss. They label this the "disposition effect" and provide some evidence for it using records of investor trading. More detailed evidence for the effect is presented by Odean (1998), who analyzes the trading activity from 1987 to 1993 of 10,000 households with accounts at a large discount brokerage firm. The phenomenon has now been replicated in several other large databases of trading behavior.[3]

It is useful to explain Odean's (1998) methodology in more detail because we adopt a similar methodology in our own analysis. For any day on which an investor in Odean's (1998) sample sells shares of a stock, each stock in the investor's portfolio on that day is assigned to one of four categories. A stock is counted as a "realized gain" ("realized loss") if it is sold on that day at a price that is higher (lower) than the average price at which the investor purchased the shares. A stock is counted as a "paper gain" ("paper loss") if its price is higher (lower) than its average purchase price, but it is *not* sold on that day. From the total number of realized gains and paper gains across all accounts over the entire sample, Odean (1998) computes the proportion of gains realized (PGR):

$$\mathrm{PGR} = \frac{\#\ \textit{of realized gains}}{\#\ \textit{of realized gains} + \#\ \textit{of paper gains}}. \tag{1}$$

[2] For recent reviews, see Fehr and Camerer (2007), Glimcher et al. (2008), Rangel, Camerer, and Montague (2008), Bossaerts (2009), Kable and Glimcher (2009), Rangel and Hare (2010), Fehr and Rangel (2011), and Rushworth et al. (2011).

[3] See, for example, Genesove and Mayer (2001), Grinblatt and Keloharju (2001), Feng and Seasholes (2005), Frazzini (2006), and Jin and Scherbina (2011).

In words, PGR computes the number of gains realized as a fraction of the number of gains that *could* have been realized. A similar ratio, PLR, is computed for losses:

$$\text{PLR} = \frac{\textit{\# of realized losses}}{\textit{\# of realized losses} + \textit{\# of paper losses}}. \qquad (2)$$

The disposition effect is the empirical fact that PGR is significantly greater than PLR. Odean (1998) reports PGR = 0.148 and PLR = 0.098.

While the disposition effect is a robust empirical phenomenon, its causes remain unclear. In particular, traditional rational models of trading have had trouble capturing important features of the data. Consider, for example, an information model in which investors sell stocks with paper gains because they have private information that these stocks will subsequently do poorly, and hold on to stocks with paper losses because they have private information that these stocks will rebound. This hypothesis is inconsistent with Odean's finding that the average return of the prior winners that investors sell is 3.4% *higher*, over the next year, than the average return of the prior losers they hold on to. Another approach involves taking into account the favorable treatment of losses by the tax code. However, this also fails to explain the disposition effect because it predicts a greater propensity to sell stocks associated with paper losses. Another model attributes the disposition effect to portfolio rebalancing of the kind predicted by a framework with power utility preferences and i.i.d. returns. However, in this framework, rebalancing is the "smart" thing to do, which implies that we should observe a stronger disposition effect for more sophisticated investors. In contrast to this prediction, the data show that it is *less* sophisticated investors who exhibit a stronger disposition effect (Dhar and Zhu (2006)).

Researchers have also proposed behavioral economics models of the disposition effect that can explain some of the empirical patterns that the rational frameworks have struggled to capture. One popular model assumes that investors have an irrational belief in mean-reversion (Odean (1998), Weber and Camerer (1998), Kaustia (2010)). If investors believe that stocks that have recently done well will subsequently do poorly, and that stocks that have recently done poorly will subsequently do well, their optimal trading strategy leads to a disposition effect. We label such beliefs "irrational" because they are at odds with Odean's (1998) finding that the winner stocks investors sell subsequently do well, not poorly. While the mean-reversion hypothesis is appealing for its simplicity, and is consistent with some evidence from psychology on how people form beliefs, some studies cast doubt on its validity. For example, Weber and Camerer (1998) ask subjects to trade stocks in an experimental market, and find that these subjects exhibit a disposition effect in their trading. To test the mean-reversion hypothesis, they add a condition in which subjects' holdings are exogenously liquidated at full value at random times, after which subjects are asked to reinvest the proceeds across stocks in any way they like. If subjects were holding on to stocks with paper losses because of a belief in mean-reversion, we would expect them to re-establish their positions in these stocks. However, they do not do so.

Another popular behavioral economics model posits that the disposition effect results from prospect theory preferences (Kahneman and Tversky (1979)). Prospect theory, a prominent theory of decision-making under risk, posits that individuals make decisions by computing the utility of potential gains and losses, where gains and losses are measured relative to a reference point that is often taken to be the status quo, and where the utility function is assumed to be concave over gains and convex over losses. At first sight, it appears that prospect theory may be helpful for understanding the disposition effect. If an investor is holding a stock that has risen in value, he may think of it as trading at a gain. If, moreover, the concavity of the value function over gains induces risk aversion, this may lead him to sell the stock. Conversely, if the convexity of the value function over losses induces risk-seeking, the investor may be inclined to hold on to a stock that has dropped in value. Barberis and Xiong (2009) have recently shown, however, that it is surprisingly difficult to formalize this intuition: They find that an investor who derives prospect theory utility from the annual trading profit on each stock that he owns often exhibits the *opposite* of the disposition effect. Kaustia (2010) discusses other problems with the prospect theory approach: For example, he shows that it predicts that investors' propensity to sell a stock depends on the magnitude of the embedded paper gain in a way that is inconsistent with the empirical facts.

Another behavioral model of the disposition effect, and the one we focus on in this paper, is based on the realization utility hypothesis (Shefrin and Statman (1985), Barberis and Xiong (2012), Ingersoll and Jin (2013)). The central assumption of this model is that investors derive utility *directly* from realizing gains and losses on risky assets that they own: they experience a positive burst of utility when they sell an asset at a gain relative to purchase price, where the amount of utility depends on the size of the realized gain, and a negative burst when they sell an asset at a loss relative to purchase price, where the amount of disutility depends on the size of the realized loss.[4] Barberis and Xiong (2012) show that, when realization utility has a linear functional form, and when the time discount rate is sufficiently positive, a trader who maximizes the expected discounted sum of future realization utility bursts will exhibit a disposition effect. The intuition is simple. If an investor derives pleasure from realizing capital gains and, moreover, is impatient, he will be keen to sell stocks at a gain. Conversely, if he finds it painful to sell stocks at a capital loss and

[4] Barberis and Xiong (2012) speculate that realization utility arises because of the way people think about their investing history. Under this view, some investors—in particular, less sophisticated investors—do not think about their investing history in terms of overall portfolio return, but rather as a series of investing "episodes," each of which is characterized by three things: the identity of the asset, the purchase price, and the sale price. "I bought GE at $40 and sold it at $70" might be one such episode, for example. According to this view, an investor who sells a stock at a gain feels a burst of positive utility right then because, through the act of selling, he is creating what he views as a positive investing episode. Similarly, if he sells a stock at a loss, he experiences a burst of disutility: by selling, he is creating a negative investing episode.

also discounts future utility at a high rate, he will delay selling losing stocks for as long as possible.[5]

While the realization utility hypothesis makes predictions about behavior that are consistent with the disposition effect, as well as with other empirical patterns, it is based on assumptions that depart significantly from those of traditional models. In particular, its predictions rely on the assumption that utility depends not only on consumption, but also on *the act of realizing* capital gains and losses. Given the unusual nature of this assumption, it seems especially important to carry out direct tests of the extent to which the hypothesized source of utility is actually computed by subjects and affects their decisions. In the rest of the paper, we show how this can be done using fMRI measures of neural activity.

II. Experimental Design and Predictions

In this section, we first describe the experimental stock market that we set up to test the realization utility model, and then lay out the specific behavioral and neural predictions of the model that we test.

A. Design

The design of our experimental market builds directly on that of an earlier nonneural experiment conducted by Weber and Camerer (1998).

Subjects are given the opportunity to trade three stocks—stock A, stock B, and stock C—in an experimental market. The experiment consists of two identical sessions separated by a one-minute break. Each session lasts approximately 16 minutes and consists of 108 trials. We use t to index the trials within a session.[6]

At the beginning of each session, each subject is given \$350 in experimental currency and is required to buy one share of each stock. The initial share price for each stock is \$100; after the initial purchase, each subject is therefore left with \$50. Every trial $t > 9$ consists of two parts, a price update and a trading decision, each of which corresponds to a separate screen that the subject sees (Figure 1). In the price update part, one of the three stocks is chosen at random and the subject is shown a price change for this stock. Stock prices only evolve during the price update screens; as a result, subjects see the entire price path for each stock. In the trading part, one of the three stocks is again chosen at random and the subject is asked whether he wants to trade the stock. No new information is revealed during this part.

[5] Time discounting is not a critical part of the realization utility hypothesis. The disposition effect can also be generated by a model with no time discounting but where realization utility has an S-shaped functional form, as in prospect theory (Barberis and Xiong (2009)). Adopting this alternative version of the realization utility hypothesis would not significantly affect our analysis.

[6] We split our experiment into two sessions in order to avoid running the fMRI machine for too long without a break, as this could lead to potential medical risks for the subjects.

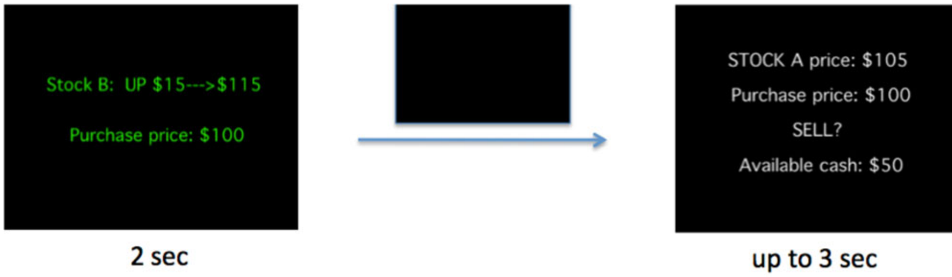


Figure 1. Sample screens from a typical trial in the fMRI experiment. For trials 10 to 108, subjects see a *price update* screen for two seconds, followed by a *trading* screen for which they have up to three seconds to enter a decision (a blank screen is displayed in between to temporally separate different types of neural activity associated with decision-making). Because the blank screen is displayed for a random amount of time, uniformly distributed between one and three seconds, the average length of a trial, consisting of all three screens, is seven seconds. The screens shown above are for a trial in which the subject owns both stocks A and B. If the subject did not own stock B at the price update screen, the purchase price would not be displayed. If the subject did not own stock A at the trading screen, he would be given the opportunity to buy it. The screens are displayed while subjects are inside an fMRI scanner, and decisions are entered using a handheld device. For trials 1 to 9, subjects see only the price update screen and the blank screen; this allows them to accumulate information about price changes before having to make any decisions.

