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A Simple Economic Conjecture of Neural Activations, Information Retrieval, and Discount Rates with an Application to fMRI

Amanda S. Bruce
University of Kansas Medical Center, abruce2@kumc.edu

John M. Crespi
Iowa State University, jcrespi@iastate.edu

Jayson Lusk
Oklahoma State University, jayson.lusk@okstate.edu

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Disciplines
Econometrics | Radiology

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Amanda S. Bruce
University of Kansas Medical Center

John M. Crespi[1]
Iowa State University

Jayson L. Lusk
Oklahoma State University

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Iowa State University

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[1] Contact author: jcrespi@iastate.edu; 515-294-1699. Dept. of Economics, 369 Heady Hall, Iowa State University, Ames, IA 50011-1070. The authors thank Andy Barkley, Giacomo Bonanno, Colin Cameron, Brad Cherry, Laura Martin, Stephan Marette and Brandon McFadden and seminar participants at Iowa State University, University of California-Davis, and Iowa State University for helpful suggestions. The authors are thankful for the technical support of the Hoglund Brain Imaging Center and funding from the Agriculture and Food Research Initiative (AFRI), Foundational Program: Economics of Markets and Development Proposal Number: 2010-04805. Crespi acknowledges partial funding from the USDA National Institute of Food and Agriculture Hatch Project No.1010309.

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When considering the length of time to make a decision, nearly all economic discussions concern either lengthy delays of years and generations or studies of necessarily quick reaction times or decisions made under significant time stress. Very little has been written about normal decision times falling within these extremes where consumers themselves determine the time to decide, yet this is how the majority of daily decisions are made. The goal of this paper is twofold: first, to provide an economic framework to a consumer's decision time and, second, to derive from that economic framework some guidance on the use of data gathered from a brain scan. The paper builds a simple theoretical model combining elements of the economic and psychological literature on decision-making in the presence of differentiated products. This model is consistent with recent efforts in the field of neuroeconomics to construct a theoretical rationale for the incorporation of the commonly used contrasts from blood-oxygenation-level-dependent (BOLD) scans generated during functional magnetic resonance imaging (fMRI).

In 1993, Payne, Bettman and Johnson's book, *The Adaptive Decision Maker* and Svenson and Maule's (eds.) *Time Pressure and Stress in Human Judgment and Decision Making* presented the results of numerous studies on how decisions in the face of time pressure are made. Discussion of decision time heuristics under time pressure such as the effort-accuracy models have been subjected to much empirical work seeking to determine how decision-makers make the risk-return calculations necessary for efficient choices and how people adapt their decision making strategies under the pressure of opportunity cost. With more recent developments in the field of neuroscience and behavioral economics, the foundations beneath how the brain makes quick decisions has emerged. Bestsellers like Gladwell's (2005) *Blink: The Power of Thinking without Thinking* and Kahneman's (2011) *Thinking Fast and Slow*, detail the scientific exploration of how decisions are made with Kahneman condensing much of the research on choices into one of two types: quicker, automatic "system 1" choices and slower, deliberative "system 2" choices. In much of economics, however, little attention has been given to what influences the decision time in everyday choices. Yet, psychologists and neuroscientists have performed a myriad of studies to better characterize decision times.

Many decisions are made quickly and often with uncertain information. With computer trading, the speed of financial decisions is approaching instantaneous. Even with so-called "breaker switches" built into the technology, human overseers find themselves making decisions in tenths of seconds, occasionally with disastrous side effects. The "flash crash" of May 6, 2010 is now famous. At 2:42 pm, a high-frequency trade program at a single mutual fund triggered a buy-and-sell chain reaction with other firms' trading programs dropping the Dow index by 600 points ($4.1 billion in market value). A combination of programs and human traders caused the index to slingshot back to its initial value by 3:07 pm leaving traders and regulators scrambling to figure out whether the drop was based on fundamental changes to market valuations, software glitches, or collusion (Bowley 2010). Though most "Financial Black Swans" are less dramatic than the 2010 event, they are nevertheless regular occurrences in today's financial markets (Johnson et al. 2012). Industry traders and regulators are considering regulations that would slow down trades to a still astoundingly quick 50 milliseconds between an offer and a trade (Popper 2012). Better economic understanding is needed for how decision times of short duration are affected.

Stock trading is a dramatic example of financial decision-making because of the size of the valuations, but all people make daily decisions in very short time intervals. Experiments have shown that humans can react with hand signals to visual stimuli in as little as 23 milliseconds (Blinkov and Nikandrov 2002). Longer times are needed when a thoughtful decision must be made, though in many decisions, the time is still measured in less than a second or two. The greater one's expertise and information (whether in trading, shopping, or driving) the less time is needed (Visser et al 2007). For comparison, a chess grand master needs roughly 650 milliseconds to determine whether a king is in peril (Johnson et al. 2012) while typical drivers need 1,500 milliseconds to brake unexpectedly but about half that time when the stop is expected (Green 2000). One could say that experienced drivers facing a typical commute are as much an expert at driving as a grand master is at playing chess as measured by reaction time. Milosavljevic, Koch and Rangel (2011) show that when faced with known products, healthy adults can take as little as 313 milliseconds to decide which of the two goods they prefer. Another study demonstrated that when hungry, participants facing pairs of real food choices take only 1,700-2,700 milliseconds to decide (Krajbich, Armel and Rangel 2010). In a study using some of the same data that will be used in the present work, Crespi et al. (2015) found that regions of interest in a decision phase of an economic choice of milk products differed from regions involved in the deliberation over that choice. What Crespi et al. (2015) did not offer was an economic theory to help understand how those ROIs fit into the decision time needed to make such economic decisions.

The goal of this paper is twofold: first, to provide an economic framework to a consumer's decision time and, second, to derive from that economic framework some guidance on the use of data gathered from a functional magnetic resonance imaging (fMRI) brain scan. The paper builds a simple theoretical model combining elements of the economic and psychological literature on decision-making in the presence of differentiated products. An extension of the general model then incorporates the commonly used contrast method from blood-oxygenation-level-dependent (BOLD) scans generated during fMRI. With the growing use of these techniques, economists have been challenged (e.g. Caplan and Dean 2007, Glimcher, Kable and Louie 2007, Bernheim 2009, Levy and Glimcher 2012, Farb 2013) to find ways of incorporating the neural findings into economic theory in a meaningful way. While arguments have been made that neuroeconomics needs better linkages between brain activity and economic theory (see reviews in Farb 2013 and Glimcher, Kable and Louie 2007), such links are arguably more difficult with BOLD variables than with other measures of brain activity because an fMRI scan provides only a snapshot of neural activity in a single task and BOLD variables are then constructed as an average across these tasks. As Webb et al. (2013) demonstrate, more theoretical work is needed to link particular constructions of BOLD contrasts to traditional utility but the more this is achieved, the greater the usefulness of fMRI. Important first steps have been made to incorporate BOLD variables in this way (see Glimcher 2009, Webb et al. 2013). The model in this paper creates such a link via well-known models of product differentiation and discounting leading to refutable hypotheses of the impact of economic and neurological variables on time-to-decision. The novelty in this paper is demonstrating that product differentiation models with exponentially discounted opportunity costs of decision-time can be manipulated to express decision-time as a percentage change in an underlying marginal valuation. As such, it is not just the measurement of decision time that is of interest, but also the relationship among the economic covariates, especially the marginal valuation expression, and decision time that leads to testable implications on the usage of BOLD percentage signal changes in areas of the brain associated with valuation. The importance of the economic theory is that it provides the comparative statics for the direction of the effects. The empirical results support the economic framework and show economic variables such as the opportunity cost of a consumer's time, magnitude of price differential among competing goods, and the certainty of the choices affect decision time in predictable ways. Most importantly, the empirical results demonstrate that BOLD activations in areas known to be associated with valuation and uncertainty also affect decision time in a manner predicted by an economic theory of product differentiation.

Background.

Until recently, when modeling decision time, economists have mostly focused on the time value of money and its impact on choices over relatively long planning horizons. Even when choices are made quickly, the emphasis is how these choices impact future payoffs in the realm of days, months or years. Examples are many but a selection of articles includes Hotelling (1925) on the optimal time to sell a depreciating asset; Diamond (1965) on the choices between consumption in one generation versus consumption in another; the impact of search costs on unemployment (Mellow 1978), inflation (Paroush 1986), and industrial organization (Stiglitz 1987, Stahl 1989); Brown, Chua and Camerer (2009) on lifetime savings rates, Andersen et al. (2008) and Andreoni and Sprenger (2012) on experimental approaches to eliciting time preferences (see Frederick et al. 2002 for a review), impulsive or seemingly self-destructive behavior and long term health effects (Becker and Murphy 1988, Chaloupka 1991, Grossman, Chaloupka and Sirtalan 1998), and the number of works on the effect of time and discount rates on consumption in the macroeconomy are so numerable that they are best left to perusals of textbook references (e.g. Romer 1996). Many works attribute the differences in choices to differences in underlying temporal discounting functions (e.g. Loewenstein and Elster 1992, Loewenstein and Prelec

1992, Laibson 1997, Myerson, Green and Warusawitharana 2001, Green and Myerson 2004). Phelps and Pollak (1968) posited a utility framework for intertemporal altruism that was subsequently adapted in work on the timing of decisions by Laibson (1997), O'Donoghue and Rabin (1999) and McClure et al. (2004). Laibson (1997) generalized the discussion to how consumers make discounting decisions. Much of the discussion in Laibson (1997) and subsequent papers concerns whether discount functions are more-or-less exponential (preferences are discounted consistently over time, Samuelson 1937) or another form like a hyperbolic discount (which could explain why agents react to nearby decisions differently than more distant ones). Yet the impact of decisions over very short time intervals has generally not been studied in economics. This is surprising given the number of daily transactions that fit such a description. Per capita, per-unit time costs of such decisions are extremely low, yet the cumulative effect of an extra second of decision time per product and per person in a large economy can be substantial.

