Neural Antecedents of a Random Utility Model

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Abstract: For over a decade, economists have sought to identify neural antecedents for economic theories. More recently, neuroeconomic work has sought to predict consumer choice using brain activations witnessed in non-choice, visual appraisals. This paper combines these two emerging strains of inquiry. Using functional magnetic resonance imaging (fMRI) data observed when consumers view a quality-differentiated food product labeled with different attributes, we seek to determine the predictive validity of the random utility model (RUM) often used in economic studies of consumer choice. Our fMRI data consist of changes in blood flow to the ventromedial prefrontal cortex (a brain region previously associated with value formation) observed when people saw low price and high labels and labels indicating high or low quality. We couple the fMRI data with data on 28 non-hypothetical choices made by each participant, which pitted higher priced, higher quality good vs. a lower priced, lower quality good. We find little evidence of a systematic difference in activation in brain areas thought to be associated with value formation when viewing high vs. low levels of attributes (prices and quality). However, differences in neural blood flow across participants related to quality (but not price) is significantly related to subsequent consumer choice both in- and out-of-sample, providing some qualified neuroeconomic support for the attribute-based RUM.

Keywords: attribute-based demand, animal welfare, choice experiment, fMRI, neuroeconomics, random utility

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For more than a decade, economists have tried, with varying degrees of success, to identify neural antecedents for economic and behavioral economic theories, seeking to determine whether particular brain regions respond in ways that theories would suggest. Examples include brain imaging studies on expected utility theory (Knutson and Peterson, 2005; for a review see Rangel, Camerer, and Montague, 2008), intertemporal choice and discounting (Kable and Glimcher, 2007; McClure et al., 2004), and social preferences (Sanfey et al., 2003; Spitzer et al., 2007).

More recently, neuro-economic work has sought to predict consumer choice (Camerer, 2007; Webb et al., 2013), particularly using brain activations witnessed in non-choice, visual appraisals (Levy et al., 2011; Tusche, 2010). Smith et al. (2014), for example, utilized brain activations witnessed when people were viewing various products and determined that these measures could predict subsequent choice when different products were paired together. Such findings suggest a neural basis for the concept of utility, and offer the promise of improving our ability to make behavioral predictions.

This paper seeks to combine these two emerging strains of neuroeconomic inquiry. Using data on changes in neural blood flow observed when consumers viewed a quality-differentiated good with different attributes levels (e.g., high vs. low prices; high vs. low quality), we examined the predictive validity of attribute-based random utility models commonly used in economic studies of consumer choice. Changes in neural blood flow were measured using functional magnetic resonance imaging (fMRI).

Since the conceptual work of Lancaster (1966), it has been suggested that consumers derive utility not from goods themselves but from the attributes and characteristics that a good possesses. This insight serves as the foundation for many popular modeling approaches including hedonic analysis (Rosen, 1974) and random utility models (RUM) (McFadden, 1973)

that are widely used in applications related to food, environmental, housing, transportation, and more (Adamowicz and Swait, 2011; Carlsson, 2011; Costanigro and McCluskey, 2011). Nevertheless, it remains unknown whether and to what extent such models of attribute-based choice can be empirically validated by the emerging field of neuroeconomics.

This paper takes an approach similar to that of Smith et al. (2014), but applies it to *attributes* rather than whole goods. Other neuro-economic studies suggest that people assign values to individual attributes arriving at a total summed "valuation" and therefore overall appraisal of the product (Kahnt et al., 2011), but further work is needed to determine whether such individual attribute appraisals can predict choice of multiple attribute goods. To explore these issues, we focus on a very specific area of the brain – the ventromedial prefrontal cortex – which has been suggested as a region which encodes the value of rewards on a common scale (Levy and Glimcher, 2012), and we test the hypothesis that activation in this brain region signals aggregate value of attributes in visual appraisals when objects are passively viewed. Moreover, we go further explore whether these activations attained during visual appraisal can be used to arrive at a combined utility for a good and predict subsequent choice.

Methods and Procedures

Participants

The present study utilizes data from healthy right-handed, English-speaking adults recruited from a metropolitan area by offering $45 for their participation. We excluded participants currently using psychotropic medication, with current or past history of substance abuse, self-reported diagnosis of severe psychopathology (e.g., depression, schizophrenia), and those on a vegan diet. A total of 50 participants were recruited, however, four participants were excluded from the analyses because of excessive head motion during the brain scan (>3 mm in any direction).

Thus, analysis is conducted using observations from 46 participants (49% Female; mean age = 29.5; age range, 21-55 years).

Product

Eggs are used as the quality-differentiated good used in our analysis. Eggs represent a familiar and widely consumed commodity, yet one for which there are many different qualities sold at widely varying prices. A recent hedonic analysis of egg prices, for example, revealed well over 100 different types of eggs in each market region and identified characteristics like cage free and free range that command 50% price premiums or more (Chang et al., 2010). The quality characteristic that is the focal point of our analysis is cage vs. cage free (or free range) eggs. Preferences for this quality characteristic are not only of interest to farmers and food retailers, but also have implications for public policy. The European Union recently implemented a ban on egg production from so-called battery cages, and the state of California has done the same. As similar measures are being considered in other states and at the federal level, there remain many questions about the costs of such legislation and about consumers' willingness-to-pay for it (e.g., see Norwood and Lusk, 2011). There have been previous fMRI studies looking at related attributes like organic or hormone free (e.g., Crespi et al., 2016; Linder et al., 2010; 2015; Lusk et al., 2015), but none of the studies focused on using fMRI to identify marginal utilities of different attributes or on using data from visual appraisals to predict subsequent choice.