We split each trial into two parts to temporally separate different types of computations associated with decision-making. At the price update screen, subjects are provided with information about a change in the price of one of the three stocks, but do not have to compute the value of buying or selling the stock, both because they are not allowed to make decisions at this stage and because they do not know which of the three assets will be selected for trading in the next screen. At the trading screen, the opposite situation holds: subjects need to compute the value of buying or selling a stock, but do not need to update their beliefs about the price process since no new information about prices is provided.

Trials 1 through 9 consist only of a price update screen; subjects are not given the opportunity to buy or sell during these trials. This initial set of trials enables subjects to accumulate information about the three stocks before having to make any trading decisions.

Each subject is allowed to hold a maximum of one share and a minimum of zero shares of each stock at any point in time. In particular, short-selling is not allowed. The trading decision therefore reduces to deciding whether to sell a stock (conditional on holding it) or buy it (conditional on not holding it). The price at which a subject can buy or sell a stock is given by its current market price.

The price path of each stock is governed by a two-state Markov chain with a good state and a bad state. The Markov chain for each stock is independent of the Markov chains for the other two stocks. Suppose that, in trial t, there is a price update for stock i. If stock i is in the good state at that time, its price increases with probability 0.55 and decreases with probability 0.45. Conversely, if it is in the bad state at that time, its price increases with probability 0.45

and decreases with probability 0.55. The magnitude of the price change is drawn uniformly from {\$5, \$10, \$15}, independently of the direction of the price change.

The state of each stock evolves over time in the following way. Before trial 1, we randomly assign a state to each stock. If the price update in trial $t > 1$ is *not* about stock i, then the state of stock i in trial t remains the same as its state in the previous trial, trial $t - 1$. If the price update in trial $t > 1$ *is* about stock i, then the state of stock i in this trial remains the same as in trial $t - 1$ with probability 0.8, but switches with probability 0.2. In mathematical terms, if $s_{i,t} \in \{good, bad\}$ is the state of stock i in trial t, then $s_{i,t} = s_{i,t-1}$ if the time t price update is not about stock i, whereas if the time t price update is about stock i, the state switches as follows:

	$s_{i,t} = good$	$s_{i,t} = bad$
$s_{i,t\text{-}1} = good$	0.8	0.2
$s_{i,t\text{-}1} = bad$	0.2	0.8

The states of the stocks are never revealed to the subjects; rather, subjects have to infer them from the observed price paths. To make it easier to compare the trading performance of different subjects, we use the same set of realized prices for all subjects.

A key aspect of our design is that, conditional on the information available to subjects, each of the stocks exhibits positive autocorrelation in its price changes. If a stock performed well at its last price update, it was probably in the good state for that price update. Since it is highly likely (probability 0.8) to remain in the same state for its next price update, its next price change is likely to also be positive.

At the end of each session, we liquidate subjects' holdings of the three stocks and record the cash value of their position. We give subjects a financial incentive to maximize the final value of their portfolio at the end of each session. Specifically, if the total value of a subject's cash and risky asset holdings at the end of session 1 is \$X in experimental currency, and the total value of his cash and risky asset holdings at the end of session 2 is \$Y in experimental currency, then his take-home pay in *actual* dollars is 15 + (X + Y)/24.[7] Subjects' earnings ranged from \$43.05 to \$57.33 with a mean of \$52.57 and a standard deviation of \$3.35.

To avoid liquidity constraints, we allow subjects to carry a negative cash balance in order to purchase a stock if they do not have sufficient cash to do so at the time of a decision. If a subject ends the experiment with a negative cash balance, this amount is subtracted when computing the terminal value of his portfolio. The large initial cash endowment, together with the constraint that

[7] In other words, we average X and Y to get (X+Y)/2, convert the experimental currency to actual dollars using a 12:1 exchange rate, and add a \$15 show-up fee.

subjects can hold at most one unit of each stock at any moment, means that it is extremely unlikely, ex-ante, that a subject would end the experiment with a negative portfolio value; indeed, none of our subjects did.

A total of 28 Caltech subjects participated in the experiment (22 male, age range 18 to 60, mean age 25.6, std. of age 7.6).[8] All subjects were right-handed and had no history of psychiatric illness, and none were taking medications that interfere with fMRI. The exact instructions given to subjects at the beginning of the experiment are included in the Internet Appendix.[9] The instructions carefully describe the stochastic structure of the price process, as well as all other details of the experiment. Subjects were not explicitly told that stock price changes are positively autocorrelated. However, they *were* told about the Markov chain governing the stock price paths; they therefore had enough information to infer the positive autocorrelation. Before entering the scanner, the subjects underwent a practice session of 25 trials to ensure that they were familiar with the market software.

There is a straightforward way to measure the extent to which a subject in our experiment exhibits a disposition effect in his trading. We simply adapt Odean's (1998) methodology, described in Section I, as follows. Every time a subject faces a decision about selling a stock, we classify his eventual action as a paper gain (loss) if the stock's current price is above (below) the purchase price *and* he chooses not to sell, and as a realized gain (loss) if the stock's current price is above (below) the purchase price *and* he chooses to sell. We then count up the number of paper gains, paper losses, realized gains, and realized losses over all selling decisions faced by the subject and compute the PGR and PLR measures described earlier. We assign the subject a disposition effect measure of PGR-PLR. When this measure is positive (negative), the subject exhibits (the opposite of) a disposition effect.

B. Optimal Trading Strategy

We now characterize the optimal trading strategy for a risk-neutral Bayesian investor whose objective is to maximize the expected value of his take-home earnings; from now on, we refer to this investor as an "expected value" investor. The optimal strategy for this investor is to sell (or not buy) a stock when he believes that it is more likely to be in the bad state than in the good state, and to buy (or hold) the stock when he believes that it is more likely to be in the good state.

Formally, let $p_{i,t}$ be the price of stock i in trial t after any price update about the stock, and let $q_{i,t} = \Pr(s_{i,t} = good | p_{i,t}, p_{i,t-1}, \ldots, p_{i,1})$ be the probability that a Bayesian investor, after seeing the price update in trial t, would assign to stock i being in the good state in trial t. Also, let z_t take the value one

[8] One additional subject participated in the experiment but was excluded from further analyses because his head motion during the scanning exceeded a prespecified threshold, thereby affecting the reliability of the neural measurements.

[9] The Internet Appendix is available in the online version of the article on *The Journal of Finance* website.

if the price update in trial t indicates a price increase for the stock in question, and minus one if the price update indicates a price decrease. Then $q_{i,t} = q_{i,t-1}$ if the price update in trial t is *not* about stock i, whereas, if the price update in trial t *is* about stock i, we have

$$\begin{aligned} & q_{i,t}(q_{i,t-1}, z_t) \\ &= \frac{Pr(z_t|s_{i,t} = good)Pr(s_{i,t} = good|q_{i,t-1})}{Pr(z_t|s_{i,t} = good)Pr(s_{i,t} = good|q_{i,t-1}) + Pr(z_t|s_{i,t} = bad)Pr(s_{i,t} = bad|q_{i,t-1})} \\ &= \frac{(0.5 + 0.05z_t)(0.8q_{i,t-1} + 0.2(1 - q_{i,t-1}))}{(0.5 + 0.05z_t)(0.8q_{i,t-1} + 0.2(1 - q_{i,t-1})) + (0.5 - 0.05z_t)(0.2q_{i,t-1} + 0.8(1 - q_{i,t-1}))}. \end{aligned} \tag{3}$$

The optimal strategy for an expected value investor is to sell (if holding) or not buy (if not holding) stock i in trial t when $q_{i,t} < 0.5$ and to hold or buy it otherwise.

Note that a trader who follows the optimal strategy described above will exhibit the opposite of the disposition effect. If a stock performed well on the last price update, it was probably in a good state for that price update. Since it is very likely to remain in the same state for its next price update, its next price change is likely to also be positive. The optimal strategy therefore involves selling winner stocks relatively rarely, and losing stocks more often, thereby generating the reverse of the disposition effect.

Of course, it is difficult for subjects to do the exact calculation in equation (3) in real time during the experiment. However, it is relatively straightforward for them to approximate the optimal strategy: they need simply keep track of each stock's most recent price changes, and then hold on to stocks that have recently performed well while selling stocks that have recently performed poorly. The fact that a stock's purchase price is reported on the trading screen makes it particularly easy to follow an approximate strategy of this kind as subjects can use the difference between the current price and the purchase price as a proxy for the stock's recent performance.[10]

C. Behavioral and Neural Predictions of the Realization Utility Model

We now lay out the behavioral and neural predictions of the realization utility model, and contrast them with the predictions of the expected value model—the benchmark model that assumes a risk-neutral, Bayesian decision-maker. The specific realization utility model we have in mind is one where, as in Barberis and Xiong (2012), realization utility has a linear functional form, the time

[10] Our rational benchmark assumes risk neutrality because the monetary risk in our experiment is small. We also considered the case of risk aversion, however, and concluded that its predictions do not differ significantly from those of risk neutrality. In some models, risk aversion can generate a disposition effect through rebalancing motives. This is not the case in our experiment, however, because the volatility of stock price changes is independent of the level of the price. Furthermore, any rebalancing motives would be of second-order importance relative to the impact of time variation in the *mean* stock return.

discount rate is strongly positive, and the agent maximizes the discounted sum of current and expected future realization utility flows.

Consider the behavioral predictions first. During the instruction session, subjects were told the structure of the data-generating process for stock prices. From this, it is straightforward to infer that price changes are positively autocorrelated. In such a market, an expected value investor will exhibit the opposite of the disposition effect; indeed, for the actual sequence of prices that our subjects see, the value of the PGR-PLR measure under the optimal trading strategy for an expected value investor is –0.76. In other words, this investor will have a much greater propensity to realize losses than gains. By contrast, a trader who experiences bursts of realization utility and who discounts future utility at a high rate will sell winner stocks more often than the expected value trader, and loser stocks less often. After all, he is keen to realize capital gains as soon as possible and to postpone realizing capital losses for as long as possible. This leads to our first prediction.