In cognitive psychology, however, there is great interest in how fast it takes a person to make a choice given the perception of the objects in the choice set. "Drift-diffusion" or "accumulator" models are used when decision time is of interest, whether "mistakes" are made as time is shortened or how response time is affected when product attributes are altered.[1] Under these types of designs, the

[1] The concept is important to understand for the model proposed in the next section. Think of two choices before a participant as being denoted the "left" choice and the "right" choice. The choice set is withheld from the participant and with no knowledge of the unseen choices it is hypothesized that an internal information signal is at the point of indifference, a midpoint. As soon as a participant views the choices, a chronometer is started. As time progresses, the participant is assumed to increase her knowledge while making the choice so that the cumulative relative value of the information signal moves leftward or rightward. Thinking of each choice as existing on the frontier of an imaginary barrier and at time t=0, the consumer is at a midpoint between the two barriers, then at t>0 a choice is made when the consumer's cumulative relative information value crosses either the right or left barrier.

theory is that a person compiles product information and once the information retrieval reaches a person-specific, but unobservable threshold level, a decision is made. As such, the recording of time-to-choice is a proxy for product information with shorter response times indicating faster information retrieval. Interested readers are referred to the discussion and reviews of the literature in Townsend and Ashby (1983), Bloxom (1985), Ratcliff and Rouder (1998), Smith and van Zandt (2000), Rustichini (2009), and Simen et al (2011). The psychological research on response time is evident in marketing research as well (e.g. MacLachlan, Czepiel and LaBarbera 1979, Tyebjee 1979, MacLachlan and Myers 1983, and Haaijer, Kamakura and Wedel 2000). Neuroeconomics, an emerging field melding economics, psychology, and neuroscience, seems the only sub-discipline in economics examining decision times with many of these being reaction time studies. Experiments such as McClure et al. (2004), Kable and Glimcher (2007), Basten et al (2010), Milosavljevic et al. (2010), Krajbich, Armel and Rangel (2010), Milosavljevic, Koch and Rangel (2011), Krajbich and Rangel (2011), Krajbich et al (2012) examine the interaction between response times, functional brain activations, and subjective valuations of the goods. Indeed, these latter models, especially Krajbich et al. (2012), make progress toward a theoretical neural model for response times based upon inferences about how the brain gathers information. Still many of these studies focus on reaction time, with interest in how quickly and accurately someone can make a decision. Further, although these models have important economic interpretations, they do not follow the standard paradigm (Sutton 2000) of providing a refutable hypothesis from an underlying economic theory; though they certainly go a long way toward developing an underlying neural theory of decisions. Although they can and do, as Basten et al. (2010, p. 4) claim, “demonstrate the power of model-driven fMRI analysis” the models utilized are typically of the drift-diffusion or related information-gathering algorithms. To our knowledge, no decision-time models using fMRI derive testable implications based upon an underlying theory of *economic* choice allowing predictions of the direction of effect when prices, qualities, or measured BOLD signals change. Further, as opposed to reaction time studies, our interest is in the more typical case of decision times under less pressure. For example, in a typical shopping trip where there is some opportunity cost of time but where shoppers may encounter new and unfamiliar products requiring deliberation. It is our hope that the simple model that follows provides fodder for future research as a complementary means of advancing the research on decision times and the use of fMRI data in an economically obvious manner.

Conceptual model.

Our interest is decision times over relatively short durations but this is not a reaction time model. In reaction time experiments, participants are instructed to make decisions quickly. Shoppers, however, are not told to move through a supermarket quickly and traders may feel pressure to buy or sell, but such pressure is self-imposed. A good starting point is asking where the pressure to make a choice comes from in these day-to-day decisions? The standard answer would be the opportunity cost of time. We begin our framework combining the intertemporal choice model of Laibson (1997) with a similar parameterization of utility used extensively in the literature on product differentiation developed by Mussa and Rosen (1978). We add to these the spirit of the information-gathering axioms as discussed in Rustichini (2009) with regard to information contained in quality signals.

Rustichini (2009, p. 42) argues “that the time to decide (the response time that we observe) is a hill-shaped function of the quality of information.” The hill shape is due to a tradeoff in decision time between collecting more information (the upward slope of the hill) and the opportunity cost of time (the downward slope). In the model we propose, participants have a monetary endowment and must make a decision that impacts this endowment with no restriction on how long that choice may take. Consider the decision of shopper *i* with endowment y_i facing a decision to purchase one of two goods offered at respective prices p_1 and p_2. Unlike Laibson (1997), we are interested in time intervals of short duration such as a typical supermarket decision and for that reason endowment and prices are unchanged over time. The goods have measurable attributes (e.g. size, shape, nutrition, color, sugar content, price-equity ratio, etc.) as well as more subjective attributes as perceived by, and hence particular to, the consumer (e.g. taste, healthiness, environmental impacts of the purchase, brand, etc.). Following the convention of Mussa and Rosen (1978) the experience qualities, denoted q_1 and q_2, of the two goods are non-negative such that larger values construe higher quality to a consumer. The consumer chooses between the two goods based upon her perception of the qualities. For example, if $q_1 > q_2$ and prices were equal then the consumer would purchase the good with quality q_1 (vertical differentiation). To induce a consumer to purchase good 2 in this case, its price must fall relative to good 1.

While the endowment, prices, and quality do not change over the short time-to-decision model, something must account for the opportunity cost of time and for the benefit of pondering a decision. Rustichini's (2009) "hill" analogy means that if there is no new information to be gained then the consumer's perceived utility decreases while pondering the choices. The need to ponder the choices arises if one or both of the qualities is uncertain. We use this assertion in our combination of the Mussa and Rosen (1978) and the Laibson (1997) models to create a model of substitute goods with time-dependent utility over quality valuation. Consumers maximize utility subject to their budget constraint and the resulting value (indirect utility) to consumer *i* considering the purchase of one unit of good *j* is given by equation (1):

$$V_{ij}(t) = \delta_i (y_i - p_j) + \beta_i q_j r_{ij}(t_i), \quad i = 1, ..., n; \ j = 1, 2; t_i \in (0, T) \tag{1}$$

Until the product is actually purchased (or consumed), equation (1) can be thought of as an expected value. The parameter $\beta_i \geq 0$ is the marginal utility of quality that is unique to each consumer. In the Mussa-Rosen treatment β_i converts the quality signal, q_j, into a money-metric marginal valuation translating a consumer's quality perceptions into her personal valuation. Each individual has her own "neural currency" an argument proffered in Levy and Glimcher (2012) and V_{ij} is measured in this neural currency. As such, consumers must also have personal exchange rates that translate market prices and income into their neural currency otherwise the valuations between prices and quality would not be comparable. δ_i denotes the individual's neural exchange rate such that if a consumer's income is given by y_i and the market price of good *j* is given by p_j then she internally exchanges these into her neural currency at the rate of δ_i. It is reasonable that, like prices and income, the exchange parameters β_i and δ_i are not time dependent in the very short run.[2]

As measured here, t_i is the time it takes the individual to make a decision with time *T* representing the moment when a purchase is made. Time is a proxy

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[2] Alternative models in line with this specification could be letting $q_i = v_i(q_i)$ with $v_i'(q_i) > 0$ and having consumers choose units of the good itself. Likewise, one could replace β with a more general formulation $g(\beta)$ where $g'(\beta) > 0$ and $g''(\beta) < 0$. As noted in Mussa and Rosen (1978, footnote 2), none of these changes would alter the fundamental aspects of the model but may prove useful in future analyses. For some purposes modeling such a choice might be undertaken by adding a time constraint, much like a labor-leisure tradeoff model. We do not do so here.

for information retrieval and it is this information gathering that affects a good's marginal valuation through the function $r_{ij}(t_i)$. There are many theories as to how information is actually received and used in the brain. Drift diffusion or accumulator models assume that information is updated over time based upon the information obtained in the most recent observation. Following this, we consider an autocorrelated function whereby $r_{ij}(t_i) = r_{ij}(t_i - 1) + u_{ij}(t_i)$ where $u_{ij}(t_i)$ is a new piece of information that is either accepted or rejected and updates the information in the consumer's decision making (assuming a Markov updating process is a common assumption in the drift-diffusion literature).

