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Adapting neuroeconomics for environmental and energy policy

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Abstract: Neuroimaging methods provide insight into the neural mechanisms underlying the decision process, characterizing choice at the individual level and, in a growing number of contexts, predicting national- and market-level behavior. This dual capacity to examine heterogeneity while forecasting aggregate choice is particularly beneficial to those studying environmental decision-making. To effectively reduce residential energy usage and foster other pro-environmental behaviors, policy-makers must understand the effects of information frames and behavioral nudges across individuals who hold a diverse array of attitudes toward the environment and face a broad range of barriers to action. This paper articulates the potential of neuroeconomic methods to aid environmental policy-makers interested in behavior change, especially those interested in closing the energy efficiency gap. Investigation into the roles of affect, eco-labeling and social norms will be discussed, as well as personal identity and climate change beliefs. Combining neuroimaging with behavioral economics experiments can inform the development of effective messaging, characterize the influence of individual differences on the decision process and aid in forecasting the efficacy of policy interventions at scale.

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Introduction

The human decisions – great and small – that can create severe local and global environmental challenges are often motivated and justified by economic rationales. In response, ecosystem services approaches have arisen to attempt to quantify the previously intrinsic and intangible benefits of natural resources in financial terms (Daily *et al.*, 2009). Eco-labeling, such as the Energy Guide and Energy Star programs, has been put in place by the US Environmental

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Protection Agency and others to direct consumers' attention to the potential economic benefits of buying energy-efficient appliances (US Environmental Protection Agency, 2016). Yet valuation measures for natural resources have encountered challenges generated by inconsistent preferences and strong emotional reactions (Sawe, 2017), and policy-makers still face an "energy efficiency gap" caused by consumer underinvestment in energy efficiency (Wilson & Dowlatabadi, 2007). In the environmental domain, as in many other contexts, human behavior seldom aligns with the economic rational actor model (Gowdy, 2008).

The importance of addressing the human behavioral elements of environmental problems has historically been overlooked by scientists and policy-makers (Gardner & Stern, 2002), but has received increased attention as behavioral economics and choice architecture approaches to public policy design have become more prevalent (Gowdy, 2008; Shogren & Taylor, 2008; Venkatachalam, 2008). Recently, neuroeconomic methods, which combine behavioral economics experiments with brain imaging, have become especially promising for their potential to assess policy-relevant decision-making at the national scale, enabling population-level behavioral prediction using small neuroimaging samples in a growing number of contexts from microlending initiatives (Genevsky & Knutson, 2015) to the efficacy of anti-smoking ad campaigns (Falk *et al.*, 2012). The ability of neuroeconomic methods to simultaneously characterize the individual heterogeneity that influences environmental decision-making (Sawe & Knutson, 2015) and scale to predict market-level choice (Karmarkar & Yoon, 2016) permits insight into specific versus generalizable responses. This may be especially crucial for environmental behavior, where the public exhibits a high degree of heterogeneity (Sahoo & Sawe, 2015) that can potentially be leveraged to achieve more sustainable outcomes (Dolnicar & Grun, 2009).

This article will delineate the potential benefits to environmental public policy of utilizing neuroimaging in concert with behavioral economics studies of environmental decision-making in order to yield sustainable behavior change, with a focus on meaningful reductions in energy usage. Many of the core elements to environmental decision-making have been well studied in neuroeconomics – how individuals allocate scarce resources (Lee, 2008), deal with uncertain or ambiguous risks (Hsu *et al.*, 2005) and make trade-offs between short- and long-term benefits (McClure, 2004) or between moral and economic values (Berns *et al.*, 2012) – as well as more direct applications such as consumer responses to organic labels (Linder *et al.*, 2010) and philanthropic decisions to protect threatened natural resources (Sawe & Knutson, 2015). A brief overview of the neural correlates of affect and experimental design using functional magnetic resonance imaging (fMRI) will be followed by discussions of

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potential contributions to the study of energy-efficient purchases, the influence of temporal discounting on residential energy usage, the roles of personal values and social norms and the impact of climate change beliefs.