Passive Viewing Phase (Step 1)

In the initial passive viewing phase of the study (Step 1), participants were placed in a brain scanner and were shown images of a typical, one-dozen carton of eggs or a Gaussian blurred baseline image. We utilized a controlled block design. Images were shown in a 13-block design

with 10 images in each block displayed in Figure 1. Blocks differed by whether the image possessed a low price label (prices randomly varied from $0.99 to $2.49 in $0.50 increments), a high price label (prices randomly varied from $2.99 to $4.49 in $0.50 increments), a label indicating an "open" production method (labels were "cage-free hens" or "free-range hens") or a label indicating a "closed" production method (labels were "caged hens" or "confined hens"). Stimulus presentation time was 2.5 seconds with an interstimulus interval of 0.5 seconds. The order of category presentation was counterbalanced across participants. The blurred images were included to allow for a baseline comparison of participants' neural reactivity to a stimulus contain similar visual information to the stimuli in experimental blocks, but lacking any semantic information regarding price or production method. One advantage of block-related designs is that they can provide a relatively powerful measurement of the contrasts of interest (e.g., neural activation when viewing high vs. low prices) and as such likely result in lower measurement error than event-related designs (see Webb et al., 2013 for a discussion of measurement error when using neural activations as a signal of utility). A downside of this design is that it only allows us to compare neural activation in one block to that in another block and we only obtain the average block contrast at the individual level (i.e., we do not have individual-level data on blood flow in response to each stimuli presented within a block).

All scans were performed at the University of Kansas Medical Center, Hoglund Brain Imaging Center on a 3-T Magnetom Skyra scanner (Siemens, Erlangen, Germany). For each participant, one anatomical (MPRAGE) scan was performed, followed by four functional (BOLD) scans: two during the "passive viewing phase," and two during the "choice phase." Each participant's functional data were co-registered using his or her own anatomical data, not a template brain.

For the anatomical scans, we acquired T1-weighted, three-dimensional, magnetization-prepared, rapid acquisition with gradient-echo (MPRAGE) anatomical images (repetition time [TR] = 2,300 ms, echo time [TE] = 2 ms, flip angle = 9°, field of view [FoV] = 256 x 256 mm, matrix = 256 x 256 mm, in-plane resolution = 1 x 1 mm, gap thickness = 0 mm, slice thickness = 1 mm).

For the functional scans, we acquired T2-weighted, gradient-echo, blood oxygenation level-dependent (BOLD) functional images in 50 contiguous, oblique, axial slices at a 40° angle (TR = 3,000 ms, TE = 25 ms, flip angle = 90°, FoV = 232 x 232 mm, matrix = 80 x 80 mm, in-plane resolution = 2.9 x 2.9 mm, gap thickness = 0 mm, slice thickness = 3 mm).

Of primary interest from Step 1 was how neural activation differed when respondents saw low vs. high price labels and how neural activation differed when viewing open vs. closed egg labels. We focused on changes in activation in one particular region of interest (ROI): the ventromedial prefrontal cortex (vmPFC). We focused on the vmPFC because of the growing evidence demonstrating activity in the vmPFC may represent value or utility. Plassmann, O'Doherty, and Rangel (2007), for example, found that the vmPFC encodes values during active choice. More generally, in their review of the literature, Levy and Glimcher (2012, p.1027) argue that, "Neuroimaging studies . . . suggest the existence of a small group of specific brain sites that appear to encode the subjective values of different types of rewards on a neural common scale . . . we show that the principle brain area associated with this common representation is a subregion of the ventromedial prefrontal cortex (vmPFC)/orbitofrontal cortex (OFC)." They further argue that (p. 1027), "the ventromedial prefrontal cortex (vmPFC)/orbitofrontal cortex (OFC) can be thought of as representing the value of nearly all reward-types on a common scale that predicts behaviorally observed comparison and choice." In

this analysis, we investigate activation in the vmPFC, based on coordinates in Levy and Glimcher (2012) with a volume of 8 mm^3.[1]

We measured the mean blood oxygenation level-dependent (BOLD) contrasts in the vmPFC between different blocks (see detailed discussion of contrast analysis in Amaro and Barker, 2006). In particular, we define $vmPFC_{price}$ as the percent change in blood flow (or BOLD signal change) to the vmPFC when people saw high prices vs. low prices (i.e., it is the difference in BOLD when viewing high prices vs. low prices). Likewise, $vmPFC_{method}$ is defined as the percent change in blood flow (or BOLD signal change) to the vmPFC when people saw eggs with an open (cage-free/free-range) as compared to when they saw eggs with a closed (caged/confined) label (i.e., it is the difference in BOLD when viewing open vs. closed labels).

fMRI data were analyzed using the software, BrainVoyager QX. Preprocessing steps included trilinear, three-dimensional motion correction, sinc-interpolated slice scan time correction, two-dimensional spatial smoothing with a four-millimeter Gaussian filter, and highpass filter temporal smoothing with sine-cosine cycle set at 2. We did not use a template brain for coregistration. Neurofunctional data were then coregistered through the transformation and translation of each functional image to align with its anatomical counterpart. These realigned images were then further transformed to conform to the spatial constraints defined by Talairach and Tournoux's co-planar, stereotaxic atlas, ensuring neurofunctional data were standardized in their spatial representation. Neural activation maps were analyzed using statistical parametric methods included with the BrainVoyager QX software. Statistical contrasts of neural activation in the experimental conditions of interest (i.e., the high price, low price, open method, and closed

[1] Levy and Glimcher (2012) calculated a weighted average area of activation x = 4.27; y = 35.18; z = -11.82 in MNI coordinates; converting these to Talairach space, which is the default in BrainVoyager, we obtain x=3, y=30, z=-11. The decision to use a volume of 8 mm3 was partially based on the practical limitations of BrainVoyager, which only allows for the definition of an ROI in terms of mm3, limiting the extent to which we could increase the volume of the ROI without its perimeter extending too far beyond the vmPFC. Empirical support for this choice is provided by Levy and Glimcher (2012) who indicated that the range of peak voxel locations was "surprisingly small."

method conditions relative to baseline-blurred condition) and those not of interest (i.e., head motion) were conducted using a general linear regression model with subject-specific random effects. Regressors representing neural activation in these conditions were modeled with a hemodynamic response filter. Results were used to generate, across all participants, a three-dimensional map depicting percent BOLD signal change between neurofunctional activity in the high vs. low price conditions (i.e., the price contrast) and in the open vs. closed production methods (i.e., the method contrast).