PREDICTION 1 (Behavioral): *For an expected value trader, the value of the PGR-PLR measure is –0.76. By contrast, for a realization utility trader, the value of PGR-PLR is greater than –0.76.*

We now turn to the neural predictions of the expected value and realization utility models. As noted earlier, a key goal of the paper is to test whether the basic assumptions of these models are consistent with the computations that subjects actually make during the choice process.

The neural predictions build on basic findings from the field of decision neuroscience. A sizable number of studies find evidence consistent with the idea that, in simple choice situations, the brain makes decisions by assigning values, often called "decision values," to the options under consideration and then comparing them to make a choice. These value signals are thought to reflect the relative value of getting the option under consideration versus staying with the status quo. In the context of a selling decision in our experiment, the decision value would reflect the value of selling a stock versus keeping it; in the context of a buying decision, it would reflect the value of getting the stock versus not buying it. A substantial body of work shows that, in particular, activity in an area of the vmPFC reliably encodes decision value computations at the time of choice.[11]

Since this finding is critical to our analysis, it is important to summarize the key lines of evidence that support it. First, across a wide range of stimuli and choice paradigms, activity in the vmPFC, a region located at the front of the brain directly behind the bridge of the nose, correlates reliably with behavioral measures of the value of the objects of choice, and does so regardless of whether

[11] See, for example, Hsu et al. (2005), Padoa-Schioppa and Assad (2006), Kable and Glimcher (2007), Knutson et al. (2007), Tom et al. (2007), Hare et al. (2008), Kennerley et al. (2008), Chib et al. (2009), Hare, Camerer, and Rangel (2009), Hsu et al. (2009), Hare et al. (2010), Levy et al. (2010), Rangel and Hare (2010), and Litt et al. (2011).

the object is actually chosen or not.[12] Second, additional studies have shown that activity in the vmPFC is more likely to be associated with the computation of value than with alternative signals that are often correlated with value, but are distinct from it. For example, Plassmann, O'Doherty, and Rangel (2010) rule out the possibility that the vmPFC responses can be attributed to confounding anticipatory emotions or anticipatory emotion signals, and show further that these responses cannot be attributed to attentional, motor, or saliency signals. Litt et al. (2011) also rule out the interpretation of vmPFC activity as attentional, motor, or saliency signals, and show that activity in many other areas of the brain that has often been interpreted as a value signal (e.g., anterior insula activity) actually fits these alternative descriptions better. Third, patients with lesions in their vmPFC exhibit impairments in decision-making (e.g., an increase in the inconsistency of their choices, as measured by generalized axiom of revealed preference (GARP) violations), a result that has been widely interpreted as *causal* evidence for the role of vmPFC decision value signals in choice (Fellows and Farah (2007), Camille et al. (2011), Camille, Tsuchida, and Fellows (2011)). Taken together, these findings provide strong support for the view, now widely held in neuroscience,[13] that vmPFC responses at the time of choice encode valuation signals for different stimuli for the purpose of guiding choice.[14]

Our first two neural predictions involve comparing the decision value signals that we observe in the vmPFC to the decision value signals that would be predicted by the realization utility model and the expected value model. To see the restrictions implied by these theories, consider first the decision value signal that would be computed at the time of making a sell decision by an individual who makes choices according to the expected value model. As noted

[12] The evidence on this point is extensive. See Kable and Glimcher (2007), Plassmann, O'Doherty, and Rangel (2007), Tom et al. (2007), Hare et al. (2008), Boorman et al. (2009), Chib et al. (2009), De Martino et al. (2009), FitzGerald, Seymour, and Dolan (2009), Hare, Camerer, and Rangel (2009), Peters and Buchel (2009), Talmi et al. (2009), Basten et al. (2010), Hare et al. (2010), Plassmann, O'Doherty, and Rangel (2010), Prevost et al. (2010), Smith et al. (2010), Tusche, Bode, and Haynes (2010), Wunderlich, Rangel, and O'Doherty (2010), Hare, Malmaud, and Rangel (2011), Hare et al. (2011), Levy and Glimcher (2011), Lim, O'Doherty, and Rangel (2011), Litt et al. (2011), Park et al. (2011), Hutcherson et al. (2012), Janowski, Camerer, and Rangel (2013), Kahnt et al. (2012), Lin, Adolphs, and Rangel (2012), and Sokol-Hessner et al. (2012).

[13] See Rangel and Hare (2010), Grabenhorst and Rolls (2011), Wallis (2011), Levy and Glimcher (2012), Rangel and Clithero (2013), and Rushworth et al. (2012).

[14] Some fMRI studies that look for neural correlates of value at the time of choice have also found such correlations in areas like the posterior cingulate cortex, the dorsolateral prefrontal cortex, the insula, and the ventral striatum. There are two important differences, however, between vmPFC activity and activity in these other areas. First, activity in these other areas is correlated with decision values in some studies but not in others, whereas the vmPFC value signals are always present (the only exceptions are studies in which the scanning parameters are not optimized to carry out measurements in the vmPFC, a region that is especially difficult to image well). Second, the additional tests described above (which are needed to make sure that the signals are really decision values, and not correlated but distinct variables) have not been carried out in these other areas. As a result, the computational basis of these areas in the process of making a decision remains an open question.

earlier, in the context of our experiment, the decision value of selling a stock is the value of selling the stock minus the value of holding it. For the expected value investor, the value of selling the stock is zero: if he sells it, he will no longer own any shares of it, and so it can no longer generate any value for him. In contrast, the value of holding the stock can be approximated by the stock's expected price change on its next price update:

$$E_t[\Delta p_{i,t+1}|q_{i,t}, \Delta p_{i,t+1} \neq 0] = 0.6(2q_{i,t} - 1). \tag{4}$$

The decision value signal at the time of making a sell decision is therefore given by $0 - 0.6(2q_{i,t} - 1)$, or $0.6(1 - 2q_{i,t})$; we will refer to this quantity throughout the paper as the *net expected value* of selling, or NEV. Note that this is only an approximation of the actual decision value because the exact value of holding a stock is the stock's expected *cumulative* price change until the subject decides to sell it. However, there is little cost to using the above approximation because the value of holding a stock only for its next price change is highly correlated with the value of holding the stock until it is actually optimal to sell it (the latter quantity can be computed by simulation).

Now consider the decision value signal that would be computed at the time of making a sell decision by an individual who makes choices according to the realization utility model. As noted earlier, we have in mind a simple form of the model in which the individual maximizes the discounted sum of expected future realized capital gains and losses. For such a trader, the value of selling is proportional to the capital gain or loss, given by $p_t - c_t$, where c_t is the purchase price, or cost basis. Meanwhile, so long as the discount rate is sufficiently high, the value of *holding* the stock is approximately zero. Thus, for this trader, the decision value of selling is linearly related to $p_t - c_t$.[15] This, together with the fact that decision value signals have been found to be encoded in the vmPFC, leads to the next prediction.

PREDICTION 2 (Neural): *For expected value traders, activity in the areas of the vmPFC associated with the computation of decision value should be linearly*

[15] We say that the value of holding a stock is "approximately" zero for a realization utility trader because, in principle, there is some value to holding, namely, an expected future realization utility flow. However, under the realization utility hypothesis, the trader is essentially myopic—he discounts future utility flows at a high rate. To a first approximation, then, the value of holding is zero. It may seem surprising that a subject would discount future utility at a high rate in the context of a 30-minute experiment. However, the literature on hyperbolic discounting suggests that discounting can be steep even over short intervals, perhaps because people distinguish sharply between rewards available right now and rewards available at all future times. Furthermore, what may be important in our experiment is not so much calendar time, as transaction time. A subject who can trade stock B now may view the opportunity to trade it in the future as a very distant event—one that is potentially dozens of screens away—and hence one that he discounts heavily. Finally, we note that discounting is not an essential part of our hypothesis. The disposition effect also follows from a model with no time discounting but where realization utility has an S-shaped functional form, as in prospect theory. To a first approximation, this model leads to the same decision value as the discounting-based model. The reason is that, under an S-shaped utility function, the utility of selling a stock at a gain (loss) immediately is significantly higher (lower) than the expected utility of holding on to it.

proportional to the NEV (given by $0.6(1-2q_{i,t})$*) at the time of making selling decisions, and thus independent of the cost basis. In contrast, for realization utility traders, activity in these areas of the vmPFC should be linearly related to the realizable gain or loss,* $p_{i,t}-c$.

The previous arguments indicate that, when making a sell decision, subjects who place larger weight on realization utility should exhibit neural activity in the vmPFC that is more strongly correlated with the realizable capital gain or loss. However, subjects who place a larger weight on realization utility should also exhibit a stronger disposition effect. It follows that subjects whose vmPFC activity is more correlated with the realizable capital gain should exhibit a stronger disposition effect in their trading.

PREDICTION 3 (Neural): *Under the realization utility model, the degree to which vmPFC activity correlates with the realizable capital gain should be correlated, across subjects, with the strength of the disposition effect in their trading.*

The final neural prediction is qualitatively different from the previous ones in that it seeks to test *directly* if subjects experience bursts of realization utility that are proportional to the capital gains they realize. One difficulty in testing this prediction is that, while the *theory* of realization utility says that the trader receives a utility burst at the moment of trade, it is hard to know, *in practice*, when exactly this burst occurs. For example, in our context, does it occur at the moment the subject presses a button to indicate his decision, or does it occur a little later when he reflects on the trade? Moreover, it is unclear what the duration of the burst is, in practice. In short, it is difficult to test the model by looking for neural markers of the hedonic response because we do not know when, exactly, to look for them.

Fortunately, we can overcome this problem with the help of an idea from computational neuroscience. A sizable body of work shows that an area located near the center of the brain, the vSt, computes a quantity known as a prediction error in response to new information.[16] The prediction error measures the change in the expected net present value of utility generated by the news, taking into account all sources of utility. It is positive if the news indicates an improvement in the expected net present value of utility, and negative otherwise. Importantly, it reflects the change in discounted utility but is insensitive to the precise timing of the hedonic impact of the news. This is useful because it means that we can test for hedonic effects associated with realizing gains and losses by looking for a burst of activity in the vSt consistent with the change in discounted utility that these effects generate. In summary, under the realization utility model, when a trader sells a stock, this is associated with a utility burst; while we do not know the exact timing or duration of the burst, we do know that it generates a change in the expected net present value of utility, one

[16] See, for example, Schultz, Dayan, and Montague (1997), McClure, Berns, and Montague (2003), O'Doherty et al. (2003), Bayer and Glimcher (2005), Pessiglione et al. (2006), Hare et al. (2008), Caplin et al. (2010), Glascher et al. (2010), Daw et al. (2011), and Lin, Adolphs, and Rangel (2012).

that should be reflected at the moment of sale in the prediction error computed by the vSt.