Neuroimaging and the role of affect

Neuroeconomic methods can quantify, explain and even predict how components of the decision process can motivate an individual's departures from the choices of an economically rational actor. Distinct neural regions of interest have been found to correlate with positive and negative emotional responses, the computation of subjective value and the performance of cost–benefit assessment, math processing, social cognition and moral judgment and more (Lieberman, 2007; Knutson & Greer, 2008; Kaufmann *et al.*, 2011).[1] Neuroimaging permits us to assess the extent and timing of these different influences on choice and how a given region's activity may change as a function of factors in the decision process (e.g., increases in the cost of an energy-efficient product), qualities of the individual (e.g., environmental attitudes) or interactions between these decision- and individual-level attributes.

The measurement of the role of affect, or emotion, in decision-making is perhaps one of the most relevant to studying environmental decisions (Sawe, 2017). Kahneman *et al.* (1999) have described responses to surveys attempting to elicit the value of natural resources as examples of "affective valuation": rather than expressing economic preferences, respondents' willingness-to-pay (WTP) measurements instead act as a proxy for their emotional and attitudinal reactions. The other powerful motivator for studying affect when assessing the implications of environmental messaging and policy nudges is that neural activity in affective systems, specifically the nucleus accumbens (NAcc), is key to predicting behavior at the population level in many of the neuroimaging studies that have successfully forecasted aggregate choice (Berns & Moore, 2011; Genevsky & Knutson, 2015; Venkatraman *et al.*, 2015; Kühn *et al.*, 2016; Genevsky *et al.*, 2017; Scholz *et al.*, 2017). Thus, affective circuitry may be central to evaluating the effectiveness of such messaging and policy interventions at scale.

Affect is often modeled on a two-axis scale by psychologists, with one axis representing valence, or how positively or negatively the individual feels toward a given stimulus, and the other representing arousal, or how intensely

1 While care must be taken to avoid reverse inference and overly specific interpretations of the functional roles of different regions, meta-analyses and related tools (e.g., NeuroSynth) provide insight into broader categories of functionality.

this response is felt (Bradley & Lang, 1999). Elicitation of strong positive or negative arousal can evoke a reaction to approach or avoid that stimuli (Knutson & Greer, 2008). These appetitive or aversive reactions, rooted in evolutionary behavior, are driven by distinct neural systems (Knutson & Greer, 2008).

The affect–integration–motivation (AIM) framework (Samanez-Larkin & Knutson, 2015) serves as one basis for thinking about the role of affective brain circuits in decision-making. The striatum, specifically the NAcc, exhibits activity strongly associated with positive arousal (Knutson *et al.*, 2014) and responds to anticipation or delivery of a wide array of rewards, from food to sex to money (Knutson & Greer, 2008). When examining the NAcc's associations in existing studies with meta-analytic maps on the NeuroSynth database (www.neurosynth.org), this role in reward and incentive processing, instrumental in motivation, rises to the fore.

In contrast, the anterior insula's response is associated more with negative arousal toward losses, risks and stimuli that are aversive both physiologically and morally (Sanfey, 2007; Knutson & Greer, 2008; Preuschoff *et al.*, 2008), though there is evidence that the anterior insula is more responsive to arousal than valence, and thus more generally scales with salience (Knutson *et al.*, 2014).

These affective circuits play a central role in the initial assessment and weighting of the considered stimuli – for instance, NAcc activity often scales with reward magnitude (Knutson *et al.*, 2005; Ballard & Knutson, 2009; Wu *et al.*, 2014) – and this information is then passed to the medial prefrontal cortex (mPFC), which integrates affective responses with other contextual or conceptual considerations to arrive at a decision (Karmarkar & Yoon, 2016). The mPFC, especially in ventral subregions, is implicated in many studies in such cost–benefit assessments and the calculation and indexing of subjective value (Montague *et al.*, 2006; Grabenhorst & Rolls, 2011; Wallis, 2012; Bartra *et al.*, 2013; Clithero & Rangel, 2013).

