



# Behavioral and Experimental Insights on Consumer Decisions and the Environment

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**Behavioral and Experimental Insights  
on Consumer Decisions and  
the Environment**

A dissertation presented by  
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to the Department of Public Policy  
in partial fulfillment of the requirements  
for the degree of  
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in the subject of  
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## **Behavioral and Experimental Insights on Consumer Decisions and the Environment**

### **Abstract**

In the following essays, I apply theoretical insights and experimental methods from behavioral science to address three questions at the intersection of environmental economics and consumer behavior.

In Chapter 1, I use an experimental intervention to explore the role of salience in the willingness to pay for climate change mitigation. The long time horizon between the mitigation decision and the benefits of that decision may hinder optimal investment in climate change mitigation. The immediate costs of the decision loom large in the decision-maker's mind while the future benefits have lower prominence in their decisions. As a result, climate change mitigation decisions may be prone to salience bias. In an online randomized control experiment, I test whether tasks focusing attention on the risks and challenges of climate change will increase the willingness to pay for climate change mitigation. In the Letter treatment, the writing task is framed as a message directed to a particular individual living in the year 2050. In Essay treatment, the writing task is framed as an essay on the risks and challenges of climate change. I find that compared to a control group, both writing tasks that focus attention on the risks and challenges of climate change increase the willingness to donate to a climate change mitigation non-profit organization. However, the two treatments appear to operate through different

pathways. These findings contribute to the understanding of how to effectively bridge the psychological distance between choice and consequence for climate change mitigation. They also have broader implications for the interplay between psychological distance and salience bias in a broad range of decision-making contexts.

In Chapter 2, coauthored with Joseph Aldy, we model the consumer welfare impacts of gasoline price volatility under expected utility theory and prospect theory. The salience of gasoline prices among the U.S. public reflects consumer concerns about the price, and the uncertainty around the price, of gasoline. Volatility in gasoline prices reduces the ability of credit-constrained households to smooth consumption, and could result in substantial welfare losses for such households. Volatility reduces the information value of prices, which can undermine consumer decision-making for new investments. Gasoline price volatility may also reflect energy and environmental policies. As decision-makers compare the welfare impacts of policies that accomplish the same goal (e.g. reduce carbon dioxide emissions) but generate different levels of volatility in energy prices (e.g. fixed carbon tax compared to a fluctuating allowance price), the effects of consumer price volatility are often left out of the analysis. The goal of this research is to understand how energy price volatility affects consumer welfare. Focusing specifically on the gasoline market, we estimate the risk premium for increased gasoline price volatility due to a carbon allowance market. Under an expected utility theory model, households with highly inelastic demand or high-risk aversion tend to prefer fixed prices but have low risk premiums. Under a prospect theory model with reference-dependent utility, loss aversion leads to a strong preference for fixed prices with risk premiums around 2% of the average price. The salience of gasoline prices creates a strong reference point and the level of attention focused on “pain at the pump” when prices rise sharply implies loss aversion. Thus, prospect theory may be particularly well-suited to this market setting. By clarifying the welfare impacts of gasoline price volatility, we will better understand the full set of tradeoffs among energy policy options that have differential effects on fuel

price volatility.

In Chapter 3, I use a series of experiments to explore the impacts of eco-friendly labels on perceptions and evaluations of product attributes. Expectations may affect how people evaluate product attributes. If people expect different levels of performance from eco-products and regular products, then the presence of an eco-product label may bias their evaluations. Six experiments examine how expectations of the objective performance of eco-products affect perceptions of those products and subsequent product preferences. Holding objective performance constant, I find that prior expectations bias the evaluations of eco-product attributes. Expecting energy efficient bulbs to generate unpleasant lighting causes people to evaluate the lighting as unpleasant; expecting toilet tissue from recycled paper to be coarse causes people to evaluate the toilet paper as coarse. Using a study designed to isolate the effects on sensory perception, I find that expectations do not bias the sensory perception of product attributes. Instead, I find that consumers follow Bayesian predictions of combining prior expectations with a new perceptual signal to form posterior evaluations. This research may help explain the slower than expected take-up of energy efficient products (referred to as the “energy efficiency gap”), and the persistence of beliefs that eco-products underperform standard products, when many objectively do not.

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## Chapter 1

# The Salience of Future Climate Impacts and the Willingness to Pay for Climate Change Mitigation

## 1.1 Introduction

Many people have a hard time making good decisions when they will not immediately be affected by the consequences of those decisions. The longer the gap between choice and consequence, the more likely people are to make mistakes. This problem arises in many contexts. People do not save enough for retirement, they procrastinate on long-term projects, and they make unhealthy diet and exercise choices that have major long-term health costs.

With relevant time horizons spanning centuries, climate change mitigation decisions are highly vulnerable to problems that arise with long-term decision-making (Pahl et al. 2014). Reducing carbon dioxide emissions today does not result in an immediate reduction in climate change. Instead, those impacts are delayed and occur over the course of decades. The decision-maker does not get an immediate climate benefit, and a significant portion of the benefits will occur after the decision-maker is dead. Because of this crucial attribute of climate change mitigation, understanding how people evaluate benefits that occur now and in the future is critical to reaching an optimal level of climate change mitigation.

This question is of utmost importance, because globally individuals and policy-makers have underinvested in climate change mitigation compared to a likely range of socially optimal mitigation pathways (IPCC 2014). In addition to the problem of long time horizons, a number of issues make it extremely difficult to achieve optimal investment in climate change mitigation. First and foremost, climate change is a global commons problem. The classic problem of free-riding that plagues the management of open-access resources arises on a global scale and reaches across generations. Additionally, the substantial uncertainties in both the costs and the benefits of mitigation make it difficult to precisely determine optimal policies and present problems for garnering

sufficient political support to address the issue. Underinvestment in climate change mitigation could also be due to more nuanced effects of the disconnection between our lives today and future climate change impacts (Moser 2010).

In this study, I focus on an intervention that may reduce the psychological gap between today's decisions about climate change mitigation and the future impacts of those decisions. Every climate change mitigation choice made today will incur most of its costs today and benefits in the future. I argue that time delay in consequences makes them less vivid and prominent in people's minds; it reduces the salience of the impacts. In economic decisions, costs and benefits that lack salience are not given optimal weight in the decision-making process, defined by the appropriate discount rate (Bordalo et al. 2012). I seek to show that by encouraging the decision-maker to think and write about the impacts of climate change, those impacts become more salient and receive more weight in subsequent decisions.

In an online experiment, I utilize three different narrative frames for a writing exercise to vary the salience of future impacts of climate change. I employ a writing task to encourage focused attention on the risks and challenges of climate change and to enable each participant to personalize the narrative. In the first treatment, I ask participants to write an essay that reflects on the risks and challenges of climate change. I refer to this as the Essay treatment. In the second treatment, I ask participants to write a letter about the risks and challenges of climate change to a particular individual living in the future. This treatment seeks to make the future impacts even more vivid by writing to someone who would be experiencing the impacts by the time they are reading the letter. For participants with young loved ones, I make this more personally relevant by asking them to address their narrative to their child, grandchild, niece, or nephew. For those without young relatives, they write to an anonymous child born "today." I refer to this as the Letter treatment. In the control, I ask participants to

write an essay describing their daily routines. I test whether these interventions affect participants' willingness to pay for climate change mitigation by measuring how much of an experimental bonus they choose to donate to a charity that helps to mitigate climate change. I also measure revealed implicit discount rates using an incentive compatible choice-based measure.

Specifically, I test the following hypotheses:

**H1:** The process of generating a narrative on the risks and challenges of climate change leads to a higher willingness to pay for climate change mitigation.

**H2:** Addressing the narrative on the risks and challenges of climate change to an individual living in the future will further increase the willingness to pay for climate mitigation.

**H3:** A future-oriented narrative frame will reduce the revealed implicit discount rate.

In addition to these hypotheses, I explore underlying mechanisms of the treatment effects. First, I explore whether the treatments increase the level of particular “decision factors” that I expect may play a role in a participant’s decision to donate to climate change mitigation (e.g. concern for climate change, guilt about one’s role in climate change, etc.). Then, I explore whether the treatments change how each decision factor is weighted in the donation decision.

The rest of the paper is organized as follows: in Section 1.2, I review the literature related to the role of salience in decision-making; in Section 1.3, I review the economic theory of demand for climate mitigation and donation measures; in Section 1.4, I detail the methods of the experiment; in Section 1.5, I describe and discuss the results of the experiment; and in Section 1.6, I conclude with theoretical and practical implications of this study.

## 1.2 Salience and Decision-Making

In a world of perfect information, perfect attention and perfect rationality, the salience of costs and benefits are irrelevant to utility maximization. However, where salience affects decision making, it is crucial to understand how temporal and social distance affects the demand for climate change mitigation. In this section, I connect salience theory from the economics literature with construal level theory from the psychology literature. I then review studies that point to the role that salience and psychological distance may have in understanding decisions about climate change mitigation.

Recently, theoretical models and applied research have begun to examine the role that salience plays in shaping and potentially biasing economic decisions. In their model of choices over lotteries, Bordalo, Gennaioli, and Shleifer replace objective probabilities of outcomes with decision weights that are biased by the relative salience of lottery payoffs (Bordalo et al. 2012, 2013). When decision weights are biased, decision makers to put too much emphasis on payoffs with high salience and too little emphasis on payoffs with low salience. Taylor and Thompson's (Taylor and Thompson 1982) definition of salience motivates their salience theory model. It is also the definition I use in this paper: "Salience refers to the phenomenon that when ones attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments." In a related vein, Koszegi and Szeidl developed a model of overweighting or underweighting attributes by excessive or insufficient focusing on those attributes (Koszegi and Szeidl 2013). Recent empirical research has explored the impact of salience and inattention in many domains (Gabaix and Laibson 2006; Finkelstein 2009; Chetty et al. 2009; Brown et al. 2010; Lacetera et al. 2012; Allcott and Greenstone 2012; Hastings and Shapiro 2013; Busse et al. 2014). I use a modified version of Bordalo, Gennaioli, and Shleifer's salience theory model to explore the role salience of future climate benefits may play in

the demand for climate change mitigation.

In this study, I seek to explore how psychological distance affects the salience of the costs and benefits of climate change mitigation decisions. Psychological distance opens up between an individual and an object, person, or event when they are separated by time, physical distance, or social distance (Trope and Liberman 2010). Psychological distance also increases when an event is hypothetical or uncertain (Liberman et al. 2007). In other words, psychological distance arises when a person thinks about an event that they do not directly experience in the present moment. However, people have the ability to construct representations of events in their minds. For example, one may imagine an event that will take place in the future or remember an event that takes place in the past (temporal distance). One may visualize their favorite vacation spot while sitting in their office (physical distance). One may try to “put themselves in someone else’s shoes” to empathize or gain a new perspective (social distance). Or, one may imagine any number of possible scenarios that may or may not come to pass (hypothetical distance). I argue that as the psychological distance of an event increases, the salience of the attributes of that event decreases.

This connection between psychological distance and salience shares commonalities with Construal Level Theory (CLT), a widely studied theory on psychological distance (Trope and Liberman 2010). In CLT, psychological distance affects the level at which a person construes an event. As the psychological distance increases, the construals become more abstract. As the psychological distance decreases, the construals become more concrete.

Focusing on temporal distance, I review a growing body of research that finds that when decisions have a future-oriented frame, more weight is given to future outcomes (Malkoc and Zauberman 2006; Rogers and Bazerman 2008; Hershfield et al. 2011; Radu et al. 2011; Israel et al. 2014). The literature on future-oriented framing of decisions is

highly relevant for this study because it lends support to the hypothesis that a writing task that focuses attention on an individual living in the future will lead to the higher willingness to pay to mitigate the future impacts of climate change. A number of these studies rely on construal level theory to explain the effects. However, I posit that the effects can also be interpreted as arising from salience theory where the focus on the future alters the relative salience of costs and benefits that occur in the present and the future. I argue that what construal level theory interprets as “low-level concrete representations” of outcomes or attributes can be thought of equivalently as high salience outcomes or attributes.

By framing choices either as deferred consumption or expedited consumption, Malkoc and Zauberan show that temporal framing affects the level of present bias (2006). When consumers think about deferring consumption, the focus is on a change from the present; when consumers think about expediting consumption, the focus is on a change from the future. In this study, Markov and Zauberan find that focusing on future consumption leads participants to be less present-biased in their choices. The authors attribute the reduction of present bias to the construal-level theory interpretation where a focus on the present leads to more concrete representations of consumption, compared to more abstract representations of future consumption.

However, their results can be reinterpreted through the lenses of prospect theory and salience theory. When a deferral frame anchors consumption on the present, then consumption in the present becomes the reference point from which outcomes are evaluated. Under prospect theory, delayed consumption would be assessed as a loss with the penalty of loss aversion while the monetary savings from deferring would be evaluated as a gain. Conversely, the expedited frame anchors consumption in the future and outcomes would be evaluated as changes from the future consumption reference point. Thus, expediting consumption is viewed as a gain while the extra cost of expediting



would be seen as a loss. Malkoc and Zauberan measure the concreteness of representations and find that these measures mediate the effect of the framing on present bias. They argue that this is evidence that the effect is distinct from a loss aversion impact and interpret their results through the lens of construal level theory. I argue that the concrete representation of the consumption event is equivalent to saying that the consumption event is highly salient. The temporal anchor drives salience and loss aversion drives the differential impact of deferred versus expedited consumption.

Rogers and Bazerman (2008) show that shifting the implementation of a choice or shifting the temporal focus of decision maker to the future can increase the likelihood of choosing “should” choices over “want” choices. Closely related to the climate change focus of this study, Rogers and Bazerman look at experimental participants’ willingness to increase the price of gasoline to reduce pollution and climate change. They find that construal level mediates the effect of the support for a policy to increase the price of gasoline either in the immediate future or the distant future. However, against the expectations of construal level theory, the effect on construal level does not hold when the policy under consideration is a decrease in the price of gasoline. This presents a puzzle for the construal level theory interpretation.

An alternative explanation can once again be found with salience and loss aversion. If the relationship between the support for a policy to change gas prices and the timing of the implementation of that price change results from differential levels of salience and subsequent weighting in the decision-making process, then the interpretation of the results is as follows. When the price increases, the personal costs of the present implementation would be more salient than the personal costs of the future implementation. When the price decreases, the personal savings in the present implementation are more salient than the personal savings in the future implementation. In the experiment, varying the timing of the implementation of a decrease in gas prices did not lead to differences

in the level of construal of the policy. These results make sense when interpreted from the perspective of loss aversion and salience. Due to loss aversion, the focus of the decision-maker would shift from the personal savings (i.e. gains) to the negative consequences (i.e. losses) of the policy. The benefits of the gas price policy are diffuse with benefits falling across the population and across time. For that reason, it is reasonable to expect that their salience is not affected by the timing of the implementation within a reasonable time scale such as the four-year delay in the experiment. The salience of these gains is largely the same in both the near and future implementation, so they do not result in differences between the two groups. This interpretation that loss aversion leads to a shift in focus from the personal gains to the social losses is further supported by the overall shift from the focus on personal costs to the focus on social costs when the policy in question is a price decrease rather than a price increase.

Studies that do not explicitly address construal level theory, but instead focus on the vividness of future outcomes also align with the hypothesis that the salience of outcomes affects intertemporal choices. Taking the concept of vividness of the future quite literally, Hershfield and co-authors (2011) use immersive virtual reality to let participants interact with an age-regressed version of themselves. They find that this visualization of oneself at age 65 increases hypothetical retirement savings. Similarly, Israel and co-authors (2014) find that priming participants with pictures of elderly people reduces their implicit discount rate.

A simple change in the numeric framing of an intertemporal choice can also affect the vividness of future outcomes. Magen and co-authors (2008) find that an explicit zero framing of intertemporal choices between payouts in the present and payouts in the future can reduce discounting. Asking participants to choose between \$5.00 today and \$8.20 in 26 days leads to more present biased decisions than asking participants to choose between “\$5.00 today and \$0.00 in 26 days” and “\$0 today and \$8.20 in 26 days.”

Radu and co-authors (2011) explore possible mechanisms for the effect of the explicit zero framing on present bias. In line with a salience interpretation, they find that the frame reduces present bias by shifting attention to the future negative consequences of the present biased option.

There is even evidence that a future-orientated perspective can affect decisions that cross generational boundaries, which is highly relevant for long-time frame climate mitigation decisions. For example, studies have found that encouraging individuals to consider the perspective of future generations can increase pro-environmental behavior (Pahl and Bauer 2013; Zaval et al. 2015; Arnocky et al. 2014). A growing literature points to the complex role that psychological distance may play in the willingness to undertake socially optimal levels of investment in climate mitigation and adaptation (Newell et al. 2014; Lorenzoni and Pidgeon 2006; McDonald et al. 2015; Weber 2006, 2010). While many researchers conclude that decreasing psychological distance will increase concern and subsequent action on climate change, others call for a more careful examination of the complex interplay of factors (McDonald et al. 2015). Climate change is an issue that involves psychological distance on four dimensions: temporal, geographical, social, and level of uncertainty.

For most people without direct experience of climate change impacts, climate change impacts have low salience. Climate change impacts are expected to take place in the future, to affect other people in other places, and have a great deal of uncertainty. When a person directly experiences climate impacts, such as anomalous weather events like Hurricane Sandy, there is no psychological distance between the person and the impacts. As it occurs, the event directly affects the person (no social distance) where they currently reside (no geographical distance) in the present moment (no temporal distance) with complete certainty (no hypothetical distance). However, uncertainty could remain in the causal connection between the event and climate change. Studies have

found that personally experiencing anomalous or extreme weather events makes people more concerned about climate change (Akerlof et al. 2013; Donner and Mcdaniels 2013; Li et al. 2011; Joireman et al. 2010; Hamilton and Stampone 2013; Egan and Mullin 2012; Zaval et al. 2014). Weather can even impact significant consumer purchases in ways that contradict rational expected utility theory. For example, the decision to buy a convertible or a four wheel drive vehicle is significantly influenced by the weather at the time of the purchase (Busse et al. 2014). The authors hypothesize that this effect is due to projection bias and salience.

Experiencing a weather event associated with climate change may change the psychological distance with which one views climate change. However, there is a long time delay between increased atmospheric concentrations of greenhouse gases and the full impacts that will result. Therefore to achieve an optimal climate strategy, we need to align the subjective perception of future impacts with the objective discounted value of those impacts. The cognitive bias that arises from the perceived psychological distance of climate impacts reduces their salience in current decision-making.

### **1.3 Willingness to Pay for Climate Change Mitigation and Public Goods Donations**

The primary outcome variable in this study is a donation to a charity that helps to sequester carbon and thus mitigate climate change. The donation measure serves as a revealed preference proxy measure for willingness to pay or individual demand for climate change mitigation. Optimal investment in climate change mitigation is achieved when the marginal cost of carbon dioxide abatement is equal to the social cost of carbon dioxide. With guidance from well-established integrated assessment models, the U.S. government uses a central value of \$36 per ton of CO<sub>2</sub> in benefit-cost analyses (Green-

stone et al. 2013; Interagency Working Group on Social Cost of Carbon 2015). With policies such as CAFE standards, renewable portfolio standards, biofuel policies, and regional carbon trading, the economy is operating under a non-zero shadow price for carbon. However, the current global level of climate change mitigation is sub-optimal (Victor et al. 2014). Even new regulations of CO<sub>2</sub> in the United States under the Clean Power Plan will impose a marginal abatement cost of carbon dioxide between \$12-\$27/ton, well below the estimated social cost of carbon (Burtraw et al. 2014).

The importance of time preference in climate change is evident. The social discount rate, determined in large part by the pure rate of time preference, is one of the most important parameters in economic models of climate change. For example, the social cost of carbon has an average value of \$36 with a discount rate of 3%, but the social cost of carbon jumps to \$56 with a discount rate of 2.5% and falls to \$11 with a discount rate of 5%. A large body of literature in environmental economics details the complex and controversial question of what is the proper social discount rate to use in cost-benefit analyses of climate change (See Arrow et al. 2013 for an overview). In climate change, the benefits of abatement are beset with a wide range of uncertainty and are realized over very long time horizons. As a result of the long time horizons, high discount rates translate to low levels of optimal climate change mitigation (Nordhaus 2007; Arrow et al. 2013, 2014; Weitzman 2001).

Energy efficiency choices are an important area of consumer behavior where time preference affects consumers' climate change impact. There is a diverse debate over whether there is an "energy efficiency gap" between the optimal and actual investment in energy efficiency (Jaffe and Stavins 1994; Gillingham et al. 2009; Allcott and Greenstone 2012; Gillingham and Palmer 2014; Gerarden et al. forthcoming). Recent work points to other explanations for this apparent gap (Allcott and Greenstone 2012; Fowlie et al. 2015), but the question of whether myopia contributes to high implicit discount rates

merits further study. While some level of discounting is optimal, decision-makers may overweight the present and underweight the future (Akerlof 1991; Zauberman and Lynch Jr. 2006). This study explores whether increasing the salience of future benefits changes the relative weighting of present and future impacts by measuring participants implicit discount rates after each treatment.

If consumer behavior is suboptimal according to the standard exponential discounting model, then we may look for an explanation from using an alternative model of time preference. The hyperbolic discounting model is one of the most robust models in behavioral economics and has contributed a great deal to understanding of time inconsistencies in time preference (Laibson 1997; Cropper and Laibson 1999). Hyperbolic discounting leads to present bias and a pattern of procrastination where the right time to make a costly decision with future benefits never arrives. The collective response to climate change is highly vulnerable to the problem of present bias due to the structure of immediate costs and far future benefits for most climate mitigation actions. In this study, I seek to test whether a behavioral intervention reduces myopia by changing the time perspective of the decision-maker.

Individuals who are operating under cognitive bias from the long time horizon of the climate change issue may make two kinds of errors. First, if individuals are myopic, they may underestimate the current value of the damages of climate change and underinvest in climate change mitigation. For example, an elected representative whose primary decision criterion is maximizing public welfare may fail to do so if she myopically evaluates public policies. She may undervalue policies with long-term benefits by discounting future benefits at a rate higher than the optimal social discount rate. Second, for myopic individuals, facing a carbon price equal to the social cost of carbon may not be sufficient to achieve optimal change. Increasing the carbon price to account for externalities may still lead to underinvestment in energy efficient technologies due to

“internalities” where consumers discount future benefits more than is personally optimal (Allcott et al. 2014). Future utility may be underweighted because it is not salient. Additional policies may be needed to encourage individuals to give adequate attention to future costs and benefits and reduce these internalities. If myopia plays a role in reducing optimal climate change mitigation through diminished salience of the risks of climate change, then interventions to increase the salience of climate risks may reduce myopia and improve climate mitigation policy choices.

In this study, I utilize voluntary donations in an experimental context to serve as an incentive-compatible, revealed preference proxy measure of willingness to pay for climate change mitigation. After the writing treatments, I explain that all study participants have a 1 in 100 chance of receiving a \$20 bonus after the study period ends. I tell them that they may donate part of their bonus to a non-profit organization, Trees for the Future. Their donation would then be used to plant trees that remove carbon dioxide from the atmosphere and thus contribute to climate change mitigation. Then, they choose how much of their \$20 bonus to keep for themselves and how much to donate.

Voluntary donations can be made out of a desire to contribute to a public good, like climate change mitigation, and out of a desire to feel good about oneself. A pure altruism model posits that donations are simply made to improve the world around us. The only utility we gain from a donation in a pure altruism model is the utility we derive from our enjoyment of the total level of public goods to which we contribute. An impure altruism donation model allows individuals also to gain utility from feeling good about the act of donating. From the classic impure altruism paper by Andreoni (1990): Individual,  $i$ , chooses donation  $g_i$  to maximize the following utility function:

$$U_i = U_i(x_i, G, g_i) \tag{1.1}$$

where  $G$  is the total amount of the public good.

Including  $g_i$  as a separate argument indicates the “warm glow” gain in utility from the act of donating.

I apply the basic impure altruism model to my donation context with the following parameters:

$$g_i = (\alpha_j + \delta_j)T_j + \gamma X_i \quad (1.2)$$

$\alpha_i$ : Change in utility weighting of perceived marginal increase in expected future climate stability (altruism, including parental “altruism” towards own child)

$\delta_i$ : Change in marginal warm glow from donation

$T_j$ : Indicator variable for treatment group

$X_i$ : Vector of individual characteristics (including beliefs about the impacts of donation on  $G$ )

For a small donation to a global public goods problem like climate change, there is the problem that the marginal effect of a small individual action on climate change is essentially zero, implying that  $\alpha_i \rightarrow 0$ . Nonetheless, individuals make decisions based on their perception of efficacy (Cryder et al. 2013; Erlandsson et al. 2014). Experimental participants may perceive a non-zero efficacy of their donation. Assuming that  $\alpha_j$  is the perceived efficacy rather than actual efficacy allows  $\alpha_j > \epsilon$ . Participants may also donate because it gives them a warm glow. Since I cannot differentiate between  $\alpha_j$  &  $\delta_j$ , I simplify by setting:

$$\beta_j = \alpha_j + \delta_j \quad (1.3)$$

In this model, I am agnostic on the relative contributions of altruism and warm glow by measuring  $\beta_j$  as  $\alpha_j + \delta_j$ . While I cannot distinguish between altruistic giving and warm-glow giving, I expect that reducing the psychological distance from the impacts of climate change will increase donations. Salience theory argues that we put more weight



on vivid outcomes and less weight on those that are not as clear (Akerlof 1991; Higgins 1996; Bordalo et al. 2012). If the benefits are more vivid when they are psychologically closer, then I hypothesize that they will receive more weight in the decision-making process. More weight on vivid benefits would then, in theory, lead to a higher willingness to pay for climate change mitigation.

## 1.4 Methods

The study consists of a pre-experimental survey, a reading task, a randomized writing task, and a post-treatment survey. The primary outcome variables are the willingness to donate to a climate change non-profit and a measure of time preference.

I used a screening survey on Amazon's Mechanical Turk to recruit individuals living in the U.S. who have children under the age of 18. In the screening survey, I collected data on demographics including age, gender, race, ethnicity, education, income, state and zip code. I also asked some political questions including the tendency to vote for Republican or Democratic candidates and concern about climate change (1 to 10 scale). In addition to the variables of interest, I included decoy questions about concern for illegal immigration, income inequality, and the budget deficit to ensure that participants did not view this as a "climate change study" which could bias participation in the follow-up study. I ended the screening survey with a question that asked the participant to write 2-3 sentences about an interesting news story they read, listened to, or watched recently as a quality screening mechanism. I excluded participants who wrote fewer than 25 characters from the follow-up study.

Between December 29, 2015, and January 10, 2016, I invited qualified participants to participate in the full study. To establish a minimum level of knowledge and to control for experimenter demand by making it clear to all participants that this study

is overtly focused on climate change, participants began by watching a three-minute video explaining the basic science and potential impacts of climate change.<sup>1</sup> Next, they read a series of climate solutions both for broad scale policy and individual action. The purpose of providing information about solutions is to reduce the level of hopelessness and arousal that some people may feel after watching an educational video that discusses the impacts of climate change. Studies have shown that when people feel hopeless or helpless about a problem, then they respond by disengaging (Rutjens et al. 2010; Moser and Dilling 2011). If learning about climate change puts them in a high stress, high arousal state, then providing concrete solutions may decrease the arousal and stress to a level more conducive for critical thinking (Weick 1984). In this study, it is important that they are aware of the problem of climate change as well as tangible solutions.

The next section varies with treatment group. Each participant is asked to spend five to ten minutes on a writing task. In the Letter treatment, participants are asked to write a message that will be delivered in 35 years. They are asked to write about the risks and challenges of climate change and how they think climate change will affect the lives of people in 2050. For those with a child, grandchild, niece, or nephew, the message is addressed to that individual, and their age in 2050 is given at the beginning of the prompt. For those without a young, related loved one, the message is addressed to an individual born today who will be 35 years old in 2050. In the Essay treatment, participants are asked to discuss the risks and challenges of climate change in an essay. In the control group, participants are asked to write about their daily routines. Participants must spend at least 5 minutes on the writing task and write at least 500 characters. See Appendix A for full question texts.

After the writing task, I explain that 1 out of 100 participants will receive an additional bonus of \$20 which they may split between themselves and a charity that

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<sup>1</sup>Video from TEDEd: <http://ed.ted.com/lessons/climate-change-earth-s-giant-game-of-tetris-joss-fong>

reduces greenhouse gases in the atmosphere. They then choose among 21 options that divide the \$20 between the participant and the donor. In a pilot study, participants were asked to type in the amount they would like to give to the charity and the amount to keep for themselves. The amounts had to add up to \$20. While this was, in theory, the best way to elicit a continuous measure of donations, most people chose to donate either \$0 (21%), \$5 (24%), or \$10 (29%). The top half of the distribution was also bimodal at \$15 (4%) and \$20 (4%). In further testing, providing options that split the money for the participant and allowing them to choose produced donations that more closely approximated a normal distribution.

Next, I use a multiple price list measure of time discounting known as Money-Earlier-or-Later (MEL). I use a choice-based measure based on the finding that choice-based measures are more strongly predictive of real world behavior than a matching measure, which would have been more efficient to implement (Hardisty et al. 2013). Participants choose between \$100 in one month and some amount of money, \$X, in four months. The payoff, \$X, ranges from \$101 and \$300. These tradeoffs correspond to a three-month discount rate of 1% and 110%. One participant is randomly chosen and one of their choices is implemented with a real-world payment. Participants take a short quiz to ensure they understand the procedure.