Time spent considering a purchase is the same for both products and affects the information retrieval functions in a similar though not necessarily identical fashion. Time spent contemplating a purchase has benefits (an upward sloping portion) and costs (downward sloping portion). It is instructive to think of $r_{ij}(t_i)$ as a compound function. For some $\overline{t}$, we posit $r_{ij}'(t_i \le \overline{t}) \ge 0$ and $r_{ij}''(t_i \le \overline{t}) \le 0$ on the portion of the information retrieval function representing an information retrieval "hazard rate." As time progresses, the retrieval function takes on more the role of discount rate where $r_{ij}'(t_i > \overline{t}) < 0$ and $r_{ij}''(t_i < T) \ge 0$. This discount portion is the cost of delaying the purchase affecting the marginal valuation of the good's quality: further deliberation may give you some information, but it is also begins wasting your time. Figure 1 provides an example using a Weibull function with an additive random error.[3] As Kahnemann (2011) discusses, deliberating is effortful and the sooner a decision is made, the sooner the brain can redirect attention to a less effortful activity.

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[3] Specifically, $r(t) = \alpha k(t-1)^{\alpha-1} \exp(-k(t-1)^{\alpha}) + u_t$ with $k = 0.03$, $\alpha = 1.6$ and the error is randomly chosen for $u_t \in (-0.05, 0.05)$.

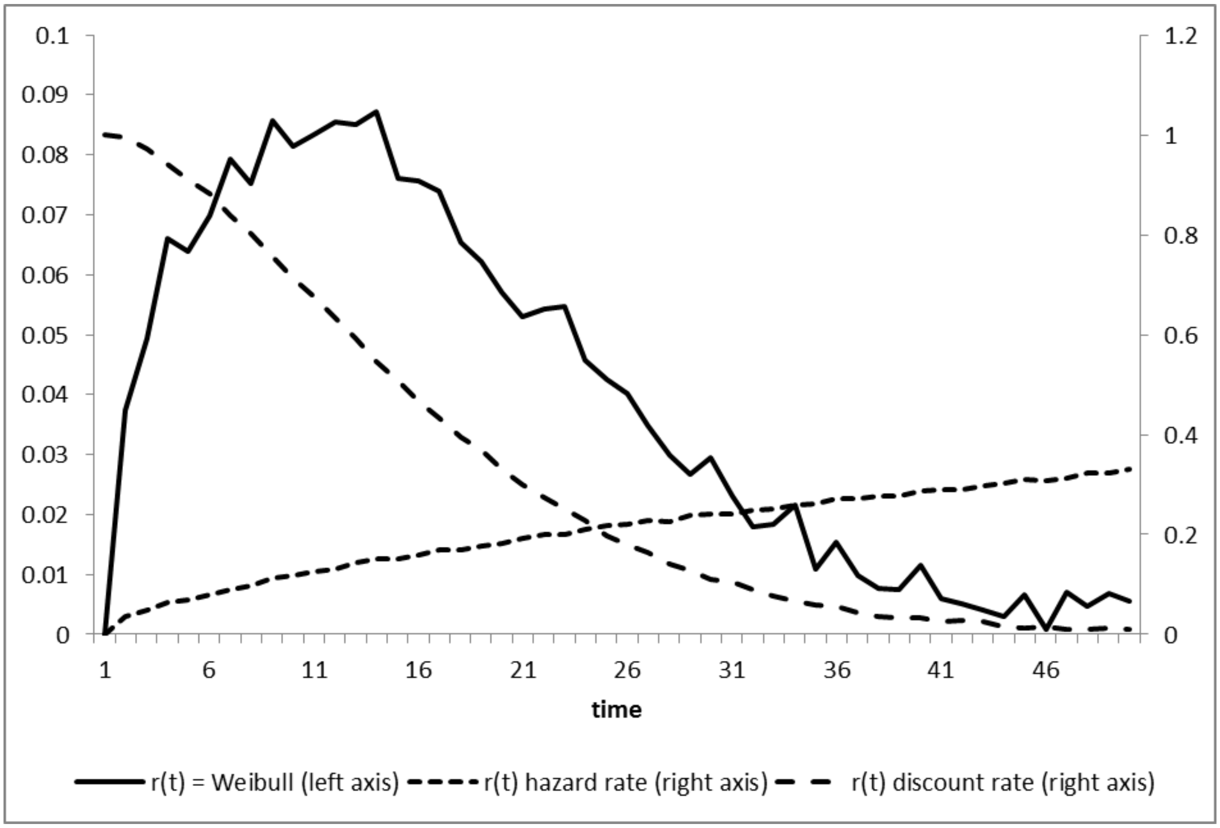

Figure 1. Example of the information retrieval functions using a Weibull distribution with error.

One would expect that upon subsequent encounters, decision time lessens, which is equivalent in this model to a higher level of utility or, more formally, the information retrieval hazard rate having less of an effect than the discount rate on deliberation.[4] Under the diffusion hypothesis, shorter decision times occur because of cumulative information reducing choice time. The analogy is similar in our model, but our model also explains why a shorter shopping decision is preferable to begin with: time negatively impacts value once an adequate amount of information has been retrieved. Many purchase decisions take mere seconds,

[4] A case for lower cost is analogous: people become practiced at a choice, allowing the more "automatic" cognitive processes to take over and this automatic process is utility enhancing because the opportunity cost of thinking time is high (Kahneman 2011).

and we are not considering large changes in welfare. However, even small changes will affect the purchasing decisions at the margin, which is a matter of importance to firms in their marketing decisions and for traders who must often make extremely fast decisions with limited information. Under Mussa-Rosen, the implication of this model is that time to decision indicates "indifference" though it might better be termed as "indecision." From equation (1), deliberation is a result of the information functions constantly rebalancing an indifference equation, $V_{i1}(t<T)=V_{i2}(t<T)$, until enough information retrieval forces an inequality. It is reasonable to believe that a consumer would determine with a heuristic developed a priori whether products are "close enough" to some preferred value. Appending error terms provides the context for an information retrieval random walk (Ratcliff 1978) so that not only are choices made with error but indifference is maintained as long as $V_{i1}(t<T)-V_{i2}(t<T)=\varepsilon_i$ with $\varepsilon_i \in [\ell, u]$ where ℓ and u provide lower and upper thresholds that must be crossed in order to make a choice. Though we do not use this formulation, doing so would allow the model to be interpretable as a simple drift-diffusion model where until some small neighborhood of T is reached it must not be the case that enough time has passed to move the consumer beyond a range of indifference between the value of the two goods. This is not the same as saying the consumer is indifferent between the two goods, just indifferent between their values. The consumer must take into account the overall impact on her valuation from prices and pondering the choices, and even though opportunity cost of time may affect both goods in the same way, quality, prices and retrieving information do not. If one considers the way in which decisions are made in this model when facing two choices, a consumer has two possible states. Once there is no added benefit from considering the goods, either the consumer has a preference or the consumer is perfectly indifferent. In either case, a choice will be made: the preferred product

in the former and either product chosen at random in the latter.[5] In this way we can examine the case of indifference near the point of decision without loss of generality.[6]

Noting that the time it takes to make a decision is an externality to the choice itself, indifference/indecision implies:

$$(2) \qquad r_{i1}(t_i)q_1 - r_{i2}(t_i)q_2 = \delta_i(p_1 - p_2)/\beta_i.$$

Without knowing more about the functional forms the impact of decision time on the relationship is uncertain. Equation (2) nonetheless provides the framework for how long a consumer will ponder a good and we can see that the relationship between the value of the good and the neural exchange rate as well as difference in prices and qualities impact the time to decision in specific ways. The difference on the left of equation (2) is demonstrated in Figure 2 along with its two information retrieval functions.[7] If one can make assertions about this difference, one could discern how the parameters in equation (2) impact decision time. We next consider an example.

[5] Think of the case of perfect substitutes where the budget line falls along the indifference curve. In that case, consumers randomly choose from either good. If the slope of the budget line differs from the marginal rate of substitution, however, a preference for one of the two goods is revealed.

[6] Since the intersection of the sets for "preference" and "indifference" is empty, the time it takes to discover one has a preference is the same time it takes to discover one has lost indifference. For a similar treatment see Andersen et al. 2008, equation (1).

[7] Specifically, $q_1 = q_2 = 1$ and the top function is the same Weibull formulation from Figure 1 while the bottom function uses $\alpha = 1.15$.