PREDICTION 4 (Neural): *Under the realization utility hypothesis, neural responses in the area of the vSt known to encode prediction errors should increase (decrease) at the precise moment when traders realize a capital gain (loss).*

III. fMRI Data Collection and Analysis

In this section, we describe how we collect and analyze the fMRI measures of neural activity. The section contains enough information to serve as a brief primer on the subject for readers who are unfamiliar with fMRI. For a more detailed discussion, see Huettel, Song, and McCarthy (2004), Ashby (2011), and Poldrack, Mumford, and Nichols (2011).

A. fMRI Data Collection and Measurement

We collect measures of neural activity over the entire brain using BOLD-fMRI, which stands for blood-oxygenated level dependent functional magnetic resonance imaging. BOLD-fMRI measures changes in local magnetic fields that result from the local inflows of oxygenated hemoglobin and outflows of de-oxygenated hemoglobin that occur when neurons fire. In particular, fMRI provides measures of the BOLD response in small "neighborhoods" of brain tissue called *voxels*, and is thought to measure the sum of the total amount of neuronal firing into that voxel and the total amount of neuronal firing within the voxel.[17]

One important complication is that the hemoglobin responses measured by BOLD-fMRI are slower than the associated neuronal responses. Specifically, although the bulk of the neuronal response takes place quickly, BOLD measurements are affected for up to 24 seconds thereafter. Panel A of Figure 2 provides a more detailed illustration of the nature of the BOLD response. It depicts the path of the BOLD signal in response to one (arbitrary) unit of neural activity of infinitesimal duration at time 0. The function plotted here is called the canonical hemodynamic response function (HRF). It is denoted by $h(\tau)$, where τ is the amount of time elapsed since the neural activity impulse, and has been shown to approximate well the pattern of BOLD responses for most subjects, brain areas, and tasks.

Fortunately, there is a standard way of dealing with this. In particular, the BOLD response has been shown to combine linearly across multiple sources of neural activity (Boynton et al. (1996)). This property, along with knowledge of the specific functional form of the HRF, allows us to construct a mapping from predicted neural activity to predicted BOLD responses. Specifically, if the

[17] The neural activity measured by fMRI in a 1 mm^3 cube (about the size of a grain of salt) represents the joint activity of between 5,000 to 40,000 neurons, depending on the area of the brain.

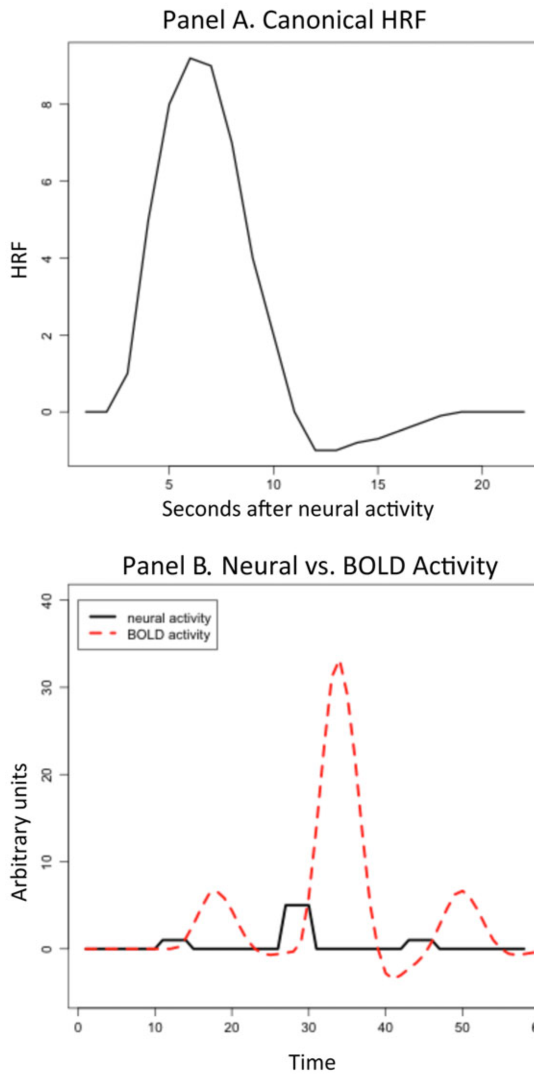


Figure 2. BOLD measurements of neural activity. Panel A: Because fMRI measures the blood-oxygenated level dependent (BOLD) response, and not neural activity itself, we need a mapping from neural activity to the BOLD response to make inferences about changes in neural activity. This mapping is known as the canonical hemodynamic response function, and is shown here as a function of one arbitrary unit of instantaneous neural activity at time 0. Panel B: This figure shows the BOLD response (the dashed line) that results from three sequential sources of neural activity (the solid line). The BOLD response combines linearly across multiple sources of neural activity.

predicted level of neural activity at any particular time is given by $a(t)$, then the level of BOLD activity at any instant t is well approximated by

$$b(t) = \int_0^\infty h(u)a(t-u)du, \tag{5}$$

which is the convolution between the HRF and the neural inputs. This integral has a straightforward interpretation: it is a lagged sum of all the BOLD responses triggered by previous neural activity. Panel B of Figure 2 illustrates the connection between neural activity and BOLD responses; it depicts a hypothetical path of neural activity (the solid line), together with the associated BOLD response (the dashed line).

During our experiment, we acquire two types of MRI data in a 3.0 Siemens Tesla Trio MRI scanner with an eight-channel phased array coil. First, we acquire BOLD-fMRI data while the subjects perform the experimental task. We use a voxel size of 3 mm^3, and collect these data for the entire brain ($\sim$100,000 voxels) every 2.75 seconds.[18] We also acquire high-resolution anatomical scans that we use mainly for realigning the brains across subjects and for localizing the brain activity identified by our analyses.[19]

B. fMRI Data Preprocessing

Before the BOLD data can be analyzed to test our hypotheses, they have to be converted into a usable format. This requires the following steps, which are fairly standard (see Huettel, Song, and McCarthy (2004), Ashby (2011), and Poldrack, Mumford, and Nichols (2011)) and which are implemented by way of a specialized but commonly used software package called SPM5 (Wellcome Department of Imaging Neuroscience, Institute of Neurology, London, UK).

First, we correct for slice acquisition time within each voxel. This is necessary because the scanner does not collect data on all brain voxels simultaneously. This simple step, which involves a nonlinear interpolation, temporally realigns the data across all voxels.

Second, we correct for head motion to ensure that the time series of BOLD measurements recorded at a specific spatial location within the scanner is always associated with the same brain location throughout the experiment.[20]

[18] More precisely, we acquire gradient echo T2*-weighted echoplanar (EPI) images with BOLD contrast. To optimize functional sensitivity in the orbitofrontal cortex (OFC), a key region of interest, we acquire the images in an oblique orientation of 30° to the anterior commissure–posterior commissure line (Deichmann et al. (2003)). Each volume of images has 45 axial slices. A total of 692 volumes were collected over two sessions. The imaging parameters are as follows: echo time, 30 ms; field of view, 192 mm; in-plane resolution and slice thickness, 3 mm; repetition time, 2.75 s.

[19] More precisely, we acquire high-resolution T1-weighted structural scans ($1 \times 1 \times 1$ mm) for each subject. These are coregistered with their mean EPI images and averaged across subjects to permit anatomical localization of the functional activations at the group level.

[20] BOLD measurements were corrected for head motion by aligning them to the first full brain scan and normalizing to the Montreal Neurological Institute's EPI template. This entails estimating a six-parameter model of head motion for each volume (three parameters for center movement,

Third, we realign the BOLD responses for each individual into a common neuroanatomical frame (the standard Montreal Neurological Institute EPI template). This step, called spatial normalization, is necessary because brains come in different shapes and sizes; as a result, a given spatial location maps to different brain regions in different subjects. Spatial normalization involves a nonlinear reshaping of the brain to maximize the match with a target template. Although the transformed data are not perfectly aligned across subjects due to remaining neuroanatomical heterogeneity, the process is sufficiently accurate for the purposes of most studies. Furthermore, any imperfections in the realignment process introduce noise that reduces our ability to detect neural activity of interest.

Fourth, we also spatially smooth the BOLD data for each subject by making BOLD responses for each voxel a weighted sum of the responses in neighboring voxels, where the weights decrease with distance.[21] This step ensures that the error structure of the data conforms to the normality assumptions on the error structure of the regression models that we use to test our hypotheses (Huettel, Song, and McCarthy (2004), Poldrack, Mumford, and Nichols (2011)).

Finally, we remove low-frequency signals that are unlikely to be associated with neuronal responses to individual trials.[22] An example of such a signal is the effect of a continuous head movement over the course of the experiment that is not fully removed by the second correction step described above.

C. fMRI Main Data Analyses

The key goals of our analysis are to test if the region of the vmPFC that has been repeatedly shown to encode decision values at the time of choice exhibits activity consistent with Predictions 2 and 3, and if the area of the vSt known to encode prediction errors at the time of utility-relevant news exhibits activity consistent with Prediction 4. To do so, we run statistical tests to see whether there are areas within these regions of the brain, given by collections of spatially contiguous voxels called *clusters,* where the BOLD response reflects neural activity that implements the computations of interest (e.g., realization utility computations). This is complicated by the fact that, since every voxel contains thousands of neurons, the BOLD responses in a voxel can be driven by multiple signals. Fortunately, the linear properties of the BOLD signal allow the neural signals of interest to be identified using standard linear regression methods.

and three parameters for rotation), and then removing the effect of the motion using these parameters. For details, see Friston et al. (1996).

[21] Spatial smoothing was performed using an 8 mm full-width half-maximum Gaussian kernel. Essentially, this step entails replacing every measurement at every voxel with a weighted sum of the measurements in a neighborhood centered on the voxel, using weights that are given by the Gaussian kernel.

[22] Specifically, we applied a high-pass temporal filter to the BOLD data with a cut-off of 128 seconds.