Choice Phase (Step 2)

Following the passive viewing Step 1, participants engaged in Step 2, the choice phase. In Step 2, subjects were presented with 84 binary choices between two egg cartons displayed simultaneously. The 84 choices were in one three different conditions (28 choices in each condition): a price condition, a production method condition, or combined tradeoff condition (although we refer to these as different conditions, in practice the different types of choices were interspersed with each other). Our analysis focuses on the 28 choices where a tradeoff had to be made, where the choice pitted a higher priced egg carton produced with hens in an open method vs. a lower price egg carton produced with hens in a closed method (see Figure 2 for an example). To cut down on the number of choices people had to make, we only used 7 price levels in the choice phase ($0.99, $1.49, $1.99, $2.49, $2.99, $3.49, and $4.49) and four production methods, making 4*7=28 possible combinations.

We do not analyze the other 56 choices associated with the price and production method conditions here because there was essentially no tradeoff to be made. In the price condition, a subject chose between a high and low priced carton of eggs with the same production method

label (in which case 95% of all the choices were for the lower priced option). In the production method condition, the prices of both options were the same but one was open (cage free or free range) and the other was closed (caged or confined) (in which case 97% of the choices were for the open method over the closed). By contrast, in the 28 choices that are the focus of this analysis, a tradeoff had to be made between paying a higher price for the open method, and indeed this was difficult tradeoff as indicated by the fact that 51% of choices went to toward the higher-priced open method and 49% went for the lower priced closed method.

To make the task non-hypothetical and incentive compatible, one of the choices was selected at random and participants were required to purchase the product they selected in that particular binding choice. Therefore, each participant left the experiment with one dozen eggs. For this analysis, we were primarily interested in whether the activations observed in Step 1 can be used to predict the choices in Step 2. Therefore, we do not use any of the fMRI data during the choices in Step 2.

Analysis of Choice Data – Reduced Form Analysis

An initial way to analyze the choice data is to define the choice variable in terms of the characteristics chosen: i.e., whether the subject chose the higher priced, open option or the lower priced, closed option. Because each person *i* made 28 choices, a subject-specific measure can be created indicating the share of choices made for the higher price, open method option, Si; a measure that ranges from 1 (if a subject always chose the higher-priced open option) to 0 (if a subject always chose the lower-priced closed option). To explore the relationship between neural activations in the passive viewing phase in step 1 and the choices in step 2, the following linear regression can be estimated:

(1) $Si=\delta 0+\delta 1 vmP\ Gp\ ricei+\delta 2 vmPFCmethodi.$

We view this analysis as a "reduced form" analysis because it does not have a straightforward interpretation in a typical random utility framework.

Analysis of Choice Data – Structural Analysis

A second approach for analyzing the choice data in Step 2 is the RUM. In this framework the variable of interest is the choice of an option (any option) and where the explanatory variables describe the characteristics or attributes of the choice (McFadden, 1973). In this framework, choice is defined by the differences in attributes, marginal utilities for attributes, and a stochastic term. In particular, assume respondent *i* derives the following utility for egg option *j*: $U_{ij} = V_{ij} + \varepsilon_{ij}$, where V_{ij} is the deterministic and ε_{ij} is the stochastic portion of utility. Now, let the systematic portion of the utility for option *j* be:

(2) $Vij=\alpha+\beta Openj+\gamma Pricej$

where α is an alternative specific constant (in this case measuring a "left-hand-side" bias - the likelihood of a respondent choosing whichever option appears on the left-hand-side vs. the right-side of the screen that cannot be explained by the characteristics), $Open_j$ is a dummy variable taking the value of 1 if egg option *j* is labeled cage-free or free-range and 0 if labeled caged or confined, β is the marginal utility of open-production method, $Price_j$ is the price of alternative *j*, and γ is the marginal utility of price.

Assuming the error terms ε_{ij} are distributed iid extreme value, a logit model can be estimated. If faced with *J* choice options (*J*=2 egg options in this case), an individual is assumed to choose option *j* if $U_{ij} > U_{ik}$. The probability of individual *i* choosing option *j* is:

(3) $\text{Proboption } j \text{ is chosen}=e\mu Vijk=1Je\mu Vik.$

where μ is a scale term inversely related to the error variance. Typically μ is set equal to one because it is not separately identified.

In this framework, any variable that is constant across choices "drops out" of the probability formula. To see this, note that the log odds of an individual choosing option *j* over *k* is $\ln(\text{Prob}(V_{ij})/\text{Prob}(V_{ik}))= \mu(Vij-Vik)$. Thus, relative choice probabilities are explained by differences in utility. Any variable (such as a demographic like gender or age) which is constant across alternatives therefore cannot explain the relative likelihood of choice. The only way to let individual-specific variables, such as the neuroimaging data we collect, affect choice is to allow the utility function to depend on (or interact with) with variable of interest; that is, to let people with different BOLD values to have different preference.