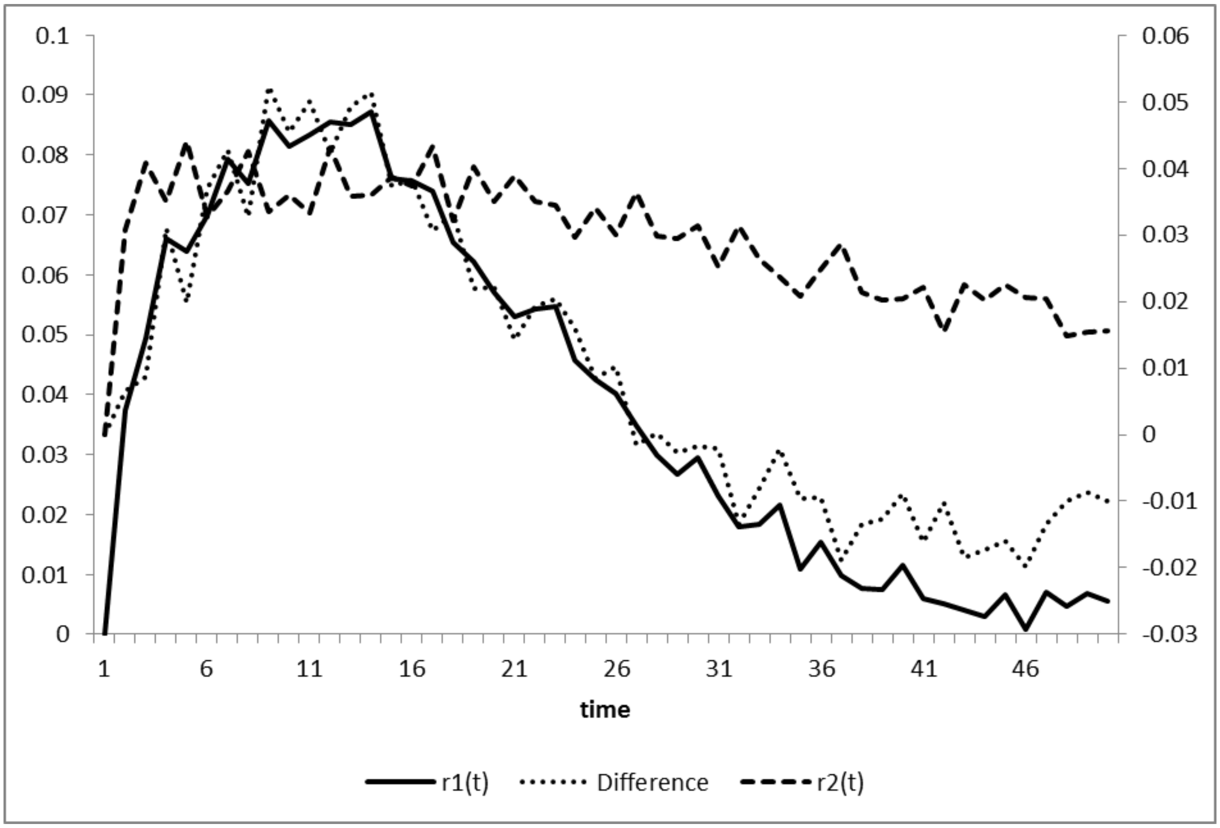

Figure 2. Differencing the information retrieval functions.

An Example: Identical Information Retrieval.

Consider the case where time reveals the same information for both goods: $r_{i1}(t_i) = r_{i2}(t_i) = r_i(t_i)$. This might be the case where, regardless how long the consumer ponders the goods, the information does not greatly distinguish them. This is not to say the two goods are identical, for that depends as well on the underlying quality, q_i. Over the ranges of t discussed above, the information retrieval function could be reasonably assumed one-to-one such that t may be solved over each interval from $t_i \leq \overline{t}$ and from $t_i > \overline{t}$:

(3) $$t_i = r^{-1}\left(\delta_i(p_1 - p_2) / \beta_i(q_1 - q_2)\right).$$

Take for example the case depicted in figures 1 and 2 using a Weibull function $r_i(t_i) = \alpha_i k_i (t-1)^{\alpha_i - 1} \exp(-k_i (t-1)^{\alpha_i})$ with $\alpha_i > 0$ and $0 < k_i < 1$ (and $u_i(t) = 0$ for simplicity). The hazard function dominating the early stage of decision (where information retrieval has a positive effect on value) is given by:

$$(4) \qquad t_i = 1 + \left(\delta_i (p_1 - p_2) / \alpha_i k_i \beta_i (q_1 - q_2)\right)^{1/(\alpha_i - 1)}, \quad i = 1, \ldots, n; t_i \in (0, \overline{t}\,],$$

whereas the discount function dominates as the opportunity cost of the shopper's time increases:

$$(5) \qquad t_i = 1 + \left(\frac{\ln \beta_i (q_1 - q_2) - \ln \delta_i (p_1 - p_2)}{k_i}\right)^{1/\alpha_i}, \quad i = 1, \ldots, n; t_i \in (\overline{t}, T),$$

Different functions and different assumptions will obviously produce different relationships. For example, one could consider the case where one good requires no information retrieval and the consumer is comparing it with a rival that is brand new (or "New and Improved"), so only one of the information retrieval functions is necessary to include in equation (2). Other assumptions can lead to other specifications. The point of the example is that although equation (2) is only implicitly defined, it still can serve as a framework for experiments. As long as it is believed the information retrieval function is composed of both a hazard rate and a discount rate, more assumptions about how information is retrieved or the types of goods offered can provide guidance to the development of refutable implications. We next demonstrate this in an experiment using fMRI.

A Closer Examination of the Discount Function in an fMRI Experiment

One can imagine after many experimental trials with repeat choices, a subject's hazard rate is likely close to constant for the choices. Furthermore, even in the case of an increasing hazard rate for one or both of the goods, a reasonable argument can be made that the discount portion of the information retrieval is identical for both goods in an experiment as the discount rate is impacted by each subject's personal opportunity cost of participating in the experiment. At some point after repeated observations, a subject's time pondering is lowering utility regardless the eventual choice. To model the idea that there is a desire for making a decision quickly, drift diffusion experiments often use thresholds that decay over time, and an empirical regularity in this research (see Milosavljevic et al. 2010) is that the contact thresholds for two goods decay identically and exponentially, making the Weibull function with $\alpha_{ij} = 1$ and $0 < k_i < 1$ a reasonable place to examine the retrieval function and show how the underlying variables can be proxied by frequently used variables obtained from fMRI analysis.

Following this framework, denoting $\tilde{p} \equiv p_1 - p_2$ and $\tilde{q} \equiv q_1 - q_2$, equation (5) can be written as:

$$(6) \qquad t_i = 1 + \frac{1}{k_i}\left[\psi_i + \ln \tilde{q} - \ln \tilde{p}\right].$$

The term $\psi_i = (\ln \beta_i - \ln \delta_i)$ is the percentage difference in a consumer's neural valuation of quality and her neural valuation of wealth. Although such valuations, like utility, are not comparable across individuals, their percentage changes would be in this formulation. fMRI can be used to measure percent signal change in brain activation between two experimental conditions known as contrast or subtraction method and such percentage changes are comparable across subjects (see for example Amaro Jr. and Barker 2006, p. 223). Kable and Glimcher (2007), Glimcher (2009) and Levy et al. (2011) argue that a participant's subjective valuation of a good is strongly correlated with particular BOLD variables extracted from centers of the brain known to be related to valuation. Specifically, Glimcher (2009, p. 509) argues, "subjective values are linearly proportional to the BOLD signal." As such, the model presented here augments the current research seeking an economic usage of BOLD contrasts from regions of interest (ROIs) as opposed to the more common usage of BOLD variables in an exogenous fashion (see Bernheim 2009 for a review). Further, the model shows that such value-laden BOLD variables have economically testable implications for time to decision over the portion of the decision where the discount rate dominates. Specifically, for a particular set of choices, consumers with a larger exchange rate for prices than for the good's value $(\psi_i < 0)$ make faster decisions than an otherwise identical consumer with a positive rate of exchange $(\psi_i > 0)$. Nevertheless, the overall impact of this rate of change on decision time during the discounting period is positive $(dt_i / d\psi_i > 0)$ thus as this rate for either type of consumer increases, the time-to-decision increases.

Equation (6) implies that as time goes on, the greater the ratio of the relative prices leads to quicker decisions ($dt_i / d\tilde{p} < 0$) as will the higher a consumer's opportunity cost of time $(dt_i / dk_i < 0)$. The greater the differentiation between the quality of the goods the longer will be the decision time ($dt_i / d\tilde{q} > 0$). At first pass this might seem counterintuitive; after all, if goods are very distinct, would not that make a decision easier? But recall we are talking about time of indifference, so the goods are substitutes. The closer the goods are to being perfect substitutes, the easier it is to make a decision: as qualities converge $(\tilde{q} \to 0)$, the choice is easier even if it is chosen randomly, so the time to make the choice declines.[8]

[8] Compounding this relationship, however is that the greater the marginal utility from the qualities also *increases* the decision time ($dt_i / d\beta_i > 0$), *ceteris paribus*. This is not immediately intuitive

Again, this is not a model of reaction times, where a consumer must make a decision as quickly as possible. In this current model, the time-to-decision is impacted not only in the relative degree of certainty between the two products, but also in their relative prices, as well as the cost of the time involved to make the decision in the first place. A straightforward extension of this model will be used in part of the experiment that follows to examine whether regions of the brain are active when the choices are between (1) quality attributes and price alone or (2) a combination of quality attributes and price with price alone. The impact on the comparative statics in doing so would be that the sign of $dt_i/d\tilde{p}$ could be either positive or negative if quality is a function of price. This is undertaken based upon experiments indicating some participants do use price to discern the quality of a good. [9]

The experiment.[10]

Fifty healthy, right-handed, English-speaking, adult participants (ages 18-55; mean = 31.6 years; SD = 11.0; 24 females) were recruited from the Kansas City

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and is why the model is important to understand the interaction of knowledge and decision time. As the utility one gets for the quality of the goods increases, a consumer's decision will be very fast if the two goods are similar $(\tilde{q} \to 0)$ but slower if the two goods are dissimilar. Suppose a consumer shopping for a new vehicle places a higher value on sport utility vehicles (*SUV*) than on passenger (*Pass*) cars ($\beta_{SUV} > \beta_{Pass}$), but is considering both vehicle types and in each vehicle type there are two choices. What the model shows is that if the difference in qualities between the two *SUV*s is equal to the difference in qualities between the two passenger cars $(\tilde{q}_{SUV} = \tilde{q}_{Pass})$, the consumer will spend more time considering the *SUV*s, the choice with the higher valuation. This result says nothing about the choice that eventually gets made; only that it is logical to spend more time considering choices with higher valuations.