I structure the choice decision to choose between two future periods, one month and four months, to eliminate the potential effect of present bias. Eliminating the role of present bias simplifies the hyperbolic discounting model to the standard exponential discounting model (Laibson 1997; Frederick et al. 2002). I make this simplification because measuring present bias with monetary rewards in experimental contexts is problematic. Present bias refers to the difference between immediate utility and non-immediate utility. Using monetary rewards to measure present bias requires the assumption that any additional money paid at time zero will be consumed at time zero and will not offset

any other consumption. These assumptions do not hold for most people. By utilizing a choice between two future payments, I avoid this confounding issue and achieve a cleaner measure of the implicit discount rate,  $\delta$ . Additionally, it is important to note the distinction between time preference and time discounting (Frederick et al. 2002). Time preference refers to the relative preference for utility experienced in different time periods, whereas time discounting refers to the lower value of future outcomes compared to those that occur in the present. Time preference or utility discounting can be measured experimentally by offering tradeoffs between consumption rewards, like food, alcohol, and work (negative reward). While it is possible to employ this paradigm in an online experiment, it requires retaining participants for a number of weeks and greatly increases the costs of the experiment. While I am interested in how time preference is affected by the framing intervention, in this paper, I seek first to establish a relationship between the treatments and implicit discount rate, which tends to correlate with the underlying time preference. For example, Reuben, Sapienza, and Zingales (2010) find that there is a correlation between the discount rates for monetary rewards and the discount rates for consumption ( $R^2 = 0.12$ ). Further studies will be needed to examine the question in more depth.

In the last section of the experiment, I ask a series of questions that serve as manipulation checks and potential decision factor variables. I ask about legacy motives using a three-question measure that replicates Zaval et al. (2015). I ask about hopefulness about the future, the vividness of the future, ease of hindsight, concern for climate change, the likelihood that climate change will negatively affect one's child. I also include questions about feelings of altruistic and parental responsibility, efficacy of personal and global actions, and sense of guilt. In all analyses except the within subjects change in climate concern, responses to these questions are standardized with a mean of zero and standard deviation equal to one.

To test my first two hypotheses (H1 and H2), I regress donations amounts on indicator variables for both the Essay and Letter treatments. While I expect other covariates to be orthogonal to treatment group due to random assignment, I test the robustness of the treatment effects with two additional specifications. First, I add the measure of prior concern for climate change that was elicited in screening survey. Then, I also add the following demographic variables: parental status (dummy), age (numeric), income (ordinal), education (ordinal), voting preferences (dummies), male (dummy), white (dummy), Hispanic (dummy), and state (dummies). In the full model, I cluster observations at the state level to adjust for correlated errors among individuals within each state. I expect some correlation both due to cultural effects of the state in which a participant lives as well as impacts of recent weather during the study period.

For the full model with treatment groups, dummies and demographic controls, I estimate the following equation using ordinary least squares:

$$y_i = \beta_0 + \beta_1 LT_i + \beta_2 ET_i + \beta_3 \text{concern}_i + \gamma X_i + \epsilon_i \quad (1.4)$$

In this equation,  $y_i$  is the donation to a climate change mitigation non-profit,  $LT_i$  is an indicator variable for participants in the Letter treatment,  $ET_i$  is an indicator variable for participants in the Essay treatment,  $\text{concern}_i$  is a baseline concern about climate change, and  $\gamma$  is a vector of control variables.

To assess H1, whether writing a narrative on the risks and challenges of climate change leads to a higher willingness to pay for climate change mitigation, I test whether  $\hat{\beta}_1 > 0$  and  $\hat{\beta}_2 > 0$ . For H2, that addressing the narrative on the risks and challenges of climate change to an individual living in the future will further increase the willingness to pay for climate mitigation, I test if  $\hat{\beta}_1 > \hat{\beta}_2$ .

To assess H3, I derive the implicit discount rate from the money-earlier vs. money-

later choices and evaluate whether it differs in each treatment group. First, I find the approximate indifference point by looking to where the participant switched from the money earlier payment to the money later payment. If they switched more than once, they are excluded from the sample. I approximate the discount rate by taking the midpoint of the discount rates implied by the monetary tradeoff before the switch and at the switch point. I calculate the discount rate for each point as an exponential rate according to the following equation:

$$r = \ln \left( \frac{x_{t+4}}{x_{t+1}} \right) \quad (1.5)$$

where periods,  $t$ , are measured in months. For those who never switch from earlier payments to later payments, or vice versa, the endpoint is used as the implicit discount rate. Using  $r$  as the dependent variable, I run the same regression models as I do to analyze donations (Eq. 1.4). To test H3, that a future-oriented narrative frame will reduce the revealed implicit discount rate, I test whether  $\hat{\beta}_1 > 0$ . Then I test whether the implicit discount rate mediates the relationship between the Letter treatment and donation amount using the mediation procedure described in the next paragraph.

Using a within-subject, before-and-after measure, I examine the impact of the treatments on climate concern. In the screening survey, I ask participants to rate their level of concern about climate change. After the treatment, I ask them the same question. I apply a difference-in-differences estimation to look at the impact of the Letter and Essay treatments on the change in concern for climate change compared to the change in concern of the control group. The estimated coefficients are defined as:

$$\hat{\beta}_{LT} = \bar{\Delta}y_{LT} - \bar{\Delta}y_C \quad (1.6)$$

$$\hat{\beta}_{ET} = \bar{\Delta}y_{ET} - \bar{\Delta}y_C \quad (1.7)$$

Next, I use mediation analysis to investigate pathways of the treatment effects. Mediation analysis attempts to measure whether the treatment changes an intermediary variable which then goes on to affect the outcome variable. Mediation analysis is widely used in psychology. However, generating unbiased estimates of causal mediation effects is very challenging, even in an experimental context. If the treatments affect more than one mediator or if there are heterogeneous impacts of the treatments or the mediator, then the mediation analysis may be biased (Bullock et al. 2010). It is unlikely that these stringent requirements are met in this study. The analysis is included in this study for two reasons. First, this study serves, in part, as a replication of Zaval et al. (2015) and mediation analysis of the role of legacy in climate change mitigation donations is a central focus in their paper. Second, the mediation analysis is meant to explore potential causal pathways to generate hypotheses for future experiments.

Mediation analysis breaks down the total causal effect,  $\tau_i$ , of each treatment,  $t$ , on the outcome variable of interest,  $Y_i$ , into the total indirect effect,  $\delta_i(t)$ , and the total direct effect,  $\zeta_i(1 - t)$ :

$$\tau_i = \delta_i(t) + \zeta_i(1 - t), \quad (1.8)$$

for  $t = 0, 1$ . The direct effect is the effect of the treatment on the outcome variable if the mediator,  $m$ , were held constant. The indirect effect, or causal mediation effect, is the effect of the treatment on the outcome variable that operates by changing the mediator variable. Figure 1.1 provides a visual illustration of the theoretical logic of mediation analysis.

Using a potential outcomes framework, the total treatment effect is defined as the difference in potential outcomes under treatments,  $t = 0, 1$ :

$$\tau_i \equiv Y_i(1, M_i(1)) - Y_i(0, M_i(0)) \quad (1.9)$$

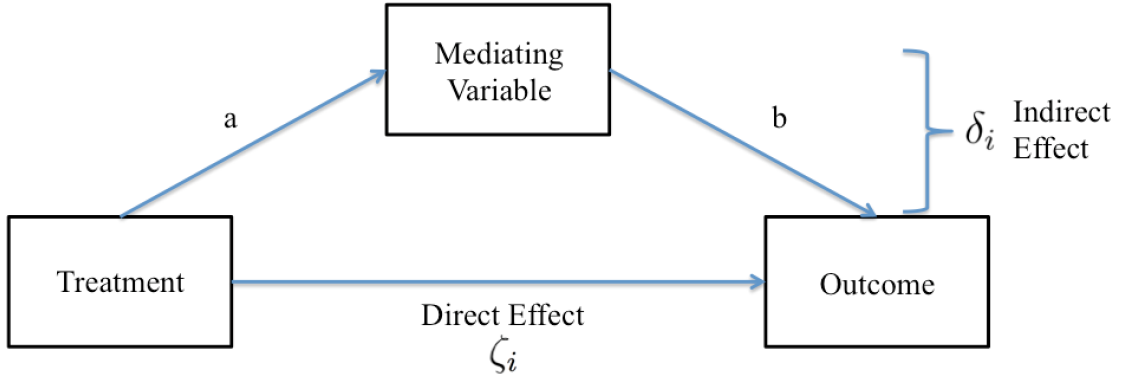


Figure 1.1: Mediation Analysis

The indirect effect is the potential outcome of the treatment,  $t$ , with the mediator at the potential value under the treatment minus the potential outcome of the treatment with the mediator at the potential value under the control:

$$\delta_i(t) \equiv Y_i(t, M_i(1)) - Y_i(t, M_i(0)) \quad (1.10)$$

I estimate the average indirect effect,  $\bar{\delta}_i$ , using the R package, ‘mediation’ which implements the following algorithm (Imai et al. 2010b; Imai and Keele 2010; Imai et al. 2010a):

$$\bar{\delta}(t) = \iint \mathbb{E}(Y_i | M_i = m, T_i = t, X_i = x) \{dF_{M_i | T_i=1, X_i=x}(m) - dF_{M_i | T_i=0, X_i=x}(m)\} dF_{X_i}(x). \quad (1.11)$$

The algorithm is estimated using a quasi-Bayesian Monte Carlo approximation. The estimates generated by this algorithm are nearly identical to those of the well-known Baron-Kenny procedure (Baron and Kenny 1986; Imai et al. 2010a). The Baron-Kenny



procedure calls for three separate regressions to analyze mediation:

$$M_i = \beta_0 + \beta_1 T_i + \epsilon_i \quad (1.12)$$

$$Y_i = \beta_0 + \tau T_i + \epsilon_i \quad (1.13)$$

$$Y_i = \beta_0 + \delta M_i + \zeta T_i + \epsilon_i \quad (1.14)$$

According to Baron and Kenny,  $\beta_1 \neq 0$ ,  $\tau \neq 0$ , and  $\delta \neq 0$  must all hold in the expected directions to indicate mediation. However, more recent work has shown that all of these relationships do not necessarily need to be significant in order to indicate mediation (MacKinnon et al. 2007; Zhao et al. 2010).

The algorithm developed by Imai et al. improves upon the basic Baron-Kenny procedure by generating sensitivity analyses and confidence intervals for hypothesis testing. (Imai et al. 2010a).

I explore mediation effects of the treatments on climate mitigation donations for five climate specific measures: change in climate concern, the belief that climate change will impact on one's children, an altruistic responsibility for climate mitigation, guilt about one's role in climate change, and the efficacy of personal and global mitigation actions on climate change. I also explore mediation effects for five measures of different aspects of time perspective: implicit discount rate, legacy motives, the vividness of the future, hindsight, and hopefulness about the future.

Finally, to measure whether the treatment increases the salience of decision factors, I look to see if decision factors carry different weights in each treatment group by regressing decision factors on donations. In the salience theory model by Bordalo, Gennaioli, and Shleifer (2012), the decision-maker evaluates choices with risky prospects with as the sum of the value of each outcome weighted by the probability that the outcome will

occur if each option is chosen:

$$V(L_i) = \sum_{s \in S} \pi_s v(x_s^i) \quad (1.15)$$

where  $\pi_s$  is the probability that the state of the world,  $s$ , will occur and  $L_i$  is the choice or lottery with  $x_s^i$  payoffs in each state  $s \in S$ . If the decision-maker is affected by the salience of particular outcomes, then the objective probability,  $\pi_s$ , is replaced with the decision weight,  $\pi_s^i$ . In other words, aspects of the decision framework that would not affect optimal decision-making in expected utility theory change the weight assigned to each possible outcome in the utility maximization choice.

In their model, salience is defined as specifically related to the ordering and differences between payoffs. In this application of the model, rather than precisely define salience in a modeling context, I test whether the treatments alter the decision weights associated with a decision factor. In this context, I define a decision factor as a potential driver of the willingness to pay for climate change mitigation. For example, if a participant feels that climate change will impact his children, then he may be willing to pay more to mitigate climate change. The outcome of a safer future climate would provide higher utility to him than if he did not anticipate possible negative impacts for his loved ones. Whether each decision factor is affected by the treatment and whether that drives higher donations is examined by the mediation analysis.

To measure the decision weight given to the decision factor, I regress potential decision factors on to the donation amount for each treatment group. Then I compare the decision weights, measured as the regression coefficients, between the treatment groups. The regression for each treatment group answers the question: Holding the values of decision factors constant, how much does each decision factor weigh in a person's willingness to pay for climate change mitigation? Comparing the decision weights between the treatments provides insight on whether the treatment increased the salience of that

decision factor.

## 1.5 Results

### 1.5.1 Revealed Preference: Donation Measure

Participants in both treatment groups donated a larger share of their bonus than those in the control group. The effect sizes in both groups were remarkably similar. In the control group, the average donation was \$6.81. The average donations in the Letter and Essay treatment groups were \$7.54 and \$7.56 respectively, an 11% increase for both groups ( $p = 0.044$ ;  $p = 0.037$ ). Including baseline climate concern and demographic control variables in the regression analysis does not significantly affect the donation levels. People with higher baseline concern for climate change donate significantly more than those less concerned, parents donate significantly more than non-parents, and women donate significantly more than men. (See Table 1.1 for more details.)

In Table 1.2, I detail the results of interaction effects between the treatments and baseline climate concern and other demographic variables on donation levels. I expected that parents would be more strongly impacted by writing a letter to their child than non-parents who wrote to a niece or nephew or to an unrelated or anonymous person. Parents overall donated significantly more than non-parents, but the interaction terms between parents and treatment groups are not statistically significant. The same pattern holds for people who had a higher baseline level of concern about climate change. However, when the interaction terms are included, the coefficients on the treatment dummies increase substantially. It is possible that the effects of being a parent and being in the Letter treatment group are simply additive. On the other hand, there may be problems resulting from an unbalanced strata. By random chance, parents make up only 68.6% of the Letter treatment group while parents are 75.2% of the Essay treatment group and

Table 1.1: Donations Analysis

	<i>Dependent variable:</i>		
	Donation to climate change mitigation		
	(1)	(2)	(3)
Letter Treatment D.V.	0.728** (0.362)	0.734** (0.355)	0.670** (0.332)
Essay Treatment D.V.	0.746** (0.358)	0.829** (0.352)	0.750** (0.351)
Baseline Climate Concern		1.292*** (0.144)	1.243*** (0.142)
Parent D.V.			0.786** (0.378)
Age (years)			0.009 (0.017)
Income (\$1000's)			0.006 (0.005)
High School D.V.			1.646 (1.301)
Trade School D.V.			1.776 (1.255)
Associate Degree D.V.			1.720 (1.234)
Bachelor Degree D.V.			1.387 (1.258)
Graduate Degree D.V.			1.971 (1.275)
Vote Republican D.V.			-0.986** (0.397)
Vote Democrat D.V.			-0.616 (0.439)
Male D.V.			-0.777** (0.337)
White D.V.			-0.398 (0.424)
Hispanic D.V.			0.579 (0.558)
Constant	6.811*** (0.255)	6.772*** (0.251)	4.182*** (1.599)
State Fixed Effects	No	No	Yes
Clustered Standard Errors	No	No	Yes
Observations	1,797	1,784	1,700
R <sup>2</sup>	0.003	0.046	0.091

*Note:* OLS regression. Dependent variable is Donation in \$. Income is a numeric variable in \$1000's. Dummy variables are included for those who vote mainly or exclusively for Democrats and Republicans. Voters who vote half Republican and half Democrat as well as those who do not vote for either party are the comparison group. Education is a categorical variable split into dummy variables and less than high school education is the comparison group. D.V. indicates binary dummy variables. Baseline climate concern is a 10 point scale measure standardized with mean=0, sd=1. Age is measured in years.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

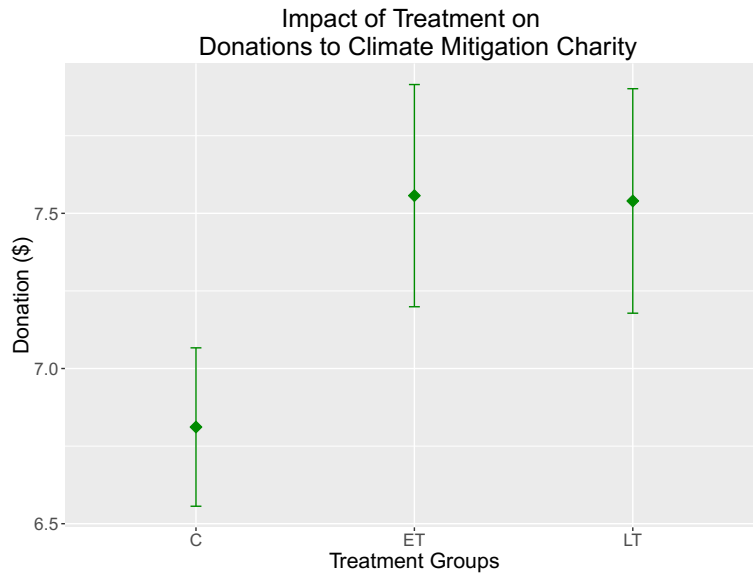


Figure 1.2: Mean donations of the control group and both treatment groups. Error bars represent standard errors. Difference between control and both treatments are statistically significant.

72.3% of the control group.

To further explore this question, I separate out average donations by parents and non-parents in each treatment group in Figure 1.3. Parents donate more than non-parents in all treatment groups, but the difference is most pronounced in the Letter treatment. Comparing only parents across treatment groups, parents in Letter treatment donate \$0.93 more than parents in the control treatment ( $p = 0.032$ ). Comparing only those in the Letter treatment group, parents donate \$1.37 more than non-parents ( $p = 0.018$ ). The differences between donations from parents and non-parents in the Essay treatment and the Control treatment are not statistically significant.

In the Letter treatment, we ask participants if they have children, grandchildren, nieces and/or nephews. Participants who report yes then address their letter specifically to one of their younger relatives. Otherwise, they write to an anonymous child. The level of donations among those who wrote a letter to a young person varied based on closeness

Table 1.2: Donations Analysis with Treatment Interactions

	<i>Dependent variable:</i>		
	Donation to to climate change mitigation		
	(1)	(2)	(3)
Letter Treatment D.V. (LT)	0.832 (0.669)	0.733** (0.355)	4.128 (3.313)
Essay Treatment D.V. (ET)	1.204* (0.684)	0.828** (0.352)	5.770* (3.265)
Parent D.V.	1.131** (0.533)		1.128** (0.570)
Parent x LT	-0.113 (0.764)		-0.447 (0.979)
Parent x ET	-0.618 (0.788)		-0.881 (0.728)
Baseline Climate Concern		1.222*** (0.246)	1.248*** (0.264)
Baseline CC x LT		0.207 (0.352)	-0.019 (0.477)
Baseline CC x ET2		0.008 (0.351)	0.032 (0.356)
Constant	5.980*** (0.462)	6.773*** (0.251)	1.538 (2.673)
Demographic Controls	<i>No</i>	<i>No</i>	<i>Yes</i>
Dems x Trt Interactions	<i>No</i>	<i>No</i>	<i>Yes</i>
State Fixed Effects	<i>No</i>	<i>No</i>	<i>Yes</i>
Clustered Standard Errors	<i>No</i>	<i>No</i>	<i>Yes</i>
Observations	1,785	1,784	1,700
R <sup>2</sup>	0.008	0.047	0.102

*Note:* OLS Regression. Demographic controls included where indicated are listed in Table 1.1. Demographic controls are interacted with treatment dummy variables where indicated. State-level fixed effects are not interacted with treatment dummies. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

of kinship. Grandparents donated the most although there were only thirty-three in the sample. They gave, on average, \$2.23 more than those writing to an anonymous child ( $p = 0.087$ ). Parents writing to their children also donated, on average, \$1.52 more than those writing to an anonymous child ( $p = 0.033$ ). Aunts and uncles gave slightly more (\$0.38) than those writing to an anonymous child, but the difference was not significant ( $p = 0.696$ ). These results are consistent with the theory of social distance: closer social distance between the writer and the recipient would magnify the effect of the treatment.

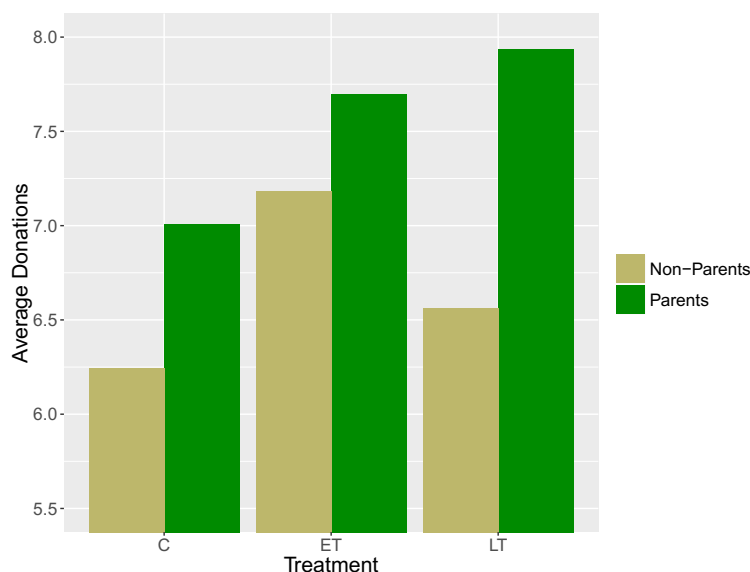


Figure 1.3: Average donations by parents and non-parents in each treatment group

While both treatments have a similar impact on the average donation, they have different effects on the likelihood of donating (Table A.1). Participants in the Letter treatment are no more likely to donate more than \$0 of their bonus than participants in the control group. Participants in the Essay treatment, however, are more likely to donate some non-zero amount. In other words, the Letter treatment affects the intensive margin of donations, but not the extensive margin, while the Essay treatment affects both the intensive and extensive margins.

A potential confound of the treatment design is that the Letter treatment asks

participants to tell the recipient what actions they have taken or plan to take to reduce their climate change impact. This adds an additional element that is not controlled in the Essay treatment and could explain why the Letter treatment did not make participants more likely to donate even though it increased the level of donations. According to a theory of moral cleansing or moral licensing, individuals who are motivated by guilt or other negative emotions tend to take a single action to relieve the feeling of guilt and do not take subsequent, similar actions (Weber 2006; Barnes Truelove et al. 2014). Discussing the actions that they are already taking to reduce their climate change impact may minimize the level of guilt that participants feel, leading to a lower donation level. The Letter treatment slightly reduces the level of reported guilt about climate change, but the effect is not significant ( $p = 0.296$ ).

Another potential confound is experimenter demand. The study design attempts to control for experimenter demand by starting the experiment with a video and written information about climate change. It should be very clear to all participants that the study is about climate change. However, without changing the control group to write about climate change, there was no way to reduce experimenter demand entirely. Those in the Essay and Letter treatments may have experienced a stronger experimenter demand effect than those in the control group.

### **Mediation Analysis of Donations**

Different variables mediate the relationship between treatment and donation for Letter treatment and the Essay treatment. In the letter treatment, the mediation analysis indicates that focusing on the future consequences of climate change for a single individual may increase legacy motives, which leads to higher donations and may decrease hopefulness about the future, which reduces donations. In the essay treatment, the mediation analysis indicates that focusing generally on the risks and challenges of cli-



mate change increases concern about climate change and increases the feeling of personal responsibility to reduce climate change, both of which increase donations.

Legacy is the primary measure of social distance in this study. Following Zaval, Markowitz, & Weber (2015), I test whether the treatments increase the desire to leave a positive legacy to the future. Compared to the control group, I find that the Letter treatment significantly increases legacy motives ( $p = 0.0018$ ), while the Essay treatment has no effect ( $p = 0.173$ ). I implement the Baron-Kenny procedure to assess whether legacy mediates the relationship between the Letter treatment and willingness to donate (Baron and Kenny 1986; Imai et al. 2010a). A quasi-Bayesian Monte Carlo approximation of the mediation effect finds an average indirect effect of 0.278 (95% CI = [0.11,0.47],  $p = 0.0018$ , Table 1.3). Thus, the Letter treatment increases legacy motive which then increases the donation by an average of \$0.28, which accounts for about a third of the total effect of the Letter treatment on the willingness to donate.

In addition to increasing legacy motives, I find that the Letter treatment increased the vividness of the future ( $p < 0.001$ ), a measure of temporal distance. In contrast to legacy motives, the vividness of the future does not increase willingness to donate. Vividness of the future does, however, increase concern about climate change ( $p = 0.010$ ) and it mediates the relationship between the Letter treatment and concern about climate change ( $\hat{\beta} = 0.036$ , CI= [0.007, 0.073],  $p = 0.01$ ).

The Letter treatment decreases the level of hopefulness participants feel about the future, but the effect is only marginally significant ( $p = 0.088$ ). Feeling hopeful about the future increases donations; a standard deviation increase in hopefulness leads to an average increase in donations of \$0.44 ( $p = 0.003$ ). The average mediation effect of hope on the relationship between the Letter treatment and donations is negative, but only marginally significant ( $\hat{\beta} = -0.045$ , CI= [-0.110, 0.006],  $p = 0.08$ ).

The Letter treatment does not have a significant impact on any other measured re-

Table 1.3: Mediation Analysis of Donations

Mediation Variable	$\delta$ (Letter Treatment)	$\delta$ (Essay Treatment)
Implicit Discount Rate	0.0004 (0.0128)	-0.0020 (0.0153)
Change in Climate Concern	0.0283 (0.0546)	0.0718** (0.0392)
Legacy	0.2785*** (0.0934)	0.0829 (0.0653)
Vividness of Future	0.0456 (0.0497)	0.0122 (0.0189)
Hindsight	-0.0020 (0.0216)	-0.0058 (0.0327)
Climate Affects Own Kids	0.0427 (0.1021)	0.0589 (0.0738)
Mitigation Responsibility	0.0978 (0.1015)	0.1651** (0.0788)
Hopeful about Future	-0.0665* (0.0445)	-0.0120 (0.0294)
Guilt about Climate Change	-0.0838 (0.0836)	0.0454 (0.0740)
Efficacy of Climate Action	-0.0216 (0.0977)	0.0367 (0.0727)

*Note:* Mediation analysis. Estimation of the treatment effect on donation that operates through the variable in the left-hand column. Estimation models include a dummy variable for the treatment group under examination and an intercept term. Models are estimated on a subset of data that includes the control group and the treatment group under examination. Standard errors are in parentheses. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

sponses to other potential donation decision factors, including self-reported assessments of: ease of hind-sight, whether climate change would impact one's children, whether taking action on climate change was part of one's responsibility as a parent or as a person who cares about the welfare of others, guilt about one's own contribution to climate change, and the efficacy of actions taken individually or globally (see Table A.3 in Appendix A for more details).

The Essay treatment increases the extent to which participants agree that taking action to help reduce climate change is part of their responsibility as a person who cares about the welfare of others ( $p = 0.035$ ). Those who more strongly agree that reducing their impact is part of their altruistic responsibility donate more: one standard deviation increase in the feeling of altruistic responsibility correlates with an average increase of donations of \$1.58 ( $p < 0.001$ ). A sense of responsibility to take actions to help reduce climate change mediates the relationship between the Essay treatment and donation ( $\hat{\beta} = 0.189, CI = [0.018, 0.373], p = 0.03$ ).

The Essay treatment does not have a significant impact on any other measured responses to other potential donation decision factors (see Table A.3 in Appendix A for more details).

In summary, I find that writing a letter to a young person living in the future increases legacy motives and the vividness of life in the year 2050. Higher legacy motives lead to increased donations, thus partially mediating the relationship between the Letter treatment and the donation. Writing in about the risks and challenges of climate change in a neutral frame increases the feeling of personal responsibility to mitigate climate change, which partially mediates the relationship between the Essay treatment and the donation.

## **Salience of Decision Factors for Donations**

In the control group, the strongest donation decision factor of those that were measured is guilt about one's own contribution to climate change ( $\hat{\beta} = 0.687, p = 0.015$ , Table 1.4). Hopefulness about the future and strength of hindsight both have a marginally significant relationship with donations ( $\hat{\beta} = 0.503, p = 0.062$  and  $\hat{\beta} = 0.463, p = 0.061$  respectively). The desire to leave a positive legacy is significant at the 10% level ( $\hat{\beta} = 0.538, p = 0.098$ ).

In the Essay treatment group where individuals focus on what they know and what they would like to learn about the risks and challenges of climate change, post-treatment concern about climate change was the only statistically significant decision factor ( $\hat{\beta} = 0.690, p < 0.001$ ).

In the Letter treatment group, legacy motives also had a strong influence on donations ( $\hat{\beta} = 0.880, p = 0.011$ ). Post-treatment concern about climate change was also a significant decision factor ( $\hat{\beta} = 0.536, p = 0.006$ ).

General concern for climate change is strongly correlated with other decision factors. For this reason, I run a second analysis that excludes general concern about climate change. In the Letter treatment, legacy motives, the belief that climate change will affect one's own kids, and the belief in the efficacy of climate change mitigation are all strong, significant donation decision factors (See Table 1.5).