In a typical discrete choice model (e.g., a choice experiment), we cannot directly observe the marginal utilities, β and γ, and they must be inferred, or estimated, using choice data. That is, we observe how choice changes with variation in $Openj$ and $Pric\ \ j$ to identify β and γ.

However, to the extent that changes in activation in the vmPFC correspond to changes in utility or reward, the BOLD activations observed in the passive viewing phase in Step 1 might provide a more direct measure of the marginal utilities, β and γ. One way to investigate this is to replace the parameters β and γ with some approximation of the random utilities, as they vary across individuals. In particular, in equation (2) we replace the parameter β with the equation β_{0+} $\beta_1 vmPFC_{Methodi}$ and the parameter γ with the expression $\gamma_{0+}\gamma_1 vmPFC_{Pricei.}$ Thus, even though this is a model fit to the aggregate data, different individuals have different preference parameters via $vmPFC_{Methodi}$ and $vmPFC_{Pricei}$. To the extent that differences in vmPFC reflect marginal utilities, the parameters β_0 and β_1 scale units of utility in the brain (as measured by BOLD activation) to units of preference in the underlying random utility model. Individuals

with a larger value for $vmPFC_{Method}$ experienced more activation when viewing cage-free vs. cage egg labels, and to the extent this reflects larger marginal utility of cage-free methods vs. cage methods, one would expect this to be reflected in larger marginal utility in Step 2 as observed via the parameter β_1. Practically speaking, the parameters β_1 and γ_1 can be estimated by interacting the attributes in (2) with the appropriate BOLD variables.

Although the variance parameter, μ, isn't identified, one can identify relative differences in variance across different datasets or people by estimating a variance function. This is important because differences in preference parameters from discrete choice model across experiment treatments or individual-specific variables are confounded by possible differences in variance across treatments or individual-specific variables (Swait and Louviere, 1993). Our hypothesis of interest is whether the BOLD variables impact preference parameters, and to ensure that the estimated effects are not simply a result of people with higher or lower *vmPFCprice* or *vmPFCmethod* making more or less "noisy" choices, the variables also need to be included in a variance function. Stated differently, if BOLD variables also affect error variance, then our estimates of β_1 and γ_1 will be biased. In addition, other research has shown that "noisiness" of choices (i.e., error variance) is affected by the difficulty of the choice task, the order with which an individual answer a choice task, and the time it takes to make a choice (e.g., Börger, forthcoming; Campbell and Erdem, 2015; DeShazo and Fermo, 1993; Hensher, 2006). To account for these issues, we investigate how μ (or more precisely $1/\mu$) varies with the time taken to make each choice (in seconds), the order of the choice (across all 84 choices), and BOLD activations observed in Step 1:

$1\mu it = \exp(\theta 1 timeit + \theta 2t + \theta 3 vmPFCmethodi + \theta 3 vmPFCpricei.$, where $timeit$ is the time (in

seconds) it took respondent *i* to answer choice *t*, *t* indexes the choice (in the order in which it appeared), and $\theta k$are parameters to be estimated.

In what follows, we successively consider how adding additional variables improves the fit of the choice model. We estimate: model (1), the simplest model that only contains a constant term (measuring the propensity to choose left over right regardless of the characteristics of the options on the left or right), model (2), a standard RUM that includes a constant term and attribute characteristics, model (3) a RUM augmented with BOLD variables that allow marginal utilities of attributes to vary with neural activations, and model (4) which is identical to model (3) except the error variance is allowed to vary by time-to-choice, order of choice, and BOLD variables. Because each participant in our experiment completed 28 choices, the standard errors in each model are clustered at the individual level.

In addition to these models, we also consider a fifth, alternative specification where we interpret the BOLD activations as "utility signals" and use these as explanatory variables in the RUM. The basic idea is that if $vmPFCpricei$ truly reflects the marginal utility of a price change, then options with higher prices should be (ignoring production method for the moment) valued at $vmPFCpricei$ and options with lower prices should valued $-1*vmPFCpricei$.[2]

In particular, redefine (2) as:

(4) $$Vij=\pi 0+\pi 1 Price\ signalij+\pi 2(Method\ signal)ij$$

where $Price\ signalij$ is the utility signal associated with price changes, which we define as $vmPFCpricei$ if the price of option *j* is higher than the price of the competing option *k* and

[2] Recall, *vmPFCprice* is the percent change in blood flow to the vmPFC when people saw high prices vs. low prices. Thus, -1* *vmPFCprice* is the percent change in blood flow to the vmPFC when people saw low prices vs. high prices.

$-1*vmPFCpricei$ if the price of option *j* is lower than the price of the competing option *k*. Likewise, $Method\ signalij$ is the utility signal associated with the egg production method, which we define as $vmPFCmethodi$ if the option *j* is cage free and competing option *k* is caged and $-1*vmPFCmethodi$ if option *j* is caged and competing option *k* is cage free.

Finally, following Smith et al. (2014), we sought to investigate not only whether including BOLD activations from Step 1 helped improve model fit associated with the choices observed in Step 2, but whether BOLD activations from Step 1 can *predict* choices in Step 2. To investigate this issue, we used a delete one jackknife procedure (Efron and Tibshirani, 1994). In particular, we removed one of the 46 people and their 28 choices from the dataset as a "holdout", and estimated Models (1)-(5) using the remaining 45*28 choice observations. Once these estimates were obtained, we then predicted the 28 choices for the holdout individual. We then repeated this exercise for all 46 respondents. This gives us 46*28 = 1,288 out-of-sample predictions. Using a threshold probability of 0.5, we calculated the percentage of choices that are correctly predicted as well as the sensitivity (the % of times the left-hand side option is predicted to be chosen given that the left hand side option was actually chosen) and specificity (the % of times the left-hand side option is predicted not to be chosen given that it wasn't actually chosen).