[9] A nice example of this is given in Otter, Allenby and van Zandt (2008) who find that when television set attributes and prices are similar, decision time declined. Implicitly, consumers with imperfect knowledge about quality use price to provide a quality signal in comparison shopping. Including price as a signal of quality in our model could lead to the same result.

[10] As noted in the introduction, much of the data used in this part of the paper was also used in Crespi et al. (2015). Hence, the discussion concerning the experimental design and extraction of the BOLD variables from the regions of interest in this and the next two sections is nearly identical to the discussion in Crespi et al. (2015). It is offered for completeness.

metropolitan area using internet advertisements and broadcast emails to undergo functional magnetic resonance imaging (fMRI) scanning.[11] All fMRI scans were performed at the Hoglund Brain Imaging Center on a 3-Tesla Siemens Skyra (Siemens, Erlangen, Germany) scanner. Participants' heads were immobilized with head cushions. Following automated scout image acquisition and shimming procedures performed to optimize field homogeneity, a structural scan was completed. T1-weighted, three-dimensional, magnetization-prepared rapid acquisition with gradient echo (MPRAGE) structural images were acquired (repetition time/echo time [TR/TE] = 23/4 ms, flip angle = 8º, field of view [FOV] = 256 mm, matrix = 256 x 192, slice thickness = 1 mm). Then, two gradient-echo BOLD functional scans were acquired in fifty contiguous, oblique, 40º axial slices (TR/TE = 3000/25 ms, flip angle = 90º, FOV = 232 mm, matrix = 80 x 80, slice thickness = 3 mm, in-plane resolution = 2.9 x 2.9 mm, 176 data points). To optimize the signal in ventromedial prefrontal regions of interest in the present study, and to minimize susceptibility artifacts, all participants were positioned such that the angle of the anterior commissure-posterior commissure (AC-PC) plane fell between 17º and 22º in scanner coordinate space, as verified by a localization scan. This careful positioning, utilized by Bruce et al. (2013), ensured the 40º acquisition angle was applied uniformly for all participants, again, minimizing susceptibility artifacts while standardizing the head positions of participants of divergent body sizes.

[11] Exclusion criteria included current psychotropic medication use, current or past substance abuse, participant report of diagnosis of severe psychopathology (e.g. depression, schizophrenia), current vegan diet, and self-reported lactose intolerance (due to the milk product stimuli). Educational attainment was reported as high school (n = 26%), some college (n = 26%), bachelor's degree (n = 40%), and graduate degree (n = 8%). Household income was evenly distributed; by self-report, annual household incomes were less than $20,000 (*n* = 15, 30%), between $20,000 and $39,999 (*n* = 10, 20%), between $40,000-$59,999 (n = 14; 28%), between $60,000-$79,999 (n = 6; 12%), between $80,000-$99,999 (n = 4; 8% and greater than $100,000 per year (n = 1; 2%).

fMRI Experimental Paradigm

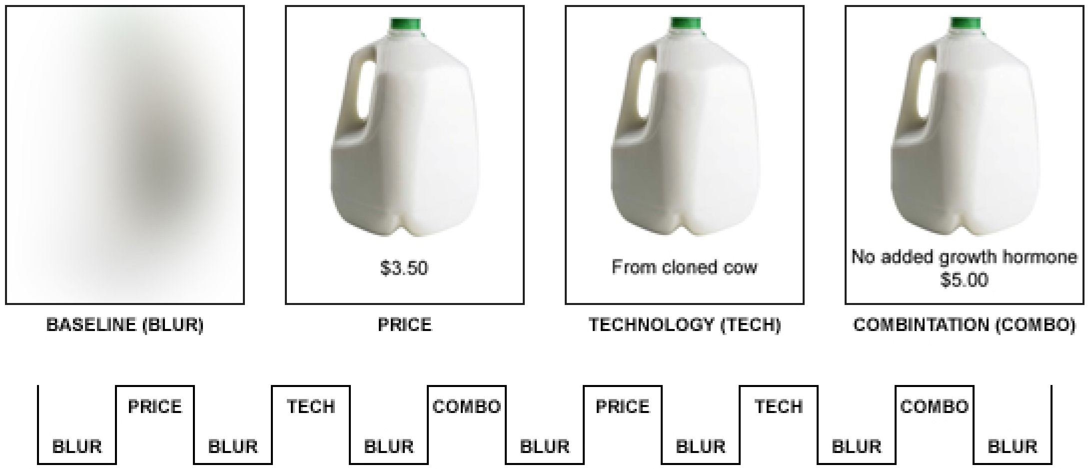
For the experiment we chose milk, a product that would be commonly known and frequently purchased. Individuals who reported lactose intolerance or a current vegan diet were excluded. Specifically, we used images of typical, handled plastic-gallon jugs of milk that would be familiar to shoppers. Aside from the wording beneath the images, the images were identical. To introduce differentiation in the choice quality, technology attribute images were labeled with the following statements: “From cloned cow” or “Not from cloned cow” and “Artificial growth hormone” or “No added growth hormone.” Milk from cloned cows has been approved by the FDA as safe for human consumption but has not entered the market at the time of this study. Milk from cows receiving growth hormones has been approved for human consumption but has proven unpopular with consumers (in fact many milk brands explicitly label that they do not contain milk from cows receiving growth hormones–particularly recombinant bovine somatotropin, or, rBST). Table 1 provides some insight into the subject’s familiarity with the labels we used as well as knowledge of other food production technologies. The first two rows of Table 1 reveal that the typical participant was mostly unfamiliar with either cloning or rBST production technologies.

Table 1. Participant familiarity with Milk Products used in the Experiment.

Question	Avg	Min	Max	Notes
1. How much do you know about farm animal cloning?	2.38	1	7	
2. How much do you know about rBST used in dairy cattle?	1.62	1	6	
3. How much do you know about artificial growth hormones?	2.80	1	7	
4. How much do you know about how organic foods are processed?	3.08	1	7	
5. Cloned cattle contain genes, but regular cattle do not.	0.02	0	1	Correct answer is 'false'.
6. Milk from cloned cows contains genes, but milk from regular cows does not.	0.06	0	1	Correct answer is 'false'.
7. All milk contains some amount of growth hormones.	0.56	0	1	Correct answer is 'true'.

Notes: In questions 1-4 the scales are 1= "No knowledge", 4= "Some knowledge" and 7= "A lot of knowledge." In questions 5-7, participants were asked to rate the statement as "False" or "True" and their answers were coded as 0=False; 1=True.

Each participant underwent a series of fMRI scans, including two localizer scans, a structural scan, and three functional scans. For the functional scans, images were back-projected onto a screen mounted at the rear of the fMRI scanner's bore, and participants viewed these images through a mirror integrated into the head coil. The first functional scan was a "passive viewing" design where subjects observed the products one by one and no decisions were made (see the top half of Figure 3). The passive viewing experiment is detailed in Bruce et al. (2014). Next, participants were presented with 84 binary choices between two milk products (see the bottom half of Figure 3 for an example). The products in each choice were labeled with information about the products' prices and the technologies used to produce them. These labels differed according to three conditions: a "price" condition, in which the price of one product was high, and the other low, but the technologies used to produce them were the same; a "technology quality," in which the technology used to produce one product was controversial, and the other conventional, but their prices were the same; and a "combination" condition, in which the prices of the two products differed, as did the technology qualities. Before choosing, participants were presented with the following instructions: "You will make a series of choices between two food products. To choose the option on the left, use your index finger. To choose the option on the right, use your middle finger. Please choose carefully, as you will receive one of the food products you choose at the end of the experiment." They were given a half-gallon of milk to take home at the conclusion of their participation in the study with the price of the milk they chose deducted from the $50 they received for participating in the experiment. To more closely simulate shopping behavior, participants were allotted unlimited time to make each choice (e.g. optimal decisions and decision time rather than speed of decision was the focus). Following each choice, participants were presented a confirmation screen indicating which choice they had selected for 0.5 seconds. There were two functional runs where participants made 42 choices (84 total choices).



Passive Viewing Example.

Active Choice Example.

Figure 3. Illustrations of fMRI experimental paradigms (top: passive viewing, bottom: active choice) including experimental conditions of interest.

fMRI Data Analysis

Functional magnetic resonance imaging data were initially analyzed using the BrainVoyager QX statistical package and random effects (Brain Innovation, Maastricht, Netherlands, 2004). Preprocessing steps included trilinear 3D motion correction, sinc-interpolated slice scan time correction, 3D spatial smoothing with 4-mm Gaussian filter, and high pass filter temporal smoothing. Functional images were realigned to the anatomic images obtained within each session and standardized using BrainVoyager Talairach transformation, which conforms to the space defined by the Talairach and Tournoux's (1988) stereotaxic atlas. Functional scans were discarded if participants moved more than 4 mm along any axis (x, y, or z). Two runs were discarded due to excess motion and three participants were unable to complete Phase 2, leaving a total of 92 runs.