To make comparisons between the isolated effects of the decision factors on donations, I compare the coefficients from a univariate regression of the decision factor on the donation for each treatment group by running a Z-test of the null hypothesis that the coefficients in each treatment are equal. I find that the decision weights in the Letter treatment group are significantly higher than those in the control group for climate concern ( $p = 0.017$ ), legacy ( $p = 0.058$ ), efficacy of climate mitigation ( $p = 0.029$ ), and impact on one's own children ( $p = 0.013$ ). The difference between the decision weight

on climate concern in the Essay treatment and the control group is not statistically significant ( $p = 0.205$ ). The differences in decision weights on all other variables are not significant.

It is striking that weights for multiple decision factors significantly shift when participants write about climate change to an individual living in the future, but they do not shift when an individual simply writes about climate change. The differential impact lends credence to the theory that salience is the causal mechanism by which the exercise of writing a letter to someone living in the future increases the willingness to pay for climate change mitigation. However, it leaves open the question of what is driving increased donations for those who write about climate change in a neutral frame.

### 1.5.2 Revealed Preference: Implicit Discount Rate

Time preference measures how much future utility is worth today. The discount rate measures how much future monetary costs and benefits are worth today. Because investment in climate change mitigation yields benefits in the future, the discount rate plays a major role in the expected willingness to pay for climate change mitigation. All else equal, the optimal upfront investment varies considerably depending on the discount rate. I hypothesized that the future-oriented frame of the Letter treatment would shift underlying time preferences. I measured implicit discount rates as a proxy for time preference and found weak evidence supporting this hypothesis.

Participants in the Letter treatment exhibit a lower implicit discount rate, but the effect is marginally significant ( $p = 0.065$ , Table 1.6). The effect of the Letter treatment decreases the three month implicit discount rate by 2.5% from an average rate in the control group of 36.2%. This effect corresponds to an annual discount rate of 10%. However, it is important to keep in mind that the experimental measure across the sample yields annual implicit discount rates between 3% and 330%. This range is well

Table 1.4: Salience of Potential Decision Factors Across Treatments

	<i>Dependent variable:</i>		
	Donation to climate change mitigation		
	C	ET	LT
	(1)	(2)	(3)
Climate Concern	0.269 (0.181)	0.690*** (0.187)	0.537*** (0.195)
Discount Rate	-0.182 (0.756)	-0.672 (0.720)	0.133 (0.801)
Legacy	0.538* (0.324)	0.419 (0.344)	0.880** (0.345)
Climate Impacts on Kids	0.249 (0.344)	-0.170 (0.371)	0.371 (0.411)
Vividness of Future	0.228 (0.263)	-0.264 (0.244)	-0.333 (0.259)
Hindsight	0.463* (0.247)	0.323 (0.235)	-0.248 (0.276)
Mitigation Responsibility	0.224 (0.438)	-0.333 (0.437)	-0.077 (0.422)
Efficacy of Climate Action	-0.247 (0.472)	0.281 (0.446)	0.602 (0.461)
Hopeful about Future	0.503* (0.270)	-0.168 (0.267)	-0.149 (0.272)
Guilt about Climate Change	0.687** (0.281)	0.488 (0.296)	0.370 (0.296)
Constant	4.989*** (1.365)	2.606* (1.433)	3.491** (1.482)
Observations	578	600	572
R <sup>2</sup>	0.100	0.095	0.164

*Notes:* OLS regression of measured potential decision factors on donation (\$'s) for each treatment group. All covariates are standardized to mean=0, sd=1 across all three treatments. Standard errors are in parentheses. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 1.5: Salience of Potential Decision Factors Across Treatments without General Concern

	<i>Dependent variable:</i>		
	Donation to climate change mitigation		
	C	ET	LT
	(1)	(2)	(3)
Discount Rate	-0.114 (0.756)	-0.718 (0.725)	0.052 (0.805)
Legacy	0.570* (0.324)	0.667* (0.340)	0.992*** (0.345)
Climate Impacts on Kids	0.459 (0.315)	0.420 (0.339)	0.926** (0.360)
Vividness of Future	0.237 (0.263)	-0.177 (0.245)	-0.282 (0.260)
Hindsight	0.442* (0.247)	0.328 (0.237)	-0.186 (0.277)
Mitigation Responsibility	0.377 (0.423)	0.142 (0.421)	0.220 (0.410)
Efficacy of Climate Action	-0.050 (0.457)	0.589 (0.442)	0.933** (0.448)
Hopeful about Future	0.476* (0.269)	-0.204 (0.269)	-0.156 (0.274)
Guilt about Climate Change	0.778*** (0.276)	0.664** (0.295)	0.468 (0.296)
Constant	6.948*** (0.362)	7.720*** (0.366)	7.437*** (0.386)
Observations	579	601	572
R <sup>2</sup>	0.096	0.074	0.152

*Notes:* OLS regression of measured potential decision factors on donation (\$'s) for each treatment group. All covariates are standardized to mean=0, sd=1 across all three treatments. Standard errors are in parentheses. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

within the norm found using these experimental methods, but it does not correspond directly to discount rates observed in real world market behavior. Nonetheless, I draw the tentative conclusion that future oriented writing task increases patience for payoffs in the future.

When treatments are interacted with demographic variables, one particularly interesting finding arises. Compared to independents and non-voters in the Letter treatment, both Democratic and Republican voters respond strongly to the Letter treatment with significant reductions in their implicit discount rates. The Letter treatment reduces the three-month discount rate by 15.1 percentage points for Republican voters ( $p = 0.002$ ) and by 12.4 percentage points for Democratic voters ( $p = 0.027$ ). In this study as in the political sphere, Republicans and Democrats differ sharply on climate change. But they are similar in exactly one dimension: the importance of legacy. On average across the sample, Republican and Democratic voters report higher legacy motives than independent voters and non-voters ( $p = 0.036$  and  $p = 0.048$  respectively). To find out whether legacy might be the key to the relationship between the Letter treatment and the implicit discount rate, I regress the discount rate on the treatment indicator variables, the legacy measure, and an interaction term. The interaction of the Letter treatment indicator and the legacy motives measure is negative and significant ( $p = 0.047$ ). Taken together, these findings lead to the conclusion that for those who have higher legacy motives, the future-oriented Letter treatment reduces their discount rate and indicates more patient time preference.

While I did not have any prior expectations on this relationship, I find that parents have a significantly higher discount rate when treatment interactions are not taken into account ( $p = 0.001$ , Table 1.6). With treatment interactions, I find that parents in both treatment groups have higher discount rates compared to parents in the control group, but the relationship is only significant for the Essay treatment (LT:  $p = 0.445$ ,



ET:  $p = 0.043$ , Table A.2). Higher discount rates for parents could arise simply because parents with dependents still in their care may be more budget constrained than those without dependents, all other factors constant. However, the fact that this effect is only seen for parents in the Essay treatment indicates that this may simply have arisen by chance.

The Letter treatment appears to cause individuals to give more weight to future monetary benefits as shown through the effect of the discount rate. The Letter treatment also increases donations. But the question of whether the Letter treatment creates a shift in time preference which then leads to a higher willingness to pay for climate change mitigation is still open. The mediation analysis does not indicate that the Letter treatment increases donations through lower discount rates. The relationship has the expected sign but is extremely small and statistically insignificant ( $p = 0.98$ ). Controlling for demographic variables leads to a somewhat more promising estimate, but the effect is still very small and very noisy with a 95% confidence interval of  $-\$0.02$  to  $\$0.07$ .

A key link in the chain in causality is the link between the implicit discount rate and donations. I find that a lower discount rate correlates with larger donations, but the relationship is not statistically significant even after controlling for other variables ( $p = 0.164$ , Appendix A, Table A.4). The magnitude of the effect is also quite small with a 10 percentage point decrease in the implicit discount rate correlating to a  $\$0.07$  increase in donations.

In analyses of optimal global investment in climate change mitigation, there is a clear and very strong relationship between the discount rate and the optimal investments. This relationship is much weaker in these experimental findings. There are a number of potential reasons for this effect. First, there are the classic problems of free riding. For a perfectly rational actor without altruism or warm glow donation effects, the optimal personal investment in climate change is zero because it is personally optimal to free

ride on others' investments. While it is clear this is not a perfect explanation since most participants chose to donate, this could weaken the link between the discount rate and donations. If the decision to donate were pure warm glow and the warm glow was independent of time preference, then I would expect no relationship between the implicit discount rate and donation. I do not think this tells the full story. Second, the implicit discount rate is an imperfect measure of time preference. We cannot capture present bias for immediate consumption and we can only measure preference over money earlier or money later, not the more fundamental tradeoff of utility earlier or utility later. Third, the nature of these measures where participants choose between different options for an experimental bonus may simply lead to a noisier relationship than expected because they are imperfectly representative of more fundamental decision processes.

### 1.5.3 Impact on Climate Concern

In the screening survey, participants were asked to rate their concern about climate change on a scale from one to ten. In the experiment, after the treatment and donation measure, the same question about concern for climate change is asked again. These two responses provide a clean within-subject pre- and post-treatment measure.

In Table 1.7, I show the results of the difference-in-difference estimation. The Letter treatment has a small, positive effect that cannot be distinguished from zero. The Essay treatment has a statistically significant, positive effect ( $p = 0.0149$ ). On average, individuals increase their concern for climate change by about one tenth of a standard deviation after writing an essay about the risks and challenges of climate change. A Wald test shows that the effect sizes of the Letter and Essay treatments are significantly different from one another ( $p = 0.038$ ).

The control group has a significant increase in concern for climate change ( $p < 0.001$ ). This is notable because the first part of the experiment involves watching a

Table 1.6: Implicit Discount Rate Analysis

	<i>Dependent variable:</i>		
	Implicit discount rate		
	(1)	(2)	(3)
Letter Treatment D.V.	-0.009 (0.020)	-0.010 (0.020)	-0.025* (0.014)
Essay Treatment D.V.	0.016 (0.019)	0.018 (0.019)	-0.005 (0.019)
Baseline Climate Concern		0.008 (0.008)	0.008 (0.008)
Parent D.V.			0.063*** (0.018)
Age (years)			-0.001 (0.001)
Income (\$1000's)			-0.001*** (0.0002)
High School D.V.			-0.059 (0.110)
Trade School D.V.			-0.063 (0.118)
Associate Degree D.V.			-0.067 (0.115)
Bachelor Degree D.V.			-0.124 (0.116)
Graduate Degree D.V.			-0.235* (0.124)
Vote Republican D.V.			-0.036 (0.024)
Vote Democrat D.V.			-0.028 (0.025)
Male D.V.			-0.014 (0.016)
White D.V.			-0.078*** (0.020)
Hispanic D.V.			0.044 (0.031)
Constant	0.362*** (0.014)	0.362*** (0.014)	0.819*** (0.112)
State Fixed Effects	No	No	Yes
Clustered Standard Errors	No	No	Yes
Observations	1,711	1,700	1,623
R <sup>2</sup>	0.001	0.002	0.129

*Note:* OLS regression. Dependent variable is implicit discount rate. Income is a numeric variable in \$1000's. Dummy variables are included for those who vote mainly or exclusively for Democrats and Republicans. Voters who vote half Republican and half Democrat as well as those who do not vote for either party are the comparison group. Education is a categorical variable split into dummy variables and less than high school education is the comparison group. D.V. indicates binary dummy variables. Baseline climate concern is a 10 point scale measure standardized with mean=0, sd=1. Age is measured in years.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

three minute video about the science and impacts of climate change. They also read about climate change mitigation policies and actions. This implies that the information given prior to the treatment was effective in increasing the concern for climate change.

Table 1.7: Difference-in-Differences Estimation of the Change in Concern for Climate Change

	<i>Dependent variable:</i>
	clim_dif
Letter Treatment (LT)	0.055 (0.100)
Essay Treatment (ET)	0.241** (0.099)
Constant	0.360*** (0.071)
Observations	1,771
R <sup>2</sup>	0.004

*Note:* OLS regression. Dependent variable is the change in stated concern about climate change before and after treatment measured on a 1-to-10 scale where 1 is labeled as “not at all concerned” and 10 is labeled as “extremely concerned.”

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 1.6 Conclusions

Optimal investment in climate change mitigation is hindered by the long time horizons between the mitigation decision and the impacts of that decision. The long time horizon and social distance from those impacted creates psychological distance from the impacts and makes the impacts less salient. In this study, I explore a behavioral intervention in an online experiment that asks participants to write a narrative about the risks and challenges of climate change. In the Essay treatment, the narrative is framed as an essay

on the risks and challenges of climate change. In the Letter treatment, the narrative is framed as a message directed to a particular individual living in the year 2050. The control group writes about their daily routine.

Compared to the control, both the Letter and Essay treatments increase the willingness to donate to a charity doing climate change mitigation work. However, the two treatments appear to affect the willingness to donate through different pathways. Writing about the risks and challenges of climate change to an individual living in the future leads to higher donations by increasing the desire to leave a positive legacy and by increasing the salience of climate mitigation benefits for one's children. Writing about the risks and challenges of climate change in an essay leads to higher donations by increasing the sense of individual responsibility to reduce one's impact on climate change.

On the temporal dimension, the Letter treatment increases the vividness of the future and has a negative but marginally significant effect on the implicit discount rate. On the social dimension, the Letter treatment increases the desire to leave a positive legacy. The Letter treatment does not increase the concern that climate change will impact one's own kids, but it causes participants to put more weight on this decision factor in their donation decision.

Returning to the initial hypotheses outlined in the introduction, I will take each in turn and discuss the evidence from this study that supports and does not support each one.

**H1:** The process of generating a narrative on the risks and challenges of climate change leads to a higher willingness to pay for climate change mitigation.

H1 is strongly supported by the results of this study. Compared to a control group that writes a narrative on an unrelated topic, writing for five minutes about the risks and challenges of climate change leads to a higher willingness to contribute to climate

mitigation. I find an effect size of about 11% for both of the treatment groups.

**H2:** Addressing the narrative on the risks and challenges of climate change to an individual living in the future will further increase the willingness to pay for climate mitigation.

H2 is not supported by the results of this study. The two treatment groups had nearly identical levels of willingness to pay for climate mitigation. However, mediation analyses suggest that the treatments are operating through different mechanisms. A narrative frame that addresses a discussion of the risks and challenges of climate change to a particular individual living in the future increases the desire to leave a positive legacy which leads to increased donations. A neutral narrative frame that discusses the risks and challenges of climate change increases the concern about climate change and feeling of responsibility to take action to reduce climate change. The heightened factors then go on to increase average donations. Additionally, the Essay treatment increases the decision weight on concern for climate change has in the donation decision and the Letter treatment significantly increases the decision weight on the belief that climate change will affect one's children, indicating increased salience for those decision factors.

**H3:** A future-oriented narrative frame will reduce the revealed implicit discount rate.

The null hypothesis of a zero effect cannot be rejected at a significance level of 0.05. The future-oriented framing in writing task where participants write a letter to an individual living in the future correlates with a small, marginally significant reduction in the implicit discount rate ( $p = 0.065$ ). The implicit discount rate weakly predicts donations with lower discount rates correlating with higher donations, however, the effect is not statistically significant ( $p = 0.164$ ).

The similarity in treatment effects points to the possibility that by actively focusing on the problem of climate change leads to higher willingness to pay. This is a more general

hypothesis than H1, but the underlying concept is very similar. A simple experiment that varies how participants focus on a given problem could test whether generating one's own narrative (H1) has a different impact than generally ruminating on the subject. In this experiment, the act of writing a narrative was chosen in part so it could be personalized by addressing it to a particular individual and in part because it requires significant focus. Participants must come up with their own arguments about the risks and challenges of climate change instead of passively reading or listening to a discussion of the subject. It is possible that the act of coming up with one's own narrative could lead individuals to donate more to climate change mitigation through the mechanism of cognitive dissonance (Festinger 1957). There are many questions and causal mechanisms to explore. This study begins an exploration of the role that salience of climate change risks and mitigation benefits may play in the willingness to pay for climate change mitigation. It is one step forward to understanding a piece of this puzzle and it raised many questions for further studies to explore.

The results of this study strongly support the conclusions of Zaval, Markowitz, and Weber (Zaval et al. 2015). The study design replicated their survey instruments for both the donation measure and the legacy measures. I improved upon their design by utilizing a tighter control group. While their control group had no writing task, the control group in this study participated in an unrelated writing exercise for the same minimum amount of time. I built upon their findings by testing two different writing prompts that focus specifically on climate change instead of focusing on legacy. The finding that the two narrative frames had a very different impact on legacy motives adds a new insight to this body of inquiry.

Time preference plays a crucial role in climate change mitigation decisions. We do not yet fully understand how time perspective over long time horizon decisions may lead to inefficient choices. This study adds to the scientific understanding by exploring the

question of how different narrative frames can shift the willingness to pay for climate change mitigation by altering the social distance across generations and making future climate change mitigation benefits more salient.



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## Chapter 2

# Gasoline Price Volatility and Consumer Welfare

## 2.1 Introduction

Energy price shocks impose costs on the economy. An extensive literature has evaluated how energy price shocks, such as in crude oil markets, adversely affect consumption and investment (Barsky and Kilian 2004; Hamilton 1983, 1996, 2003; Kilian 2008a,b, 2009). Investigating the underlying mechanisms has provided insights on both the distribution of the costs as well as the opportunity for policy responses to mitigate the costs of shocks (Bernanke et al. 1997; Ferderer 1996). The costs reflect not just an increase in the price level for oil, but also the uncertainty represented by increasing oil price volatility (Bernanke 1983; Dixit and Pindyck 1994; Ferderer 1996).

There is less clarity in the literature on how energy price volatility affects consumer welfare. However, theoretical work based on standard neoclassical models of consumer behavior suggests that price volatility has ambiguous impacts on consumer welfare (controlling for the level of the commodity price) (Turnovsky et al. 1980; Newbery and Stiglitz 1981). These papers suggest, however, that increasing price volatility for a product that comprises a meaningful household budget share and is characterized by inelastic demand could make consumers worse off. These characteristics are prevalent in consumer demand for transportation fuels, heating fuels, and electricity. If demand is inelastic, then price volatility reduces the ability of credit-constrained households to smooth consumption. Thus, energy price volatility could lead to welfare losses for low-income households with few credit options. Price volatility also reduces the information value of prices by making it difficult to distinguish between the price signal and the noise. As a result, investment in energy-using capital may be sub-optimal when the price fluctuation noise drowns out the signal of the expected price.

A number of more recent studies have addressed questions related to energy price volatility (Brown and Yu 2002; Bushnell and Mansur 2005; LeClair 2006; Cita et al.



2007; Kilian 2008c; Jensen and Møller 2010; Giacomo et al. 2011; Lin and Prince 2013; Hastings and Shapiro 2013). Similar to our research question, Jensen and Møller's (2010) study how oil price volatility may impact cost-benefit analyses. They find that volatility does not have an impact on cost-benefit analyses, but with a reduced form measure of the risk premium, they fail to account for demand elasticities or consumer expenditures. We improve on this analysis by developing consumer utility models based on expected utility theory and prospect theory. We then estimate the risk premium with a Monte Carlo simulation of gasoline price volatility. Under standard expected utility theory, price volatility reduces the welfare of highly risk-averse consumers and those with highly price inelastic demand. However, the welfare effects are fairly small under expected utility theory. If, as predicted by prospect theory, consumers are loss averse and their utility is reference dependent, price volatility has significant negative impacts on consumer welfare for nearly all consumers. We estimate that, under the prospect theory model, consumers would be willing to pay a risk premium of between 2% and 4% of gasoline expenditures, equivalent to \$0.06 to \$0.12 per gallon of gasoline, at the mean price of \$3.05 per gallon. This research helps us better understand the consumer welfare implications of energy price volatility generally and allows us to evaluate policies that affect energy price volatility, such as environmental regulations.

In expected utility theory, the welfare impacts of price volatility depend on demand elasticities, risk aversion, and the commodity's budget share. Prospect theory adds an additional layer. In addition to utility derived from overall consumption, utility also depends on the level of consumption compared to prior expectations. If energy prices suddenly increase and crowd out consumers' expenditures on other goods, then those consumers will experience a loss relative to their reference level of consumption. Likewise, if energy prices decrease and they can consume more, consumers will experience a gain relative to their reference consumption. Moreover, most consumers exhibit "loss aversion," the tendency for losses to reduce welfare more than an equal gain would

increase welfare (Kahneman et al. 1991; Tversky and Kahneman 1991; Benartzi and Thaler 1995; Dhimi and Al-Nowaihi 2007; Abdellaoui et al. 2008; Crawford and Meng 2011; Herweg and Mierendorff 2013). As a result, even when there is an equal chance that the price will rise or fall, increases in price volatility lead to decreases in average utility.

To address the questions posed above and assess the welfare implications of energy price volatility, we will define the conditions under which households prefer fixed prices or stochastic prices. We also estimate the consumer welfare impacts of gasoline price volatility. To estimate welfare impacts, we model the risk premium households would pay for fixed gasoline prices compared to stochastic gasoline prices. We estimate risk premiums under both an expected utility theory model and a prospect theory model. We can apply our estimates to several policy scenarios to characterize how regulation-induced volatility and instrument choice (among price and quantity instruments) influence consumer welfare beyond the conventional approach of assessing deterministic changes in the level of consumer goods prices.

The rest of the paper proceeds as follows. In Section 2.2, we lay out the context for this paper with a discussion of the public policy implications of energy price volatility. In Section 2.3, we lay out consumer utility models of households facing fixed or volatile gasoline prices under expected utility theory and reference-dependent prospect theory. In Section 2.4, we discuss the role of elasticity and risk aversion in the welfare impacts of price volatility. In Section 2.5, we describe the data and calibrations of the model simulations. In Section 2.6, we present our results. And in Section 2.7, we conclude by discussing key takeaways from the simulation results.

## 2.2 Energy Price Volatility and Public Policy

Since the 1970s, the price of gasoline has been among the most salient of consumer prices. As a result, policymakers have sought various tools to mitigate the adverse impacts of oil price shocks. For example, the EPA may grant petitions to waive temporarily fuel content regulations (such as reformulated gasoline) in response to supply shocks, such as those resulting from hurricanes (Aldy 2016). Recent policy ideas have been proposed to reduce oil price volatility. For example, some policy analysts have discussed the idea of buying and selling oil from public stocks to smooth oil prices (Clayton 2012). Bordoff and Metcalf (2009) proposed an oil tax that increases when oil prices fall and decreases when oil prices rise, resulting in little variation in the U.S. after-tax oil price.<sup>1</sup>

Some public policies inadvertently affect energy price volatility. First, high fuel taxes in many OECD countries, as well as state-controlled fuel prices in developing countries, mitigate the effects of crude oil price volatility passed through to petroleum product price volatility. Second, environmental regulations may affect energy price volatility. Regulations of transportation fuel pollution, biofuels mandates, and air pollution emission controls have contributed to retail energy price volatility (Brown et al. 2008; McPhail and Babcock 2012; Aldy and Viscusi 2014). Third, the design of environmental regulations – whether through a price or a quantity instrument – can directly influence fuel price volatility since one instrument sets the price (e.g., a pollution tax) while the other leaves price uncertain (e.g., cap-and-trade). For example, the annualized price volatility for sulfur dioxide, nitrogen oxides, and carbon dioxide cap-and-trade programs and the California low-carbon fuel standard have ranged between 100 and 300%, exceeding the volatility of oil prices (Aldy and Viscusi 2014).<sup>2</sup>

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<sup>1</sup>Bordoff and Metcalf cite loss aversion, which is modeled in this paper, as one justification for such a policy.

<sup>2</sup>Annual volatility is measured as the annualized absolute logarithmic month-to-month change in allowance prices (Nordhaus 2007; Aldy and Viscusi 2014).

### 2.2.1 Volatility in Allowance Markets

Since the sulfur dioxide cap-and-trade program was established by the 1990 Clean Air Act to address acid rain, emissions markets have flourished as a method to reduce environmental pollution at a lower cost than command-and-control regulations. For example, tradable allowances have been used to regulate sulfur dioxide and nitrogen oxide emissions in the United States. They are used to regulate carbon dioxide in the European Trading System (ETS), Regional Greenhouse Gas Initiative (RGGI), and California's state-level carbon market. Tradable renewable energy credits (REC) are also widely used to meet renewable portfolio standards, which are currently in place in twenty-nine states and the District of Columbia.

Pollution pricing mechanisms have been studied extensively (see Nordhaus 2007; Aldy and Stavins 2012a,b for reviews). One major question in the literature is whether a price-based approach or quantity-based approach leads to higher expected total welfare (Weitzman 1974; Pizer 2002). However, one dimension of the prices-versus-quantities comparison has been insufficiently studied. The two policy instruments fundamentally differ in the level of volatility of the allowance price. Economists have demonstrated that some policies, such as renewable fuel standards (McPhail and Babcock 2012), local gasoline content regulations (Muehlegger 2006), and carbon cap-and-trade allowance prices (Pizer 2002; Metcalf 2009; Murray et al. 2008; Aldy and Viscusi 2014), may add substantial volatility to gasoline prices.

This question is not just of theoretical value. In practice, many allowance markets have shown a very high level of volatility. Aldy and Viscusi (2014) assess the price volatility of U.S. nitrogen oxide allowances, U.S. sulfur dioxide allowances, and EU ETS allowances (Figure 2.1) and find a range of annual volatility from 130% to nearly 300%. There is also major volatility in the state-level RECs markets. From 2007 to 2014, the average annual volatility of Texas RECs was 98%, that of Connecticut Class I RECs was

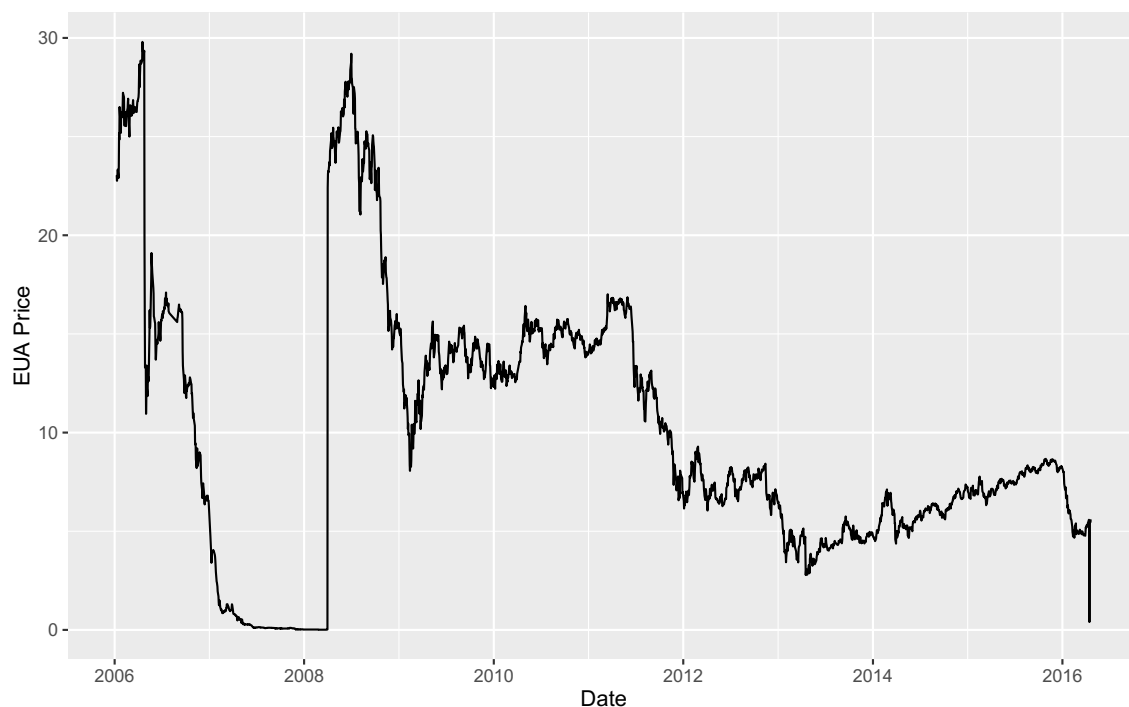


Figure 2.1: EU ETS Allowance Prices from 2006-2016

68%, and that of Maryland Tier I RECs was 116%. New Jersey and Pennsylvania RECs markets experienced even greater volatility at 268% (2007-2012) and 223% (2009-2014) respectively.

In 2006, California enacted the first low carbon fuel standard as part of Assembly Bill (AB) 32. The LCFS set a cap on the life cycle carbon intensity of transportation fuels sold in California. In 2015, the cap was set at a one percent reduction in carbon intensity (gCO<sub>2</sub>eq/MJ) from 2010 baseline levels (Yeh et al. 2015). That cap will tighten to a ten percent reduction by 2020. The law also created a market to buy and sell LCFS credits. In 2013, the price of LCFS credits ranged from \$20-\$80/ton of carbon dioxide equivalent intensity (Argus Media). These markets have experienced significant volatility. For example, in 2014-2015, the average annualized volatility was 162%. This volatility is passed to fuel prices, but the LCFS allowances are a very small part of the overall cost

of gasoline. For perspective, an LCFS price around \$20-\$25 adds about one-third of one cent to the price of a gallon of gasoline (Yeh et al. 2015). However, as the LCFS becomes much more stringent in 2020, the prices will likely rise, leading to a larger impact on gasoline prices.

The 2005 Energy Policy Act and the 2007 Energy Independence and Security Act (EISA) amendments set a renewable fuel standard (RFS) for transportation fuels and a market for tradable compliance credits called Renewable Identification Numbers (RINs). McPhail and Babcock (2012) examine the impact of the RFS and find that it reduces the price elasticity of demand for both corn and gasoline. As a result, supply shocks in the corn and gasoline markets lead to higher price volatility than they would if the renewable fuel standards were not in place.