Experimental design using functional magnetic resonance imaging

A number of methods including electroencephalography and transcranial magnetic stimulation exist to deconstruct the roles of different brain regions, but our discussion of neuroeconomic methods to inform environmental policy will center on fMRI. FMRI is particularly suited to measuring activity in structures deep in the brain like the NAcc (Karmarkar & Yoon, 2016) and is widely used as it strikes a balance between spatial and temporal resolution when collecting neural data (Cohen, 2005). This resolution is still limited to the scale of millimeters and seconds, in part because fMRI measures neural activity by

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proxy through the blood oxygenation level-dependent (BOLD) signal, which changes as oxygenated blood rushes to meet the metabolic demands of brain activity. Optogenetic research in animal models, which uses specific light wavelengths to activate neurons that have been modified via viral vectors, has been paired with fMRI to confirm that the BOLD signal can serve as an appropriate index of neural activity (Lee *et al.*, 2010).

Experimenters must strictly control the timing and complexity of the presented stimuli to yield interpretable neural responses to each factor within a given decision process. This is often achieved by breaking down an fMRI decision task into discrete packets of information, frequently presented for several seconds each. For instance, in an environmental philanthropy study (Sawe & Knutson, 2015) where participants were asked to donate in order to protect a park from being utilized for a new proposed land use, participants were first shown the threatened park, then the land use, then the requested donation amount and finally the option to donate or not; information was presented additively in phases of four seconds each for a total trial length of 16 seconds. This sequential design permitted researchers to analyze brain response as a function of qualities of the park, the destructiveness of the proposed land use, the magnitude of the requested donation and the interactions of these factors.

More holistic approaches without this stepwise design are still possible if experimenters are focused on output models (e.g., identifying brain regions that predict choice). However, in complex multi-attribute decisions, this may obscure the mechanisms by which each attribute drives decision-making. In the context of sound policy design, understanding how a given messaging frame or behavioral nudge is successful at inspiring environmental behavior change is key to finding solutions across a diverse array of environmental problems and barriers to action.

Yet fMRI is not a skeleton key for studying environmental decision-making. To improve the signal-to-noise ratio, the same type of decision must be made numerous times by each subject (Huettel & McCarthy, 2001). Many environmental decisions that policy-makers may wish to study are not easily adapted to these repeated measures designs because they are essentially one-shots (e.g., voting on a given piece of legislation). For charitable giving or consumer purchasing paradigms, this is less problematic as the particulars of each decision (e.g., the energy efficiency of a given appliance) can be systematically varied in a fashion that maintains both participants' engagement and a sense of realism. Real decisions can also be studied in these contexts despite the high number of trials, because one or more decisions can be chosen at random to count as binding. For instance, if a purchase or donation was made, the amount can be removed from an endowment or payment for study participation. As the participant does not know which decision will be binding, they make each independently and under the assumption that it will be implemented.

FMRI's repeated measures design can be both beneficial and a potential confound, as it raises implicit comparisons across goods or services. Studies on joint evaluation of multiple goods (Kahneman & Ritov, 1994; Ritov & Kahneman, 1997; Kahneman *et al.*, 1999) have shown potentially drastic effects on WTP when evaluating multiple goods together or in sequence, rather than in isolation. However, this effect appears to be large when the goods are perceived to be in different categories, but minor when they are within the same category (Bonini *et al.*, 2008), as would be the case in many neuroimaging tasks. Even so, repeated trials may cause individuals to anchor to characteristics of early stimuli, creating problematic reference points that influence decision-making. Randomizing the presentation of stimuli across participants can help mitigate these order effects. More complex changes in decision-making strategies over time, as individuals attempt to compare and contrast information across trials, may be more difficult to model. This could be a source of confounds that are difficult to anticipate or control for experimentally. Alternatively, this dynamic evolution of choice strategies could indicate that subjects are calibrating their evaluation criteria as they gain familiarity with a given market (or choice set), offering a better representation of informed decision-making. This market familiarity may be more realistic in some contexts with environmental impacts (e.g., comparison shopping for refrigerators) than others (e.g., valuation of the worth of ecosystem services). Indeed, lack of familiarity with (or existence of) markets for environmental public goods is one of the great challenges facing environmental economists and policy-makers (Shogren & Taylor, 2008).