Activation maps were analyzed using statistical parametric methods (Friston et al. 1995) contained within the BrainVoyager QX software. Statistical contrasts, or differences, in the blood oxygenation level-dependent (BOLD) activations between the price and technology conditions and price and combination conditions were conducted using multiple regression analysis with the general linear model (GLM) with motion parameters included as nuisance regressors. Regressors representing the experimental conditions of interest were modeled with a hemodynamic response filter and entered into the multiple-regression analysis using a random-effects model. Contrasts between conditions of interest were assessed with *t* statistics. Multiple comparisons were corrected for using a familywise error rate based on a Monte Carlo simulation conducted within the BrainVoyager software (k = 16 voxels) (Goebel et al. 2006; Lieberman and Cunningham 2009); further details of these tests are left out of the present paper but are available from the authors.

Milk produced using new technologies is posited to impact consumers' valuation of milk, hence our focus after the whole brain analysis was on ROIs related to valuation. Levy and Glimcher (2012) synthesized much of the fMRI literature on revealed preferences to find common activation areas hypothesized to be related to valuation in vmPFC and other areas. They challenged the profession to begin focusing in on valuation as a target of analysis "where the high resolution physiology of valuation can become a tractable goal" (p. 9). As they opine, "Indeed, there is now broad consensus in the neuroscience of decision-making community that reward magnitude is represented in a small number of well-identified areas" (p. 1) and as such "[t]his could lead to more concrete and testable predictions using hypothesis testing" (p. 9). After reviewing much of the fMRI research, Kable and Glimcher (2007), Glimcher (2009) and Levy et al. (2011) argue that a participant's subjective valuation of a good is strongly correlated with particular BOLD variables extracted from these "well-identified areas." We extracted percent signal change from regions asserted to be associated specifically with valuation in the decision-making process (Levy and Glimcher, 2012, Table 1).

Value is a tradeoff between the desirability or benefits of the product which differ from consumer to consumer and the price of the product which is the same for each consumer. In order to take both of these components into account, we narrowed our search of the areas identified by Levy and Glimcher (2012) to only those areas with significant activation when looking at images of technology qualities and significant activation when looking at images with price alone (*Tech v. Price*) or when looking at images of a combination of technology and price and images of price alone (*Combo v. Price*). This additional degree of narrowing the definition of neural activity adds even greater conservatism to the analysis. We were able to do this because of the large subject sample we had available. The BOLD variables in this paper are the percentage signal change difference in activation from the images that contain the qualities, e.g. the technology or combination images, and the activation from the images that contain the prices alone, which is a significant difference from the BOLD construction in Crespi et al (2015), who were not guiding their BOLD choices from an underlying economic theory that implicated the differences between quality an prices.[12]

Given these constraints set on our ROIs, our experiment showed significant differences in the eight value-related areas shown in table 2.

Table 2. Brain Activation Regions of Interest, BOLD percent signal change contrasts (N = 47)

Region of Interest (Max Voxel Coordinates x,y,z)	*fMRI phase*	*BOLD Differences*	*Mean (Std Dev)*	*Variable Name*
1. Left dorsolateral prefrontal cortex* (-43, 13, 24)	passive	*Tech – Price*	0.021 (0.091)	*ldlPFC-t*
2. Left dorsolateral prefrontal cortex* (-43, 13, 24)	passive	*Combo – Price*	0.045 (0.085)	*ldlPFC-c*
3. Left insula* (-40, -5, 12)	active choice	*Combo – Price*	-0.108 (0.209)	*lINS*
4. Right insula* (47, -14, 18)	active choice	*Combo – Price*	-0.092 (0.196)	*rINS*
5. Left caudate* (-10, 1, 9)	active choice	*Combo – Price*	0.135 (0.462)	*lCAU*
6. Left dorsomedial prefrontal cortex/anterior cingulate cortex* (-4, 4, 48)	active choice	*Tech – Price*	0.160 (0.417)	*ldmPFC/ACC*
7. Ventromedial prefrontal cortex (5, 26, -10; 12 mm cube)	active choice	*Tech – Price*	0.041 (0.275)	*vmPFC-t*
8. Ventromedial prefrontal cortex (5, 26, -10; 12 mm cube)	active choice	*Combo – Price*	0.052 (0.290)	*vmPFC-c*

Notes: * significant at $p < 0.01$ for the whole brain analysis. Regions 7 and 8 are based on ROI analysis.

[12] Specifically, the percent signal change in bloodflow in an ROI from an image showing a technology or combination attribute is subtracted from the percent signal change in bloodflow when the participant sees a fixation point. See Amaro Jr. and Barker (2006).

Empirical Focus on the Discount Impact.

Subjects in our experiment had familiarity with the products from both a passive viewing stage as well as repeated choices among the products in the active choice stage. Our prior is that very little if any new information would be retrieved during the choice making, meaning the discount function dominates the decision time. As such, equation (6) provides our refutable hypotheses for the model in this experiment. In that equation, ψ_i is a percentage difference, and our proxy for ψ_i is the percentage signal change difference in activation from the images that contain the qualities, e.g. the technology or combination images, and the activation from the images that contain the prices alone.[13]

Results.

An initial test of the hypotheses is first performed by examining simple correlations for 47 participants (as 3 were unable to complete Phase 2 of the fMRI paradigm). We calculate the average decision time over all choices for each participant. We then compare this with the average percent signal change in brain activations, ψ_i, for each participant for the eight ROIs identified in Table 2. Next we estimate the simple correlation, *r*, between these % signal changes and the average decision times for the 84 choices facing each participant. Figure 4 plots time (milliseconds) on the vertical axes and the difference in brain activations on the horizontal axes (linear trend included). The correlation ranges from a low of 0.04 in the correlation between decision time and the activation in the left caudate (*lCAU*) and 0.41 when comparing decision time and activity in the right insula

[13] Specifically, the percent signal change in bloodflow in an ROI from an image showing a technology or combination attribute is subtracted from the percent signal change in bloodflow when the participant sees a blurred image. This is our proxy for $\ln \beta_i$. Our proxy for $\ln \delta_i$ is the percent signal change when observing a price-alone image and the percent signal change from observing the blurred baseline; hence $\psi_i = (\ln \beta_i - \ln \delta_i)$.

(*rINS*). As hypothesized, all areas show *i*) a positive correlation between the spread in the ROI activation differences and *ii*) that in participants with negative average percentage differences (e.g. ROI activation due to price is higher than activation due to combination or technology) generally have quicker decision times than participants with positive percentage differences (e.g. ROI brain activation due to price is lower than activation due to combination or technology), all else equal. These simple correlations are meaningful given the large sample size for studies in neuroeconomics (N = 47). Having a large sample size allows us to control for other covariates.

The second test of the hypotheses uses the full dataset from the two phases of the scanning experiment. The data are composed of i=1,…,47 participants who make s=1,…,84 sequential but randomized decisions where each decision requires the choice of one of a pair of goods for a total of 3,948 observations. The time to make each decision for each participant is $t_{is} = 0,...,T$ milliseconds. The average time to decision over all participants and all choices is 2,637.51 milliseconds with a standard deviation of 1,216.13 milliseconds.