Beyond this rather crude measure of model fit, we also calculate the out-of-sample log likelihood function (OSLLF) value for each model. The out-of-sample log-likelihood function approach has long been used in for model selection in the analysis of consumer choice (Erdem, 1996; Roy et al., 1996) and the approach is discussed and developed in detail by Norwood, Roberts, and Lusk (2004) and Norwood, Lusk, and Brorsen (2004). As discussed by these

authors, the OSLLF has desirable properties in judging the predictive fit of discrete choice models and it is our preferred selection criteria.

Results

Neuroimaging Results from Step 1

We begin by investigating the individual-level BOLD contrasts that arise from the ROI analysis focused on the vmFP (recall *vmPFCprice* is the difference in in BOLD signals when viewing high vs. low prices and *vmPFCmethod* is the difference in in BOLD signals when viewing open vs. closed production systems).[3] There were no significant differences observed in the vmPFC when people where observing high vs. low prices (mean difference in BOLD activations = -0.017%; p-value from paired t-test = 0.28). Similarly, there were no significant differences observed in the vmPFC when people were observing open production method labels (cage-free/free-range) vs. closed production method labels (cage/confined) (mean difference in BOLD activations = 0.005%; p-value from paired t-test = 0.68). On the surface, these results would seem to suggest that the vmPFC does not encode differences in subjective value across different attribute levels. However, it is important to note that there is substantial variability across people in their response to the changes in attribute levels. Although the means of $vmPFC_{price}$ and $vmPFC_{method}$ were, as just noted, both near zero the [minimum, maximum] values were [-0.35, 0.25] and [-0.27, 0.22], respectively, and standard deviations for both variables were around

[3] We have also conducted a whole brain analysis and after cluster correction we did not find any regions that significantly differed for the open vs. closed method contrast. The appendix shows the results of the whole brain analysis associated with the low vs. high price contrast for areas that showed significant activation after cluster correction ($P<0.01$). It is also possible to conduct whole brain analysis for contrasts between, for example, high price versus blurred baseline, which yields many significant results; however, these aren't particularly interesting or relevant for our present analysis. We focus on the vmPFC as the ROI because of previous research suggesting it as a key area coding for reward value and for parsimony of discussion insofar as the results associated with it are similar to that of ROIs such as the OFC or dlPFC that could also have been extracted from the whole brain analysis.

0.10. This begs the question as to whether these overall differences in BOLD activations across people might predict subsequent choice behavior.

Choice Data – Reduced Form Analyses

In step 2, 51% of the choices were for the higher priced eggs from the open method and 49% were for the lower priced eggs from the closed method. If we look the percent of choices each individual made (across all the 28 choices) for the higher-priced, open method (over the lower-priced, closed method), we find that across the 46 subjects, this ranges from 100% (for 10 subjects) to 0% (for 5 subjects). The average is 51% and the standard deviation is 37%. About 37% of the subjects chose the higher-priced, open method at least 75% of the time, 24% of the subjects chose the higher-priced, open method at least 25% of the time, and the remaining 39% of the subjects chose the higher-priced, open method between 25% and 75% of the time.

Before proceeding to the structural RUMs, it is useful to examine simple summary statistics that do not rely on a particular econometric specification or model. People with values for $vmPFC_{price}$ and $vmPFC_{method}$ that were positive selected the higher priced cage free eggs 65.2% of the time. The choice frequency fell by almost half (to 34.6%) for people with negative values for both $vmPFC_{price}$ and $vmPFC_{method}$. This initial investigation provides preliminary evidence that BOLD activations observed in visual appraisal in Step 1 might relate to choices in Step 2.

The relationship can be investigated directly by a linear regression model, where the dependent variable is the share of times an individual chose the higher priced eggs from the open method over the lower priced eggs from the closed method. The estimated equation is

$$S_i = 0.506 + 0.214\,vmPFCprice_i + 1.361\,vmPFCmethod_i, \quad N=46, \quad R2=0.12$$
$$\begin{matrix} & (0.054) & (0.498) & & (0.607) \\ & [0.001] & [0.669] & & [0.030] \end{matrix}$$

where the numbers in parentheses are standard errors and numbers in brackets are p-values. Changes in the vmPFC when viewing high vs. low prices was not significantly related to the share of choices that went toward the higher-priced open option. By contrast, changes in the vmPFC when viewing open vs. closed methods in step 1 significantly predicted the frequency of an individual choosing the higher-priced, open method in the choice phase in step 2. A 0.1% increase in $vmPFC_{method}$ is associated with a 0.1361 increase in share of choices that went toward the higher priced eggs from the open method. Figure 3 further elucidates these results, and it shows S_i plotted against $vmPFCmethod_i$. Clearly, the two variables are positively related.

Choice Data – Structural Analysis

The structural analysis analyzes choices is based on a RUM where choice is defined by the attributes of the choice. One of the attributes is the position on the screen (as reflected by the estimate associated with the intercept term). At the individual level, the percent of times a subject chooses the option on the left-hand-side of the screen ranges from 32% to 68% with a mean of 50.3% and standard deviation of only 5%. The mode is 50%, and 27 out of 47 subjects, or 57%, chose the left-hand side option exactly half the time. This indicates our randomization of choice options to the side of the screen was effective and that subjects were not simply picking options only on one side of the screen.

Table 1 reports the estimates from five different random utility models. The first model only includes a constant term. Including attribute information (model 2) significantly improves

the model fit, and both marginal utilities are significantly different from zero. The estimates suggest that respondents were willing to pay a premium of 1.637/0.795=$2.06 for cage-free/free-range eggs relative to cage/confined eggs.