Allowance markets have shown substantial volatility. Volatility in allowance markets passes through additional volatility in energy prices. With the widespread use of allowance markets as a policy tool to reduce carbon dioxide emissions, it is imperative to understand how the increased price volatility may affect consumer welfare.

### **2.2.2 Markets to Reduce Exposure to Volatility**

Consumers focus attention on fluctuations in gasoline prices, but they have few feasible options to reduce their exposure to price volatility. In contrast, hedging measures against gasoline price fluctuations are standard practice for commercial operations. It is puzzling that where consumer demand may exist, market options to hedge against gasoline price volatility are extremely limited. In some product markets, consumers pay a premium to reduce the risk of price shocks. Consumers will pay a premium to avoid price risks by choosing a fixed-rate mortgages (Campbell and Cocco 2003), flat-fee phone contracts (Herweg and Mierendorff 2013), and fixed price contracts for natural gas and electricity. Where prices are fixed, but expenditures fluctuate, they pay a premium

to avoid expenditure risks by choosing strictly-dominated health plan options with low deductibles (Bhargava et al. 2015).

In states with deregulated electricity markets, energy suppliers offer a variety of rate plans to consumers. Most electricity suppliers offer both fixed and variable rates, but some offer only fixed rate plans. For example, the two largest electricity utilities in Massachusetts, Eversource and National Grid, both offer six-month fixed-rate plans or six-months of preset variable rates.<sup>3</sup> The unweighted average of the variable rates for six months is about \$0.002/kWh lower than the fixed rate, roughly a 2% discount. Thus, depending on seasonal energy consumption patterns, consumers pay a small premium for the fixed rate. According to best estimates by a customer service representative from National Grid, around 90% of customers choose fixed rate plans over variable rate plans even though they have a higher expected cost.

The gasoline market structure sharply differs from the electricity market structure. Namely, the electricity market is characterized by contracts between households and utilities which set up the utility as the sole distributor of electricity to a given household. In contrast, consumers can purchase gasoline from any gas station and, except for very rare, small-scale gas co-ops that allow consumers to prepay for gasoline from particular gas stations, contracts between buyers and sellers in the consumer market are practically non-existent. If long-term retail contracts were the norm in gasoline markets as they are in electricity markets, options to secure fixed gasoline prices would, perhaps, be more prevalent.

While operating on a small scale, there is at least one option for consumers to reduce exposure to gasoline price volatility. Mygallons.com is a company that essentially allows customers to go long on gasoline prices and cash-in if the price of gasoline rises.

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<sup>3</sup>Rates and plans retrieved from company websites: <https://www.eversource.com/Content/ema-e/residential/my-account/my-bill/basic-service> and [https://www9.nationalgridus.com/masselectric/non\\_html/MA\\_Residential\\_Table.pdf](https://www9.nationalgridus.com/masselectric/non_html/MA_Residential_Table.pdf)

Consumers “prepay” for gas credits at the current average local price, hold on to the prepaid credits, and “cash-in” purchased gas credits when the prices rise. Mygallons.com pays consumers the average local gasoline price at the time when consumers cash-in and charges a processing fee for their services.<sup>4</sup> Consumers must be somewhat financially sophisticated to understand and take advantage of what is essentially a hedging strategy. Moreover, they must have the financial liquidity to invest in “pre-paid” gasoline and wait for a price increase to cash-in.

Historically, there has been experimentation with programs to reduce exposure to price volatility by offering incentives to increase automobile sales. In 2005, gasoline prices became quite volatile and, for the first time in years, jumped consistently above \$2 per gallon. In 2006, General Motors offered a cap on gasoline prices at \$1.99/gallon for consumers who purchased certain GM models in California and Florida. They provided a credit to customers for every gallon of gas they consumed in the first year of owning the vehicle if the price went over \$1.99. This short-term marketing effort was an attempt to move inventory for high fuel consumption vehicles at a time where high gasoline prices received a lot of attention. It does not appear that such incentives are still available to vehicle buyers. However, it speaks to the potential implications of volatility on investment in fuel efficiency. GM recognized that consumers may want to buffer the risks of volatile prices before investing in a high fuel consumption vehicle that would expose a larger share of their budget to fuel price risk. Conversely, price volatility could also pose a risk for consumers considering the financial payback of investing in fuel efficient vehicles. This paper sets the stage for exploring how energy volatility impacts energy efficiency demand, but that analysis is outside of our initial scope.

When markets are characterized by long-term contracts between consumers and suppliers, such as in large commercial fleets and household electricity, there appears to

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<sup>4</sup>Consumers pay a 6% pre-purchase processing fee plus a \$0.06/gallon cash-in processing fee.



be a preference for securing fixed prices. The structure of the consumer gasoline market is not characterized by long-term contracts where sellers could offer price guarantees to customers willing to pay for them. The missing market of hedging mechanisms for retail gasoline consumers presents a puzzle. By defining the conditions under which consumers would be willing to pay a premium to avoid gasoline price volatility, we can better understand whether this puzzle can be explained by a lack of demand for such a product that reduces price risk or if it may instead be an issue of high transaction costs and other market barriers. Furthermore, given the lack of available options to hedge against price volatility, consumers are fully exposed to the price risk and subsequent welfare impacts.

## 2.3 Consumer Welfare Models

In this section, we describe a model that estimates consumer welfare in a single period with either fixed or stochastic gasoline prices. First, we describe the general model under standard expected utility theory. Second, we extend the model to include prospect theory by making utility reference dependent and by allowing for loss aversion.

In the following sections, we discuss the particular issues that arise due to risk aversion and price elasticity. Then, we describe the data that we use to set our model parameters.

### 2.3.1 Expected Utility Theory

We assume a representative household maximizes utility by purchasing gasoline,  $g$ , and an aggregated measure of all other goods,  $x$ . They maximize the following utility function:

$$U = U(x, g) \tag{2.1}$$

In line with the literature (Basso and Oum 2007; Lin and Prince 2013), we describe the demand for gasoline,  $g$ , as a function of price,  $p$ , income,  $I_i$ , and determinants of demand such as vehicle fuel efficiency and commuting distance,  $d$ :

$$g_i = g(p, I_i, d) \tag{2.2}$$

Income is a key parameter in the demand for gasoline and this model overall. The level of household income has a major effect on the estimated risk premium. For this reason, we simulate the risk premium for a representative household in each income quintile. We index parameters that vary directly with income quintiles with  $i \in [1, 5]$ .

In our short-run model, we assume that  $I_i$  is fixed in the short-run and does not change as the price of gasoline changes:

$$\frac{\partial I}{\partial p} = 0 \tag{2.3}$$

There are real-world scenarios where  $p$  could rise (or fall) so sharply that it would affect income. The relationship between price and income depends on the extent to which gasoline is an input in the household's labor production function. For example, taxi or ride-sharing drivers may reduce their hours in response to higher fuel costs. Our model assumes that these cases are negligible for the representative household at each income quintile.

The primary determinants of demand,  $d$ , such as the distance of commutes, fuel efficiency of vehicles, and available public transportation options, are fixed in the short-run. Households have some options to adjust fuel consumption in the short-run. In response to a price increase, households could, for example, reduce non-essential trips and increase their use of public transportation. The availability of options to substitute away from fuel consumption is a major determinant of short-run price elasticity. We

do not model these relationships explicitly but rely on the empirically observed price elasticities to capture these tradeoffs.

The relationship between the change in the price of gasoline and the change in the quantity of gasoline consumed is determined exogenously using a range of empirical estimates of the price elasticity of demand,  $\epsilon_g$ . These empirical estimates measure the uncompensated price elasticity of demand. We can break down the elasticity into substitution effects and income effects via the Slutsky equation:

$$\epsilon_g = \epsilon_{g,c} + s_g \eta_g \quad (2.4)$$

where  $\epsilon_{g,c}$  is the compensated price elasticity of demand which captures the substitution effect,  $s_g$ , the proportion of income spent on gasoline, and  $\eta_g$ , the income elasticity of demand, together capture the income effect. Under the assumption that income is fixed, no further income-related effects would result from the income elasticity of demand outside of the uncompensated price elasticity.

Baseline gasoline demand,  $g_i^*$ , is exogenously fixed at the baseline price,  $p^*$ .<sup>5</sup> For every price  $p$ , there is a corresponding quantity demanded,  $g_i$ . The price elasticity of demand describes the relationship between the baseline price and quantity demanded, and the realized price and quantity demanded:

$$\epsilon_g = \frac{\left(\frac{g_i - g_i^*}{g_i^*}\right)}{\left(\frac{p - p^*}{p^*}\right)} \quad (2.5)$$

Solving this equation for gasoline demand,  $g_i$ , we find the quantity of gasoline

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<sup>5</sup>Baseline price is the average price of gasoline in the United States from 2004-2013 (Administration 2016). Baseline gasoline demand is based on gasoline consumption in the United States during the same period and differentiated by income quintile using the income elasticity of gasoline demand. Section 2.5 further details how these parameters are determined.

demanded under the price,  $p$ , for each income quintile:

$$g_i = g_i^* \left( 1 + \epsilon_g \left( \frac{p - p^*}{p^*} \right) \right) \quad (2.6)$$

In our model, households buy gasoline and all other goods. With the price of all other goods,  $x$ , normalized at  $p_x = 1$ , the household faces budget constraint:

$$I_i - x_i - pg_i = 0 \quad (2.7)$$

We assume that the household maximizes an isoelastic utility that is a function of  $x_i$ :

$$U(x_i) = \frac{x_i^{(1-\rho)}}{(1-\rho)} \quad (2.8)$$

where  $\rho$  is the coefficient of relative risk aversion.

This functional form makes the simplifying assumption that households do not derive utility from purchasing gasoline. Changes in the household's utility depend entirely on changes in  $x_i$ . Changes in  $x_i$  are driven entirely by the change in  $p$  and the subsequent change in  $g_i$ . Thus, the choice to purchase the quantity of gasoline,  $g_i$ , given the price of gasoline,  $p$ , affects the utility of the household indirectly by determining the attainable bundle of  $x_i$ .

By leaving out the direct utility of gasoline, this model underestimates the utility value of driving. This likely causes our estimates of the risk premium of stable gasoline prices to be lower than if we included the utility of driving. Our model does not account for the disutility of waiting for the bus or the utility of taking a road trip. Without the exogenous determination of baseline gasoline consumption and how much consumers shift from that baseline in response to price changes, the model would predict that utility-maximizing households would eliminate their use of gasoline. For this

reason, the choice between purchasing gasoline and purchasing all other goods is fully determined by the baseline demand, price elasticity, and prices. We use empirically estimated price elasticities of gasoline demand to determine the relationship between gasoline price changes and quantity of gasoline purchased. Consumers making tradeoffs between the utility of consuming gasoline and the utility of consuming all other goods drive the observed market responses to changes in prices. As a result, these tradeoffs are represented in the purchasing decision. However, they are underrepresented in the estimation of the resulting total utility. Depending on the curvature of the utility of gasoline consumption, this could affect risk premium estimates. If the marginal utility of gasoline consumption is diminishing ( $U''(g) < 0$ ), then this simplifying assumption will lead us to underestimate the risk premium for stable gasoline prices.

Therefore, in our model, the household “chooses”  $x$  and  $g$  to maximize utility by maximizing the consumption of  $x$  subject to the budget constraint:

$$\max_{x_i, g_i} U(x_i) \text{ s.t. } I_i - x_i - pg_i = 0 \quad (2.9)$$

Because utility is derived only from consumption of  $x_i$  and demand for gasoline,  $g_i$ , is exogenously constrained by the price elasticity of demand, the Marshallian demand for  $x_i$  is simply the income left after purchasing  $g_i$  at price,  $p$ .

$$x_i = I_i - pg_i \quad (2.10)$$

By substituting demand for  $x$  into the utility function, we find the indirect utility. Indirect utility is a function of  $I_i$  and  $p$  and serves as the basis of our welfare analysis.

$$V = V(I_i, p) = \frac{(I_i - pg_i)^{(1-\rho)}}{(1-\rho)} \quad (2.11)$$

With this model of the representative household's utility, we run a variety of scenarios comparing a fixed price of gasoline,  $\bar{p}$ , to a stochastic price of gasoline,  $\tilde{p}$ , with a mean-preserving spread. The volatility of the stochastic price simulates added volatility from a carbon market. In Section 2.5, we describe these parameters in detail.

In a single-period model, we estimate the risk premium a representative household would be willing to pay to avoid the uncertainty of the stochastic price,  $\tilde{p}$ , compared to a fixed price equal to the expected value of the stochastic price:  $\bar{p} = E[\tilde{p}]$ . We estimate the expected value of the risk premium,  $\pi_i$ , with a Monte Carlo simulation.

$$\min_{\pi_i} V(I_i, \bar{p}) - E[V(I_i + \pi_i, \tilde{p})] \quad (2.12)$$

With the assumption of narrow framing, put forth by Benzarti and Thaler to explain the equity premium puzzle (1995), consumers focus narrowly on the risk associated with gasoline price volatility separately from other risks to consumption. Given the salience of gasoline prices compared to other price changes, this is a reasonable assumption when income is fixed. Other shocks to discretionary consumption, such as a sudden expenditure for out-of-pocket health costs, are assumed to be exogenous.

### 2.3.2 Prospect Theory

There are four fundamental differences between expected utility theory and prospect theory (Kahneman and Tversky 1979). First, in prospect theory, the value function takes the place of the utility function. Value is a function of the difference between an outcome and a reference point rather than a function of wealth or consumption. Second, consumers are loss averse. With loss aversion, losses carry more weight in the value function than a gain of equal magnitude. Third, gains are concave in value and losses are convex in value. This leads to diminishing sensitivity as the outcome is further from

the reference point. Fourth, consumers use decision weights instead of direct probabilities when evaluating uncertain prospects. In our prospect theory-driven model, we allow for the first three characteristics of prospect theory, but for simplicity, we leave decision weights equal to probabilities.

Building on Kahneman and Tversky’s prospect theory model, Koszegi and Rabin (2006) develop a model of reference-dependent utility. They explicitly model consumers as deriving utility both from their overall consumption and from the value of losses and gains they experience relative to a reference point. We follow Koszegi and Rabin by separably adding “gain-loss utility” to standard “consumption utility” described in Section 2.3.1. With the utility of  $\theta$  as the reference point and  $\phi$  as the weight the household places on gain-loss utility:

$$U(x_i|\theta_i) = U(x_i) + \phi\nu(U(x_i) - U(\theta_i)) \quad (2.13)$$

The gain-loss utility,  $\nu(U(x_i) - U(\theta_i))$ , uses the value function, from Tversky and Kahneman (1992). The value function,  $\nu(y)$ , is a piecewise function oriented around the reference point that separates outcomes with losses from outcomes with gains:

$$\nu(y) = \begin{cases} y^\alpha & \text{if } y \geq 0 \\ -\lambda(-y)^\beta & \text{if } y < 0 \end{cases} \quad (2.14)$$

From Eq. 2.13, we have  $y = U(x_i) - U(\theta_i)$ . When the realized consumption utility is greater than or equal to the reference consumption utility,  $y > 0$ . Conversely, when the realized consumption utility is less than the reference consumption utility,  $y < 0$ . The loss aversion coefficient,  $\lambda$ , increases the weight on losses relative to the reference point when  $\lambda > 1$ . The coefficients,  $\alpha$  and  $\beta$ , create diminishing sensitivity to changes in the outcome as the distance from the reference point increases.

Defining the reference point is key to the results of the reference-dependent model. Koszegi and Rabin define the reference point as the decision maker's rational expectation of a given value. In our model, the reference point is a function of the expectation of the price of gasoline,  $E[\bar{p}] = \bar{p}$ . Thus, we define the reference point as the utility experienced at consumption level  $x = \theta_i$ , where:

$$\theta_i = I_i - \bar{p}g_i \quad (2.15)$$

That is, we are assuming that the gain or loss is based on the change in the utility of overall consumption relative to the reference point. If households experience gain-loss utility based on the price they face at the pump or the total cost to fill up their tank, then the impact of volatile prices would be larger.

The demand for gasoline in the reference-dependent utility model is the same as in the non-reference dependent utility model. Demand is determined using exogenous parameters for baseline consumption and price elasticities. Since the observed responses to changes in market prices could have resulted from the behavior of utility-maximizing households holding either type of utility function, the relationship between price and quantity is constant between models.

The indirect utility function, however, is much different under the assumption of reference dependent preferences. Substituting the Marshallian demand for  $x$  (Eq. 2.10) into the reference dependent utility function (Eq. 2.13), we get the following indirect utility function:

$$V = V(I_i, p, \theta_i) = \begin{cases} \frac{(I_i - pg_i)^{(1-\rho)}}{(1-\rho)} + \phi \left( \frac{(I_i - pg_i)^{(1-\rho)}}{(1-\rho)} - \frac{(I_i - \bar{p}g_i)^{(1-\rho)}}{(1-\rho)} \right)^\alpha & \text{if } p \leq \bar{p} \\ \frac{(I_i - pg_i)^{(1-\rho)}}{(1-\rho)} - \phi \lambda \left( -\frac{(I_i - pg_i)^{(1-\rho)}}{(1-\rho)} - \frac{(I_i - \bar{p}g_i)^{(1-\rho)}}{(1-\rho)} \right)^\beta & \text{if } p > \bar{p} \end{cases} \quad (2.16)$$



Then we estimate the risk premium,  $\pi_i$  under reference dependent utility with a Monte Carlo simulation:

$$\min_{\pi_i} V(I_i, \bar{p}, \theta_i) - E[V(I_i + \pi_i, \tilde{p}, \theta_i)] \quad (2.17)$$

We compare the risk premiums in the expected utility theory model to those found when preferences are reference dependent under a variety of parameters and price scenarios. But first, we look more closely at the role of elasticity, risk aversion, and welfare under price volatility. This discussion frames both models' analyses.

## 2.4 Elasticity, Risk Aversion and Welfare

Risk averse consumers prefer to avoid uncertainty in consumption. Imagine a person must choose between two lotteries: one that has a 50% chance of winning \$100 and a 50% chance of winning \$0 and the other that has a 100% chance of winning \$50. Risk averse consumers would choose the sure bet even though the lotteries are the same in expectation. Jensen's inequality formalizes this phenomenon. By Jensen's inequality, due to the concavity of the utility function for risk-averse households ( $\rho > 0$ ):

$$E[U(x)] \leq U(E[x]) \quad (2.18)$$

Without substitution in response to gasoline price changes, there would be a linear mapping between the price of gasoline and consumption  $x$ . In that case, the choice between a world with more volatility in prices and less volatility in prices would be clear:

$$E[U(\tilde{p})] \leq U(\bar{p}) \quad (2.19)$$

However, this simple case where households are always better off with less price volatility does not account for demand elasticity. If households can substitute away from a good when the price is high and increase consumption of the good when the price is low, then price instability can increase consumer welfare. This reflects Waugh's (1944) original finding that price volatility improves consumer welfare because consumers could buffer changes in prices with changes in stock. The ability to increase or decrease the stock of a good as the price fluctuates is not very relevant for gasoline and other forms of energy. Storage options are limited for most forms of energy. Moreover, available substitutes are imperfect. As a result, consumers are limited in their ability to store gasoline when prices are low or substitute away from gasoline when prices rise. The lack of substitutes for gasoline leads to highly inelastic demand.

Inelastic demand is one of the most important factors determining whether price volatility harms or hurts consumers, but it is not the only factor. Turnovsky, Shalit, and Schmitz (1980) derive an equation that allows us to calculate whether, under a particular set of conditions, price instability increases or decreases welfare.<sup>6</sup> We refer to this equation as the "Turnovsky rule." This equation produces,  $\omega$ , the coefficient of relative risk aversion with respect to price risk for one good<sup>7</sup>:

$$\omega = \frac{-\partial^2 V}{\partial p^2} p \tag{2.20}$$

$$= s_g(\eta_g - \rho) - e_g, \tag{2.21}$$

where  $s_g$  is the proportion of income spent on  $g$ ,  $\eta_g$  is the income elasticity of demand for good  $g$ ,  $\rho$  is the coefficient of relative risk aversion, and  $e_g$  is the uncompensated price elasticity of demand for good  $g$ . If  $\omega < 0$ , then price stability will increase household

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<sup>6</sup>Newbery and Stiglitz derived a similar theorem in their book published the following year (Newbery and Stiglitz 1981).

<sup>7</sup>They extend the analysis to allow for price risk for an arbitrary number of goods. See Turnovsky et al. (1980) for details.

utility. Figure 2.2 graphically depicts the parameter values under which low-income consumers would benefit from price stability.

Most consumer goods have sufficiently high price elasticities and income elasticities that price instability increases welfare. Gasoline, on the other hand, is characterized by inelastic demand, especially in the short-run. For many households, gasoline expenditures also comprise a significant portion of their budget.

Gasoline demand is highly inelastic. To answer the question of how gasoline price volatility impacts welfare, the precise degree of inelasticity matters (Figure 2.2). Over the past forty years, numerous studies have estimated the price elasticity of gasoline (See Table 2.1 for a selected overview). Price elasticity of gasoline tends to be significantly less elastic in the United States than on average across the world Brons et al. (2008). There is also evidence of a shift over time in the elasticity of demand for gasoline in the United States. According to Hughes et al. (2008), structural changes have brought down the short-run price elasticity in the United States from -0.21 to -0.34 for 1975-1980 to -0.034 to -0.077 for 2001-2006. Income elasticities did not change over the same period (Hughes et al. 2008).

Focusing only on studies of the U.S. market using data primarily from the 1990s and 2000s, the range of price elasticities is -0.027 to -0.37, with a mean value of -0.13. The full range of income elasticities in the U.S. market is -0.067 to 0.941, with a mean value of 0.3. Using these average values for elasticities and the proportion of income spent on gasoline, we can find the level of risk aversion at which households prefer fixed prices over volatile prices.

According to the data we use in our model, the median household in the lowest income quintile spends 23.6% of their income on gasoline and 63% of those households own or lease at least one vehicle (Consumer Expenditure Survey, 2014; see Section 2.5.2 for more information on income data sources). With  $s_g = 0.236$ , volatile gasoline prices

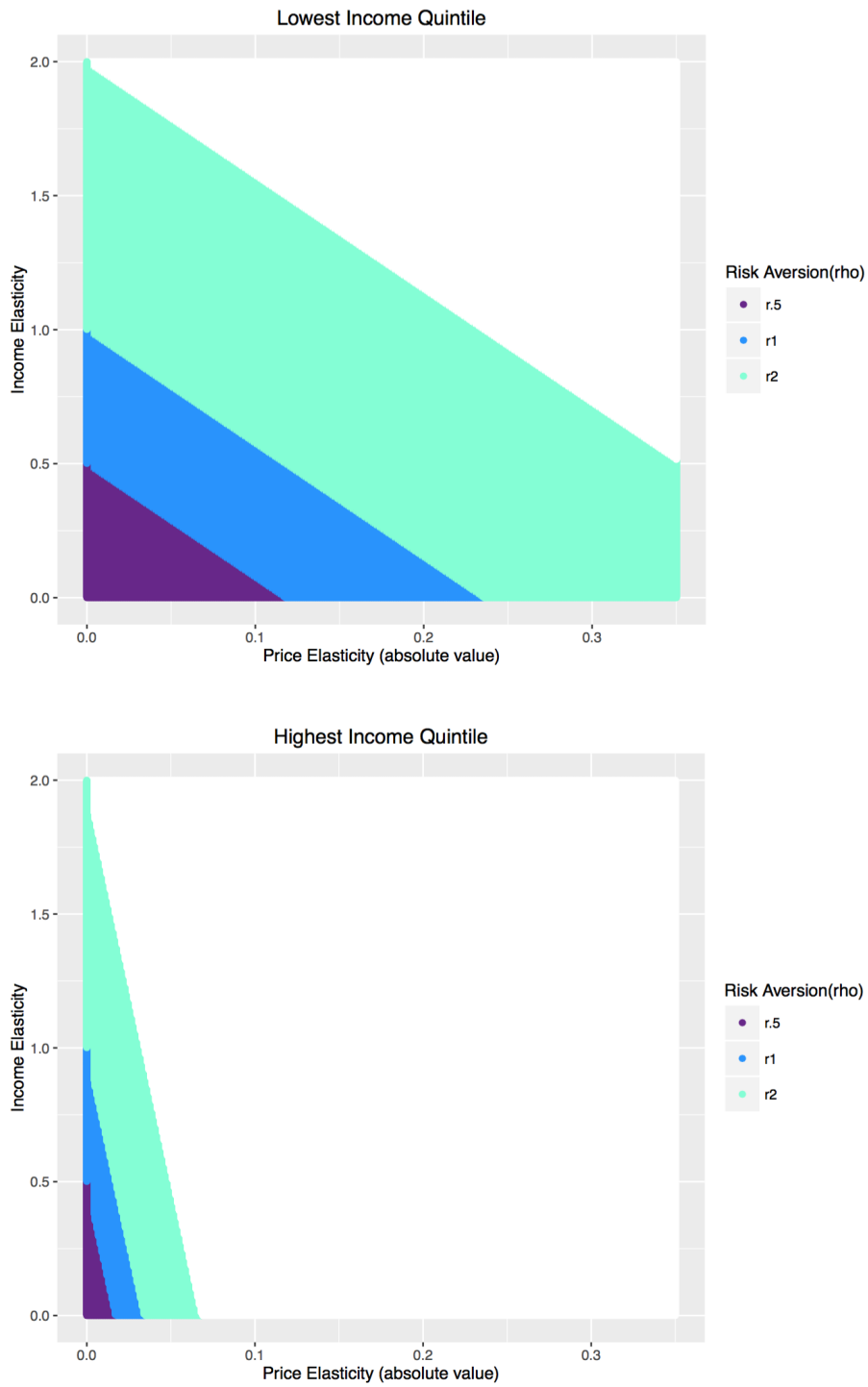


Figure 2.2: Parameter combinations under which price stability is welfare improving for the lowest and highest income quintile groups (where  $s_g = 23.6\%$  and  $s_g = 3.4\%$ , respectively). The colors indicate the minimum level of risk aversion for this combination of elasticities to result in welfare gains from price stability.

Study	U.S. Only/ Multi Country	Years/ or Meta- Analysis	Price Elasticity	Income Elasticity
Small and Van Dender 2007	U.S.	1997-2001	-0.067	-
Hughes et al. 2008	U.S.	2001-2006	[-0.034,-0.077]	[0.21,0.75]
Coglianesi et al. 2016	U.S.	1989-2008	-0.37	-
Lin and Prince 2013	U.S.	1990-2012	-0.027	-
Liu 2014	U.S.	1994-2008	-0.062	0.162
Gillingham 2014	U.S.	2006-2008	-0.22 <sup>2</sup>	-
Kayser 2000	U.S.	1981	-0.23	0.49
Nicol 2003	U.S.	1980-1992	[-0.598,-0.026] <sup>1</sup>	[0.285,0.941] <sup>1</sup>
Small and Van Dender 2007	U.S.	1966-2001	-0.089	-
Hughes et al. 2008	U.S.	1975-1980	[-0.21,-0.34]	[0.21,0.75]
Wadud et al. 2009	U.S.	1984-2003	[-0.17,-0.35] <sup>4</sup>	[-0.067,0.465]
Ng and Smith 2015	U.S.	1952-1978	-0.134	0.008
Dahl and Sterner 1991	Multi	Meta	-0.26	0.48
Espey 1998	Multi	Meta	-0.23	0.39
Brons et al. 2008	Multi	Meta	-0.34	-
Brons et al. 2008	US,Can,Aus <sup>3</sup>	Meta	-0.21	-
Havranek et al. 2012	Multi	Meta	-0.09	-
Havranek and Kokes 2015	Multi	Meta	-	0.1

Table 2.1: Empirical Estimates of Short-run Elasticities of Gasoline Demand

<sup>1</sup>Estimated for different types of households.

<sup>2</sup>Price elasticity of vehicle miles travelled, not of demand for gasoline.

<sup>3</sup>Meta-analysis found estimates from the US, Canada, and Australia were, on average, 0.13 higher than those estimated for the rest of the world.

<sup>4</sup>Elasticities were calculated by income quintile and by rural and urban households. Rural households had the least elastic demand, poorest households had the most elastic demand.

will be welfare improving until the coefficient of relative risk aversion is at least  $\rho = 0.85$ . This level of risk aversion is slightly below the mean of the U.S. population (Chetty 2006). For the second lowest income quintile with  $s_g = 6.7\%$ , consumers must have a level of risk aversion of  $\rho = 1.57$  to prefer fixed prices over volatile prices. This level of risk aversion is above average, but within the range observed in the United States (Chetty 2006). For higher income quintiles, the risk aversion must be even higher. Therefore, with a price elasticity of  $\epsilon_g = -0.133$  and an income elasticity of  $\eta_g = 0.325$ , only risk averse, low-income households are harmed by volatile prices according to Turnovsky's rule. As is shown in Figure 2.2, households with lower than average price elasticities, such as those living in rural or suburban areas with few transport alternatives, would benefit from fixed prices at much lower levels of risk aversion or higher levels of income.

With the "Turnovsky rule," we can determine whether consumers are expected to gain or lose from increases in gasoline price volatility under the assumptions of expected utility theory. This theoretical baseline provides a check on our modeling results. In the next section, we estimate the magnitude of these welfare impacts under expected utility theory. We then show how the estimates of the welfare effects change under the assumptions of prospect theory.