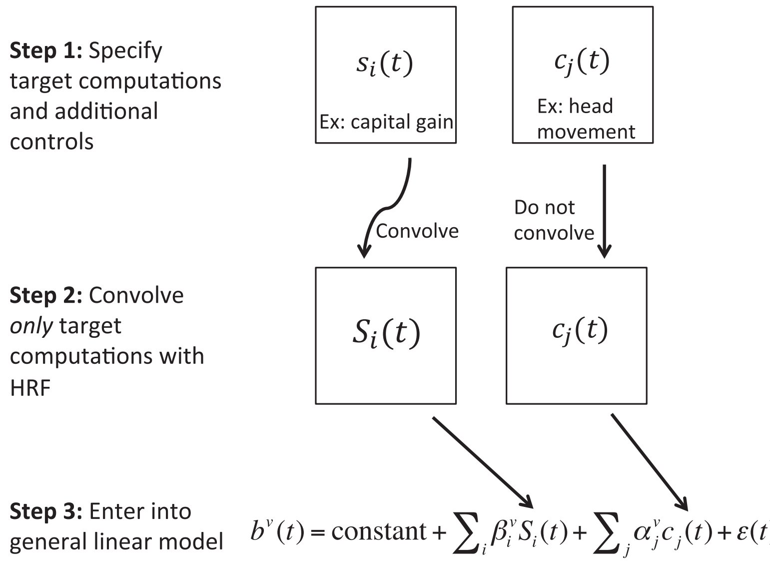


Figure 3. Constructing a general linear model (GLM). There are two sets of regressors: target computations and additional controls. Target computations reflect the signals of interest whereas additional controls are used to clean up noise that is inherent in the BOLD signal. Because the target computations are induced by neural activity, we convolve them; we do not convolve additional controls because they do not trigger a hemodynamic response. Finally, we enter the two sets of variables, one of which is convolved, into a GLM with AR(1) noise.

The general statistical procedure is straightforward, and will be familiar to most economists (see Figure 3 for a summary). The analysis begins by specifying two types of variables that might affect the BOLD response, namely, target computations and additional controls. The target computations reflect the signals we are looking for (e.g., a realization utility signal at the time of selling a stock). They are specified by a time series $s_i(t)$ describing each signal of interest. For each of these signals, let $S_i(t)$ denote the time series that results from convolving the signal $s_i(t)$ with the HRF, as described above. The additional controls, denoted by $c_j(t)$, are other variables that might affect the BOLD time series (e.g., residual head movement or time trends). These are introduced to further clean up the noise in the BOLD signal, but are not explicitly used in any of our tests. The control variables are not convolved with the HRF because, while they affect the measured BOLD responses, they do not reflect neural activity that triggers a hemodynamic response.[23]

The linearity of the BOLD signal implies that the level of BOLD activity $b^v(t)$ in any voxel v at time t should be given by

$$b^v(t) = \text{constant} + \sum_i \beta_i^v S_i(t) + \sum_j \alpha_j^v c_j(t) + \varepsilon(t), \tag{6}$$

[23] For example, linear trends are often included as controls because the scanner heats up with continuous operation, inducing a linear change in the measured BOLD responses.

where $\varepsilon(t)$ denotes AR(1) noise. This model is estimated independently in each of the voxels that fall within the relevant region of interest (the vmPFC for Predictions 2 and 3, and the vSt for Prediction 4). Our hypotheses can then be restated as tests about the coefficients of this regression model: signal i is said to be associated with activity in voxel v only if β_i^v is significantly different from zero.

Two additional considerations apply to most fMRI studies, including this one. First, we are interested in testing hypotheses about the distribution of the signal coefficients in the population of subjects, not hypotheses about individual subject coefficients. This would normally require estimating a mixed effects version of the linear model specified above, which, given the size of a typical fMRI data set, would be computationally intensive. Fortunately, there is a shortcut that provides a good approximation to the full mixed effects analysis (Penny et al. (2006)). This shortcut involves estimating the parameters separately for each individual subject, averaging them across subjects, and then performing t-tests. This is the approach we follow here.

Second, since our tests are carried out in each of the voxels in the relevant regions of interest (429 voxels for the vmPFC, and 68 for the vSt), there is a concern about false-positives. To address this problem, we correct for multiple comparisons within the relevant region of interest, a procedure known in the fMRI literature as a small volume correction (SVC). We report results as significant if they pass SVC correction at a level of $p < 0.05$.[24]

As noted earlier, we conduct our tests in an area of the vmPFC that has been linked to the computation of decision values and in an area of the vSt that has been linked to the computation of prediction errors. Specifically, for the vmPFC region of interest, we construct a sphere with a 15 mm radius around the coordinates (MNI-space, $x = 3$, $y = 36$, $z = -18$) found to exhibit peak correlation with decision values at the time of choice in Plassmann, O'Doherty, and Rangel (2010), and then intersect this sphere with an anatomical mask of the vmPFC.[25] For the vSt region of interest, we construct a sphere with a 15 mm radius around the coordinates (MNI-space, $x = -15$, $y = 6$, $z = -12$) found to exhibit peak correlation with prediction errors in Lin, Adolphs, and Rangel (2012), and then intersect this sphere with an anatomical mask of the vSt.[26] As discussed in Section II, many studies find results that are very similar to those of the two studies listed above; it is therefore not crucial which exact papers we use to define the regions of interest (so long as the radii of the spheres are sizable, as they are here).

[24] Specifically, we report results as significant if voxels within the prespecified region of interest pass $p < 0.001$ uncorrected with a 15-voxel extent threshold and if they pass SVC with a family-wise error rate of less than 0.05.

[25] The vmPFC anatomical mask was identified using the AAL digital atlas of the human brain (Tzourio-Mazoyer et al. (2002)), and includes the rectus, the orbital part of the superior frontal gyrus, and the orbital part of the middle frontal gyrus.

[26] The vSt anatomical mask is taken from Chib et al. (2012) and consists of the nucleus accumbens and the ventral putamen.

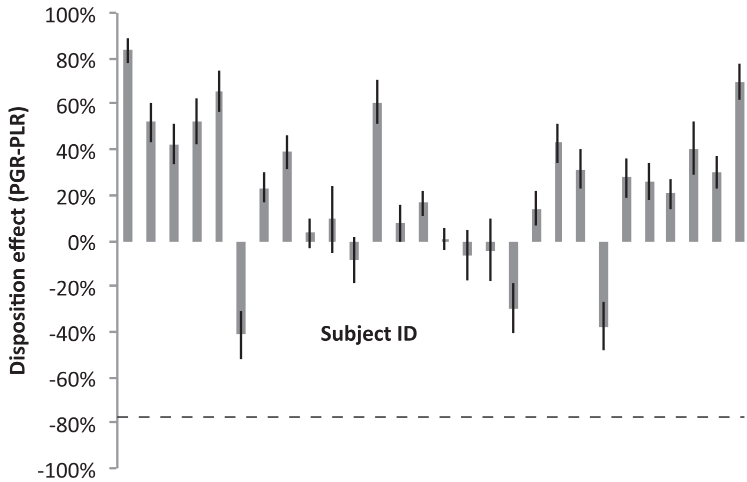


Figure 4. Measures of the disposition effect (PGR-PLR) for each subject. Each vertical column corresponds to a specific subject in our experiment. We compute standard error bars as in Odean (1998). The dashed line indicates the level of the disposition effect that an expected value trader would exhibit, namely, –0.76. All subjects exhibit a disposition effect greater than this benchmark level, and a majority have a disposition effect that is significantly *positive.* The figure also shows that there is significant heterogeneity in the size of the disposition effect across subjects (std: 0.32).

IV. Results

A. *Test of Behavioral Prediction 1*

We begin our test of Prediction 1 by computing the strength of the disposition effect for each subject using the PGR-PLR measure described at the end of Section II.A. We find that the average PGR and PLR across subjects are 0.412 and 0.187, respectively. This implies an average PGR-PLR value of 0.225, which is significantly greater than zero ($p < 0.001$, in a two-tailed t-test against zero). In other words, not only is the average value of PGR-PLR significantly greater than the expected value model benchmark of –0.76, but it is actually significantly positive. These results are inconsistent with the hypothesis that our subjects are all expected value investors, but are consistent with the hypothesis that some of them are influenced by realization utility.

Figure 4 depicts tests of Prediction 1 at the individual level. Each vertical bar shows the value of PGR-PLR for a particular subject. The horizontal dashed line near the bottom of the figure marks the –0.76 value of PGR-PLR that corresponds to an expected value investor. The figure shows that *every* subject exhibits a disposition effect greater than –0.76. The hypothesis that the average disposition effect is not different from –0.76 is rejected with a t-statistic of 16.52.[27]

[27] We also test for the possibility that, due to learning, the disposition effect decreases in size over time. We find that the mean disposition effect is smaller in the second half of the experiment

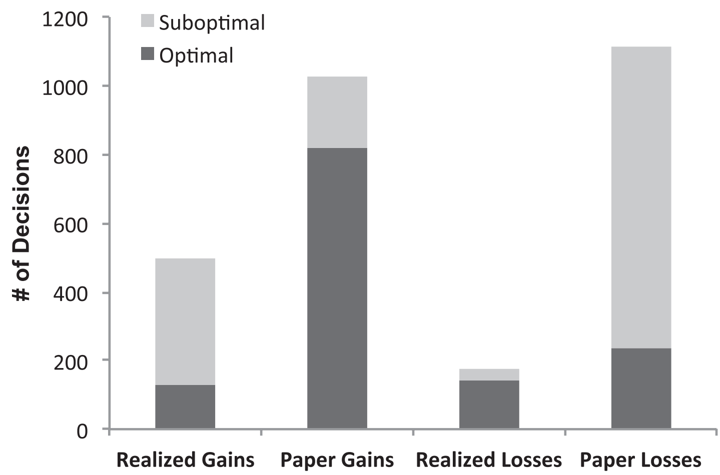


Figure 5. Total number of sell decisions by decision type and optimality. A realized gain (loss) refers to a decision where a subject sells a stock trading at a gain (loss) relative to purchase price. A paper gain (loss) refers to a decision where a subject decides to hold a stock trading at a gain (loss). The optimality measures show an important aspect of our design: selling winners and holding losers, which leads to a disposition effect, are typically suboptimal decisions. Decisions are pooled across all subjects.

The figure also shows that there is significant heterogeneity in the strength of the disposition effect across subjects: the value of PGR-PLR ranges from –0.41 to 0.83 and has a standard deviation of 0.32. This cross-individual variation is consistent with Dhar and Zhu (2006), who, using data on actual trading decisions, also find significant variation in the strength of the disposition effect across investors. Interestingly, while both PGR and PLR vary a good deal across subjects, the two variables have a correlation of only 0.03: subjects who are slow to sell losing stocks are not necessarily also quick to sell winning stocks. This independence between selling behavior in the gain and loss domains is also consistent with the empirical findings of Dhar and Zhu (2006).[28]

Figure 5 provides additional insight into our subjects' selling behavior by showing, for each of the four types of decisions that a subject could make (decisions to realize a gain, decisions to realize a loss, decisions not to realize a gain, and decisions not to realize a loss), the fraction of decisions that are optimal, where "optimal" is defined by the expected value benchmark. For example, the figure shows that our subjects realized gains on 495 occasions

compared to the first half (0.145 versus 0.259, $p = 0.087$, a reduction of 11.2% relative to the optimal level of –0.76), but that it is still positive and sizable in the second half (0.145 versus the optimal level of –0.76, $p < 0.001$).