Model 3 incorporates the vmPFC percent signal change from Step 1 and allows the marginal utilities of the attributes to vary with $vmPFC_{pricei}$ and $vmPFC_{methodi}$. A likelihood ratio test rejects the null hypothesis that the coefficients associated with the two BOLD activations are equal to zero (chi-square value of 104.96 with 2 degrees of freedom, p-value<0.01). With model (3), WTP for eggs from open vs. closed production systems for individual *i* is: -[1.739+7.061*$vmPFCmethod_i$]/[-0.859+0.642*$vmPFCprice_i$]. This is the difference in price between open and closed methods that makes individual *i* indifferent between (i.e., have the same utility as) eggs from the open vs. closed system. Given the way model is estimated, $vmPFCprice_i$ is linearly related to the marginal (dis)utility of price but non-linearly related to WTP since it is in the denominator of the WTP formula. As noted above, the standard deviation on both vmPFC contrasts was roughly 0.10. Moving from the mean value of approximately zero for $vmPFC_{methodi}$ to twice the standard deviation (0.2) in the sample while holding the price effect at its mean value (also approximately zero), increases the willingness-to-pay premium for cage-free eggs from 1.739/0.859=$2.02 to (1.739+7.061*0.2)/0.859=$3.67. Likewise, moving two standard deviations in the other direction (-0.2) results in a discount of about 38 cents per carton. The variation in activations across our participants fluctuates more than 80 percent, a sizable effect that could be missed by simply looking at $vmPFC_{method}$ value alone and misinterpreting its zero mean as the lack of an effect. Perusing the local supermarket, indeed, shows that eggs have high price differentials when one compares conventional with specialty attributes (Koelkebeck et al., 2001; Chang, Lusk and Norwood 2010). Thus, not only are the effects statistically

significant, they are economically large and consistent with that observed in real consumer purchases reflected in scanner data.

The fourth model includes the variance function estimates, and the results suggest that variation in vmPFC not only affects the mean utility by affects the variance as well. A likelihood ratio test rejects the null that the additional coefficients associated with the variance function are equal to zero (chi-square value of 11.68 with 4 degrees of freedom, p-value=0.02). Increases in $vmPFC_{method}$ and decreases in $vmPFC_{price}$ are associated with an increase in error variance (or noise). The direct utility coefficient associated with $vmPFC_{method}$ and $vmPFC_{price}$ are both statistically significant and similar in sign and magnitude to that in model 3, although sign of the coefficient on $vmPFC_{price}$ is opposite of that expected. While previous research has suggested the possibility that order of choices and the time-to-choice might affect error variance, we find no evidence of such a phenomenon here.

Model 5 shows the alternative specification which depends on utility "signals" from the step 1 neuroimaging task focused on the vmPFC. This model shows that the signal related to high vs. low prices did not significantly affect subsequent choice; however, the utility signal related to open vs. closed methods in the vmPFC did, in fact, relate to subsequent choice.

Table 2 shows the out-of-sample prediction performance of the four models. Model 1, which only includes the constant term, performs the worst with only 50.3% correct predictions (barely better than a coin toss). The model scores high on sensitivity (because it always predicts the option on the left-hand side will be chosen), but it performs miserably in terms of specificity. It is also the worse model in terms of the preferred measure, the OSLLF. The best prediction model in terms of all four measures is model (3), which includes the BOLD interactions. Comparing model (3) to model (2) shows that including the brain imaging data to the typical

RUM model improves the percent of correct predictions from 61.1% to 65.9%, sensitivity from 63.7% to 66.4%, and specificity from 58.1% to 65.4%. Across the 46 participants in this study, model (3) performed better than chance at predicting their out-of-sample observations in 35 cases (74.5% of the time); for model (2), this was only true for 30 people (63.8% of the sample). Comparing the prediction performance of model (2) with that that of model (3), the latter model which includes the BOLD activations, does a better job at predicting the choices of 58.7% (27 of 46) of the respondents. These findings suggest that not only are the BOLD signal responses in passive viewing correlated with subsequent choices, but that passive viewing activations can help predict the choices of individuals whose decisions are unknown. It also has the lowest out-of-sample log likelihood function value.

Conclusions

Economists have long been interested in attribute-based demand models, where it is assumed that consumers derive utility from a good's attributes rather than the good itself. Although there is a rich empirical literature utilizing attribute-based hedonic and random utility models, the neural underpinnings for these models has received much less attention. This paper sought to add to the literature on this topic, and in the process to explore additional questions of inquiry related to the ability of data from neuroimaging studies to predict choice.

These issues were studied empirically by focusing on consumer choice for eggs. Despite the fact that eggs are often viewed as a standardized commodity, the variability in attribues is substantial. Relatedly, egg prices even within a single grocery store fluctuate widely. Not only do consumers have choices over standard grades and sizes, they are faced with choices on organic, cage-free, grain fed, Omega 3, color, and more. Prices for eggs with these different attributes can vary greatly. A standard willingness to pay experiment can help discern premia

and discounts. Yet advancing neuroscience provides us with tools to augment these traditional approaches. As neuroimaging methods like fMRI allow researchers to ascertain more specific physiological changes during product appraisal, we may gain a greater understanding of such market variation. Furthermore, these methods allow researchers to perform analyses which were heretofore impossible using standard methods.