## 2.5 Data and Model Parameters

In this section, we discuss the real-world data that informs our model parameters. First, we calibrate the uncertainty in gasoline prices under a quantity-based carbon instrument based on historical experience with emissions allowance markets. We abstract away from gasoline price volatility resulting from non-environmental regulatory reasons (such as crude oil price volatility). Then, we estimate baseline gasoline demand by income quintile. Finally, we discuss the parameter values that we will use to evaluate risk

aversion and loss aversion.

### 2.5.1 Carbon Price Volatility and Gasoline Prices

To simulate the impact of a fixed and volatile carbon price on gasoline prices, we use the social cost of carbon as the expected price and calibrate the volatility using data from existing allowance markets. We use a target carbon price of \$36/tCO<sub>2</sub> which is the 2015 estimate under a 3% discount rate from the Interagency Working Group on Social Cost of Carbon (SCC) estimates (Interagency Working Group on Social Cost of Carbon). We run sensitivity analyses for the SCC drawn from the same report of \$11, \$56, and \$105.

We model the distribution of carbon allowance prices with a range of variances drawn from existing pollution allowance markets. For each allowance market,  $m$ , we estimate the variance in the month-to-month change in average monthly prices. Then, we scale it down from the allowance price by dividing by the overall mean allowance price:

$$\sigma_m^2 = \frac{Var(|\bar{\gamma}_{t+1} - \bar{\gamma}_t|)}{\bar{\gamma}}, \quad (2.22)$$

where  $t$  indexes monthly average allowance prices and  $\bar{\gamma}$  is the average price across all months.

We estimate  $\hat{\sigma}_m^2$  for fifty-six different allowance markets including the European Union Emissions Trading System, U.S. NO<sub>x</sub> and SO<sub>2</sub> markets, and many state renewable energy credits (RECs) markets. We find a broad range of price volatility from practically zero variation in many RECs markets to extreme month-to-month volatility in ozone, NO<sub>x</sub> and SO<sub>2</sub> markets. The scaled volatility,  $\sigma_m^2$ , has a median value of  $\sigma_m^2 = 0.25$ . For the EUA market, the volatility is  $\sigma_m^2 = 0.62$ . We use these volatilities to inform what we might see in a U.S. carbon market. We run every scenario with the following range of volatility:  $\sigma_m^2 = \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$ . Figure 2.3 shows

the actual distribution of month-to-month changes in average allowance prices as well as the simulated changes with different levels of  $\sigma_m^2$ .

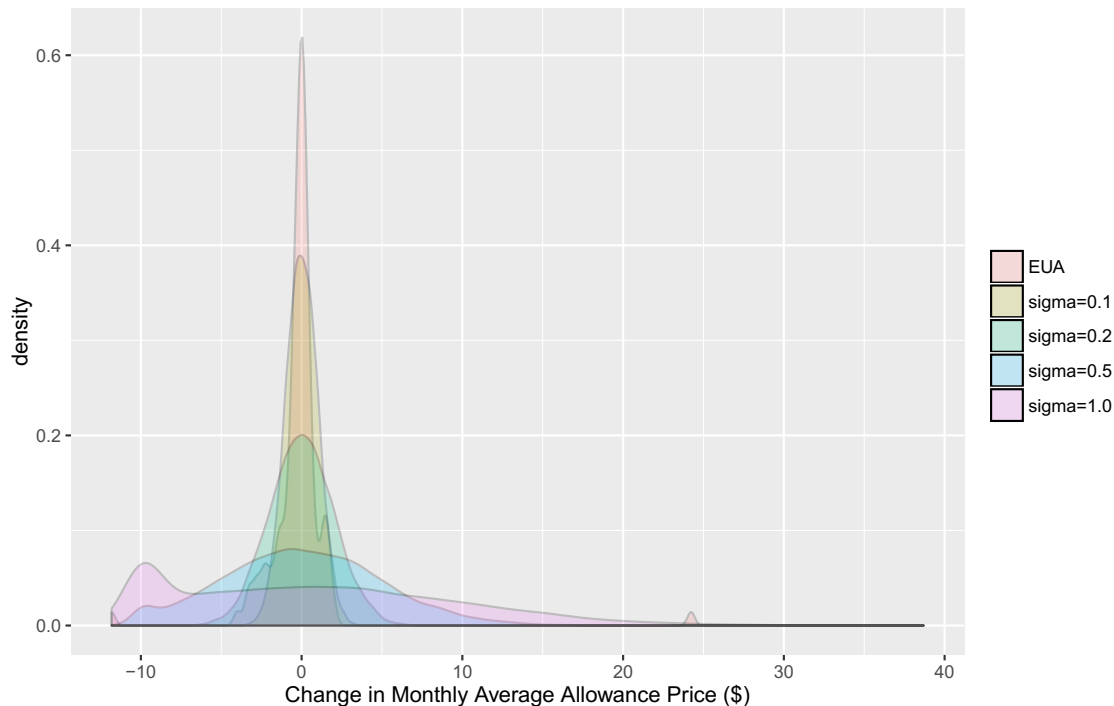


Figure 2.3: The distribution of the change in average monthly carbon allowance prices from one month to the next in the EUA price data and in simulated prices with different levels of volatility ( $\sigma_m^2$ )

We draw a vector of 10,000 prices from a normal distribution with the mean equal to the social cost of carbon (SCC) and the rescaled variance  $\sigma_{SCC}^2 = \hat{\sigma}_m^2 * SCC$ . We impose a floor for the allowance price at \$0 and replace negative values with a price of \$0. Figure 2.4 shows the simulated allowance price distribution for a social cost of carbon of \$36.

$$\tilde{c}_{scc} \sim \mathcal{N}'(SCC, \sigma_{SCC}^2) \quad (2.23)$$

We assume perfect pass-through of the cost of the allowance to the price of gasoline. We calculate the addition to the price of gasoline by multiplying the price of the allowance



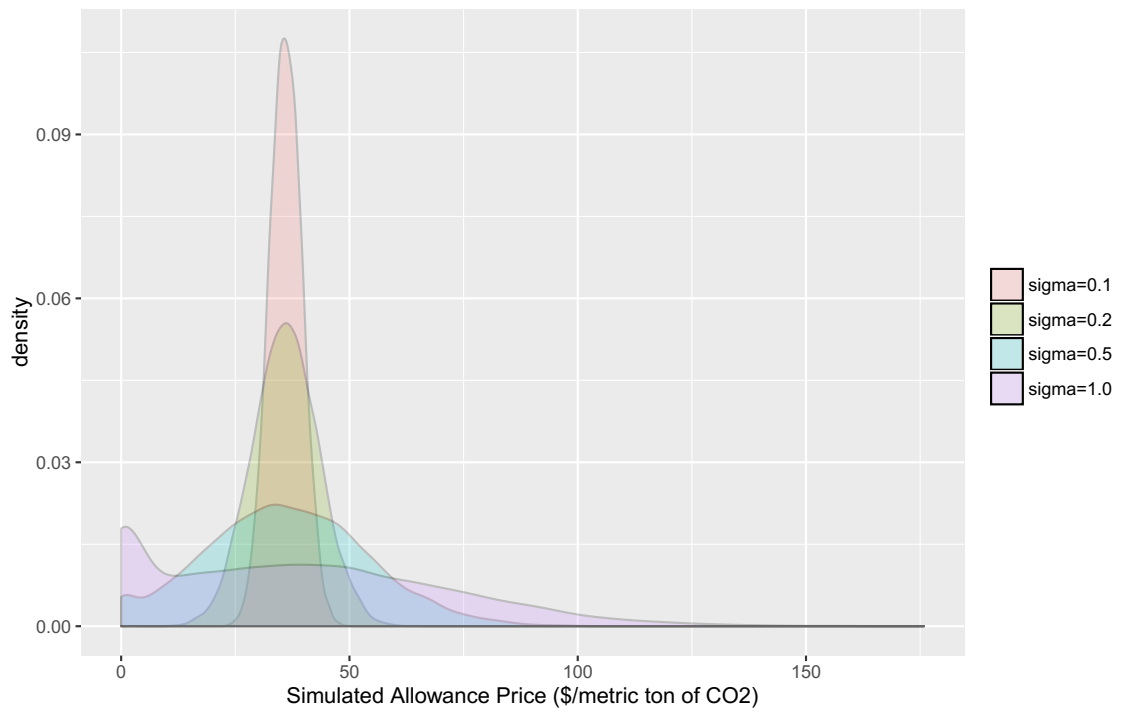


Figure 2.4: Distributions of Simulated Allowance Prices Based on the Social Cost of Carbon of \$36

per metric ton of carbon dioxide times the carbon dioxide content of a gallon of gasoline.<sup>8</sup> With a carbon intensity of 8.91 kg of CO<sub>2</sub> per gallon, every dollar of a carbon tax per metric ton adds \$0.00891 to the price of a gallon of gas.<sup>9</sup> For example, a carbon tax of \$36/metric ton of CO<sub>2</sub> adds \$0.32 to the price of a gallon of gasoline.

The baseline price of gasoline,  $p_b$ , (i.e. the price without the added pass-through cost of the carbon price) is set at \$2.74, the average price for a gallon of regular gasoline in the United States from 2004-2013 (Administration 2016). To focus specifically on whether price volatility in gasoline prices increases or decreases welfare, we abstract away from the existing volatility in gasoline prices and assume a fixed baseline price. If the allowance volatility were added to existing gasoline volatility, the directional effect on the results would depend on the covariance of allowance prices and oil prices.

The stochastic price of gasoline in our model,  $\tilde{p}$ , is the base price of gasoline plus the added cost of the stochastic carbon allowance price,  $\tilde{c}_{scc}$ , as defined in Eq. 2.23. Figure 2.5 shows the distribution of gasoline prices,  $\tilde{p}$  with the added costs of allowances with a target price of \$36/metric ton of CO<sub>2</sub>.

$$\tilde{p} = p_b + 0.00891\tilde{c}_{scc} \quad (2.24)$$

The fixed price of gasoline in our model,  $\bar{p}$ , is approximately equal to the base price of gasoline plus the added cost of an optimal carbon price fixed at the social cost of carbon.<sup>10</sup>

$$\bar{p} = E[\tilde{p}] \quad (2.25)$$

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<sup>8</sup>CO<sub>2</sub> emissions from gasoline: <http://www.eia.gov/oiaf/1605/coefficients.html#tbl2>

<sup>9</sup>Carbon intensity from [https://www.eia.gov/environment/emissions/co2\\_vol\\_mass.cfm](https://www.eia.gov/environment/emissions/co2_vol_mass.cfm)

<sup>10</sup>Because the distribution of  $\tilde{c}_{scc}$  is constrained at zero, when volatility is higher,  $\bar{p}$  will be slightly higher than the base price of gasoline plus the optimal carbon price. This effect is small. At the highest level of volatility,  $\bar{p}$  is about \$0.03 higher than it is with zero volatility. In all cases, the fixed price is equal to the expectation of the stochastic price.

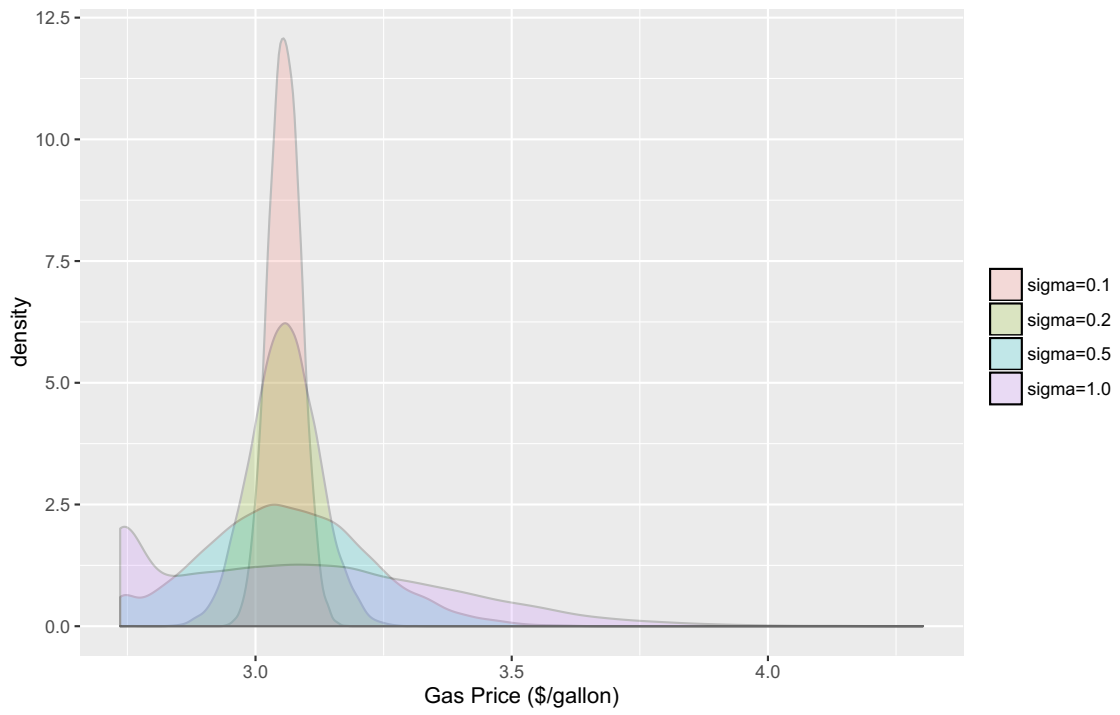


Figure 2.5: Distributions of Simulated Gasoline Prices based on the Social Cost of Carbon of \$36

## 2.5.2 Gasoline Demand by Income Quintile

We anchor the quantity of gasoline purchased on a weekly basis,  $\bar{g}$ , to the average weekly gasoline consumption of households in the United States between 2004-2013 (Sivak 2015). Over this period, the average household consumed 21.2 gallons per week with an average price of \$2.74 per gallon. Then we use the short-run income elasticity of demand for gasoline to estimate the baseline quantity demanded by the representative household in each income quintile. Finally, we use the short-run price elasticity of demand for gasoline to estimate the quantity demanded under a range of gasoline prices.

Income is a key parameter in estimating the risk premiums for volatile gasoline prices. We use after-tax income data from the 2014 Consumer Expenditure Survey separated by averages for each pre-tax income quintile.<sup>11</sup> The after-tax income level includes all sources of private income plus government transfers of social security, food stamps, veterans benefits and other monetary transfers. It does not include the value of Medicare, Medicaid, and health benefits from employers. Table 2.2 summarizes the annual and weekly after-tax income levels for each income quintile.

Income Quintile	Annual Income	Weekly Income	$g_i(\bar{p}_{36} = \$3.05)$	$s_i(\bar{p}_{36})$
Q1	\$10,750	\$207	15.9 gal/wk	23.6%
Q2	\$27,597	\$531	17.8 gal/wk	10.2%
Q3	\$44,686	\$859	19.6 gal/wk	7.0%
Q4	\$69,084	\$1,329	22.3 gal/wk	5.1%
Q5	\$139,658	\$2,686	29.9 gal/wk	3.4%
Average	\$58,364	\$1,128	21.1 gal/wk	5.7%

Table 2.2: Income and Gasoline Expenditures by Income Quintile for Fixed Gasoline Prices Including a \$36 Carbon Tax

Choosing the best household income data is not straightforward. The results of

<sup>11</sup>Consumer Expenditure Survey: <http://www.bls.gov/cex/2014/combined/quintile.xlsx>

the model would be somewhat different for the lowest and highest income groups under other reasonable options. The Consumer Expenditure Survey includes data on both income and expenditures. These numbers differed sharply, especially in the lowest and highest income quintiles. For example, for the lowest income group, mean after-tax annual income was \$10,750 while mean annual expenditures were \$23,713. For the highest income group, the values were \$139,658 and \$104,363 respectively. The lowest income quintile is likely borrowing or drawing down savings while the highest income group is likely saving. Our single-period model does not include savings and borrowing. To the extent that the lowest income quintile's spending was increasing their debt, using expenditures would have underestimated the true welfare impacts of price volatility. Conversely, using after-tax income may overestimate the true welfare impacts of price volatility for low-income groups.

The price and income elasticities of demand for gasoline are important empirical measures that have been estimated in many studies, as discussed in the previous section (Brons et al. 2008; Havranek et al. 2012; Lin and Prince 2013; Coglianese et al. 2016). See Table 2.1 for a range of elasticity estimates. In our model, we use a short-run price elasticity of -0.13 and run sensitivity analyses at -0.23 and -0.03. We use a short-run income elasticity of 0.3 and run sensitivity analyses at 0.1 and 0.5.

$$g_i^* = \bar{g} \left( 1 + \eta_g \left( \frac{I_i - I}{I} \right) \right) \quad (2.26)$$

Above,  $\bar{g}$  is the average weekly gasoline consumption of households in the United States between 2004-2013 at an average price of \$2.74,  $\eta_g$  is the income elasticity of demand for gasoline,  $I$  is mean income for all quintiles and  $I_i$  is the mean income for each quintile,  $i$ .

Thus, at the baseline price of \$2.74, the representative household from each income

quintile demands  $g_i^*$  gallons of gasoline. The costs passed through from a fixed carbon tax or carbon allowance add to the baseline gasoline price. Gas consumption,  $g_i$ , is determined by the total price and the price elasticity of demand.

### 2.5.3 Risk Aversion and Loss Aversion

The level of risk aversion is also an important parameter for this model. The impact of risk aversion on the welfare impacts of price volatility is substantial. More risk averse consumers will be willing to pay a higher the risk premium to avoid price volatility than less risk-averse consumers. Holt and Laury measure relative risk aversion using lottery experiments and find that with payoffs similar in magnitude to those in this model, approximately 6% of study participants are risk loving ( $\rho < 0$ ), 13% are risk neutral ( $\rho \approx 0$ ), and 81% are risk averse ( $\rho > 0$ ) (Holt and Laury 2002). Of the risk-averse participants in Holt and Laury's experiments, 17% were highly risk averse with  $\rho$  close to or above 1. Chetty uses labor market data to estimate risk aversion and finds a mean value of approximately  $\rho = 1$ , or log utility, with an upper bound of  $\rho = 2$  (Chetty 2006). We estimate the model with the coefficient of relative risk aversion,  $\rho = 1$  and run sensitivity analyses at  $\rho = 0.5$  and  $\rho = 2$ .

For the reference-dependent utility model, we must choose parameters for loss aversion, diminishing sensitivity, and utility weighting of gain-loss utility. The median values from Tversky and Kahneman (1992) for the loss aversion coefficient is  $\lambda = 2.25$ . In an experimental estimation of the prospect theory parameters, Abdellaoui and co-authors (2008) find a median value of  $\lambda = 2.61$ , similar to Tversky and Kahneman. They report an interquartile range of  $\lambda = [1.51 - 5.51]$ . Following these estimates, we use  $\lambda = 2.5$  and run sensitivity analyses for  $\lambda = 1.5$  (which corresponds to equal weighting of losses and gains and thus zero loss aversion) and  $\lambda = 3.5$ . In our model, we rely solely on the diminishing marginal utility of consumption for diminishing sensitivity and set the

parameters  $\alpha = \beta = 1$ .

The parameter,  $\phi$ , determines the weight given to the gain-loss utility. A value of  $\phi = 0$  simplifies to the expected utility theory model. A value of  $\phi = 1$  indicates that individuals put equal weight on consumption utility and gain-loss utility. Crawford and Meng empirically estimate taxi-drivers' labor supply with the reference-dependent model (Crawford and Meng 2011). They do not separately estimate  $\phi$  and  $\lambda$ . Instead, they estimate  $\phi(\lambda - 1)$ . If  $\lambda = 2.5$ , then their estimates indicate that  $\phi = [0.34, 0.86]$ . In our models, we use an intermediate value of  $\phi = 0.5$  and run sensitivity analyses at  $\phi = 0.1$  and  $\phi = 1$ .

## 2.6 Results

Volatility in gasoline prices has very different impacts on consumer welfare in the expected utility model compared to the prospect theory model. We estimate the risk premium that a representative household in each income quintile would be willing to pay to have a fixed price for gasoline compared to a stochastic price. Under most scenarios, the expected utility model yields a negative risk premium for households in all income quintiles. Conversely, under most scenarios, the prospect theory model yields a positive risk premium for households in all income quintiles. In both models, the estimated risk premium is sensitive to the price elasticity, the price volatility, and the magnitude of the social cost of carbon. The prospect theory model is also very sensitive to the level of loss aversion and the weight parameter for gain-loss utility.

The base scenario for the model results uses expected values for parameters based on the empirical literature and the best available data.<sup>12</sup> Figure 2.6 illustrates the results

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<sup>12</sup>The price elasticity of demand for gasoline,  $\epsilon_g = -0.13$ ; the income elasticity of demand for gasoline,  $\eta_g = 0.3$ ; the coefficient of relative risk aversion,  $\rho = 1$ ; the coefficient of loss aversion,  $\lambda = 2.5$ ; the weighting parameter for gain-loss utility,  $\phi = 0.5$ ; the social cost of carbon is \$36/metric ton of CO<sub>2</sub>.

of the base scenario for both the expected utility theory model and the prospect theory model. The EUT model yields negative values for risk premiums across all levels of volatility. With the highest level of volatility modeled, the representative household in the highest income quintile would be willing to pay \$4.40/year to face volatile prices instead of fixed prices; for the lowest income quintile, they would pay \$0.30/year to face volatile prices instead of fixed prices.<sup>13</sup> The PT model shows a dramatically different story. With the highest level of volatility modeled, the representative household in the highest income quintile would be willing to pay \$105.40 (2.2% of gasoline expenditures) to avoid volatile prices; those in the lowest income quintile would be willing pay \$60.28 (2.4% of gasoline expenditures) to avoid volatile prices. This 2% risk premium aligns with the 2% premium for fixed electricity rates charged by the electricity utilities discussed in Section 2.2.2.

Next, we run a high-risk premium scenario that draws from the parameter ranges established in Section 2.5 and uses the lowest magnitude values for elasticity and the highest values for risk aversion. We use  $\epsilon_g = -0.03$  and  $\eta_g = 0.1$ . We also increase the coefficient of relative risk aversion from  $\rho = 1$  to  $\rho = 2$ . Pushing the model to the empirically supported upper bound, while leaving the carbon market at a more moderate level leads to higher risk premiums in both models. In the EUT model, households in the lowest quintile are willing to pay a risk premium of \$8.87 at the top of the range of allowance market volatility (See Figure 2.7). All but those in the highest income quintile have positive risk premiums at all levels of volatility and the risk premium for the richest quintile are close to 0 at approximately -\$0.10.<sup>14</sup> In the PT model, low-income

<sup>13</sup>By comparison, the Turnovsky rule finds that under these parameters, the lowest income group would benefit from price stability. The Turnovsky coefficient,  $\omega$ , and the risk premium are both close to zero. The small difference between these models likely arises from the exclusion of the direct utility of gasoline consumption from the expected utility theory model.

<sup>14</sup>The Turnovsky rule finds that under these parameters, all income quintiles benefit from price stability. The Turnovsky coefficient,  $\omega$ , and the risk premium for the highest income quintile are both close to zero. The difference in the models is likely due to the exclusion of the direct utility of gasoline consumption from the expected utility theory model.



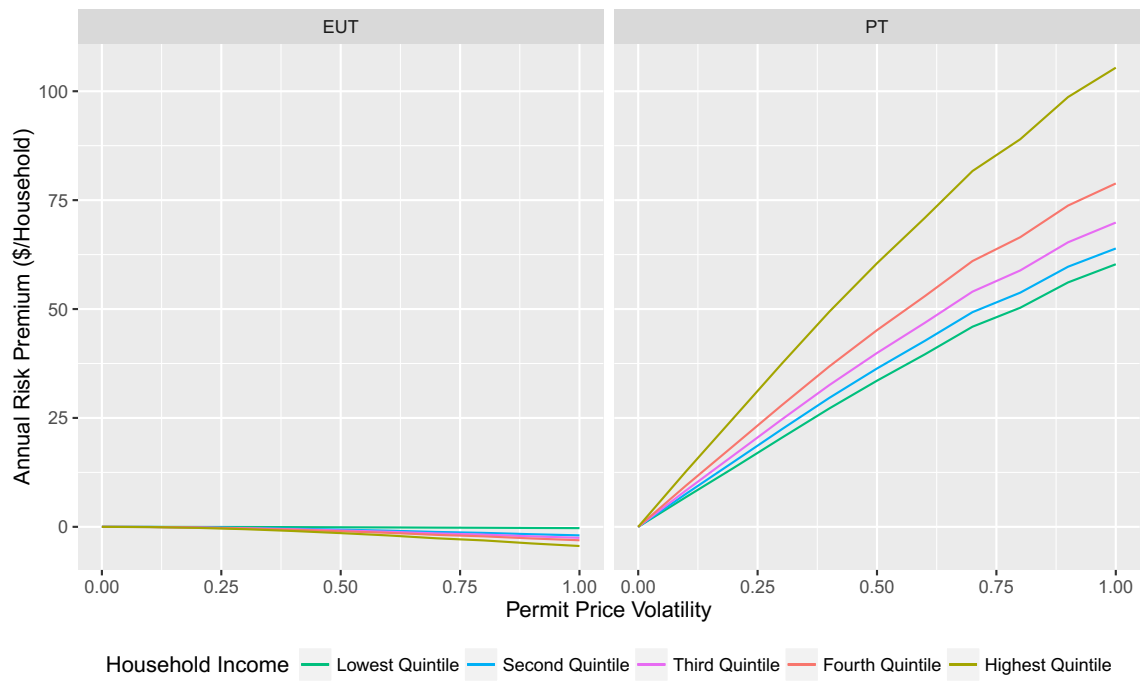


Figure 2.6: Base Scenario: Estimated annual price risk premiums by income quintile for increasing levels of price volatility. Fixed parameter values:  $\epsilon_g = -0.13$ ,  $\eta_g = 0.3$ ,  $\rho = 1$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$ ,  $SCC = \$36/\text{metric ton of CO}_2$

households will pay up to \$101.63 and high-income households will pay \$103.21. From this scenario, we can conclude that under either utility model, risk-averse households who are limited in their ability to reduce gasoline consumption in response to price increases are most negatively affected by gasoline price volatility.

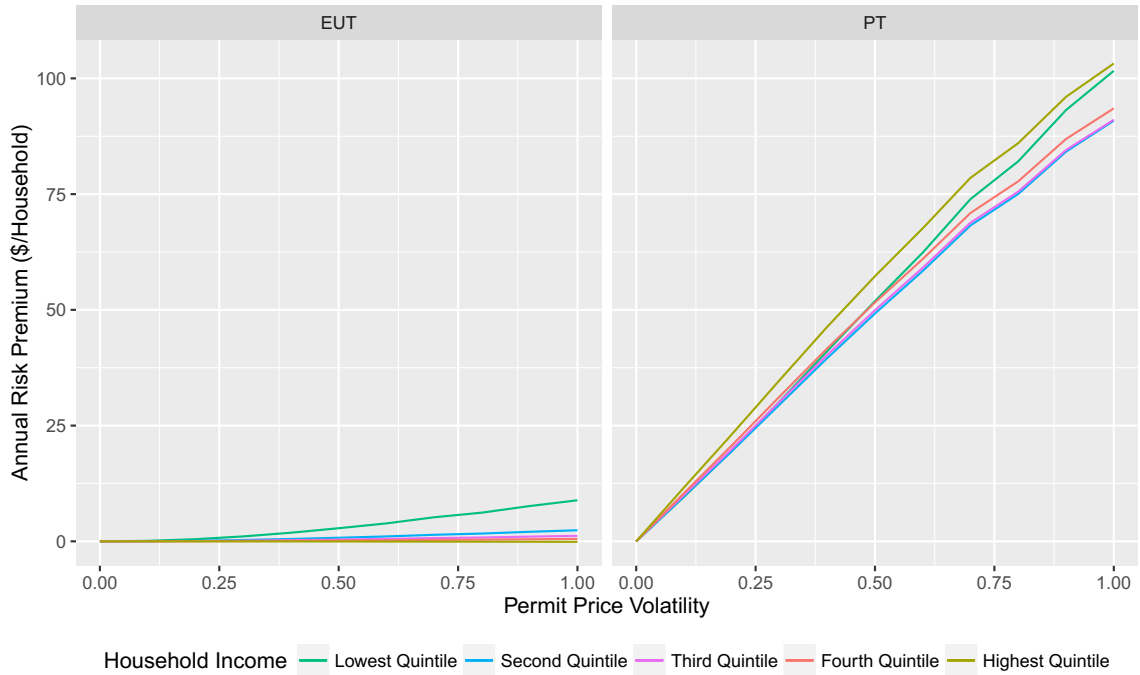


Figure 2.7: High Risk Premium Scenario: Estimated annual price risk premiums by income quintile for increasing levels of price volatility. Fixed parameter values:  $\epsilon_g = -0.03$ ,  $\eta_g = 0.1$ ,  $\rho = 2$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$ ,  $SCC = \$36/\text{metric ton of CO}_2$

In the expected utility model, the most important parameter inherent to the household is the price elasticity of demand. Figure 2.8 shows model simulations for risk premiums that result with price elasticities of demand,  $\epsilon_g = \{-0.23, -0.13, -0.03\}$ . When demand is elastic, households benefit as volatility increases because they can shift their consumption from gasoline to other goods. The simplifying assumption that households do not derive utility from gasoline makes this finding more dramatic. When demand is very inelastic, households in the lowest three income brackets prefer fixed prices but have

small risk premiums.<sup>15</sup> Because they are unable to shift their consumption away from gasoline towards other goods, higher prices result in higher expenditures on gasoline and lower expenditures on everything else. Price elasticity is also important in the prospect theory model. The outcomes follow a similar pattern as in the EUT model, but the risk premiums are uniformly positive and have larger magnitudes.