Energy-efficient purchases and eco-labeling

Consumers routinely underinvest in energy efficiency, behaving as if they steeply discount future energy savings (Hausman, 1979; Train, 1985). US consumers have been shown to inadequately consider fuel costs during vehicle purchases (Allcott, 2011a), with approximately 30% of consumers ignoring fuel costs entirely (Leard, 2013). This gives rise to the "Energy Efficiency Gap" or "Energy Paradox" (Jaffe & Stavins, 1994), where favorable technologies with beneficial ratios of capital investment to payback periods are underutilized (Wilson & Dowlatabadi, 2007). Such systematic underinvestment is posited to slow the diffusion of energy-efficient products into the marketplace (Gillingham & Palmer, 2014). The potential returns on energy efficiency investment are considerable and far-reaching: a consulting report by McKinsey & Co. estimated that a $520 billion investment across US businesses and residences would yield returns of $1.2 trillion, reducing end-use energy consumption in 2020 by 23% of projected demand and abating up to 1.1 gigatons of greenhouse gas emissions annually (Granade *et al.*, 2009). As 2020 draws closer, we have fallen short of this investment target.

This underinvestment in energy efficiency may be due in part to cognitive limitations. In a bounded rationality framework (Gigerenzer & Selten, 2002; Kahneman, 2003), our finite cognitive bandwidth prevents us from sustaining the perfect attentional focus and memory capacity to retain and evaluate all the information necessary for complex decisions, and thus we fall back on "maximizing" and "satisficing" heuristics to streamline the decision process (Schwartz *et al.*, 2002). In energy efficiency decisions, this may lead to inattention to energy consumption data (Sahoo & Sawe, 2015). Such inattention to energy data may in fact be rational: Sallee (2014) asserts that when consumer preferences for other product attributes (e.g., brand) are sufficiently strong, considerations of energy efficiency differences are insignificant, and finds that car consumers experience only a small welfare loss when making decisions without detailed fuel cost data. However, for the policy-maker who is concerned with reductions in energy use and greenhouse gas emissions, this inattentiveness to energy consumption data remains problematic.

One natural strategy to counteract this inattention is by increasing the salience of energy consumption data through the use of detailed eco-labels (e.g., EnergyGuide in the USA). Sallee (2014) counters that these labels are still imperfect and contain uncertainty due to heterogeneity in usage patterns. Thus, more simplistic attentional cues, such as the binary Energy Star certification logo, may be a preferable alternative, balancing across salience, informational complexity and outcome (Newell & Siikamäki, 2013).

However, visual salience can come at a cost, overriding preferences to determine choice, especially under cognitive load or time constraints (Denny *et al.*, 2012). Houde (2011) provides evidence that the Energy Star label may crowd out efforts to assess electricity costs, acting as an informational substitute and prompting many individuals who would have invested more in energy efficiency in the label's absence to view Energy Star-certified products as "good enough." Alternatively, the Energy Star could serve to focus consumers' attention on more concrete energy consumption data. In a discrete choice experiment, Sahoo and Sawe (2015) found that, on average, the Energy Star increases the value that consumers place on energy consumption savings. These accounts need not be at odds; the Energy Star's effect on decision-making may differ across individuals. The study identified heterogeneity in the Energy Star label's effects, decreasing the weight placed on energy consumption in 13% of a national sample of homeowners ($n = 1550$), while increasing it in the majority (Sahoo & Sawe, 2015).

Neuroimaging may be helpful in determining the effect of these eco-labels on attention and energy consumption valuation. Stepwise presentation of information, as discussed earlier, would permit assessment of the response to an eco-label like the Energy Star, as well as the label's subsequent influence on the processing of energy data. The Energy Star elicits a price premium (Ward *et al.*, 2011) similar to that found in an fMRI study of organic food labeling (Linder *et al.*, 2010). It is likely that both labels operate through similar mechanisms, increasing NAcc activation, which is often highly predictive of purchasing behavior both within laboratory populations (Knutson *et al.*, 2007) and when forecasting national behavior (Berns & Moore, 2011; Kühn *et al.*, 2016). We might also hypothesize that the Energy Star's presence would be correlated with changes in activity in the mPFC when energy consumption data are shown due to the region's role in cost–benefit assessment and value computation. If the Energy Star facilitates closer consideration of energy consumption, mPFC activity may increase in instances where the label is present.