[28] The low correlation between PGR and PLR is not inconsistent with realization utility; it simply suggests that realization utility is not the only factor driving subjects' trading. For example, if our subjects are influenced to varying extents by realization utility but also differ in how much they enjoy trading in general, they may exhibit a near-zero correlation between PGR and PLR—the negative correlation between the two variables induced by realization utility may be offset by the positive correlation induced by the taste for trading.

and that most of these decisions were suboptimal. Given that stocks exhibit short-term price momentum in the experiment, it is generally better to hold on to a stock that has been performing well. This explains why most (77.9%) of subjects' decisions to hold winning stocks were optimal, and why most (67.5%) of subjects' decisions to sell winning stocks were suboptimal. Similarly, in the experiment, it is generally better to sell a stock that has been performing poorly. This explains why most (79.2%) of subjects' decisions to sell losing stocks were optimal, while most (80.3%) of their decisions to hold these stocks were suboptimal.

The disposition effect exhibited by our subjects is stronger than that found in empirical studies (Odean (1998), Frazzini (2006)). One possible reason for this is that the current price and the cost basis of a stock are both prominently displayed on the trading screen.[29] If, because of realization utility, a subject has a preference for realizing gains and not realizing losses, the fact that we report the purchase price may make it easier for him to cater to this preference and hence to exhibit a disposition effect.[30]

In summary, the behavioral results indicate that our average subject exhibits a strong disposition effect. This is inconsistent with the expected value model, but is consistent with the realization utility model.

B. Test of Neural Prediction 2

We now turn to Prediction 2. This prediction states that, for subjects who experience realization utility, activity in an area of the vmPFC known to encode decision values at the time of making a decision should be correlated with the capital gain variable $p_t - c_t$. By contrast, it states that, for expected value subjects, activity in this area should correlate with the NEV variable, but not with the capital gain.

The prespecified region of the vmPFC in which we test for the decision value signals (see the end of Section III) is the area colored yellow and orange in Figure 6; as noted in Section III, it contains 429 voxels. To carry out the main

[29] One natural question about our experiment is: How much of the realization utility effect that we have found depends on the fact that we display the original purchase price on the trading screen in a salient way? We emphasize that it is unlikely that the presence of a realization utility effect depends critically on this aspect of the design. In follow-up work, we carry out behavioral experiments to study the impact of the saliency with which the purchase price information is displayed (Frydman and Rangel (2013)). We find that eliminating the purchase price from the trading screen diminishes the size of the disposition effect, but that the effect is still well above the optimal level that an expected value investor would exhibit. This suggests that reporting the purchase price on the trading screen is not a critical aspect of our current design. Moreover, given that most investors in real-world financial markets have at least a rough sense of the price at which they purchased a stock, displaying the cost basis on the trading screen is likely a better approximation of reality.

[30] At the same time, because our experimental design induces a negative correlation (equal to –0.55) between the capital gain and the NEV of selling, the fact that we report the purchase price also makes it easy for an expected value subject to trade in a way that is close to *his* optimal strategy, namely, to hold a stock when it has a capital gain and to sell it when it has a capital loss.

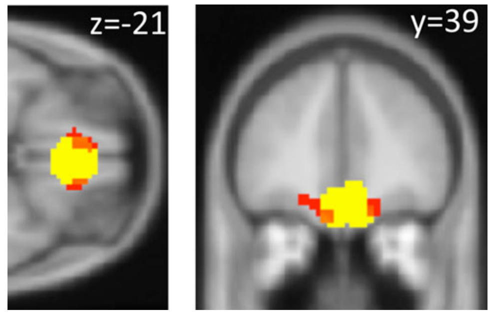


Figure 6. vmPFC activity reflects realization utility. The figure presents estimation results from equation (7),

$$b^v(t) = \text{constant} + \beta_1^v I_{\text{dec}}(t)(p_t - c_t) + \beta_2^v I_{\text{dec}}(t)\text{NEV}_t + \beta_3^v \text{controls} + \varepsilon(t).$$

Yellow voxels are those in our prespecified region of interest in the vmPFC. Red voxels are those that exhibit activity at the time of trading screen onset that significantly correlate with the realizable capital gain. Orange voxels are in the intersection of the two groups. For illustration purposes, the significance threshold for the image is $p < 0.001$ with a 15-voxel extent threshold, but all statistics reported in the paper are also small volume corrected at $p < 0.05$ using familywise error (FWE). The $z = -21$ coordinate and the $y = 39$ coordinate indicate which two-dimensional plane is shown in each of the two brain maps.

test of Prediction 2, we estimate the following general linear model (GLM) of BOLD activity in every subject and voxel:

$$b^v(t) = \text{constant} + \beta_1^v I_{\text{dec}}(t)(p_t - c_t) + \beta_2^v I_{\text{dec}}(t)\text{NEV}_t + \beta_3^v \text{controls} + \varepsilon(t), \quad (7)$$

where $b^v(t)$ denotes the BOLD signal at time t in voxel v, I_{dec} is an indicator function that equals one if, at time t, the subject is presented with an opportunity to *sell* a stock, $p_t - c_t$ is the realizable capital gain, and NEV_t is the net expected value from selling the stock under consideration at time t, namely $0.6(1 - 2q_{i,t})$. Finally, the "controls" vector includes the following variables: (1) an indicator function denoting the onset of a selling opportunity, (2) an indicator function denoting the onset of a buying opportunity, (3) an indicator function denoting the onset of a buying opportunity interacted with the NEV of buying the asset, (4) an indicator function denoting the onset of a price update screen when the subject owns the asset, (5) an indicator function denoting the onset of a price update screen when the subject owns the asset interacted with the price change, (6) an indicator function denoting the onset of a price update screen when the subject does not own the asset, (7) an indicator function denoting the onset of a price update screen when the subject does not own the asset interacted with the price change, (8) regressors controlling for physical movement inside the scanner, and (9) session indicator variables. Controls 1 to 7 are convolved with the HRF, whereas controls 8 and 9 are not. As described in Section III.A, these controls are necessary because the BOLD signal is affected

As a result, we do not think that presenting the purchase price on the trading screen should bias an expected value trader toward exhibiting a disposition effect.

up to 24 seconds after the initial neural impulse generated by the onset of a decision screen or price update screen (Figure 2).[31] Therefore, some portion of the variance in the BOLD signal we observe at the time subjects are computing their sell/hold decision can be attributed to the specific events we are controlling for. We use this same vector of control variables in each GLM we estimate in this paper. Finally, inferences about the extent to which the signals of interest are encoded in a given voxel are made by carrying out a one-sided t-test against zero of the average of the individually estimated coefficients (i.e., of the average β_1^v across subjects, and of the average β_2^v across subjects), and by correcting for multiple comparisons within the prespecified vmPFC region of interest.

As shown in Figure 6, the results from these tests are consistent with the predictions of the realization utility model, but not with those of the expected value model. Within the prespecified 429-voxel vmPFC target region associated with the computation of decision values in previous studies, we find a cluster of 27 voxels in which β_1^v, averaged across subjects, is significantly positive. Below, we refer to these 27 voxels as the vmPFC$_{\text{ROI}}$. In contrast to the significant results we find for the capital gain regressor, there are no clusters that significantly relate to the NEV variable at our statistical threshold.

The previous analysis identifies a region of the vmPFC, the vmPFC$_{\text{ROI}}$, in which responses at the time of choice are consistent with the computation of the decision value predicted by the realization utility model. We now carry out two additional tests of the properties of the signals in this area. The first test investigates whether the capital gain variable $p_t - c_t$ is reflected in the vmPFC$_{\text{ROI}}$ to differing extents in trials involving capital gains and trials involving capital losses. To do this, we estimate the following subject- and voxel-level GLM:

$$b^v(t) = \text{constant} + \beta_1^v I_{\text{dec}}(t) I_{\text{cap.gain}}(t)(p_t - c_t) + \beta_2^v I_{\text{dec}}(t) I_{\text{cap.loss}}(t)(p_t - c_t) + \beta_3^v \text{controls} + \varepsilon(t), \quad (8)$$

where $I_{\text{cap.gain}}$ and $I_{\text{cap.loss}}$ are indicator functions for trials involving capital gains and capital losses, respectively. For each individual, we compute the mean β_1^v and the mean β_2^v across the voxels in the vmPFC$_{\text{ROI}}$; we then average these means across subjects. The resulting values of $\beta_1 = 0.028$ and $\beta_2 = 0.029$ are not significantly different from each other ($p = 0.94$). Thus, we cannot reject the hypothesis that the net capital gain signal has a linear functional form.

The second test checks whether, as predicted by the realization utility model, the signal in the vmPFC related to decision values is both positively correlated with p_t *and* negatively correlated with c_t. This test is important because it goes to the core of the "irrationality" implicit in the realization utility model,

[31] Since the computations that take place during the price update screens do not play a role in testing the realization utility model, we do not focus on them in the current study. However, in a companion paper we analyze the neural activity during the price update screens (Frydman, Camerer, and Rangel (2012)); in particular, we use these data to test regret-based models of investing. We find that activity in the ventral striatum correlates positively with price changes at the time of a price update for assets that are owned by the subject. Interestingly, the sign of this correlation reverses for assets that are not owned by the subject.

namely, that people are influenced by the cost basis when deciding whether to sell an asset. The test is based on the following GLM:

$$b^v(t) = \text{constant} + \beta_1^v I_{\text{dec}}(t) p_t + \beta_2^v I_{\text{dec}}(t)\, c_t + \beta_3^v \text{controls} + \varepsilon(t). \tag{9}$$

The key hypothesis of interest is that $\beta_2 < 0$. We cannot conduct this test in the vmPFC$_{\text{ROI}}$—since this region consists of voxels that correlate with $p_t - c_t$, the test would be biased in favor of the hypothesis. To avoid this bias, we first estimate equation (9) for each of the 429 voxels in the independent vmPFC target region (taken, as described in Section III.C, from Plassmann, O'Doherty, and Rangel (2010) and an anatomical mask of the vmPFC) and then identify voxels that exhibit significant correlation with p_t ($p < 0.05$, SVC); we give this set of voxels the label vmPFC$_{\text{p}}$. We then test whether voxels in this region correlate significantly with the cost basis. The effect size, averaged across voxels in vmPFC$_{\text{p}}$ for each subject, and then across subjects, is given by $\beta_2 = -0.019$, ($p = 0.03$). This result provides further evidence in support of the realization utility hypothesis.