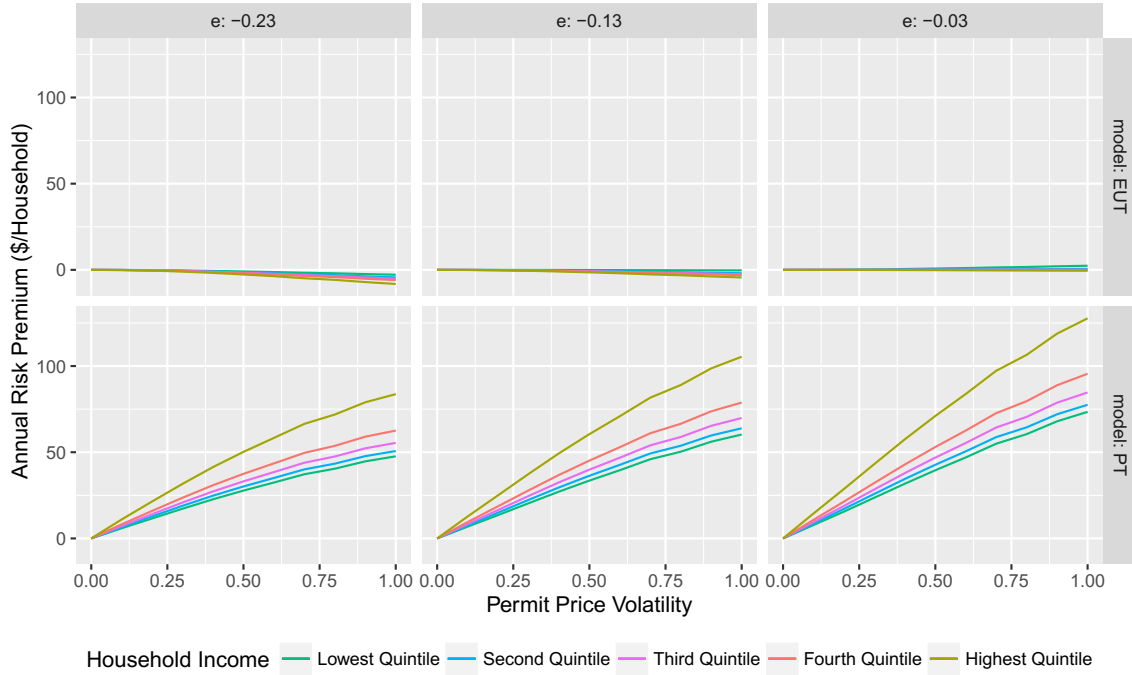


Figure 2.8: Price Elasticity Sensitivity Analysis: Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\epsilon_g$ . Fixed parameter values:  $\eta_g = 0.3$ ,  $\rho = 1$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$ ,  $SCC = \$36/\text{metric ton of CO}_2$ .

Risk aversion plays a much smaller role than price elasticity in the risk premiums to avoid volatile gasoline prices. With moderate price elasticity of gasoline demand ( $\epsilon_g = -0.13$ ), increasing risk aversion from  $\rho = 0.5$  to  $\rho = 2$  barely moves the needle (Appendix B, Figure B.1). Only those in the lowest income quintile move from preferring volatile prices to preferring fixed prices.

<sup>15</sup>By the Turnovsky Rule, the second highest income quintile also prefers fixed prices.

Income elasticity of gasoline demand affects the differences in quantities of gasoline purchased across income quintiles. With higher income elasticity, poorer households buy much less gasoline than richer households compared to the relative quantities under lower income elasticity. Larger differences in gasoline consumption lead to larger differences in risk premiums for each income quintile (Appendix B, Figure B.2).

In the prospect theory model, loss aversion has a strong impact on the risk premiums. Loss aversion does not factor into the expected utility theory models. If households are not loss averse ( $\lambda = 1$ ), that is, they care just as much about gains from a reference point as they do about losses from a reference point, then the prospect theory model does not differ much from the expected utility model. The estimates in the expected utility model have the same sign, but they are slightly magnified because households care both about consumption utility and gain-loss utility compared to a reference point, but they give equal weight to gains and losses. When loss aversion increases, households begin to show very high-risk premiums as volatility in prices increase. This result captures the idea that if prices jump up from one week to another, then households feel “pain at the pump.” If prices drop, then households enjoy the extra money in their pocket, but the utility impact is much less pronounced.

The final variable inherent to consumer behavior that is the least studied and thus hardest to justify a particular value without empirical testing is the weight a consumer places on the gain-loss utility in the prospect theory model. Even at a low value of  $\phi = 0.1$ , the prospect theory model predicts that households in all income quintiles prefer fixed prices for moderate to low levels of volatility. The top three income quintiles switch to prefer price volatility when volatility is very high ( $\sigma_m^2 > 0.8$ ) as the gains from switching from gasoline to the consumption of all other goods outweighs the gain-loss disutility.

Finally, we run sensitivity analyses for the social cost of carbon. With moderate risk

aversion ( $\rho = 1$ ), higher or lower costs of carbon increase or decrease the magnitude of the risk premiums, but do not fundamentally change the analyses (Appendix B, Figures B.5, B.6, B.7). In fact, the difference in allowance price does not change the preference for fixed prices over stochastic prices in most scenarios.

## 2.7 Conclusions

Energy price shocks reduce consumption and investment. The effect of energy price volatility on consumer welfare, however, is less clear. In this paper, we seek to clarify whether volatility in gasoline prices has a net positive or net negative effect on consumer welfare. We use both expected utility theory and prospect theory to estimate the household level welfare effects of volatility that would be passed through to gasoline prices from a carbon allowance market. In a single period model, we estimate the risk premium households would be willing to pay to have a fixed gasoline price instead of a stochastic price.

In expected utility theory, the net effect of price volatility depends on the relationship between the price of the good and the curvature of the overall consumption utility function (Turnovsky et al. 1980; Newbery and Stiglitz 1981). The essential question is the households' ability to change their level of consumption of the good when the price increases and, if they are unable to substitute away from the good when the price rises, how much does the price increase affect their overall budget. When demand for a good is highly inelastic, expenditures on that good constitute a substantial portion of the household's budget, and households are risk averse, price volatility reduces consumer welfare. These characteristics describe gasoline demand for some portion of the U.S. population, but the extent of gasoline price volatility's negative impact depends largely on the actual distribution of price elasticity of demand for gasoline and the joint distribution of price

elasticity and risk aversion.

In prospect theory, price volatility has much more pronounced impacts on consumer welfare due to loss aversion and the dependence of utility on changes from a reference level of consumption. Under the vast majority of scenarios for different levels of price elasticity, risk aversion, and loss aversion, households experience a welfare loss when prices are volatile compared to when prices are fixed, but the magnitude of the impact is very small. Prospect theory and the reference-dependent utility model we use in this paper has seen limited empirical applications. As a result, less is known about the empirically grounded range of critical parameters used in the model. To account for this uncertainty, we explore a broad range of possible parameter values. Increased volatility always has a stronger negative impact on households when utility is reference dependent than when it is independent of expectations. Under most scenarios, households prefer fixed prices over volatile prices. However, the magnitude of the welfare impacts cannot be tightly bounded without looking to experimental or quasi-experimental behavior on the impacts of loss aversion on the willingness to pay a premium to avoid price risk.

The strong separation in the predictions of the expected utility theory model and the prospect theory model make this domain an excellent candidate to test which theoretical model best describes human behavior. This missing market for hedging gasoline price shocks could be seen as evidence that the expected utility theory model describes behavior more accurately. Conversely, the prevalence of fixed-price contracts for residential electricity and phone service could be seen as evidence that the prospect theory model describes behavior more accurately, but that fixed-price gasoline contracts' transactions costs outweigh their benefits. In this study, we have described the conditions under which each model predicts that consumers would prefer fixed prices or volatile prices. Further studies are needed to test which model predictions are most accurate. With the clear separation between the predictions of each model, we could answer the

question of whether loss aversion plays a major role in how energy price volatility affects consumer welfare.

The importance of this question merits further exploration. As states implement the Clean Power Plan and choose from a variety of policy instruments and as nations seek to reduce their carbon dioxide emissions to meet the targets set out in the Paris Agreement, understanding the welfare impacts of generating more volatility in energy prices is crucial. While the environmental economics literature has extensively explored the relative merits of carbon taxes compared to cap-and-trade markets as tools to reach an efficient level of carbon dioxide emissions, this paper contributes to a gap in this analysis. This paper also expands prior analyses to incorporate important behavioral insights into how consumers care not only about the level of consumption but also how that level compares to their expectations. The endless stream of references to “pain at the pump” in popular media hints that the prospect theory framework is highly relevant to this domain. As we craft policies to address climate change, we may be able to limit the pain inflicted on consumers by providing a steady price at the pump.

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## Chapter 3

# Perceptions and the Energy Efficiency Gap

### **3.1 Introduction**

The energy efficiency gap describes the widely studied theory that consumers and firms do not invest in products with the optimal level of energy efficiency attributes. Many hypotheses for why we observe underinvestment in energy efficiency have been proposed and explored, but none can fully explain the energy efficiency gap that remains. In this study, I propose a new hypothesis for why we see slower than expected diffusion of energy efficient technologies. Drawing from the literature in psychology, I examine how the dependence of perception on both expectations and motivations may help us draw new insights into the energy paradox. These findings not only provide insight to the energy paradox, but they also contribute to the broader economic and psychological literature. I show that when consumers hold different expectations about eco-friendly product attributes compared to the expectations about standard product attributes, their evaluations of those attributes are biased when the product is labeled as eco-friendly. This leads to a delay in achieving objectively accurate expectations, even after they test the product first hand.

To illustrate the role that expectations and perceptions could play in the energy efficiency gap, I will start with a brief anecdote before introducing the main hypotheses and the structure of the paper. Suppose that an individual receives a free energy efficient compact fluorescent light (CFL) bulb from a government agency working to promote energy efficiency. She takes the light bulb home and installs it in her bathroom light fixture. She has no prior experience with CFL bulbs and no prior expectations of how the CFL will perform. But when she flips the switch, she is struck by the lurid blue tint to the light. She looks in the mirror and sees that it makes her skin tone look sickly and garish. So she takes the light bulb out of the bathroom fixture and relegates it to a basement light socket. From her experience with this poorly performing bulb, she forms very negative expectations of the quality of CFL light bulbs. Because expectations

shape preferences, after forming negative expectations she is much less likely to purchase another CFL, regardless of what it could save on her energy bills.

A year later, after the quality of CFLs has improved significantly, her husband comes across a promotional sale on CFL bulbs at the local hardware store, buys a pack and brings it home. When his wife sees him installing a spiral CFL bulb in the living room, she recalls her previous negative experience with the energy efficient bulbs and expects the light to be garish and unpleasant. He flips on the switch. He thinks the quality of the light is perfectly fine. She thinks the light is very unpleasant. They look at the same light, and they experience the light very differently. Her perception has been biased by her negative expectations. His perception has not been similarly biased. These subjective points of view are indeed very different. Each has been colored by different experiences and expectations and those expectations change the way they evaluate the color and quality of light from the same light bulb.

This anecdote illustrates my first hypothesis:

*H1: When people expect an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

My second hypothesis stems from a related line of psychological research on motivated reasoning. Just as expectations may bias perceptions, so to motivations may also bias perceptions. For example, if a person is concerned about the environmental impact of the products they choose, they may want eco-products to perform well so they and others will use them. Similar to H1, this hypothesis states that people will subjectively perceive energy efficient products as performing differently than standard versions of the products on objectively identical attributes:

*H2: When people are motivated for an eco-product to perform less well than a*

*standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

My third hypothesis posits a causal relationship between experience biased perception and product choice. I suggest that prior expectations bias the perceptual experience of product quality, not just the evaluations of those perceptions. The biased perception prevents consumers from obtaining full information of the objective product quality. This information bias goes on to influence product choice. I argue that prior expectations affect product choice by biasing perceptual experience:

*H3: Prior performance expectations of eco-products influence post-testing product choice through the mechanism of biased sensory perception.*

In two online experiments and four artefactual field experiments, I study how individuals' prior expectations and motivation for eco-products to perform well influence their perceptions and evaluations of eco-products.<sup>1</sup> By randomizing the labels on identical products, I control for actual product performance and isolate the effects of the eco-product label. I test my hypotheses for two different eco-products: energy efficient compact fluorescent light bulbs and toilet paper made from recycled paper. I find that expectations about the performance of eco-products strongly influence subjective evaluations of product performance, and subsequent product preferences. I find mixed results for the influence of one's motivation for eco-products to perform well on the perception of product quality, but I find that motivation strongly influences product preference. I am unable to find evidence that prior expectations bias sensory perceptions in addition to biasing individual evaluations of their perceptions.

In the next section, I lay out a brief description of the energy efficiency gap. In Section 3.3, I discuss the concepts of expectations, motivations, and perception in the

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<sup>1</sup>Artefactual field experiments, a term adopted by Harrison and List (2004), are similar to laboratory experiments but take place outside of the laboratory in order to recruit a non-traditional participant pool.



context of the psychology literature. In Section 3.4, I propose a modification to an existing model of energy efficient capital investment decisions that incorporates the theoretical impact of expectations and motivations on perceptions and subsequent preferences. In Sections 3.5 and 3.6, I describe six experimental tests of my hypotheses and analyze the results of each study and in Section 3.7, I bring the results together in a meta-analysis. And in Section 3.8, I conclude with a brief discussion of the implications of this theory for the energy and environmental economics and policy.

## **3.2 The Energy Efficiency Gap**

Energy efficient lights and appliances often have higher up-front costs than their less efficient counterparts, but for many energy efficient products, the energy savings make up the initial difference in price over the life of the product. Yet, many consumers appear to ignore medium to long term savings and instead buy the less efficient product. For decades, economists have been working to understand what leads people to make such choices that appear to be irrational from the standpoint of utility or profit maximizing behavior.

A long literature provides a variety of explanations for what is known as the energy efficiency gap (Gerarden et al. forthcoming). The energy efficiency gap is the disparity between the observed level of investment in energy efficient capital and the level of investment in that would generate an optimal tradeoff between upfront costs and future savings using a discount rate that individuals and businesses apply to other types of investment decisions (Jaffe and Stavins 1994b). For example, if a business is willing to accept an internal rate of return of 10% on a capital investment in new production equipment, then if they are profit-maximizing and the investments carry similar levels of risk, they would also invest in an energy efficient product with an internal rate of return

of 10%. However, there is evidence that households routinely pass on energy efficiency investments that appear to be cost-effective.

In a seminal paper, Hausman (1979) finds that individuals use surprisingly high implied discount rates to trade-off upfront capital costs and future operating costs of energy consuming durables. From Hausman's work and many others that followed, it appears that individuals are failing to adopt new energy efficient technologies at a rate that would be expected given the magnitude of potential savings. To describe the slower than optimal diffusion of energy efficient technologies, Jaffe and Stavins coined the term, "energy paradox" (Jaffe and Stavins 1994a). For the past three decades, economists have sought to understand why some consumers do not adopt energy efficient technology that appears to be cost-effective (Hirst and Brown 1990; Howarth and Andersson 1993; Levine et al. 1995; Jaffe and Stavins 1994b; Golove and Eto 1996; Brown 2001; Allcott and Greenstone 2012; Gillingham and Palmer 2014). Economists have identified a number of market failures that may impede the optimal adoption of energy efficiency technologies.

Part of the energy efficiency gap may not be a paradox at all, but may simply be the result of incomplete analysis of the utility maximization problem. Additional costs may exist that are hard to observe. For example, transaction costs and search costs are difficult to measure, thus are often excluded from economic analysis. Transaction costs and search costs could play in many significant energy efficiency investments, which often require the inconvenience of multiple energy audits and construction on one's home or place of business. Moreover, engineering models that project energy use from energy efficiency investments may tend to overestimate savings. Yet, these issues do not explain underinvestment in simple energy efficiency products like compact fluorescent light bulbs.

Another potential reason for the slow adoption of energy efficient products could be that the energy-efficient version of a product may not perform as well as the standard version (Levine et al. 1995). Or, as we explore in this paper, the product may perform

equally well, but individuals may expect the performance to be inferior. If expectations of product quality differ from actual product quality, then even after testing a product first hand, people will still have incomplete information because their evaluations of product attributes may be biased. Therefore part of the energy efficiency gap could be caused by an expectation bias that prevents people from attaining complete information about the objective product attributes.

The energy efficiency literature has not addressed the potential interplay between expectations and perceptual experience. New experiences with products should be incorporated into future expectations according to the theory of Bayesian updating. But research in psychology suggests that objective information is perceived subjectively. According to that body of research, perception is influenced by expectations and motivations. If perceptual experience is strongly influenced by expectations and motivations, then objective information is biased before it is incorporated into one's beliefs through a normal Bayesian learning process. As a result, expectations and preferences may continue to be biased even after experiencing repeated first-hand perceptual information that may objectively contradict one's expectations. If individuals in the population carry with them heuristic biases against the performance of energy efficient products, then this psychological phenomenon could provide an additional explanation for the persistence of the energy efficiency gap.

### **3.3 The Roles of Expectations and Motivation in Perception**

It is natural to think that people see the world as it is. But numerous studies in psychology have shown that perception is rather unstable. In the following section, I give a brief overview of the psychological literature on how the concepts of expectations and motivation relate to perceptual experience.

### 3.3.1 Expectations and Perception

People's evaluations of the world are guided by their expectations. Expectations about another person's abilities guide evaluations of his or her ability (Jones et al. 1968; Darley and Gross 1983). People find cartoons more amusing when they are told beforehand that they are funny (Wilson et al. 1989). Expectations about the quality of a vacation or a movie impact the post-evaluation of the experiences (Klaaren et al. 1994). Knowing of a distasteful 'secret ingredient' in a beer before tasting it leads bar patrons to give the beer lower ratings compared to when they taste it 'blind' (Lee et al. 2006). Changing the price of wine can affect the level of activity in the part of the brain that encodes "experienced pleasantness" (Plassmann et al. 2008). In this study, I examine how the self-fulfilling nature of expectations about product performance may be one reason why eco-friendly products have had slower adoption rates than might otherwise have been expected.

Eco-products have the desirable quality of being eco-friendly, which compensates for the relatively poor performance that is common for early versions of such products. Over time, and as technologies improve, eco-product performance may improve. But if the perception of product performance is biased by previously formed expectations, then perceptions of performance will lag behind objective improvements in performance.

While it is almost tautological that expectations of performance affect preferences for products, I focus on what precedes preference formation. Consumers rely on their perceptual experience of product performance to inform their preferences. However, if the subjective experience of objective performance is biased by expectations, then the preferences that are informed by these experiences will be biased. This would diminish the potential for people's experience with improved products to update their expectations and preferences.

### 3.3.2 Motivated Reasoning and Perception

Perception may be influenced by expectations, as I have discussed above, but it may also be influenced by one's motivations. Motivations, in this sense, are defined as internal states, such as one's desires or preferences (Balcetis and Dunning 2006). Motivations can be thought of as preferences over different states of the world. For example, a person may prefer a world where eco-products perform just as well as or better than their regular counterparts. If her motivational state influences her perception, then she would perceive eco-friendly products as performing better than she would if she did not have that motivation.

Visual perception involves the evaluation of a great deal of visual information. Not every piece of visual information receives equal attention or scrutiny. When it is possible to interpret a visual stimulus in more than one way, top-down cognition can make certain interpretations more available than others (Balcetis and Dunning 2006). If an interpretation of an ambiguous visual stimulus is treated as a hypothesis, then the individual evaluating the stimulus seeks out information that confirms the hypothesis and gives less attention to information that would disconfirm it (Balcetis and Dunning 2006). Similarly, studies that examine motivated reasoning find that information that would confirm a favored hypothesis is not subjected to as much scrutiny as information that would confirm the favored hypothesis (Dawson et al. 2002).

Due to improved methodologies for studying motivated reasoning, there has been a recent surge in attention given to the topic in the field of psychology. In one recent experiment, Balcetis and Dunning explore whether motivated reasoning creates a filter for perception and changes the way an individual sees the world (Balcetis and Dunning 2006). This extends earlier studies that find motivated reasoning affects higher order processes like conscious deliberation and judgment calls. In a separate study, Balcetis and Dunning find that internal goal states impact the perception of one's distance from

the desired object (Balcetis and Dunning 2010). Balcetis and Dunning (2007) explore the impact of cognitive dissonance as a motivational state that drives perception. They find that to minimize cognitive dissonance, individuals modulate their visual perception of their environment . All of these findings support the hypothesis that an individual's motivations change the way they perceive the world around them. In this paper, I seek to test the theory of motivating reasoning in the domain of product attribute evaluations of products labeled as eco-friendly.

### **3.4 A Model of Expectations Bias**

While psychology has had a long history of examining the influence of expectations and motivations on perception, these concepts have had little application in the field of economics. Behavioral economics has begun to incorporate a number of biases and heuristics into economic theory through concepts such as bounded rationality (Kahneman 2003). However, the potential impacts of biased perception of product attributes have not been addressed in the behavioral economics literature. In the context of experienced utility and its role in utility maximization, Kahneman (2006) discusses how choices will be biased if the memories of past experiences are biased. I take this concept one step further to ask whether expectations, which are based in part on memories of past experiences, bias the perceptual experience of product attributes. In this sense, biased perception could affect both hedonic forecasts of utility and experienced utility. Biased hedonic forecasts of utility affect product choice. While there are many potential applications of expectation biases in economic models, in this section, I will suggest one approach that incorporates an expectation bias into the utility or profit maximizing investment decision on energy efficient products. Using Allcott and Greenstone's energy efficiency investment model as a starting point, I describe the effect that expectation biased perception or expectation biased evaluations could have on the decision to invest in an energy-consuming durable

product (Allcott and Greenstone 2012).

Allcott and Greenstone conceptualize the energy efficiency gap as a problem primarily caused by inattention to future energy costs; thus, they weight the future energy costs with a parameter that captures inattentiveness. They assert that this inattention parameter drives much of the energy efficiency gap. I argue that the energy efficiency gap may have another source that is separate from inattentiveness to future energy costs. In addition to inattentiveness to future energy costs, I assert that some consumers have negative expectations of the performance of energy efficient products. First, people who have negative expectations of energy efficient products will evaluate those products as less effective compared to the evaluations of people with neutral or positive expectations. Second, people who are motivated for energy efficient products to perform poorly will evaluate those products as less effective compared to the evaluations of people with neutral or positive expectations.

Allcott and Greenstone's model describes how a profit-maximizing firm or a utility-maximizing individual chooses whether to purchase an energy efficient or a regular product. In period 1, the agent purchases the product and in period 2, the agent uses the product. The regular product is denoted with a subscript of 0 and the energy efficient product is denoted with a subscript of 1.

The authors focus on energy consuming durables and denote the energy intensities of each version of the product as  $e_0$  and  $e_1$ , where  $e_0 > e_1$ .<sup>2</sup> The upfront capital cost of the product is denoted as  $c$ , the private cost of energy is represented as  $p$ , the discount rate is  $r$ , and the intensity of product utilization is denoted as  $m$ . To account for unobserved utility costs or benefits or incremental opportunity costs, they introduce a parameter,  $\xi$ . The attention-weighted future energy costs minus the unobserved costs or benefits of using the eco-product are compared to the upfront capital cost,  $c$ . The agent

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<sup>2</sup>To extend this model to a product that is not an energy consuming product, such as toilet paper, let  $e_0 = e_1 = 0$ .

will choose to purchase the eco-product if and only if:

$$\frac{\gamma p m_i (e_0 - e_1)}{(1 + r)} - \xi > c \quad (3.1)$$

Allcott and Greenstone discuss various ways in which the unobserved utility costs or benefits,  $\xi$ , could affect the utility maximizing decision. For example, they note that weatherizing a home often makes it less drafty and more comfortable. They also note that an energy efficient light bulb might produce a different quality of light. I extend this discussion by suggesting that the existence of a bias based on expectations and motivations would shape this parameter in predictable ways. If there is a bias in the experienced utility of an eco-product based on prior expectations of performance, then the parameter  $\xi$  will be heterogeneous across individuals and will depend on their prior expectations of the product's performance.

Each individual,  $i$ , evaluates two products,  $j = 0, 1$ . Products are identical in attributes except the label that designates product,  $j = 0$ , as a “standard” product, and product,  $j = 1$ , as an “eco-friendly” product.

I decompose the utility parameter,  $\xi$ , from Eq 3.1 into three parts: the expectations bias, the motivation bias, and all other unobserved utility costs or benefits,  $\epsilon$ . The term “expectations bias” does not necessarily indicate that an individual is not behaving rationally according to Bayesian learning. Instead, it indicates that expectations of eco-product performance are affecting the experienced utility of that product. Essentially, the term “bias” is used because the presence or absence of a eco-label changes the way in which an otherwise identical product is evaluated. In this paper, I attempt to show that expectations bias both sensory perceptions and evaluations of those sensory perceptions. For the purposes of this model, we will consider the evaluations of the sensory perceptions as the measure of experienced utility. The expectations bias is a



function of relative performance expectations of attributes,  $\alpha_i$ , from each product. This parameter,  $\alpha_i$ , is normalized with a mean of zero. Higher values for  $\alpha_i$  indicate that the individual has higher expectations for eco-products to outperform regular products. That is, they expect the eco-product to have better attributes, such as the pleasantness of light or the softness of toilet paper. The motivation bias is a function of one's motivation for the energy efficient product to perform well,  $\delta_i$ .

$$\xi(\theta_j, \lambda_j, \delta_i, \alpha_i) = \theta_0(\alpha_i) - \theta_1(\alpha_i) + \lambda_0(\delta_i) - \lambda_1(\delta_i) + \epsilon \quad (3.2)$$

If expectations bias the experienced utility of the product, then:

$$\theta_0(\alpha_i) \neq \theta_1(\alpha_i) \quad (3.3)$$

If motivations bias the experienced utility of the product, then:

$$\lambda_0(\delta_i) \neq \lambda_1(\delta_i) \quad (3.4)$$

Without an eco-bias, expectations and motivations can still influence experienced utility, but the presence or absence of an eco-label does not change the experienced utility. In that case, the effects of expectations on product choice cancel out. After both products are tested, expectations would have no influence on the choice between an objectively identical products labeled eco-friendly and regular. Motivations could continue to influence the product choice through  $\epsilon$ , but would not have a separate impact on experienced utility from perceptions.

With an eco-bias,  $\theta_1(\alpha_i)$  and  $\lambda_1(\delta_i)$  are monotonically increasing functions while  $\theta_0(\alpha_i)$  and  $\lambda_0(\delta_i)$  are monotonically decreasing functions. That is, if individuals have higher expectations of eco-product performance or are motivated to believe that eco-

products perform well, they perceive better performance from a product when it is labeled as eco-friendly than when it is not labeled as eco-friendly. The converse holds for individuals with negative expectations of performance of eco-products or who are motivated to believe that eco-products perform poorly.

In the next section of this paper, I will use experimental data to test whether  $\theta_0(\alpha_i) = \theta_1(\alpha_i)$  and  $\lambda_0(\delta_i) = \lambda_1(\delta_i)$ . If the equalities do not hold, then the experienced utility of eco-products is biased.

Including this bias in the evaluation of eco-products has important implications for the market penetration of eco-products over time. For example, this bias may lead to a lag in the diffusion of energy efficiency products (i.e. the energy efficiency gap). If sensory perceptions are biased by expectations, then even repeated experiences under Bayesian learning lead to a self-perpetuating cycle. If an individual expects poor performance from an energy efficient product, they will perceive a lower level of performance compared to what they would objectively perceive. The biased experience of performance will be incorporated in future expectations of the product. Those expectations will continue to bias the perception of the product performance in the future. In our experiments, we find little evidence for this strict version of biased perception for eco-product attributes. However, we find ample evidence that prior expectations influence the evaluations of the sensory experience.

If evaluations of sensory perceptions are biased by expectations, then prior expectations will combine with new sensory information to form posterior evaluations. Depending on the rate of learning, these expectations will continue to influence product evaluations and product preferences over time, even after product attributes change. With a slow rate of learning, expectations and preferences will lag behind changes in objective product quality. This lag due to the influence of expectations on evaluations could be a contributing factor to the slower than expected rate of diffusion of energy efficient

technologies. The extent to which it could be a factor depends on initial expectations, the consistency of product quality within an eco-product category, the interrelatedness of expectations across eco-product categories, and the rate of learning.

## **3.5 The Impact of Expectations on the Evaluation of Attributes**

### **3.5.1 Study 1: Reported Perception of Energy Efficient Lighting (Online)**

In an online experiment, Study 1 examines ratings of light quality in photographs. Each photograph was evaluated by participants randomly assigned to one of two treatment groups. The treatment groups differed only in what type of light bulb participants were told was used in each photo. Participants in one treatment group were told that the photo was taken using an incandescent light bulb while participants in the other treatment group were told that the identical photo was taken using an energy efficient compact fluorescent light (CFL) bulb. Before evaluating the lights in the photos, participants were asked about their prior expectations and motivations with regards to the two different types of light bulbs.

To illustrate this concept, I will introduce two different hypothetical consumers: Alice and Betty. Alice is unconcerned with energy efficiency. Her landlord pays her electricity bills. She never really thinks about the connection between electricity consumption and air pollution or climate change. She has very little desire for energy efficient products to perform well because energy efficiency and energy cost are not part of her utility function. Thus, she has low motivation to perceive energy efficient products as high performing.