While the NAcc and mPFC act as neural correlates of positive arousal and cost–benefit assessment, and also correlate with WTP (Knutson *et al.*, 2007; Plassmann *et al.*, 2007; Linder *et al.*, 2010), there is a more direct path to studying how the attentional effects of eco-labeling are related to energy information processing. FMRI has been combined with eye-tracking to study the relationships between visual attention, neural activity and consumer decisions (Lim *et al.*, 2011). This multimethod approach could be used to assess the degree to which attention to eco-labeling like the Energy Star enhances or detracts from the consideration of concrete energy data. Moving beyond binary labels to information-rich alternatives, it becomes even more crucial to understand attentional dynamics. The EnergyGuide's complex provision of energy data presents a multitude of numbers, including annual electricity use in kWh, cost ranges for similar models and annual operating cost (for some products, these are presented twice with different cost estimates for electric versus natural gas water heaters). These translated attributes are a form of choice architecture, serving as signposts for individuals to understand how a product's energy efficiency aligns with their values and goals (Ungemach *et al.*, 2017). Understanding the degree to which this complexity in energy labeling impacts decision-making, and whether a parsimonious optimum might be achieved between the levels of detail proffered in the Energy Star and EnergyGuide labels could be an important contribution to the design and optimization of new ecolabels.

Beyond optimization, neuroimaging's ability to forecast population-level behavior offers the greatest potential for policy-makers. FMRI studies have successfully predicted sales of music and chocolate (Berns & Moore, 2011;

Kühn *et al.*, 2016), the success of advertisements (Venkatraman *et al.*, 2015), microloan and crowdfunding ventures (Genevsky & Knutson, 2015; Genevsky *et al.*, 2017) and public health campaigns (Falk *et al.*, 2015), generally through some combination of NAcc and mPFC activity.

If neuroimaging studies can establish robust prediction of national sales of appliances with energy-efficient and eco-labeled options and verify the neural circuits involved in this prediction, these can serve as targets for optimization. For example, if NAcc activation predicts national sales, then future eco-labels can be chosen in part based on their ability to elicit NAcc activation. While neuroimaging studies that predict national behavior to date have used pre-existing stimuli (e.g., public crowdfunding campaigns, products or advertisements), such techniques could be used earlier in the design process to decide on energy labeling or environmental messaging before deployment as an A/B testing ground. Because fMRI designs can dissociate the influence of different informational attributes on both choice and neural activity, labels or other messaging could be deconstructed across a number of dimensions to understand which constituent elements are the most impactful at eliciting neural activity that scales to predict choice at the population level. Of course, the goal of the policy-maker is not purely to increase appliance sales, but rather to increase the market share of products that offer the largest gains in energy efficiency. This argues for balanced labeling schemes that not only elicit activation patterns that are the most predictive of success, but also retain enough focus on energy consumption gains that consumers can make informed decisions.

Residential energy usage and intertemporal trade-offs

Energy economists have found variation in the individual financial discount rates implied in purchasing behavior for different domestic energy technologies, clustering in the 5–40% range, but reaching as high as 300% for air conditioning (Wilson & Dowlatabadi, 2007). This suggests both heterogeneity in individual discount rates within the population as well as heterogeneity that is dependent on the type of appliance. One can imagine a number of contingencies that may contribute to such disparities; air conditioners may be bought when the need for them is greatest, leading to greater inattention to product specifics and more frequent use of satisficing heuristics. Similarly, pragmatic constraints (e.g., dimensions of the appliance) or brand dominance may overwhelm efficiency considerations (Young *et al.*, 2010) and lead to higher implicit discount rates in specific appliance types. By granting the ability to disaggregate responses to individual product attributes, neuroeconomic experiments can identify potential disparities in neural response and subsequent behavior

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between appliance types. Armed with an understanding the dynamics underlying this heterogeneity, policy-makers can evaluate whether a one-size-fits-all approach to eco-labeling and information provision is appropriate or whether different messaging or behavioral nudges need to be deployed based on the specific product.