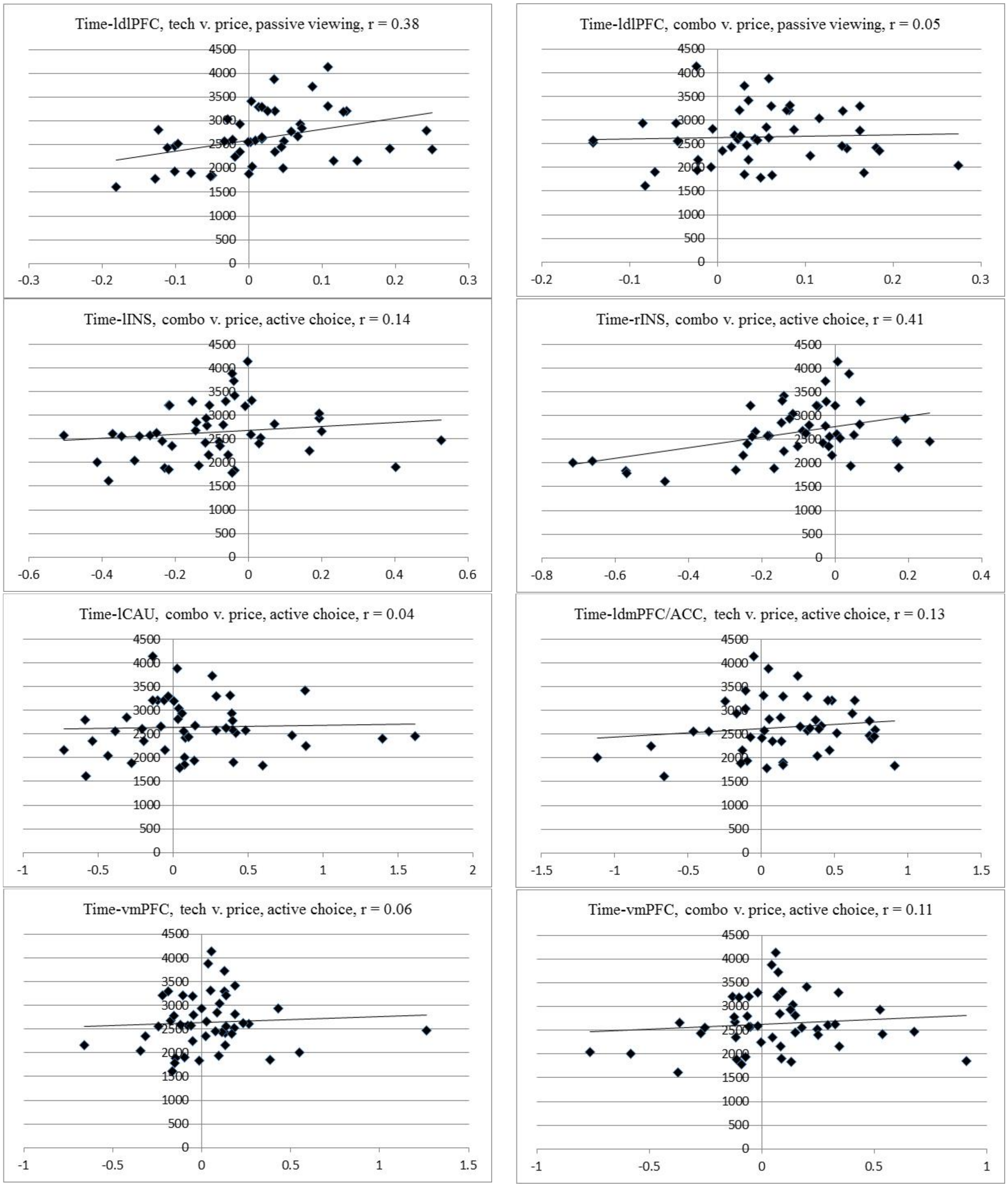


Figure 4. Correlation between Decision Time (milliseconds) and Brain Activation Differences

Because time is non-negative and the data are panel, where individual heterogeneity due to preferences is likely important, we model a multivariate regression using a random effects, exponential model with decision time parameterized using a vector, z_{is} , an estimated vector of parameters that is identical for each participant, η ,and a random, participant-and-sequence specific parameter, η_{is} , such that

$$(7) \qquad E[t_{is} \mid z_{is}] = v_i \gamma_{is} = e^{(z_{is}^{'}\eta + \eta_{is})},$$

where $v_i \sim Beta(a,b)$; see Cameron and Trivedi 2005, pp. 803-808.[14] We estimated the model using NLOGIT 5.0.

The key variable of interest is ψ_i. Because of its construction, ψ_i differs by participant *i* but not by sequence *s*, which is why the random effects procedure is chosen over the fixed effects panel approach. We again use the eight regions of interest in table 2.[15]

Our variable reflecting the price spread, *Price*, is the absolute value of the difference in logged prices. The mean of this *Price* variable was 0.33 with a standard deviation of 0.29. Equation (6) shows that as this spread increases, the decision-making time decreases.

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[14] The technical motivation is an assumption that $t_{is} \sim Poisson(\mu_{is})$ with $\mu_{is} \sim \Gamma(v_i \gamma_{is}, \sigma)$, gamma distributed with mean $v_i \gamma_{is}$ and standard deviation σ. In our case, we are not interested in this model for its count-data properties, only for its estimation of the continuous underlying, conditional mean. We are thankful to Colin Cameron for helpful discussions on this point.

[15] One of the complications with examining brain activations is the potential correlation among many different areas. However, in this analysis, we are examining not the activations among different areas but rather the differences in activations and, as such, there are no *a priori* expectations that such correlations should be high. Indeed, regressing the activations in the ROI's on each other to check for multicollinearity revealed little concern with R^2 values ranging from a low of 0.07 with *ldlPFC-c* as the dependent variable to 0.34 with *lCAU* as the dependent variable.

We cannot measure quality directly because we do not know how the participants perceive the quality of the products. Nonetheless, the only difference in the images presented to the participants is in the wording of the labels and the prices. To control for quality in the empirical model, we include binary variables denoting the types of choices appearing in the decision phase. Letting the "familiar" product (i.e. milk created using non-hormone added, non-cloning technologies) be denoted "N," a "hormone" technology denoted "H," a "cloned" technology denoted "C," then the binary variables show the pairs of choices facing a participant at the time of decision. Specifically, the variable *CC* is equal to one if the choice is between two "cloned" products and zero otherwise; *HH* is equal to one if the choice is between two "hormone" products and zero otherwise (mean of *CC* and *HH* is 0.08 with a standard deviation of 0.28); *HN* is equal to one if the choice is between a hormone product and a traditional product; *CN* is equal to one if the choice is between a cloned product and a traditional product (mean of *HN* and *CN* is 0.33 with a standard deviation of 0.47). The default is *NN*, a choice between two familiar products (mean of *NN* is 0.17 with a standard deviation of 0.37). Combinations of choices expand the number of sequences that must be offered, and the expense of the experiment itself, not to mention the time involved on the part of the participants, therefore pairings were conservatively chosen. After consulting with experimental design specialists, the chosen experiments were 1/3 of all pairs being choices between the same technology (e.g. the aggregate share of *HH*, *CC*, and *NN* choices equal 1/3) and 2/3 of the choices comparing one unfamiliar technology with a familiar one (e.g. 1/3 of the decisions were *HN* and 1/3 of the decisions were *CN*). Participants never faced a choice between 2 unfamiliar technologies (e.g. *HC* is never a choice). Future research should consider such choices as well as consider the case of more than two choices; however, based upon the theoretical model, we should find that when facing a choice between familiar products (*NN*), the decision time should be longer than in cases where an unfamiliar product is in the choice set. Although his model tests information signals and response time, we note that Rustichini (2009, p. 41) also opines that "when the quality of the signal is better … [it] may produce what we observe: longer response times with the better, more informative signal." A confounding factor in the experiment is that the labels on the images for *NN* contain more characters than the labels for the other products. As such these binary variables are also controlling for the amount of reading that is undertaken from image to image providing two reasons for a positive correlation between time to decision and *NN*.

The hypothesized correlation between the discount rate and time from equation (6) is negative. We created two variables as proxies for the discount rate. During prescreening, the participants underwent a test to determine their long-run discount rates from a series of questions about delayed monetary rewards following the procedures in Mitchell (1999). This discounting rate, denoted *k*, averaged 0.022 with a standard deviation of 0.044. As another measure of the opportunity cost of time, we also included the sequence order, $s = 1, 2, ..., 84$, the simple order of the choice pairs in the active decision making phase. The sequence of pairs was randomized *a priori* and identical for all participants. We would expect that as *s* increases, the decision time decreases because participants are becoming better choice makers but also because they are getting tired of being in the confined scanner hence impinging on the opportunity cost of their time.

Finally, because decision times and certain demographic and physiological factors are known to be correlated, we also included a gender dummy variable (*Gender*=1 if male; 0 if female) and a chronological *Age* variable. The average age of the 23 males and 24 females in the experiment was 31.67 years (standard deviation 11.09).

Table 3 presents the results of the eight regression models, which were similar in many ways. Model fit as measured by the log-likelihood and Akaike information criterion (AIC) showed little difference among the configurations with model 7 (*vmPFC-t*) exhibiting a slightly larger likelihood and smaller AIC than the other models. The parameters *a* and *b* were statistically significantly different from zero at the 1-percent hypothesis level for all eight models indicating that the panel nature of the data benefits from the random effects treatment and equidispersion is rejected.

In all eight models, as prices diverged, participants made quicker decisions *ceteris paribus* as predicted. Likewise, the presence of an unfamiliar product attribute and fewer characters to read in the choice labels as measured using the *HH*, *HN*, *CC* or *CN* variables lowered the response time compared to the familiar product (*NN*).

As participants grew more familiar with the process and stayed in the scanner longer, the response time as measured by the coefficient on *s* in all eight models also declined. This is consistent with the conceptual model that decision time imposes an opportunity cost on the participant so as participants become more familiar with the products and the process, the decision-making becomes more automatic. Participants likely develop a heuristic for deciding and that heuristic makes decisions less effortful and faster. The constructed discount rate, *k*, likewise had the predicted negative sign in all models though was statistically insignificant in the model examining ROI 7, the ventromedial prefrontal cortex under the *Tech-Price* BOLD difference. That both of these measures of personal discount rates were so consistent and with the posited negative sign is an important finding showing that the higher one's discount rate, the quicker one will make a decision. The older the participant, the longer was the response time in each model. Males also reacted more quickly than females; this negative correlation was statistically significant in five of the models.

Finally, all but one of the BOLD activation variables for the regions of interest were of the predicted positive sign and all but two (the left insula, *lINS*, and the left caudate, *lCAU*) were statistically significantly different from zero.[16] The negative though significant sign on the ventromedial prefrontal cortex in the *Tech-Price* BOLD (ROI 7, *vmPFC-t*) is contrary to our hypothesis, which is interesting as it is posited as a particular area of interest in Levy and Glimcher (2012); however when the BOLD activation for this same ROI is taken from the *Combo-Price* choices, the sign is positive as hypothesized and statistically significant. The contradictory but significant correlations are fascinating for this ROI in particular. This region is known as not only important in valuation but as necessary for *quick* decisions in which subtle valuation tradeoffs must be made. People with physical damage to the ventromedial prefrontal cortex take much longer to make decisions that are similar in terms of payoffs (Gladwell 2005, p. 59-60; Farb 2013, p. 6). For this reason, activity in the *vmPFC* will correlate with faster decisions and there are arguably at least two operations occurring in this region (e.g. making decisions more quickly but also making decisions related to value tradeoffs) for which we cannot adequately control under the present experiment. We agree with Levy and Glimcher (2012) that more analysis of this particular area and its potential as a generator of a neural money metric is an important next step for future research.