Betty is a consumer who prioritizes energy efficiency. She pays close attention to her

monthly electricity bills. She is also very concerned about how her energy consumption contributes to air pollution and climate change. Betty is always looking for ways to reduce her energy consumption. She uses energy efficient products whether they are high performing or not. Even so, she would be very happy if the energy efficient products that she uses also perform well. Betty is highly motivated to perceive energy efficient products as high performing. If energy efficient products perform well, she gains positive utility from reducing her energy consumption and positive utility from having a product that performs well. As such, the two sources of utility are positively correlated. Thus, it is in her interest to believe that the energy efficient product performs well. Perhaps she would pay less attention to negative aspects of product quality and more attention to positive aspects of product quality. Regardless of the psychological pathways that may be employed, she can increase her overall utility with a perception bias. The strength of the motivation for energy efficient products to perform well leads to a stronger perception bias. Essentially, the motivation parameter captures preferences over different possible states of the world. If an individual has a strong motivation to use energy efficient products, then she would prefer a state of the world where energy efficient products perform well. This preference for a state of the world where energy efficient products perform well motivates her to perceive better performance for energy efficient products.

In Study 1, I test the following two hypotheses:

*H1: When people expect an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

*H2: When people are motivated for an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

## **Study 1: Methods**

### **Participants**

Participants were recruited online through Amazon MTurk and paid \$1 to complete the 10-minute survey. Of the 211 participants who began the survey, 199 completed most of the questions (94.3% completion rate). See Appendix C for the demographics of the study population.

### **Procedure**

In this study, participants rated the quality of light in four photographs. Each photo is labeled as taken under the light of either an energy efficient CFL or an incandescent light.

Before they evaluate any photos, participants answer questions about their prior expectations of the relative performance of energy efficient CFLs and incandescent lights and their motivation for energy efficient CFLs to perform well. Then they are shown a camera and its specifications, a lamp and its specifications, and both the energy efficient CFL bulb and incandescent light bulb. They are told that each photo was taken using the same camera without a flash, the same lamp, and one of the two light bulbs. Before each photo is shown and evaluated, they are told that the photo was taken with either the energy efficient CFL or the incandescent light. These labels are randomized across participants, and each participant evaluates two photos with the energy efficient CFL label and two photos with the incandescent light label.

Participants rate each photo on four different light qualities: bluishness, yellowish-ness, brightness, and pleasantness. They rate each aspect of light quality on a 6-point numeric scale where one is labeled as “Not at all bluish/yellowish/bright/pleasant” and

six is labeled as “Very bluish/yellowish/bright/pleasant.”

After evaluating the lighting in all four photos, they are asked a number of questions on demographics and political and environmental beliefs.

Using an OLS regression with errors clustered at the individual, I employ the following model to analyze the relationship between expectations and perception and the relationship between motivation and perception:

$$y_i = \beta_0 + \beta_1 L_{CFL} + \beta_2 \alpha_i + \beta_3 \alpha_i L_{CFL} + \beta_4 \delta_i + \beta_5 \delta_i L_{CFL} + \epsilon \quad (3.5)$$

$y_i$ : Rating of light pleasantness on a 6-point scale where 1=“Not at all Pleasant” and 6 = “Very Pleasant”

$\alpha_i$ : Expectations on a standardized 7-point scale where higher ratings indicate higher expected relative performance of CFL lighting compared to incandescent lighting

$\delta_i$ : Motivations is a standardized 5-point scale where higher ratings indicate increased intensity of happiness if CFL lighting outperforms

$L_{CFL}$ : Dummy for photo labeled as lit with a CFL light

I focus my analysis on the perception of light pleasantness because it proxies experienced utility while allowing for heterogeneity in tastes for levels of bluishness, yellowishness, and brightness.

First, Hypothesis 1 predicts that those who have low expectations of the overall performance of energy efficient CFLs, they will perceive light labeled as CFL to be less pleasant. Thus, in the model above, the variation of interest is  $\beta_3$ , where I measure

expectation bias from Eq 3.2:

$$\theta_1(\alpha_i) = (\beta_2 + \beta_3 L_{CFL})\alpha_i \quad (3.6)$$

$$\theta_0(\alpha_i) = (\beta_2)\alpha_i \quad (3.7)$$

After controlling for light quality ratings of CFLs and incandescents for all participants,  $\beta_3$  measures the additional impact on pleasantness ratings of light labeled as CFL from those who have higher relative expectations of the performance of CFLs compared to the performance of incandescent lights. If  $\beta_3 > 0$ , then the pleasant ratings are affected by the label which activates prior expectations.

Hypothesis 2 posits that individuals who have a stronger motivation for energy efficient CFLs to perform well will perceive light labeled as CFLs to be more pleasant than when it is labeled as incandescent. Using the same model specified above, the variable of interest for H2 is  $\beta_5$ , which captures the expectation bias from Eq 3.2:

$$\lambda_1(\delta_i) = (\beta_2 + \beta_5 L_{CFL})\delta_i \quad (3.8)$$

$$\lambda_0(\delta_i) = (\beta_2)\delta_i \quad (3.9)$$

The coefficient  $\beta_5$  measures the impact on pleasantness ratings of light labeled as CFL interacted with the 5-point numeric measure of “happiness” if CFLs perform well. If  $\beta_5 > 0$ , then pleasant ratings are biased by motivations.

### Study 1: Results

The results support H1 ( $\hat{\beta}_3 = 0.446$ ,  $p < 0.001$ , Table 3.1); those who expect CFL light to perform better than incandescent light give higher ratings to light when it is labeled as CFL than when it is labeled as incandescent compared to the ratings of those who

have lower expectations of the relative performance of CFLs.

I find that H2 is not supported by the results of Study 1 ( $\hat{\beta}_5 = -0.0538, p = 0.472$ , Table 3.1). Participants who reported higher motivations for CFLs to perform well gave higher pleasantness ratings to all photos regardless of the CFL or incandescent label ( $p = 0.004$ ). The effect did not vary based on the label of the light.

Adding demographic controls does not significantly change the coefficient estimates. Exploring interaction effects between demographic controls and the CFL label yields a few interesting patterns. Participants who are more conservative give higher ratings to light when it is labeled as a CFL ( $\hat{\beta} = 0.134, p = 0.015$ ). This finding was unexpected given the political resistance from conservative politicians to policies that restricted the sale of traditional incandescent light bulbs. Older participants give higher ratings on average ( $\hat{\beta} = 0.010, p = 0.050$ ) but judge light with CFL labels more harshly than light with incandescent labels ( $\hat{\beta} = -0.012, p = 0.092$ ).

### 3.5.2 Study 2: Reported Perception of Energy Efficient Lighting (Field)

To explore the how expectations affect the experience of actual lighting (as opposed to the lighting of photographs viewed online), and to see if the results generalize to a different category of eco-products, I conducted two artefactual field experiments in a shopping mall in a Boston suburb.

In Study 2, I examine how expectations of product performance affect the subjective experience of energy-efficient compact fluorescent light bulbs and incandescent light bulbs.

I test the same two hypotheses that were tested in Study 1:

*H1: When people expect an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it*



Table 3.1: Study 1 Results: Reported Perception of Energy Efficient Lighting (Online)

	<i>Dependent Variable:</i>			
	Pleasantness (Standardized Likert Scale)			
	(1)	(2)	(3)	(4)
CFL	0.278*** (0.0811)	0.278*** (0.0752)	0.278*** (0.0816)	0.279*** (0.0756)
Expectations		-0.132* (0.0664)		-0.173** (0.0632)
Expectations x CFL		0.433*** (0.0760)		0.446*** (0.0764)
Motivations			0.134* (0.0642)	0.176** (0.0602)
Motivations x CFL			0.0530 (0.0912)	-0.0538 (0.0759)
Constant	-0.139* (0.0634)	-0.139* (0.0628)	-0.136* (0.0630)	-0.136* (0.0620)
N	796	796	792	792
$R^2$	0.020	0.074	0.046	0.096

*Notes:* OLS Regression of light pleasantness (6-point scale standardized with mean = 0 and sd = 1) on moderating variables with errors clustered at the individual. Expectations are measured with a standardized 7-point scale where higher ratings indicate higher expected relative performance of CFL lighting compared to incandescent lighting. Motivation is measured with a standardized 5-point scale where higher ratings indicate increased intensity of happiness if CFL lighting outperforms incandescent lighting. Standard errors are in parentheses.

\* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

*objectively does not exist).*

*H2: When people are motivated for an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

Study 2 showed that expectations about the relative performance of CFL bulbs and incandescent bulbs influenced participants' subjective experience of the performance of the light bulbs. Those who expected CFL bulbs to perform poorly compared to incandescent light bulbs experienced what they expected, and vice versa for those participants who expected the opposite.

## **Study 2: Methods**

### **Participants**

Study 2 took place at a shopping mall kiosk in a Boston suburb from April 3, 2012 to May 1, 2012. I recruited 380 passersby at a shopping mall in a Boston suburb by offering \$5 gift cards to Dunkin' Donuts. Of those, I determined that 22 completed surveys should be dropped from the analysis due to research assistant implementation errors during the experiment or because the participants were ineligible for the study due to language barriers or mental disabilities. See C for demographics of the study population. Those who participated in Study 2 also took part in Study 3.

### **Procedure**

In Study 2, I asked participants to evaluate the quality of lighting from two lamps. I set up two light boxes each with identical reading lamps. Lamp A illuminated a sock monkey cookie jar and lamp B illuminated a teal vase with colorful fake flowers.

Each lamp was positioned so participants could not see the bulb in the lamp. Before participants evaluated the lighting, they took a brief survey about their past experiences with, and expectations of, CFL and incandescent light bulbs. Then, they looked into each box and rated the quality of the lighting produced by the bulbs.

To isolate the effect of expectations on perceptions, I randomly varied the labels on the light boxes: in one treatment I said that light box A contained an incandescent bulb and light box B contained a CFL bulb; in the other treatment the labels were reversed. After completing the experiment, participants took a brief survey with demographic questions as well as questions about their political ideology and environmental beliefs.

Similar to the analytical approach in Study 1, I use an OLS regression of moderating variables on ratings of light pleasantness with errors clustered at the individual level (Eq. 3.5).

## **Study 2: Results**

The results of Study 2 support H1 ( $\hat{\beta}_3 = 0.217$ ,  $p = 0.002$ , Table 3.2). Those who expect CFL light to perform worse than incandescent light give lower ratings to light when it is labeled as CFL than when it is labeled as incandescent compared to those who have higher expectations of the relative performance of CFLs.

In contrast to Study 1, H2 is supported by the results of Study 2 ( $\hat{\beta}_5 = 0.244$ ,  $p = 0.001$ , Table 3.2). Those who would be happy if energy efficient CFL lights perform well gave higher pleasantness ratings of the light when it was labeled as CFL than when it was labeled as incandescent compared to those who said they would not be as happy if CFLs performed well.

Table 3.2: Study 2 Results: Reported Perception of Energy Efficient Lighting (Field)

	<i>Dependent Variable:</i>			
	Pleasantness (Standardized Likert Scale)			
	(1)	(2)	(3)	(4)
CFL	0.752*** (0.0623)	0.753*** (0.0612)	0.752*** (0.0609)	0.753*** (0.0602)
Expectations		-0.0629 (0.0501)		-0.0709 (0.0505)
Expectations x CFL		0.264*** (0.0679)		0.217** (0.0697)
Motivations			0.0263 (0.0466)	0.0414 (0.0478)
Motivations x CFL			0.288*** (0.0714)	0.244*** (0.0731)
Constant	-0.376*** (0.0456)	-0.377*** (0.0457)	-0.376*** (0.0456)	-0.377*** (0.0457)
<i>N</i>	883	881	883	881
<i>R</i> <sup>2</sup>	0.142	0.164	0.191	0.204

*Notes:* OLS Regression of light pleasantness (6-point scale standardized with mean = 0 and sd = 1) on moderating variables with errors clustered at the individual. Expectations are measured with a standardized 7-point scale where higher ratings indicate higher expected relative performance of CFL lighting compared to incandescent lighting. Motivation are measured with is a standardized 5-point scale where higher ratings indicate increased intensity of happiness if CFL lighting outperforms incandescent lighting. Standard errors are in parentheses.

\* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

### 3.5.3 Study 3: Reported Perception of Eco-Friendly Toilet Paper

Study 3 examines how expectations about the performance of regular toilet paper and toilet paper made from recycled paper affect how participants evaluate the softness of toilet paper when it is labeled as made from recycled paper compared to when it is labeled as made from virgin wood pulp. In Study 3, I also measure participants revealed preference between the two types of toilet paper by giving asking them to choose one of the two rolls of toilet paper they tested and take it home as a bonus gift.

I test the same two hypotheses as in Studies 1 and 2, but apply them to a different product category:

*H1: When people expect an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

*H2: When people are motivated for an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

However, extending these hypotheses from light bulbs to toilet paper adds additional clarity and depth to the analysis. First, I am testing whether the perception bias extends beyond visual perception. Second, I am testing whether these hypotheses hold for a much different eco-product category. Third, toilet paper has a less complex definition of “performance” compared to lights. Incandescent lights and CFL lights have widely disparate electricity costs associated with their use: incandescent light bulbs require approximately five times as much electricity to use than CFLs. CFLs also last up to twelve times longer than incandescent lights. For these reasons, I am concerned that the general measure of performance expectations of CFL lights may have been influenced by factors other than the quality of lighting. For example, someone who says that

CFLs perform well may be referring to the fact that they last a long time and consume little electricity instead of focusing on the light quality. Additionally, testing toilet paper allowed us to include a low-cost behavioral measure of revealed preference. At the end of the experiment, I offer participants a bonus gift of a roll of one of the toilet papers they tested.

Study 3 showed that expectations of the performance of toilet paper made from recycled paper strongly influenced the softness participants reported experiencing when touching the toilet paper. Expectations of performance also affect product choice. Participants who expect toilet paper made from recycled paper to perform better are more likely to prefer toilet paper made from recycled paper over regular toilet paper, but the relationship is not statistically significant.

### **Study 3: Methods**

#### **Participants**

Those who participated in Study 2 also took part in Study 3. See Study 2 and Appendix C for participant details.

#### **Procedure**

I displayed two rolls of toilet paper labeled A and B. For the two rolls, I randomized labels of toilet paper made from recycled paper and regular toilet paper. Each participant evaluated one roll labeled as regular toilet paper and one roll labeled as recycled. Participants first answered questions about their experiences and expectations of the performance of regular and toilet paper made from recycled paper. Then, I gave each participant a four-sheet sample of toilet paper A to test for softness and strength and repeated the procedure for toilet paper B. After evaluating each toilet paper individu-

ally, participants were asked which they preferred and how much they would be willing to pay for a four-pack of toilet paper A and B. <sup>3</sup>

I test H1 and H2 with two different measures of toilet paper performance: softness and strength. I use a similar analytical model to that used to analyze light pleasantness in Study 2 to analyze the softness and strength ratings in Study 3 (Eq 3.5). In place of the dependent variable of the rating of the pleasantness of light, two separate dependent variables are used: a rating of softness and a rating of strength. All ratings are standardized with the mean equal to zero and the standard deviation equal to one.

H1 predicts that when evaluating toilet paper labeled as made from recycled paper, those with higher expectations of the relative performance of toilet paper made from recycled paper will perceive the toilet paper to be softer and stronger compared to those who have lower expectations of the performance of toilet paper made from recycled paper.

H2 predicts that those with higher levels of motivation for toilet paper made from recycled paper to perform well will perceive the toilet paper labeled as made from recycled paper to be softer and stronger compared to those who have lower levels of motivation for toilet paper made from recycled paper to perform well.

After participants had completed the study, they were told that in addition to the gift card, they would also receive a free roll of toilet paper. They were asked to choose one of the two rolls they tested. I analyzed the choice of toilet paper in a logistical regression model. For approximately half of the participants, toilet paper A was labeled as recycled while toilet paper B was labeled as regular. I parameterized the model so that the dependent variable equals to 1 when the toilet paper labeled as “Made from recycled paper” was chosen and 0 when the toilet paper labeled as “Regular” was chosen.

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<sup>3</sup>Willingness to pay for the two types of toilet papers will be analyzed in a separate paper. It is included in the study description for completeness.

### Logistic Regression Model: Toilet Paper Choice

- $y_i = 1$  when the individual chooses the toilet paper labeled as “Made from recycled paper”
- $y_i = 0$  when the individual chooses the toilet paper labeled as “Regular”
- $\alpha_i$ : Expectations about the relative performance of toilet paper made from recycled paper and regular toilet paper
- $\lambda_i$ : Motivations for toilet paper made from recycled paper to perform better than regular toilet paper

$$y_i = \beta_0 + \beta_1\alpha_i + \beta_2\lambda_i + \epsilon_i \quad (3.10)$$

If expectations affect choice, even after testing the product first hand, then I would expect to see  $\beta_1 > 0$ . If motivations affect choice, then I would expect to see  $\beta_2 > 0$ .

### Study 3: Results

For evaluations of softness, H1 is supported ( $\hat{\beta}_3 = 0.234$ ,  $p < 0.001$ , Table 3.3). Those who expect toilet paper made from recycled paper to perform worse than regular toilet paper give relatively lower ratings to toilet paper when it is labeled as recycled than they do to toilet paper labeled as regular compared to those who have higher expectations of toilet paper made from recycled paper.

For evaluations of softness, the results of Study 3 support H2 ( $\hat{\beta}_5 = 0.156$ ,  $p = 0.008$ , Table 3.3). I find that those who would be happy if toilet paper made from recycled paper performs well gave higher ratings to the softness of toilet paper when it was labeled as made from recycled paper compared to those who said they would not be as happy if toilet paper made from recycled paper performed well.



In contrast to the results that confirmed H1 and H2 when the rating of softness is used as a proxy for overall performance, the ratings of toilet paper strength do not support H1 or H2 ( $\hat{\beta}_3 = 0.067, p = 0.384$ ;  $\hat{\beta}_5 = 0.072, p = 0.362$ ). For H1, expectations of the relative performance of regular and recycled paper had no effect on the perception of the strength of toilet paper. For H2, motivation did not predict ratings of strength for toilet paper made from recycled paper. However, those with higher levels of motivation did give higher ratings of strength to both regular and toilet paper made from recycled paper ( $\hat{\beta}_4 = 0.139, p = 0.035$ ). This could be indicative of a tendency for “positive” responses to correlate within individuals.

I do not find that the dependent variable of toilet paper strength supports either H1 or H2. This could be because I did not differentiate between two aspects of strength, which have positive and negative impacts on overall performance. Strength between sheets makes it harder to tear apart the sheets, a negative attribute. Strength overall leads to more durable paper, a positive attribute. During the testing of the toilet paper, many people noted the strength or lack thereof when the sheets were torn off of the roll. Others also tore individual sheets of toilet paper to test overall strength. Thus, I suspect that some participants were rating strength as a positive aspect of performance and others were rating strength as a negative aspect of performance.

Expectations weakly predict toilet paper choice ( $\hat{\beta}_1 = 0.223, p = 0.092$ , Table 3.4). Those with higher expectations of the performance of toilet paper made from recycled paper were more likely to choose to take home the toilet paper made from recycled paper, but the result is not statistically significant. Motivation for toilet paper made from recycled paper to perform well is a strong predictor of toilet paper choice ( $\hat{\beta}_2 = 0.402, p = 0.002$ , Table 3.4). Those who would be happiest if toilet paper made from recycled paper performs well are more likely to choose toilet paper made from recycled paper than those who would be less happy if toilet paper made from recycled

Table 3.3: Study 3 Results: Reported Perception of Eco-Friendly Toilet Paper

	<i>Dependent Variable:</i>			
	Softness (Standardized Likert Scale)			
	(1)	(2)	(3)	(4)
Recycled Label	0.312*** (0.0582)	0.312*** (0.0573)	0.306*** (0.0575)	0.304*** (0.0565)
Expectations		-0.0176 (0.0518)		-0.0270 (0.0515)
Expectations x Recycled		0.220*** (0.0657)		0.234*** (0.0642)
Motivation			0.00975 (0.0499)	0.0101 (0.0501)
Motivation x Recycled			0.159** (0.0590)	0.156** (0.0581)
Constant	-0.156*** (0.0467)	-0.156*** (0.0467)	-0.152** (0.0467)	-0.152** (0.0467)
<i>N</i>	883	883	881	881
<i>R</i> <sup>2</sup>	0.024	0.045	0.038	0.059

*Notes:* OLS Regression of toilet paper softness (6-point scale standardized with mean = 0 and sd = 1) on moderating variables with errors clustered at the individual. Expectations are measured with a standardized 7-point scale where higher ratings indicate higher expected relative performance of toilet paper made from recycled toilet paper compared to regular toilet paper. Motivation is measured with a standardized 5-point scale where higher ratings indicate increased intensity of happiness if toilet paper made from recycled paper outperforms regular toilet paper. Standard errors are in parentheses. \* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

Table 3.4: Study 3 Results: Product Choice

	<i>Dependent Variable:</i>		
	Choose Recycled (Binary)		
	(1)	(2)	(3)
Expectations	0.233 (0.138)		0.172 (0.157)
Motivations	0.402** (0.132)		0.484** (0.155)
Difference in Softness		0.785*** (0.191)	0.735*** (0.200)
Difference in Strength		0.484** (0.181)	0.562** (0.190)
Constant	1.179*** (0.139)	1.313*** (0.169)	1.400*** (0.181)
<i>N</i>	303	265	264
Pseudo- <i>R</i> <sup>2</sup>	0.0360	0.1262	0.1615

*Notes:* Logistic regression of the choice between regular and recycled toilet paper (where choosing recycled = 1 and choosing regular = 0) on standardized moderating variables. The difference in attributes is measured by subtracting the rating for the regular toilet paper from rating for the recycled toilet paper. Standard errors are in parentheses. \* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

paper performs well.

When ratings of softness and strength are included, the impact of prior expectations diminishes but the impact of motivations remain high. Motivations driving choice is not surprising given that those who want recycled products to perform well are also those who are most likely to choose recycled products. In essence, the motivation measures non-performance factors that drive demand for recycled products.

## **3.6 The Impact of Expectations on Sensory Perception of Attributes**

### **3.6.1 Study 4: Sensory Perception of Eco-Friendly Toilet Paper**

In Study 4, I delve deeper into the eco-product perception bias with additional treatment variations. I examine whether I can reduce the effect of the expectation bias on product preference. The key question is whether expectations and preferences are only linked directly or whether they are linked through biased perception. Consumers make choices to maximize their expected utility. Expectations about product attributes play a major role in predicting one's own utility from consuming a product. When new information is incorporated, such as the information obtained through direct product testing, expectations are updated according to Bayes' rule. However, economic theory does not predict that expectations bias sensory perceptions which then go on to bias product evaluations and product choice. If sensory perceptions are biased, then consumers will be unable to attain perfect, unbiased information about product performance because their evaluations will be influenced by both biased priors and biased sensory signals. As discussed in Section 4, the concept of biased perception has significant implications for the widespread economic problem of imperfect information.

While the effect of motivation on the perception of product quality is not well incorporated into economic theory, the effect of motivation on product preference is straightforward. I expect consumers to gain positive utility from a "warm glow" that arises from knowing that the product they are consuming has a low impact on the environment. If we assume that the level of motivation they have for environmental products to perform well is directly related to the magnitude of the utility gain from the warm glow, then motivation should correlate with a preference for eco-products. In other words, it is evident that people who are excited about eco-friendly products are more likely to buy eco-friendly products.

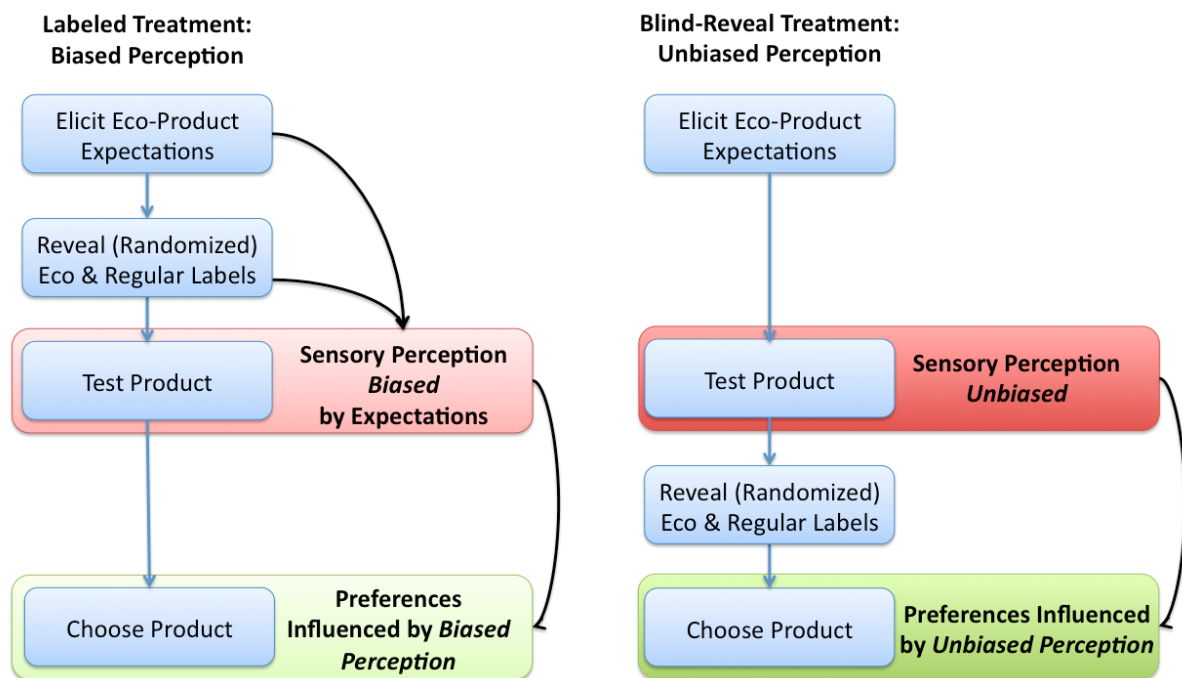


Figure 3.1: Experimental design and intuition on how the labeled and blind-reveal treatments isolate the effect of expectations on sensory perceptions

To explore these questions, I follow a methodology used in a paper by Lee, Frederick, and Ariely (Lee et al. 2006). I add a treatment group where I have participants evaluate the toilet paper without labels; I do not disclose whether the toilet paper is made from recycled paper or virgin wood fiber. Removing the eco-label prevents eco-label dependent expectations from biasing the product evaluations. After participants in this treatment record their ratings of toilet paper softness, I “reveal” the labels of “regular” and “made from recycled paper.” After receiving this additional information, participants choose which toilet paper they would like to take home. This design removes the impact that expectations may have on product preference through biased sensory perception. At the same time, it controls for the direct impact of expectations on product choice. Figure 3.1 shows the design of and the intuition behind these two treatments.

In addition to H1 and H2, Study 4 tests an additional hypothesis. H3 posits a chain

of causality where prior expectations bias perception which then goes on to influence product preference:

*H3: Prior performance expectations of eco-products influence post-testing product choice through the mechanism of biased sensory perception.*

The results of Study 4 provide some insight into how expectations and motivations affect both perception of a product's performance and how those perceptions go on to inform product preference. The results indicate that the perception of toilet paper softness is biased by prior expectations of product performance. These biased perceptions go on to inform product preference. When I neutralize the bias using a blind test, then reveal the eco-label before a preference is expressed, prior expectations play no role in product preference. However, the relationships between expectations and choice in the labeled and revealed treatments are not statistically different. The motivation for toilet paper made recycled paper to perform well influences product preference, but does not appear to bias perception of softness.

## **Study 4: Methods**

### **Participants**

Study 4 took place in the South Station Boston T-Stop between July 31, 2012, and August 8, 2012. I recruited passersby by offering \$4 Dunkin' Donuts gift cards. The experiment took each participant approximately four minutes to complete. There were 468 eligible participants included in the analysis.<sup>4</sup> See Appendix C for the demographics of the study population.

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<sup>4</sup>482 people completed the study and 12 were excluded from the analysis due to research assistant implementation errors in the experiment procedure, language barriers, and mental disabilities.

## Procedure

Study 4 has a similar procedure to Study 3, but I include a blind treatment and a blind-reveal treatment in addition to the standard labeled treatment, which was employed in Study 3. Participants first take a survey about their expectations and motivations regarding regular toilet paper. They also answer some demographic and political questions. Then, participants test both types of toilet paper and rate it for softness. Next, they answer a question about the willingness to pay for a four-pack of toilet paper B from a list of 15 prices in descending order from \$8.00 to \$0.00 with an anchor price for toilet paper A of \$4.00.<sup>5</sup> Finally, I tell them that in addition to the gift card, I would like to give them a bonus gift of a roll of one of the toilet papers they tested. They can choose to take home either a roll of toilet paper A and toilet paper B.

Study 4 included the following treatment groups:

**Blind Treatment:** Toilet papers A & B are unlabeled throughout the experiment

**Labeled Treatment:** Toilet papers A & B are labeled throughout the experiment.

**Labeled Sub-treatment 1:** Toilet paper A is labeled as made from recycled paper; Toilet paper B is labeled as made from wood pulp (regular)

**Labeled Sub-treatment 2:** Toilet paper A is labeled as made from wood pulp (regular); Toilet paper B is labeled as made from recycled paper

**Blind-Reveal Treatment:** Toilet papers A & B are unlabeled during the testing phase of the experiment, where individuals feel the toilet paper and rate its softness. Then, the labels are revealed and participants state their willingness to pay for toilet paper B and choose to take home either toilet paper A or toilet paper B.