C. Test of Neural Prediction 3

We now test Prediction 3. Specifically, we check whether, as predicted by the realization utility model, subjects whose neural activity in the vmPFC at the time of a sell decision is particularly sensitive to the realizable capital gain also exhibit a stronger disposition effect.

To make the logic of the test clearer, we conduct it separately for decisions involving capital gains and decisions involving capital losses. In particular, for each subject, we compute a neural measure of the degree to which a positive capital gain is represented in the vmPFC at the time of choice, and also a neural measure of the degree to which a negative capital gain—in other words, a capital loss—is represented in the vmPFC at the time of choice. These subject-level statistics are given by the maximum value, across voxels in the vmPFC$_{\text{ROI}}$, of β_1^v and β_2^v from equation (8).[32]

According to Prediction 3, subjects with a high maximum value of β_1^v—in other words, subjects whose computations, at the time of a sell decision about a stock with a capital gain, are particularly consistent with the realization utility model—should exhibit a higher value of PGR (i.e., a higher propensity to realize gains). Consistent with this prediction, we find that the correlation, across subjects, between the maximum β_1^v and PGR is 0.58 ($p = 0.001$). The top panel in Figure 7 illustrates this graphically.

Prediction 3 also implies that there should be a negative correlation, across subjects, between the maximum β_2^v and PLR: subjects with a high maximum value of β_2^v—again, subjects whose computations at the time of making a sell

[32] We use the maximum statistic instead of the average statistic because of the heterogeneity in anatomical and functional structure of the vmPFC across subjects. Since we are testing for a correlation, rather than for a particular mean value, using the maximum statistic will not bias our results.

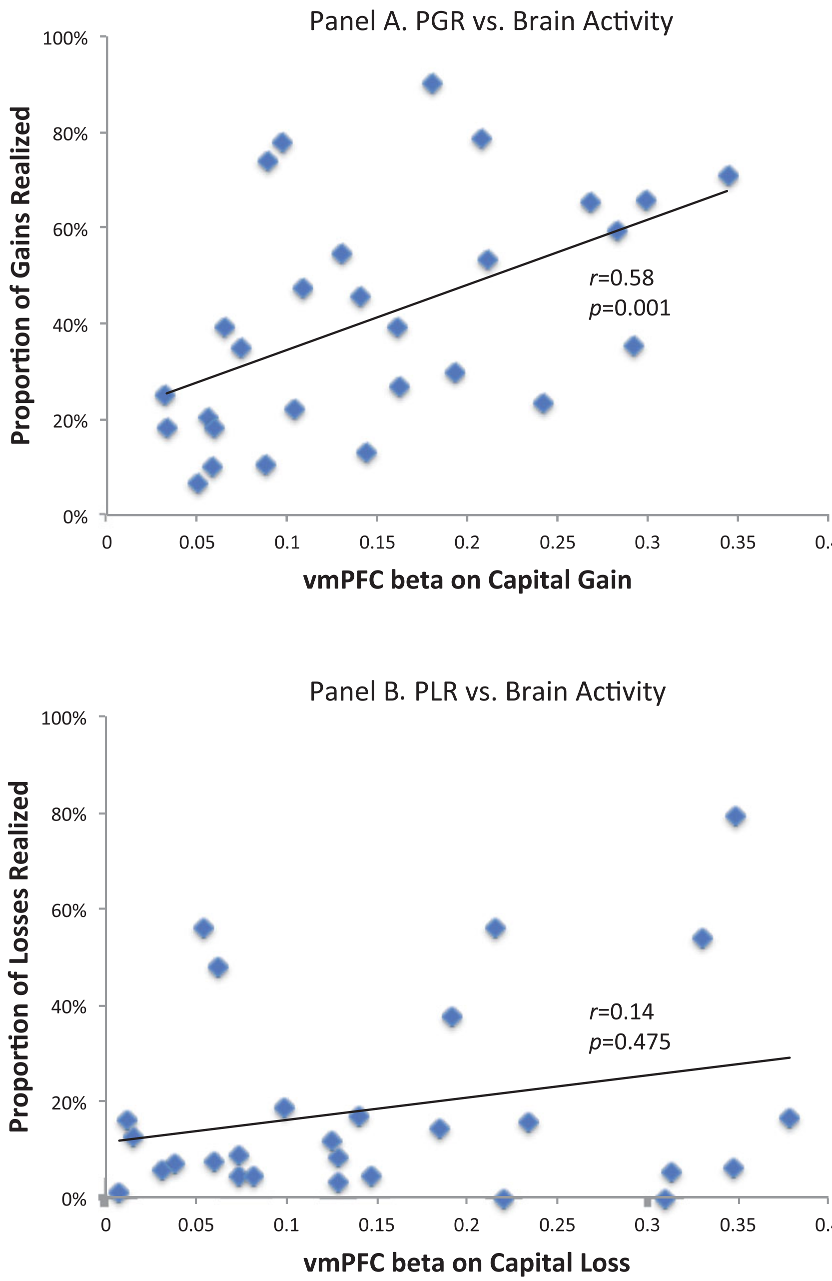


Figure 7. Correlation between brain activity and measures of the disposition effect. Each data point in the figure represents a single subject. Panel A: We find that, across subjects, the degree to which vmPFC activity during a sell decision for a stock with a gain is correlated with the gain is itself correlated with the proportion of gains realized. Panel B: We do not find a similar correlation between the proportion of losses realized and the degree to which vmPFC activity during a sell decision for a stock with a loss is correlated with the loss.

decision about a stock with a capital loss are particularly consistent with the realization utility model—should exhibit a lower propensity to realize losses. However, we do not find a significant correlation between the maximum β_2^v and PLR ($p = 0.475$). This can be seen in the lower panel of Figure 7.

In summary, then, the results in this section are consistent with Prediction 3 for sell decisions involving capital gains, but not for sell decisions involving capital losses. In Section V, we discuss why this might be the case.

D. Test of Neural Prediction 4

Prediction 4 tests a basic assumption of the realization utility model. The model posits that selling a stock at a gain generates a positive hedonic effect, and that selling a stock at a loss generates a negative hedonic effect, independent of the impact of the trade on lifetime consumption. As discussed in Section II, while in theory this hedonic impact occurs at the moment of sale, in practice it is hard to know what its precise timing and duration are. However, we do know that the utility burst corresponds to a change in discounted lifetime utility; as such, it should generate a prediction error at the moment of sale. This leads to the following form of Prediction 4: controlling for the size of a capital gain, a decision to realize the gain should lead to a positive response in the areas of the vSt known to correlate positively with prediction errors.

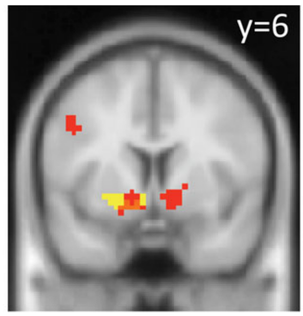
The region colored yellow and orange in Figure 8 shows the prespecified region of the vSt identified in previous studies as being involved in the computation of prediction errors. It is in this region—one that, as noted in Section III.C, contains 68 voxels—that we look for a positive effect of realizing capital gains.[33] Specifically, our test of Prediction 4 is based on the following GLM:

$$\begin{aligned} b^v(t) = \text{constant} &+ \beta_1^v I_{\text{dec}}(t) I_{\text{cap.gain}}(t)(p_t - c_t) \\ &+ \beta_2^v I_{\text{dec}}(t) I_{\text{cap.gain}}(t) I_{\text{sell}}(t) \\ &+ \beta_3^v I_{\text{dec}}(t) I_{\text{cap.loss}}(t) + \beta_4^v \text{controls} + \varepsilon(t). \end{aligned} \tag{10}$$

As before, I_{dec} is an indicator function denoting an opportunity to sell a stock, $I_{\text{cap.gain}}$ is an indicator function denoting an opportunity to sell a capital gain, and $I_{\text{cap.loss}}$ is an indicator function denoting an opportunity to sell a capital loss. Finally, I_{sell} is an indicator function denoting that the subject actually sold the stock. Note that this model allows us to estimate the marginal effect

[33] Before continuing with our test of Prediction 4, we further validate, using data from our own 28 subjects, that our a priori target region of the vSt is responsible for computing a prediction error signal. Specifically, we test whether news about a positive price change for an owned stock—an event that should induce a positive prediction error—is positively correlated with activity in our vSt target region. We can use the estimation results from equation (7) to test this hypothesis because the price change during the price update screen is included as a control in that model. The results indicate that voxels within the vSt target region do indeed exhibit positive correlation with the price change ($p < 0.05$, whole-brain corrected FWE). This provides independent validation that our vSt target region computes a prediction error.

Panel A. vSt Exhibits Greater Activity When Selling vs. Holding Capital Gains



Panel B. Time-Course of Activity in vSt

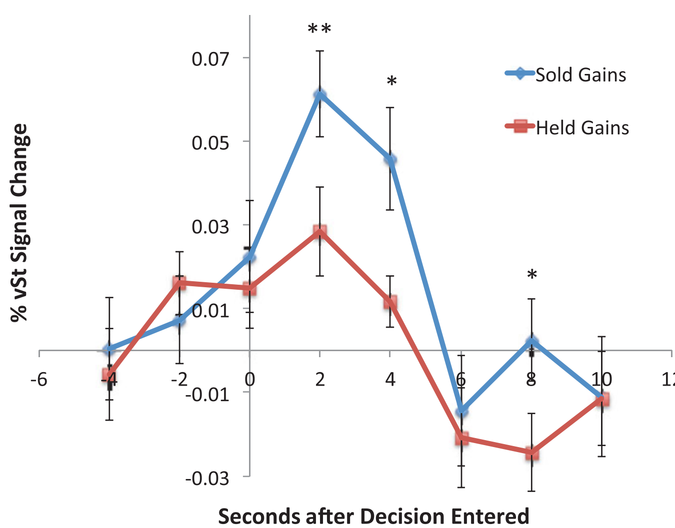


Figure 8. Direct tests of the realization utility hypothesis. Panel A: Yellow voxels are those in our a priori region of interest in the vSt. Red voxels are those that exhibit greater activity when subjects realize capital gains compared to when they hold capital gains (shown at $p < 0.001$ uncorrected with a 15-voxel extent threshold, for illustrative purposes only). Orange voxels are those that are in the intersection of the two groups. The $y = 6$ coordinate indicates which two-dimensional plane is shown in the brain map. Panel B: The figure shows the time-course of activity in the vSt, averaged over the a priori region of interest, during trials when subjects are offered the opportunity to sell a stock trading at a gain. The blue line plots the average activity in trials where subjects decide to realize the gain, while the red line plots the average activity in trials where subjects instead decide not to realize the gain. ** denotes $p < 0.01$, * denotes $p < 0.05$ (paired t-test). $t = 0$ corresponds to the instant at which the subject enters his trading decision on a hand-held device.

that realizing a capital gain (the second nonconstant regressor) has on neural activity in the vSt, after controlling for the size of the capital gain (the first nonconstant regressor).[34] The key test of interest is whether there are voxels within the target vSt region for which β_2^v, averaged across subjects, is significantly positive.