Neuroeconomic experiments can also address differences in discount rates between individuals. Addressing this heterogeneity could be of paramount importance to messaging approaches, with individuals who possess high financial discount rates (i.e., those who steeply devalue future profits against near-term gains) potentially also devaluing information about annual energy operating costs, since research has found no significant difference in individuals' discount rates in financial versus environmental domains (Hardisty & Weber, 2009). These individuals may need to be reached through alternative methods, perhaps via emotional appeals or by emphasizing financial or environmental losses, which are less subject to discounting than gains (Hardisty & Weber, 2009).

Temporal discounting has been well-studied in neuroeconomics (McClure, 2004; McClure *et al.*, 2007; Ballard & Knutson, 2009), with the NAcc appearing more responsive to immediate rewards and particularly sensitive to reward magnitude. This predilection toward short-term rewards is unsurprising given the striatum's involvement in addictive and impulsive behaviors (Diekhof *et al.*, 2008; Ballard & Knutson, 2009). Yet the NAcc's association with positive arousal (Knutson & Greer, 2008) may also mean that positive emotional messages, or those that appeal to impulsivity (e.g., by offering an evaluative shortcut), may help close the energy efficiency gap in high discounters. Since we have seen that eco-labeling can increase WTP for goods via NAcc activation (Linder *et al.*, 2010), it is entirely possible that the Energy Star elicits its price premium through the same mechanism. By measuring individual discount rates either inside or outside of fMRI and then evaluating appliance purchases, researchers could indeed evaluate whether different types of energy information have differential influences on individuals based on their discount rate. With most consumers acting "as if" they have a very high discount rate where energy efficiency is concerned, this could be a powerful optimization tool.

Personal values, social signaling and social norms

Beyond discount rates, it is important to identify the degree to which policy interventions and behavioral nudges are effective across a population that possesses a diverse range of environmental attitudes. Individuals endeavor to make decisions that are consistent with their own self-identity, and the degree to

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which they self-identify as an environmentalist can, naturally enough, correlate with pro-environmental behaviors (Heimlich & Ardoin, 2008).

Neuroimaging of environmental charitable giving has revealed that widely used survey measures of pro-environmental attitudes such as the revised New Ecological Paradigm (NEP) scale (Dunlap *et al.*, 2000) can be used to examine how neural response during decision-making changes as a function of differences in these environmental attitudes (Sawe & Knutson, 2015). The study showed that individuals with stronger pro-environmental attitudes exhibited increased anterior insula activity when they were shown proposed land uses that had a higher destructive impact on the natural landscape (e.g., mining), and this anterior insula activity predicted a greater likelihood of donation to block the destructive land uses and conserve the natural landscapes across the study population (Sawe & Knutson, 2015). Notably, NAcc activation in response to positive environmental stimuli (e.g., iconic landscapes) did not significantly differ as a function of pro-environmental attitudes. This example emphasizes the capacity of neuroimaging to distinguish the specific mechanisms by which attitudes can translate into actions, enabling policymakers to better understand when and how to apply behavioral levers.

Nor is this capacity limited to cases of "preaching to the choir," describing only the behavior of strongly pro-environmental individuals. Neuroimaging studies could reveal the mechanisms by which messaging can reach those who care little for the environment, but who may be moved through appeals to other salient identities, as in the famously successful "Don't Mess with Texas" anti-littering campaign that appealed to citizens' state pride. As discussed in an eco-labeling context, messaging can be compared and deconstructed to study how variations in each component can influence neural activity and subsequent decision-making. But as the study of environmental philanthropy shows, the efficacy of each component at eliciting pro-environmental behaviors can be assessed as a function of individual differences and attitudes. This process could, for example, identify messaging components that may be aversive to individuals with specific beliefs or attitudes, but rarely explicitly discussed through other modalities (e.g., behavioral focus groups).

However, tailoring behavioral nudges in such a way can be interpreted as paternalistic or not directly beneficial to the target population (Hausman & Welch, 2010). This suggests that the ethical implications and welfare benefits of each potential application of nudges (identity-related and otherwise) should be articulated and debated, especially when leveraging insights from neuroscience studies.