In this study, we examined the brains of adult consumers as they passively appraised photos of eggs in cartons while prices and quality attributes varied. Without asking participants to make any choices, we recorded changes in neural blood flow associated with both price changes and production method changes during this passive viewing. Focusing on an area of the brain that has been implicated in valuation, the ventromedial prefrontal cortex (vmPFC), we then used activation in the vmPFC as key data in an otherwise standard attribute-based random utility model. We found little evidence of significant differences in activation in the vmPFC when viewing high vs. low levels of price and quality attributes, upon further examination, we discovered significant heterogeneity across consumers. The important heterogeneity in BOLD signal changes for egg labels related to housing conditions during the passive viewing of the egg attributes across participants was significantly related to their subsequent choices among eggs with differing attributes. BOLD signal changes observed during passive viewing accounted for a great deal of the variation in WTP for eggs across our subjects and provided evidence that, even in the absence of choice making, the brain is in the process of "valuing" the quality of an item (put perhaps not integrating the price) - something that could not be discerned with a traditional approach. Overall, outcomes of this research study suggest some promise in incorporating functional neuroimaging methodology into hedonic analyses.

An important caveat is that variation in the vmPFC when viewing high vs. low prices was not a significant predictor of subsequent choice between higher and lower priced eggs. There are a variety of possible reasons for this null result. One option is that responses to pecuniary stimuli may be encoded in a location other than the vmPFC. However, the whole brain analysis did not reveal any additional neural regions that might serve this function. Another possibility is that, when passively viewing objects in a non-binding exercise, price differences are not salient enough to invoke a significant BOLD signal change. There is a large literature on the phenomenon of hypothetical bias showing that willingness-to-pay in hypothetical settings is typically much higher than is the case in non-hypothetical settings, suggesting that price sensitivity is lower in hypothetical settings (Murphy et al., 2005).

This research reveals a number of avenues of future research. For example, this analysis made no use of the fMRI data collected when consumers were actually choosing. We presented choices in a simultaneous manner, but a sequential analysis might provide more direct insights into the determinants of attribute-based choices. Stated differently, our null finding that the vmPFC did not seem to encode values of attributes in passive viewing tasks does not mean that it wouldn't do so during active choice. Moreover, we have rather crude analyses of neural activations. From our block design in step 1, we only know average neural activation when observing, for example, high vs. low prices, but not the activation observed for each and every price stimuli. Future research might utilize parametric modulation analysis to identify how neural activation changes with the exact price level and identify how within-subject variability for a given price or method stimuli might affect subsequent choice. Neuro-economic research might also be used to provide insights into the causes of hypothetical bias and explore whether price changes have differential neural impacts when the task is real vs. hypothetical.

Nonetheless, this study provides proof of concept that neural activations when viewing varying attribute quality levels has the potential to predict subsequent choice.

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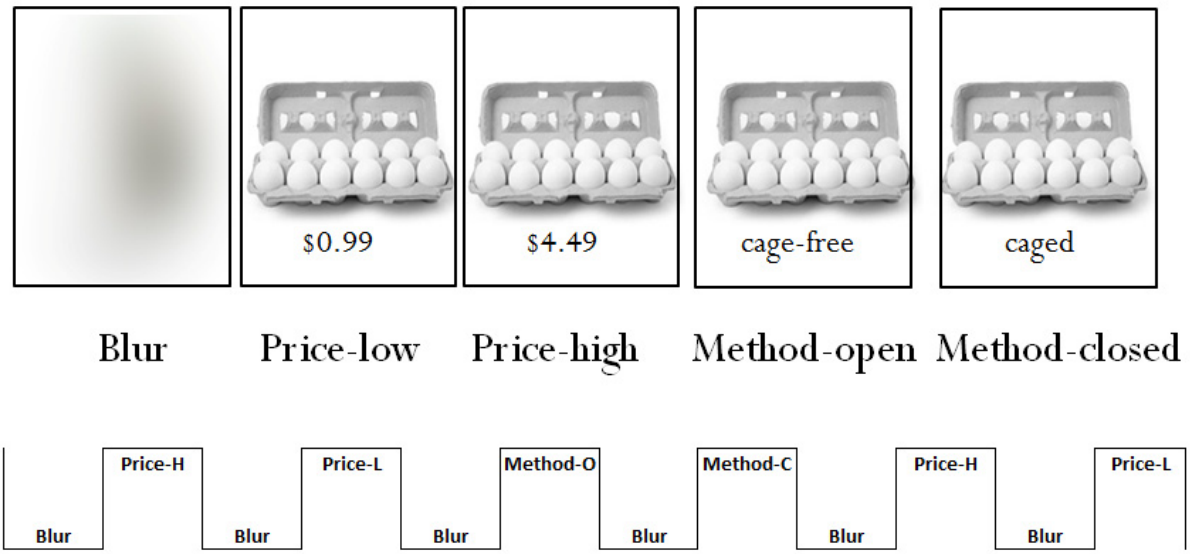

Figure 1. Step 1 involving passive viewing block design (each image was displaced for 2.5 seconds with 10 different images per block)

Confined hens
$0.99

Free-range hens
$2.49

Figure 2. Example choice question from step 2 involving 28 choices between higher priced eggs from an open production method and lower priced eggs from a closed production method