[16] There is some evidence that subjects may still have been learning about the choices early on in the active choice portion of the experiment even after participating in the lengthy passive viewing portion. Deleting the first quarter of observations in the data set and re-estimating the regressions did not change the sign or lower the significance on any of the ROIs except that for *rINS*, which became positive and significant with a coefficient of 0.62 and std. error of 0.04.

Table 3. Results of Time-Dependent Model of Consumer Choice

		Regions of Interest (ROI)		
Variable	*1. ldlPFC-t*	*2. ldlPFC-c*	*3. lINS*	*4. rINS*
Constant	2.37979***	2.37256***	2.39967***	2.43846***
	(0.03293)	(0.0378)	(0.03296)	(0.0346)
Price	-.12866***	-.13112***	-.12903***	-.12060***
	(0.01378)	(0.01354)	(0.01342)	(0.01267)
HH	-.04937*	-.05069**	-.04992**	-.05287**
	(0.02608)	(0.02497)	(0.02501)	(0.02548)
HN	-.06286***	-.06344***	-.06376***	-.06085***
	(0.01756)	(0.01718)	(0.01685)	(0.01627)
CC	-.07804***	-.07846***	-.07808***	-.07951***
	(0.02729)	(0.02499)	(0.02497)	(0.02724)
CN	-.05992***	-.06084***	-.06054***	-.05806***
	(0.01801)	(0.01689)	(0.01684)	(0.01718)
ROI	.29364**	.40294***	0.02279	.46503***
	(0.13501)	(0.11991)	(0.04723)	(0.03347)
s	-.00288***	-.00290***	-.00288***	-.00284***
	(0.00015)	(0.00016)	(0.00015)	(0.00016)
k	-1.44278***	-1.55096***	-1.65078***	-1.84128***
	(0.17896)	(0.15876)	(0.18299)	(0.1512)
Gender	-.04918**	-0.03132	-.04726**	-0.01935
	(0.02255)	(0.02668)	(0.02277)	(0.02402)
Age	.00404***	.00382***	.00383***	.00386***
	(0.00092)	(0.00094)	(0.00104)	(0.0012)
a	20.9924***	18.9838***	19.0952***	22.0773***
	(7.72174)	(6.94624)	(6.70717)	(6.08865)
b	5605.87***	5047.62***	5083.12***	5857.97***
	(2089.533)	(1881.867)	(1781.439)	(1601.556)
log-likelihood	-32132.33	-32131.45	-32133.13	-32116.09
AIC	64290.7	64288.9	64292.3	64258.2

Continued.

Table 3. Results of Time-Dependent Model of Consumer Choice-Continued

		Regions of Interest (ROI)		
Variable	*5. lCAU*	*6. ldmPFC/ACC*	*7. vmPFC-t*	*8. vmPFC-c*
Constant	2.39832***	2.38167***	2.35905***	2.37920***
	(0.03393)	(0.03352)	(0.03669)	(0.03431)
Price	-.12910***	-.12656***	-.13705***	-.12149***
	(0.0136)	(0.01321)	(0.01384)	(0.01259)
HH	-.04994**	-.05283**	-.04675*	-.05309**
	(0.02507)	(0.02473)	(0.02500)	(0.02418)
HN	-.06367***	-.06317***	-.05824***	-.06427***
	(0.01686)	(0.01649)	(0.01754)	(0.01687)
CC	-.07802***	-.07929***	-.07744***	-.07544***
	(0.02539)	(0.02513)	(0.02312)	(0.02577)
CN	-.06042***	-.06156***	-.05629***	-.06203***
	(0.01676)	(0.01742)	(0.01690)	(0.01676)
ROI	0.00232	.16582***	-.50661***	.25278***
	(0.02701)	(0.0144)	(0.03341)	(0.02903)
s	-.00288***	-.00287***	-.00290***	-.00287***
	(0.00015)	(0.00015)	(0.00014)	(0.00016)
k	-1.60701***	-1.82425***	-0.10047	-2.30068***
	(0.16302)	(0.14794)	(0.37602)	(0.16613)
Gender	-.04720**	-0.03262	-.05195**	-.04721*
	(0.02263)	(0.02444)	(0.02132)	(0.02483)
Age	.00376***	.00351***	.00524***	.00453***
	(0.00096)	(0.00089)	(0.00095)	(0.00104)
a	19.0573***	18.6687***	14.2857***	17.8170***
	(6.61623)	(6.12647)	(5.08861)	(6.28361)
b	5072.67***	4944.15***	3705.54***	4710.44***
	(1756.052)	(1650.047)	(1347.723)	(1674.904)
log-likelihood	-32133.16	-32124.745	-32107.18	-32125.07
AIC	64292.3	64275.5	64240.4	64276.1

Notes: dependent variable is time (milliseconds) with observations= 3948; participants=47; periods= 84. Standard errors appear below the coefficients in parentheses with ***, **, * indicating significance at the 1-, 5-, and 10-percent critical levels, respectively. Variable *ROI* refers to the region of interest specified at the top of each column as defined in table 2.

Other findings of particular interest are the positive and significant coefficients on the two activations taken from the left dorsolateral prefrontal cortex (*ldlPFC-t* and *ldlPFC-c*). These BOLD activations were taken from the passive viewing experiment stage when no choices were made. The Mussa and Rosen (1978) model posits that consumers come to a decision with their valuations already in hand and uncertainty impacts those valuations. The dorsolateral prefrontal cortex has been shown to be associated with tasks requiring effortful decision-making, processing of uncertainty, and conscious deliberation especially in intertemporal choices (McClure et al. 2004, Volz et al. 2005, Huettel et al. 2006, Bach et al. 2009, Hare et al. 2009) also as a processing area for future decisions. Given the predicted positive sign on this ROI is upheld, consider the motivating case of the financial "black swan" and what happened in May of 2010. A well-known phenomenon in trading markets is that volume and volatility are positively correlated and that correlation is often higher in downturns than in upturns (Hamilton and Lin 1998). In the case of the flash crash, consider what our model would have predicted. If a trader's internal neural exchange rate for money remained mostly unchanged but her belief about value drops while seeing shares unexplainably plummeting (e.g. $\ln \beta_i$ falls relative to $\ln \delta_i$), the coefficients on *ldlPFC-t* and *ldlPFC-c* combined with the economic model predict that trades would have gotten faster (ψ_i declines). Faster trading leads to more volume and increasing volatility. Thus while computers may have been responsible for the initial plummet, human traders made it worse because they responded to increased uncertainty with more frequent trades exactly as the model predicts. This hyper-selling is precisely what Lee, Ready and Seguin (1994) observed in markets where trading halts were called because values declined quickly. The same story could be made for any of the other ROIs in this model with the possible exception of the ventromedial prefrontal cortex in the

Tech-Price BOLD activation. The dorsolateral prefrontal cortex is of particular interest because it has been discerned to be responsible for pre-processing value information especially in time decisions (see discussion in Kim, Hwang and Lee 2008). This is significant as brain activation in dlPFC during the passive viewing phase predicted decision times in the active choice phase. As others have noted, the dlPFC appears to be an important brain region for understanding decision time when economic valuation is involved.

Conclusion.

This paper improves our understanding of the relationship between decision time and neural activations by unifying traditional economic theories of product differentiation and temporal discounting with models of decision time in the cognitive psychology and neuroscience literature. The economic model results in testable hypotheses for a subsequent empirical study. As an attempt to conceptualize a choice decision, the refutable hypotheses of the model were generally borne out in the experiment. Further empirical studies built on theoretical foundations is needed. This model is the first economic model to show that it is not simply uncertainty over quality or variance in prices that impact decision time, but the linkage between these two measures stemming from one's internal valuation for a product's quality and one's personal valuation of money itself. Because of that, the type of brain signal extraction from a neuroeconomic experiment can be guided by economic theory and those signal extractions can then be measured against decision time as proxies for these valuations. By comparison, a purely empirical study of decision time using similar data in Crespi et al. (2015), while instructive, lacks that economic underpinning for the construction of the BOLD variables used in the analysis.

In this paper, participants in a neuroimaging (fMRI) experiment made choices regarding types of milk produced with or without an unfamiliar technology process (cloning or growth hormone) while their decision times were recorded. The findings from simple correlations as well as multiple-regression, random-effects models largely support the hypothesized relations in areas of the brain known to be important to valuation and decisions under uncertainty. It is important to note that the correlations between the BOLD variables and time have been found in other studies as well (Kable and Glimcher 2007, Basten et al 2010, Hare et al. 2009, 2011 and Crespi et al. 2015) but what differs here is that the correlations we find are consistent with the refutable hypotheses from an economic model of product differentiation. We did not conduct a post-hoc, whole-brain analysis with decision-time but instead, used a priori defined regions of interest known to be associated with valuation from the cognitive neuroscience literature. We then used only these in the econometric model to test the a priori hypothesis that marginal valuation should be positively correlated with time to decision as predicted by an economic theory thus expanding upon and complementing past studies while providing future guidance on the usage of fMRI in economic models.

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