However, in cases where pro-environmental behaviors are consistent with an individual's identity, social norms and spillover effects can have powerful

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impacts on the adoption and diffusion of positive behaviors and technological solutions. This is especially true of high-visibility actions such as the adoption of solar photovoltaic panels; Bollinger and Gillingham (2012) find that an additional solar panel installation increases the likelihood of another installation in the same zip code by 0.78%. Consistent with Ajzen's Theory of Planned Behavior (TPB), consumers are more likely to adopt behaviors if they perceive them to be a social norm (Ajzen, 1991). TPB has also been employed to describe and predict electric vehicle adoption patterns (Lane & Potter, 2007).

Academic work showing the influence of social norms on energy and water conservation (Schultz *et al.*, 2007; Goldstein *et al.*, 2008; Nolan *et al.*, 2008) has led to a growing focus on social comparisons by startups and utility companies aiming to reduce energy and water use. Opower is one of the most frequently cited success stories, using comparisons to the energy use of similar households to incite residential energy use reductions of approximately 2.0% (Allcott, 2011b). Promisingly, these reductions appear to sustain over time through at least one year of follow-up (Ayres *et al.*, 2013).

Social cognition recruits an array of brain regions that often activate together in networks, with specific regions appearing to process theory of mind (e.g., temporoparietal junction and posterior superior temporal sulcus), moral decision-making (e.g., dorsal mPFC) and other aspects of complex social interactions (for a detailed account, see reviews from Lieberman, 2007; Doré *et al.*, 2015; Tremblay *et al.*, 2017, among others). Of particular interest to the instantiation of environmental social norms, a meta-analysis of fMRI studies explicitly assessed the neural correlates of social conformity (Wu *et al.*, 2016). Their findings suggest an affective account similar to the AIM framework: when individual actions deviated from group norms, this was accompanied by deactivation of the ventral striatum and increased activation in the anterior insula and dorsal mPFC (Wu *et al.*, 2016). This implied negative emotional responses toward deviating from group behavior, and furthermore, the dorsal mPFC activity predicted that people would adjust their behavior to conform (Wu *et al.*, 2016). Lastly, stimuli that were endorsed by others elicited a stronger response in the ventral striatum (Wu *et al.*, 2016). Given the region's role in assessing the magnitude of rewarding stimuli during valuation, this suggests that social endorsement adds positive weight to the behaviors under consideration.

These findings provide a foundation for experimentation to better understand the influence of social norms on pro-environmental behavior, especially the framing effects that may impact this relationship. For instance, adding a simple emoticon – a smiling face to denote good energy use performance – alongside social comparison information was sufficient to prevent a rebound effect (where individuals who received positive feedback would increase energy usage) (Schultz *et al.*, 2007). Such messaging variations could be tested in a similar fashion to the eco-labels discussed earlier in order to provide a more complete picture of the evoked mechanisms. For instance, does the emoticon evoke higher dorsal mPFC or ventral striatal activity during consideration, and can this activity predict reduced rebound effects and sustained behavior change? If activation in one circuit is increased but not the other, what implications does this have for how social norms impact environmental behavior and the framing effects that should be employed or avoided?

Climate change belief and pro-environmental behaviors

A discussion of environmental decision-making would be remiss if it did not address climate change, especially where intertemporal trade-offs are concerned. Climate change suffers from yet another paradox: while polling finds that the majority of the USA views its risks as a serious problem, it also repeatedly ranks near the bottom in terms of priorities (Leiserowitz, 2006). In another facet of bounded rationality, a "finite pool of worry" forces us to prioritize which risks we address, and increasing concern for one risk can decrease concern for another (Weber, 2006). Unfortunately for climate change, many of the dimensions upon which humans prioritize risks – ones that happen in the here and now, to us personally and for certain – do not work in its favor (Gattig & Hendrickx, 2007), with outcomes that are ambiguous in their timeline, exact nature, geographic impact and severity.

This ambiguity and uncertainty can compound as one transitions from climate change predictions to impact assessments, in what has previously been called a cascade of uncertainty or an uncertainty explosion (Jones, 2000). Ellsberg (1961) first provided evidence of aversion to ambiguity where our decision-making curves to avoid ambiguous circumstances. Information credibility and disagreement among experts have since been cited as key sources of ambiguity (Camerer & Weber, 1992) and likely contribute greatly to public disengagement with climate change. Furthermore, unfavorable information under ambiguity is less likely to be integrated into decision-making when open to subjective interpretation (Peysakhovich & Karmarkar, 2015), promoting dismissal of cautionary climate change data.