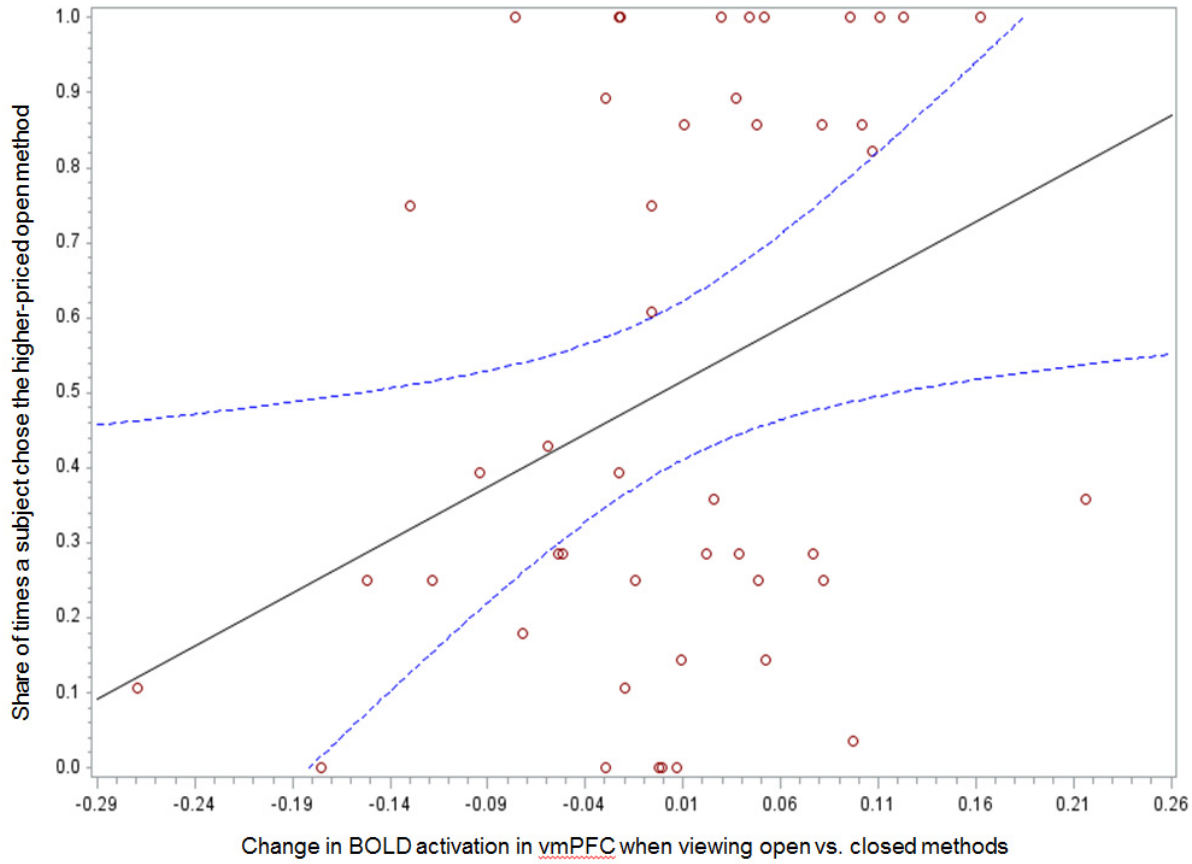

Figure 3. Share of times a subject chose the higher-priced open method plotted against the difference in activation in the vmPFC when passively viewing eggs produced via open vs. closed production method (N=46; black line is the best fitting line; bivariate correlation coefficient = 0.34, p-value=0.02)

Table 1. Random Utility Models - Logit Estimates

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Constant	0.015	0.018	0.019	0.033	0.017
	(0.030)	(0.034)	(0.037)	(0.078)	(0.032)
Price	---	-0.795**	-0.859**	-1.101**	---
		(0.113)	(0.123)	(0.263)	
Open	---	1.637**	1.739**	2.283**	---
		(0.291)	(0.317)	(0.546)	
Price*vmPFC$_{price}$	---	---	0.642	1.500*	---
			(1.096)	(0.528)	
Cage-free*vmPFC$_{method}$	---	---	7.061*	9.136**	---
			(2.966)	(2.309)	
Price Signal	---	---	---	---	1.046
					(1.938)
Method Signal	---	---	---	---	6.025*
					(2.613)
Variance function					
Response time (seconds)	---	---	---	0.102	---
				(0.059)	
Question order	---	---	---	-0.001	---
				(0.003)	
vmPFC$_{price}$	---	---	---	-1.947*	---
				(0.841)	
vmPFC$_{method}$	---	---	---	2.046*	---
				(0.882)	
Log Likelihood	-892.74	-803.03	-750.55	-744.71	-847.75
AIC	1787.7	1612.1	1511.1	1507.4	1701.5
N choices	1288	1288	1288	1288	1288
N people	46	46	46	46	46

Numbers in parentheses are standard errors clustered at the individual-level.
Two (**) and one (*) asterisks represent statistical significance at the 0.01 and 0.05 levels, respectively.

Table 2. Out-of-Sample Prediction Performance of Competing Models

Model	**% correct**	**Sensitivity**	**Specificity**	**Out-of-Sample Log Likelihood**
model (1)	50.3%	100.0%	1.4%	-892.584
model (2)	61.1%	63.7%	58.4%	-825.608
model (3)	65.9%	66.4%	65.4%	-807.576
model (4)	63.7%	64.1%	63.4%	-1038.128
Model (5)	61.6%	61.5%	61.7%	-875.84

Appendix. Whole Brain Analysis for the High vs. Low Price Contrast: Regions reaching significance from a whole brain analysis during the passive viewing price phase ($P < 0.01$, family-wise error corrected, random effects).

Contrast and Region	Talairach Coordinates				Brodmann Area	Contiguous Voxels
	x	y	z	t		
Low vs. High Price						
Postcentral gyrus/Parietal (R)	69	-8	18	-5.20	43	225
Insula (R)	38	-8	12	-3.7	13	15
Precuneus (R)	38	-71	36	-3.72	19	26
Superior frontal gyrus (L)	-4	-20	57	-3.68	6	26
Inferior parietal lobule (L)	-49	-35	54	-4.16	40	51