Consistent with Prediction 4, we find a region of the vSt in which activity correlates positively with the realization of capital gains (see Panel A of Figure 8, $p < 0.05$, SVC), while controlling for the magnitude of the capital gain. Panel B of Figure 8 shows the time-course of the average BOLD response in the original 68-voxel target vSt region when subjects issue a command to sell a capital gain (the blue line) compared to when they issue a command to hold a capital gain (the red line).[35]

Ideally, we would also carry out a test for the case of capital losses; specifically, we would test for a negative impact in the same area of the vSt when a capital loss is realized. Unfortunately, the data do not allow us to do this. As predicted by the realization utility hypothesis, subjects realized very few losses over the course of the two fMRI sessions they went through (the mean number of realized losses per subject session is three). As a result, we do not have the statistical power we need to look at the difference in neural responses when a loss is realized versus not realized.

E. Tests of the Mean-Reversion Theory of the Disposition Effect

As discussed in Section I, one prominent alternative theory of the disposition effect is that investors believe that stock prices mean-revert (Odean (1998), Weber and Camerer (1998), Kaustia (2010)). In our setting, such a belief would be irrational, as stock prices in our experiment exhibit *positive* autocorrelation. Nonetheless, if, for some reason, our subjects *think* that stock prices in our experiment are mean-reverting, this could potentially explain why they tend to sell stocks that have recently gone up and hold on to stocks that have recently gone down. In this section, we test this alternative theory using both behavioral and neural data.

To investigate whether a belief in mean-reversion is driving our subjects' behavior, we estimate the following mixed effects logistic model, which tests

[34] We include the onset of the decision screen for capital loss trials only as a control variable in this model.

[35] The time-course of BOLD responses is based on a GLM specification that uses a series of dummy variables that correspond to our events of interest: holding a capital gain and selling a capital gain. For each of these two events, $x = hold$ and $x = sell$, with additional controls for the onset of price update screens, buying opportunities, and capital loss trials, and for $n = 1, \ldots, T$, we define a series of dummy variables, $d(t|x, n) = \begin{cases} 1 & \text{if } x \text{ occurred at } t - n \\ 0 & \text{otherwise} \end{cases}$. The GLM is then specified as $b^v(t) = \text{constant} + \sum_{x,n} \gamma_{x,n}^v d(t|x, n) + \beta_1^v \text{session} + \beta_2^v \text{movement} + \varepsilon(t)$. The estimate of the change in the BOLD response n seconds after the presentation of stimulus x is then given by $\gamma_{x,n}$. "Session" and "movement" are control vectors for session-specific effects and physical movement inside the scanner, respectively.

whether, as predicted by the mean-reversion hypothesis, recent price changes can significantly predict subjects' decisions to sell or hold a stock:

$$sell_t = \text{constant} + \beta_1 \text{NEV}_t + \beta_2(p_t - c_t) + \beta_3 \Delta^1 p_t + \beta_4 \Delta^2 p_t + \varepsilon_t. \tag{11}$$

Here, $sell_t$ equals one if the subject sells the stock under consideration at time t and zero if he holds it, and $\Delta^m p_t$ denotes the m^{th} most recent price change for this stock (these price changes may not have occurred in consecutive trials because price updates in the experiment take place at random times). We find that the capital gain has a coefficient of 0.017 and is a significant predictor of the propensity to sell (t-stat $= 2.93$), but that none of the other variables are. In particular, neither β_3 nor β_4 is significantly different from zero ($p = 0.569$ and $p = 0.197$, respectively). In other words, contrary to the mean-reversion hypothesis, recent price changes do not significantly predict the decision to sell.[36]

We can also use the neural data to test the mean-reversion hypothesis. In particular, we test if neural activity in the target region of the vmPFC, defined at the end of Section III.C, is correlated with recent price changes. We do this by estimating the following GLM:

$$b^v(t) = \text{constant} + I_{\text{dec}}(t)[\beta_1^v(p_t - c_t) + \beta_2^v \Delta^1 p_t + \beta_3^v \Delta^2 p_t] + \beta_4^v \text{controls} + \varepsilon(t). \tag{12}$$

Under the mean-reversion hypothesis, the decision value of selling should be positively correlated with recent price changes: a recent price increase indicates a lower expected future return and hence a higher decision value of selling. This hypothesis thus posits that responses in the vmPFC (i.e., the area involved in the computation of decision values) should correlate positively with past price changes. Contrary to this hypothesis, however, we do not find any activity in the vmPFC that is significantly associated with the past price-change regressors at our omnibus threshold of $p < 0.05$ SVC. In summary, both the behavioral and neural analyses cast doubt on the mean-reversion hypothesis.[37]

[36] Our experimental design implies a high correlation between NEV and recent price changes. To check the robustness of our result to any collinearity issues, we also estimate the logistic regression without the NEV variable. We again find that the capital gain significantly predicts the sell decision, but that neither of the two most recent price changes does.

[37] While our results cast doubt on the hypothesis that mean-reverting beliefs are driving our subjects' decisions, one can ask whether there are other non-Bayesian belief specifications that could explain the observed trading patterns (see, for example, Kuhnen and Knutson (2011)). In Frydman and Rangel (2013), a companion behavioral paper, we shed some light on this issue. In that paper, we compare subjects' trading behavior across a variety of treatments that differ only in the information shown on the trading screen. One of the treatments is the one used here. In another treatment, however, we also give subjects the NEV statistic on each trading screen; in other words, we effectively give them the correct Bayesian beliefs. As a result, if subjects persist in exhibiting a disposition effect, it is very difficult to attribute this to non-Bayesian beliefs. We find that the addition of the NEV statistic decreases the size of the disposition effect that subjects exhibit, but that it nonetheless remains substantial. This suggests that at least some portion of the disposition effect that we find in the current study is not due to non-Bayesian beliefs.

V. Discussion

In this paper we use neural data, obtained through fMRI while our subjects trade stocks in an experimental market, to test the key assumptions of the realization utility theory of investor trading. We find broad (albeit not perfect) support for the neural predictions of this theory. First, we find that activity in the vmPFC, an area known to encode decision values, is correlated with the capital gain (the decision value under realization utility), but not with a measure of the net expected value of future returns (the decision value under the expected value model). Second, we find that the strength with which the capital gain is reflected in the vmPFC decision value signal is correlated, across subjects, with the proportion of gains realized; we do not, however, find the analogous correlation for capital losses. Finally, and perhaps most striking of all, we find that activity in the ventral striatum, an area known to encode information about changes in expected lifetime utility, exhibits a positive response when subjects realize capital gains, controlling for the size of those gains. This finding is striking because it provides a direct test of the key mechanism at work in the realization utility model; it would have been very hard to carry out such a test without neural data.

As noted in the previous paragraph, we do not find a correlation across individuals between the strength with which a capital loss is reflected in the vmPFC and the proportion of losses realized. Here we speculate as to why. One possibility is that the simple model of linear realization utility that we test is incomplete in important ways. First, recall that individuals who experience realization utility at the time of selling, and who are sufficiently myopic, will accelerate the sale of assets involving capital gains and delay the sale of assets involving capital losses, even though this is suboptimal under the expected value model. When we compute the decision value of selling for realization utility traders, we assume that they are fully myopic. However, if the cross-individual variation in the discount rate for losses is sufficiently larger than that for gains (a hypothesis that has not yet been tested), then the decision value of selling a loss will be measured in our regression models with more noise than the decision value of selling a gain.[38] If this is the case, we are more likely to detect a behavioral-neural correlation for capital gains than for capital losses, even if subjects experience realization utility in both cases. Second, the cross-subject correlation between the extent to which capital gains and capital losses are reflected in the vmPFC is only 0.01, while the cross-subject correlation between the propensity to realize gains and the propensity to realize losses is only 0.03. This suggests that individuals may attend differently to gains and

[38] Recall from Section II.C that, when computing the decision value of selling for a realization utility agent, we assume that he is fully myopic. This means that he places zero value on holding the stock, so that the decision value simply equals the value of selling. If, instead, the agent does not fully discount the future, the value of holding will be nonzero, and the actual decision value of selling will be different from what we specify. If there is more heterogeneity in the discount rate across subjects for losses than for gains, there will be a more severe misspecification in the decision value of selling a loss compared to the decision value of selling a gain.

losses in a way that is not captured by our realization utility model (Karlsson, Loewenstein, and Seppi (2009), Kuhnen and Knutson (2011)).

These modifications of the benchmark realization utility model are inspired by the data, but are clearly also post-hoc and speculative. The good news, however, is that the same methodology that we use here can also be applied to test these alternative specifications. We emphasize that the methods we present in this paper are not a substitute for traditional empirical methods in finance. On the contrary, brain imaging techniques are complementary tools that can be used to test assumptions about investor behavior that are difficult to evaluate using field data or experimental data alone. In particular, we see neural data as a valuable resource when studying the more psychological dimensions of investor behavior, precisely because these may derive from variables that are only observable at the neural level. For example, using the same data set as in this study, we are examining how neural measures of regret, which are very difficult to measure objectively in the field, can impact trading behavior in a systematic way (Frydman, Camerer, and Rangel (2012)). The identification of investors' reference points—the reference rates of return that they use to determine whether an investment outcome is a "gain" or a "loss"—is another challenging question that neural data may help us answer.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Appendix S1: Internet Appendix.