The demotivation caused by the perceived ambiguity of climate change risk is further compounded by individual beliefs about the inefficacy of their personal environmental actions (Cleveland *et al.*, 2005), as well as poor conceptions of the actual energy impacts of different behaviors (off by a factor of 2.8 on average; Attari *et al.*, 2010).

Neuroimaging may provide insight into the roles of self-efficacy and ambiguity as barriers to pro-environmental behavior. Anecdotal discussions with participants in an fMRI study of environmental philanthropy (Sawe & Knutson, 2015) indicated that those who rarely donated rationalized their actions by commenting on the small scale of their impact relative to the scale of the problem; low donation was associated with increased mPFC activity, indicating that the process of weighing costs and benefits during value calculation may have convinced individuals that self-interested behavior trumped pro-environmental actions. Measures of environmental locus of control (Cleveland *et al.*, 2005) could be combined with neuroimaging to more explicitly test this relationship.

FMRI comparison of ambiguity versus probabilistic uncertainty (Hsu *et al.*, 2005) reveals that ambiguous circumstances preferentially elicit activation in the amygdala, often correlated with fear and aversion responses (Kang & Camerer, 2013), dorsal mPFC (implicated in modulation of amygdala activity) and lateral orbitofrontal cortex (implicated in emotional and cognitive information integration). In contrast, the striatum responded more to probabilistic risk. This provides some foundation for study of the degree to which ambiguity- or even fear-based processing influences disengagement from climate change messaging and associated low engagement in pro-environmental behaviors. If it is found that perceived ambiguity in the extent and severity of climate change outcomes is related to amygdala activity, messaging approaches and information presentation methods that successfully shift individuals to instead recruit circuitry involved in the assessment of probabilistic risks may encourage more strategic and engaged environmental decision-making. More broadly, if neuroscientists find a replicable neural response to ambiguity in environmental decision contexts that mirrors findings in other tasks (including attempting to predict temperatures; Hsu *et al.*, 2005), this could be used to understand when, how, and why ambiguity aversion may be influencing the public's environmental choices.

Ultimately, discussion of climate change is a political one, and belief in climate change risk has been shown to transcend an individual's science literacy and numeracy, relating instead to their liberal or conservative values (and indeed, polarizing in the USA along party lines as individuals become more learned) (Kahan *et al.*, 2011). Policy-makers will have to decide the degree to which climate change should be invoked in messaging when engaging individuals to undertake pro-environmental actions. Here, too, fMRI's capacity to not only examine individual differences in decision-making, but also to predict population-level responses to campaign appeals (e.g., to quit smoking; Falk *et al.*, 2012) can facilitate an understanding of which messaging may be most impactful or most generalizable.

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Conclusion

Neuroimaging studies have examined a rapidly expanding array of decision-making contexts in recent years, but environmental applications remain relatively unexplored. However, neuroeconomic areas of study such as consumer behavior and temporal discounting have clear implications for how humanity makes decisions with significant environmental impacts. Environmental choice paradigms can similarly benefit neuroeconomic researchers by providing a complex, real-world context where neuroimaging's capacity for prediction and understanding of mechanisms can benefit policy-makers and practitioners. In particular, the development of behavioral nudges and better information provision methods to optimize individual decisions surrounding energy efficiency is a promising area of research, with outcomes that both save money for the individual and benefit the environment.

The primary benefits of neuroimaging studies for environmental policy fall broadly into three categories: understanding how constituent elements of informational and behavioral nudges can influence the decision process; understanding how decision-making processes may differ across individuals; and employing neural data as a tool to predict national behavior. These may overlap and interact: for instance, seeing how different types of individuals react to specific messaging elements, or what types of decision processes are the most predictive of national behavior. Armed with a more detailed understanding of the decision process and its behavioral drivers, environmental policy-makers can design more precise and tailored policies and behavioral interventions to meet the needs of a diverse population.

Neuroeconomic methods should be considered as a complement to more traditional survey and econometric methods of studying environmental decision-making, offering a window into the mind as we each make choices that, in aggregate, have far-reaching consequences across the globe.

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