**Blind-Reveal Sub-treatment 1:** Toilet paper A is labeled as made from recycled

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<sup>5</sup>WTP measures will be analyzed in a separate paper, but are included in the procedures for completeness.

pled paper; Toilet paper B is labeled as made from wood pulp (regular)

**Blind-Reveal Sub-treatment 2:** Toilet paper A is labeled as made from wood pulp (regular); Toilet paper B is labeled as made from recycled paper

I use the same analytical model from the previous studies to analyze the ratings of toilet paper softness (Eq. 3.5). I analyze the model separately for the blind, labeled, and blind-reveal treatments. As in Study 3, after participants completed the study, they were told that in addition to the gift card, they would also receive a free roll of toilet paper. They were asked to choose one of the two rolls they tested. I test my final hypothesis, H3, with a comparison of product choice between the labeled treatment and the blind-reveal treatment.

*H3: Prior performance expectations of eco-products influence post-testing product choice through the mechanism of biased sensory perception.*

Basic economic theory predicts that product preference is influenced by information the consumer has about the product. In my experiment, participants are given the opportunity to gain information about the performance of the product through product testing. The primary contribution of this paper is that expectations of product performance based on the eco-product label bias the consumer's evaluation of product performance. When a consumer tries a product, her expectations appear to bias the product performance information she uses to determine her preferences.

H3 takes this idea step further and posits that the perception bias is the causal mechanism through which product preference is biased. In other words, H3 predicts that expectations will influence product preference because they bias the sensory information about the product the consumer receives while testing it.

In Study 3, H3 predicts that expectations will influence product choice more in the labeled treatment than in the blind-reveal treatment. In the labeled treatment,



prior expectations would bias the perceptual experience of the product testing. Thus, I would see an influence of prior expectations on product preference. In the blind-reveal treatment, prior expectations cannot influence the perceptual experience of product quality because participants do not know which toilet paper is an eco-product when they test the two rolls. If product choice is influenced by the perceptual experience of the product testing, then when this mechanism is disrupted through blind-testing, the impact of expectations on product choice would be diminished.

I employ the same logistical regression model in Study 3 (Eq.3.10) to test whether expectations bias choice. I run this model for both the labeled and blind-reveal treatments. If expectations bias choice through the mechanism of biased perceptions, then the effect of expectations on choice will be stronger in the labeled treatment than it is in the blind-reveal treatment. From Eq.3.10 for the labeled treatment,  $L$ , and the blind-reveal treatment,  $BL$ , H3 predicts  $\beta_{1L} > \beta_{1BR}$ .

#### **Study 4: Results**

The results from the ratings of softness in Study 4 support H1 ( $\hat{\beta}_3 = 0.231, p = 0.044$ , Table 3.5). In the labeled treatment, those who expect toilet paper made from recycled paper to perform worse than regular toilet paper give lower ratings to toilet paper when it is labeled as recycled compared to when it is labeled as regular.

In contrast to Study 3, I find that motivation for toilet paper made from recycled paper to perform well has no effect on the evaluation of softness ( $\hat{\beta}_5 = -0.041, p = 0.774$ ). This contrasts with findings from the earlier toilet paper study (Study 2), but is in line with findings from the online light study (Study 1).

In the blind treatment and the blind-reveal treatments, those who have higher expectations of the performance of toilet paper made from recycled paper give higher

ratings to all toilet paper. This could have occurred because even without labels, participants suspected that they were evaluating toilet paper made from recycled paper because they were asked questions about regular and toilet paper made from recycled paper at the beginning of the experiment.

The results weakly support H3, but the null hypothesis cannot be rejected. In the labeled treatment, those who have low expectations of the performance of toilet paper made from recycled paper compared to that of regular toilet paper are more likely to choose the regular toilet paper over the toilet paper made from recycled paper ( $\hat{\beta}_{1L} = 0.465$ ,  $p = 0.027$ , Table 3.6). In the blind-reveal treatment, where the participant tests the toilet paper before the labels are revealed, expectations do not significantly affect the choice of whether to take home regular or toilet paper made from recycled paper ( $\hat{\beta}_{1BR} = 0.0645$ ,  $p = 0.747$ , Table 3.6). However, the coefficients are not significantly different ( $p_{one-sided} = 0.084$ ,  $p_{two-sided} = 0.168$ ). These results weakly support the hypothesis that the perception bias is the primary driver of the influence of expectations on product preference, but are not conclusive.

In summary, Study 4 provides additional evidence that expectations bias evaluations of product quality (H1), evidence against the influence of motivations on product quality (H2), and a statistically insignificant trend that may point to a causal relationship between expectation-biased sensory perceptions of product quality and a bias in product preference. By implementing a blind test before revealing the “recycled” label, I eliminate the effect of the bias on product preference. In the blind-reveal treatment, the preference for toilet paper made from recycled paper over regular toilet paper no longer shows a relationship with prior expectations. This suggests that the expectation bias affects the sensory information gathered during the testing of the product. However, because I cannot show that the effects in the labeled and blind-reveal treatments are not statistically different, I cannot rule out the possibility that this finding came about due

Table 3.5: Study 4 Results: Reported Perception of Eco-Friendly Toilet Paper

	<i>Dependent Variable:</i> Softness (Standardized Likert Scale)		
	Labeled Treatment (1)	Blind-Reveal Treatment (2)	Blind Treatment (3)
Recycled Label	0.271** (0.0911)	0.101 (0.0928)	
Expectations	0.0804 (0.0815)	0.186* (0.0867)	0.303** (0.0902)
Expectations x Recycled	0.231* (0.114)	-0.106 (0.122)	
Motivation	0.0669 (0.0897)	0.0892 (0.0840)	0.0583 (0.0770)
Motivation x Recycled	-0.0410 (0.143)	-0.0960 (0.123)	
Constant	-0.0795 (0.0697)	-0.0992 (0.0714)	0.00267 (0.0891)
<i>N</i>	372	402	160
<i>R</i> <sup>2</sup>	0.078	0.029	0.102

*Notes:* OLS Regression of toilet paper softness (6-point scale standardized with mean = 0 and sd = 1) on moderating variables with errors clustered at the individual. Expectations is a standardized 7-point scale where higher ratings indicate higher expected relative performance of toilet paper made from recycled toilet paper compared to regular toilet paper. Motivations is a standardized 5-point scale where higher ratings indicate increased intensity of happiness if toilet paper made from recycled paper outperforms regular toilet paper. Standard errors in parentheses. \* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

Table 3.6: Study 4 Results: Product Choice in Labeled and Blind-Reveal Treatment Groups

<i>Dependent Variable:</i>				
Choose Recycled (Binary)				
	Labeled Treatment	Blind-Reveal Treatment	Labeled Treatment	Blind-Reveal Treatment
	(1)	(2)	(3)	(4)
Expectation	0.465* (0.210)	0.0645 (0.200)	0.351 (0.241)	0.148 (0.211)
Motivation	0.316 (0.183)	0.340 (0.191)	0.397 (0.229)	0.430* (0.207)
Difference in Softness			1.136*** (0.234)	0.626*** (0.170)
Constant	1.428*** (0.194)	1.610*** (0.193)	1.503*** (0.228)	1.734*** (0.216)
<i>N</i>	185	199	185	199
pseudo R-sq	0.0540	0.0195	0.2423	0.1062

*Notes:* Logistic regression of the choice between regular and recycled toilet paper (where choosing recycled = 1 and choosing regular = 0) on standardized moderating variables. The difference in attributes is measured by subtracting the rating for the regular toilet paper from rating for the recycled toilet paper. Standard errors are in parentheses. \* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

to chance.

### **3.6.2 Study 5: Sensory Perception of Eco-Friendly Toilet Paper, Part II**

#### **Study 5: Methods**

In Study 4, I found promising, but inconclusive results to support H3. In Study 5, I attempt to clarify the results by running a similar study with a few improvements in the study design.

#### **Participants**

Study 5 was carried out in the Harvard Square T station. I recruited 670 people to participate in the study. Of these, I included 639 in the analysis. Those removed were taken out due to irregularities in the study procedures or disqualifications from language barriers. See Appendix C for demographic information about the study population.

#### **Procedure**

Study 5 replicates Study 4, but makes two improvements on the methods in an attempt to achieve cleaner results. It also removed the blind evaluation and blind choice. First, I put a blank page between the blind evaluation and the revealed labels. In Study 4, I was concerned that being able to see through to the labeled page could have undercut the blind evaluation of the toilet paper. This would have diminished the impact of the blind-reveal treatment and led to noisier results. Second, I added a question that asks people to say which roll of toilet paper is softer in a joint evaluation after doing a separate evaluation. In the blind reveal design, I place this question directly after revealing the

labels. Participants are not allowed to retest either roll of toilet paper.

### Study 5: Results

While I find the same expected direction of the relationship between expectations and ratings of softness, for the first time, the study results do not strongly support H1; the relationship is statistically insignificant ( $\hat{\beta}_3 = 0.101$ ,  $p = 0.145$ , Table 3.7). Motivations also have no effect on softness ratings which leads to further evidence, along with Study 1 and Study 3, to reject H2 ( $\hat{\beta}_3 = -0.0482$ ,  $p = 0.485$ , Table 3.7).

Comparing the role of expectations in product choice in the Labeled and Blind-Reveal treatments, I find very different patterns than those predicted by H3. Expectations have no effect on product choice for the Labeled treatment ( $\hat{\beta}_{1L} = 0.064$ ,  $p = 0.675$ , Table 3.8). Conversely, in the Blind-Reveal treatment, expectations increase the likelihood of choosing the eco-product option ( $\hat{\beta}_{1BR} = 0.284$ ,  $p = 0.110$ , Table 3.8). After controlling for the difference of the participants' ratings of the softness of each roll of toilet paper, expectations significantly predict the likelihood of choosing toilet paper made from recycled paper ( $p = 0.018$ ). H3 predicts that  $\hat{\beta}_{1L} > \hat{\beta}_{1BR}$ . In Study 5, we find that the relationship between expectations and product choice are not statistically different between the Labeled and Blind-Reveal treatments. Moreover, the coefficients have the opposite sign than is predicted by H3. Thus we strongly reject H3 in Study 5.

In Study 5, we added a joint evaluation question after testing the products and after the labels were revealed in the Blind-Reveal treatment. Participants were asked which toilet paper was softer and were not given an option to indicate that they were equally soft. The relationship between expectations, motivations, and reported softness followed the same pattern in the joint evaluation as in the separate evaluation. When comparing the softness ratings given to each product in the separate evaluation and the joint evaluation directly comparing the softness of the two products, one interesting

finding emerged. In the Blind-Reveal treatment, 22% of participants reported that the regular toilet paper was softer in the joint evaluation even though they gave higher softness ratings to the recycled toilet paper in the unlabeled testing phase just minutes before. In contrast, only 3% of participants in the Labeled treatment flipped to favor regular toilet paper in the joint evaluation after giving higher ratings to recycled paper in the separate evaluation. The difference between the rate of “flipping” evaluations is significantly higher in the Blind-Reveal treatment ( $p < 0.001$ ). Conversely, very few participants flip from giving higher evaluations to toilet paper labeled as recycled in the separate evaluation to reporting that regular toilet paper is softer (2% in the Blind-Reveal treatment and 2.5% in the Labeled treatment). These findings are compelling evidence that adding the “recycled” label creates a bias in consumer evaluations of the product attributes. However, expectations do not predict the likelihood of “flipping” to favor regular toilet paper for the Blind-Reveal group ( $p = 0.465$ ). Additionally, those in the Blind-Reveal treatment who appear to be strongly biased against the recycled label are *more* likely to choose the toilet paper labeled as recycled ( $p = 0.027$ ). These contradictory findings paired with the divergent results for repeatedly confirmed hypotheses seem to indicate that this study was anomalous or flawed in a way that we cannot trace through the existing data.

### 3.6.3 Study 6: Sensory Perception of Energy Efficient Lighting

The two artefactual field experiments that attempted to definitively show that sensory perception is biased by expectations had mixed results. To avoid some of the possible confounding factors and to readily reach a study population outside of Cambridge, Massachusetts, I moved this experimental paradigm online and improved the design of the experiment to significantly reduce experimenter demand.

The results are striking in their departure from the previous five studies. The results

Table 3.7: Study 5 Results: Reported Perception of Eco-Friendly Toilet Paper

	<i>Dependent Variable:</i> Softness (Standardized Likert Scale)	
	Labeled Treatment (1)	Blind-Reveal Treatment (2)
Recycled Label	0.116 (0.0632)	0.128* (0.0633)
Expectations	0.0866 (0.0622)	0.151* (0.0623)
Expectations x Recycled	0.101 (0.0692)	-0.0496 (0.0713)
Motivation	0.0951 (0.0640)	-0.0970 (0.0546)
Motivation x Recycled	-0.0482 (0.0690)	0.0589 (0.0691)
Constant	0.00898 (0.0568)	-0.128* (0.0534)
<i>N</i>	624	648
<i>R</i> <sup>2</sup>	0.032	0.023

*Notes:* OLS Regression of toilet paper softness (6-point scale standardized with mean = 0 and sd = 1) on moderating variables with errors clustered at the individual. Expectations is a standardized 7-point scale where higher ratings indicate higher expected relative performance of toilet paper made from recycled toilet paper compared to regular toilet paper. Motivations is a standardized 5-point scale where higher ratings indicate increased intensity of happiness if toilet paper made from recycled paper outperforms regular toilet paper. Standard errors in parentheses. \* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$



Table 3.8: Study 5 Results: Product Choice in Labeled and Blind-Reveal Treatment Groups

<i>Dependent Variable:</i>				
Choose Recycled (Binary)				
	Labeled Treatment	Blind-Reveal Treatment	Labeled Treatment	Blind-Reveal Treatment
	(1)	(2)	(3)	(4)
Expectation	0.0664 (0.159)	0.284 (0.178)	0.0159 (0.167)	0.445* (0.187)
Motivation	0.467*** (0.133)	0.608*** (0.145)	0.571*** (0.146)	0.597*** (0.154)
Difference in Softness			0.714*** (0.156)	0.918*** (0.174)
Constant	1.576*** (0.157)	1.747*** (0.167)	1.683*** (0.174)	1.927*** (0.195)
<i>N</i>	306	318	306	318
pseudo R-sq	0.0448	0.0860	0.1291	0.2065

*Notes:* Logistic regression of the choice between regular and recycled toilet paper (where choosing recycled = 1 and choosing regular = 0) on standardized moderating variables. The difference in attributes is measured by subtracting the rating for the regular toilet paper from rating for the recycled toilet paper. Standard errors are in parentheses.

\* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

do not support H1 or H3 and weakly support H2. These results paired with the design changes shed doubt on the interpretation of the results of the previous experiments. It is possible that experimenter demand played a major role in the findings of the first five studies.

## **Study 6: Methods**

### **Participants**

I recruited 351 participants on MTurk. Of those, 304 completed the online study and were included in the analysis (89%). See Appendix C for a summary of the demographic characteristics of the study population.

### **Procedure**

In this study, I went to great lengths to obscure the purpose of the study. Instead of asking only about eco-products, I attempted to position the study as a marketing survey interested in how to improve their customer satisfaction and market share. The survey began by asking about the brands of light bulbs purchased, the retailers from which those purchases were made, and the level of satisfaction with the selection at those retailers. These questions were added to reduce or eliminate any potential impact of experimenter demand.

Next, I explained the different types of light labels (CFL, incandescent, soft white, etc.) and asked participants to indicate which types of light bulbs they had used before. Then, I asked about the participants expectations of the relative light quality of energy efficient compact fluorescent light bulbs compared to standard incandescents. I followed up with additional comparisons on different types of light bulb technologies (LED, halogen), light colors (Reveal, soft white, daylight, bright white), and brands

(General Electric, Phillips, and Ace Hardware). I also asked about how participants use different types of lighting in different rooms of the house. These questions were designed to fully obscure the purpose of the study as one focused on energy efficient light bulbs to reduce the confounding effects of experimenter demand.

Similar to Study 1, participants were given information on the camera and lighting set-up used to take the photos. Then, they evaluated photos taken of the same subject (colorful stuffed animals) with different light bulbs. This differs from Study 1 where each participant evaluated four photos, each with a different subject. This design change was implemented to increase the realism of the study.

Those in the labeled treatments evaluated eight photos and those in the blind-reveal treatments evaluated four photos. In the labeled treatments, participants were given information about the light bulb that was used to illuminate the subjects in the photo. They received information about the brand, bulb color, brightness, and bulb type (incandescent, etc.). Then they saw a photo of the package of the light bulb used. Next, using a 7-point numeric scale with labeled endpoints, they evaluated the light in a photo on four qualities: pleasantness, bluishness, yellowishness, and brightness.

In the blind-reveal treatments, participants were given the same information and made the same evaluations except that the light bulb type was excluded, and participants were shown a logo of the brand instead of the photo of the package.

Next, I gave instructions to participants about the lottery for a survey bonus. Participants would choose their preferred light bulbs in six pairwise comparisons of the four light bulbs they evaluated in the previous section. To create incentive compatible choices, I explained that 25 participants would be chosen to receive a survey bonus of one of the packages of light bulbs that they chose in this section. For the participants chosen, one of the six choices were chosen at random and the package of light bulbs they chose was sent to their home address. Winners of the survey bonus also received

a \$25 gift certificate to Amazon.com to incentivize providing their home addresses and ensuring a real choice scenario. Participants completed a quiz after these instructions to ensure comprehension of the product choice set-up.

Before making the product choices, I reminded them of the information about the bulb and showed them the same photo they had previously evaluated. Next, they received information about the energy costs associated with the two types of light bulbs. The purpose of providing this information is two-fold. First, it helps to control for differences in knowledge about energy costs that may correlate with differences in expectations. Second, it is a subtle way to naturally reveal the bulb type to those in the blind-reveal condition. Revealing the type in a more obvious manner could have created experimenter demand. Finally, participants chose between the two bulbs by clicking on the photo of the package they preferred. Differential retail costs of the bulbs were roughly equalized by increasing the number of incandescent bulbs offered compared to the more expensive compact fluorescent bulbs.

The final part of the survey included questions on demographics and light bulb preferences.

## **Study 6: Results**

The results do not support H1 ( $\hat{\beta}_3 = -0.002$ ,  $p = 0.981$ , Table 3.9). These results contradict the statistically significant findings in Studies 1 through 4. Study 5 also did not find statistically significant support for H1, however the direction of the relationship did align with the previous studies. This result is striking because it is not just a null finding, it is a precise null finding. These results indicate a 1.9% chance that the actual value of  $\beta_3$  differs from 0.

The biggest difference in this study compared to the previous five studies, as well as

many pilot studies preceding them, is the focus on obscuring the purpose of the study to reduce experimenter demand. This indicates a high likelihood that previous results may have come about due to experimenter demand rather than a real underlying effect of expectations on perceptions. It is also possible that the new design reduced experimenter demand, reduced the effect size of expectations, and then was underpowered to detect an effect.

Another possible explanation is the difference in expectations question between Study 6 and previous studies (Appendix C, Figure C.1). In contrast to previous studies that elicited expectations of the overall performance, in Study 6, the question asks specifically about light quality. Additionally, the middle value on the 7-point scale was labeled as indicating the two types of bulbs performed about the same, whereas previously, only the end points were labeled. The distributions of responses to the expectations question in Study 6 roughly follow a normal distribution centered at 4, the value indicating that the expectations of light quality from incandescent light bulbs and CFL light bulbs are the same. This distribution differs sharply from the distributions of expectations in the previous lighting studies, which are very skewed with the mode at the highest rating for CFL light bulbs. However, the expectations of product performance from recycled versus regular toilet paper also follow a roughly normal distribution and those studies strongly confirmed H1.

The results are less decisive for H2 than they are for H1. I broke motivations down into two components: preference for energy savings and preference for low environmental impact. A stronger preference for energy savings from light bulbs is correlated with higher relative ratings for light labeled as CFL ( $\hat{\beta}_5 = 0.124$ ,  $p = 0.053$ , Table 3.9). A stronger preference for a light bulb with a low environmental impact did not correlate with higher relative ratings for light labeled as CFL ( $\hat{\beta}_5 = 0.044$ ,  $p = 0.471$ , Table 3.9).

The results do not support H3. In the labeled treatment, higher prior expectations

of light quality from CFL light bulbs does not increase the likelihood of choosing a CFL light bulb. In fact, the results indicate the opposite, but the relationship is not statistically significant. In the labeled treatments, those with higher prior expectations of light quality from CFL light bulbs may be less likely to choose CFL light bulbs over incandescent light bulbs after evaluating the quality of their light in photographs ( $\hat{\beta}_{L1} = -0.174$ ,  $p = 0.199$ , Table 3.10). In the blind-reveal treatment, higher prior expectations of light quality from CFLs has a slightly positive but statistically insignificant impact on the likelihood of choosing the CFL light bulbs over the incandescents ( $\hat{\beta}_{BR1} = 0.083$ ,  $p = 0.467$ , Table 3.10). The effect of expectations on choice in the labeled and blind-reveal treatments are not significantly distinguishable from one another ( $p = 0.146$ ).

While I included motivation as a control variable in the product choice analysis, I did not plan to include a direct test of motivation-biased perception on product choice. With that caveat, I did see an interesting pattern emerge. For both energy savings motivation and environmental impact motivation, I see a significantly stronger impact of motivation on product choice in the labeled treatment compared to the blind-reveal treatment. For energy savings motivations, the effect on product choice is significantly stronger in the labeled treatment than in the blind-reveal treatment ( $p < 0.001$ ). For environmental impact motivations, the effect on product choice is significantly stronger in the labeled treatment than in the blind-reveal treatment ( $p = 0.001$ ), but the direction of the relationship was the opposite of what I expected. Those who said they were more concerned about the environmental impact of the light bulb were less likely to choose the CFL. It is possible that participants interpreted the environmental impact question as referring to the mercury content of the CFL light bulbs. This explanation is more likely given that participants were first asked about energy savings and then asked about environmental impact. They may have thought this implied that environmental impact was meant to exclude the differences in energy consumption. It is important to note that despite the statistical strength of these results, they differ from the relationships

between motivations and product choice in the labeled and blind-reveal treatments in Study 4 and Study 5.

Finally, it is interesting to note that the actual ratings of light pleasantness do not have a substantial impact on the product choice. One possible explanation is that participants simply do not care about the pleasantness of the light bulbs they use. However, 38% of participants ranked light quality as the most important consideration in buying a light bulb. An additional 28% ranked light quality as the second most important consideration. Another possible explanation is that participants ranked many light bulbs and made many choices between light bulbs. The time that elapsed between initially ranking the light in the photo and choosing between the light bulbs may have created a disconnect between the ratings and the product choice. I attempted to prevent this potential problem by showing the photos where they rated the light quality and the information about the bulbs again before making the choice, but it appears that this may not have been a sufficient measure.

## **3.7 Meta-Analysis of Results**

The results of these six studies varied for all three hypotheses under consideration. To draw out statistically robust conclusions of whether the data support the stated hypotheses, I conduct a meta-analysis of all six studies.

### **3.7.1 Methods**

For each hypothesis, I identified the parameter(s) of interest on which to carry out the hypothesis test. In this meta-analysis, I take the estimates of those parameters to be the effect size (ES). In the meta-analysis that estimates the overall effect size, the individual study effect sizes are inversely weighted by their standard errors. More

Table 3.9: Study 6 Results: Reported Perception of Energy Efficient Lighting

	<i>Dependent Variable:</i>			
	Pleasantness (Standardized Likert Scale)			
	(1)	(2)	(3)	(4)
CFL	-0.0159 (0.0610)	-0.0381 (0.0610)	-0.0311 (0.0614)	-0.0405 (0.0616)
Expectations	0.121 (0.0702)	0.115 (0.0758)	0.117 (0.0728)	0.126 (0.0757)
Expectations x CFL	0.0281 (0.0748)	-0.00227 (0.0752)	0.0207 (0.0761)	-0.00178 (0.0752)
Motivations: Energy		0.0149 (0.0655)		-0.0460 (0.0718)
Motivations: Energy x CFL		0.124 (0.0638)		0.128 (0.0730)
Motivations: Impact			0.0781 (0.0628)	0.0988 (0.0692)
Motivations: Impact x CFL			0.0441 (0.0610)	-0.0115 (0.0690)
Constant	0.0551 (0.0645)	0.0567 (0.0657)	0.0468 (0.0649)	0.0495 (0.0654)
<i>N</i>	584	568	568	564
<i>R</i> <sup>2</sup>	0.018	0.024	0.028	0.031

*Notes:* OLS Regression of light pleasantness (7-point scale standardized with mean = 0 and sd = 1) on moderating variables with errors clustered at the individual. Expectations are measured with a standardized 7-point scale where higher ratings indicate higher expected relative performance of CFL lighting compared to incandescent lighting. Motivations are measured with a standardized 7-point scale where higher ratings indicate that the participant places a higher degree of importance on the energy efficiency of their lighting or on the environmental impact of their lighting. Standard errors are in parentheses. \* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$



Table 3.10: Study 6 Results: Product Choice in Labeled and Blind-Reveal Treatment Groups

	<i>Dependent Variable:</i> Choose CFL (Binary)			
	Labeled Treatment	Blind-Reveal Treatment	Labeled Treatment	Blind-Reveal Treatment
	(1)	(2)	(3)	(4)
Expectation	-0.176 (0.135)	0.0826 (0.113)	-0.174 (0.135)	0.0820 (0.114)
Motivation: Energy	1.509*** (0.184)	0.737*** (0.117)	1.510*** (0.184)	0.738*** (0.117)
Motivation: Impact	-0.655*** (0.176)	0.0753 (0.128)	-0.656*** (0.177)	0.0744 (0.128)
Difference in Pleasant Rating			0.0150 (0.0883)	0.0665 (0.0789)
Constant	1.852*** (0.146)	1.764*** (0.131)	1.851*** (0.146)	1.757*** (0.131)
<i>N</i>	564	568	564	566
pseudo R-sq	0.1917	0.1166	0.1918	0.1172

*Notes:* Logistic regression of the choice between incandescent and regular light bulbs (where choosing CFL = 1 and choosing incandescent = 0) on standardized moderating variables. The difference in attributes is measured by subtracting the rating for the incandescent light from rating for the CFL light. Standard errors are in parentheses. \* $p < 0.05$  \*\* $p < 0.01$  \*\*\* $p < 0.001$

precisely estimated effect sizes are given more weight while those with more statistical variance are given less weight.

The meta-analysis is conducted with both fixed-effects assumptions and random-effects assumptions. The fixed effects model assumes that each study is measuring the same underlying effect and that any variance is due to sampling error. In the fixed effects model, the inverse variance method is used to measure the overall effect. The random effects model relaxes this assumption and allows for a heterogeneous effect among studies. In the random effects model, the DerSimonian and Laird estimate is used to estimate the overall effect.

Using a random effects model is more appropriate for higher levels of heterogeneity because the fixed effects assumption of a single underlying true effect across studies is violated. The measure of heterogeneity between studies indicates how much of the variation between effect sizes is due to statistical chance in sampling variation and how much is due to differences in the true effect size between studies. Very high heterogeneity sheds doubt on the consistency of the effect sizes in the meta-analysis.

The heterogeneity of the effect size is measured by Cochran's  $Q$ , the squared sums of differences of individual study effect sizes from the overall estimate, weighted by the inverse of their variance:

$$Q = \sum w_i(\beta_i - \beta_{IV})^2 \quad (3.11)$$

The  $I^2$  statistic is the percentage of variation in the effect size that can be attributed to heterogeneity in the true treatment effect in each study rather than sampling variation (Higgins et al. 2003; Higgins and Thompson 2004; Harris et al. 2008):

$$I^2 = 100\% * \frac{Q - df}{Q}. \quad (3.12)$$

A value of  $I^2 = 0\%$  indicates perfect homogeneity in effect sizes. A value of  $I^2 = 100\%$  indicates that all of the variation in the measured variation is a result of actual differences in the true effect size. Intermediate values indicate some heterogeneity in effect size. A p-value that indicates the rejection of the null hypothesis of perfect homogeneity ( $I^2 = 0\%$ ) is reported along with the estimate of  $I^2$ . If the null hypothesis of perfect homogeneity is rejected, then the random effects model is more appropriate. If the null hypothesis is supported, then the fixed effects model is more appropriate.

For the inverse variance method used in the fixed effects model, the overall effect size is measured as the weighted average effect size:

$$\beta_{IV} = \frac{\sum w_i \beta_i}{\sum w_i} \quad (3.13)$$

where the weights are measured as the inverse of the squared standard errors of the effect size estimate:

$$w_i = \frac{1}{SE(\beta_i)^2} \quad (3.14)$$

The standard error of the overall effect size estimate is:

$$SE(\beta_{IV}) = \frac{1}{\sqrt{\sum w_i}} \quad (3.15)$$

In the random effects model, the effect sizes in each study are allowed to be heterogeneous. The effect size in each study are assumed to have a normal distribution with a variance equal to  $\tau^2$ . I use the DerSimonian and Laird estimate of  $\tau^2$ :

$$\tau^2 = \frac{Q - (k - 1)}{\sum w_i - \frac{\sum w_i^2}{\sum w_i}} \quad (3.16)$$

The weighting of each effect size in the overall estimate is adjusted by the estimate

of  $\tau^2$ :

$$w' = \frac{1}{SE(\beta_i)^2 + \tau^2} \quad (3.17)$$

The pooled effect size and the standard errors are calculated in the same manner as in the inverse variance method, but  $w'$  is substituted for  $w$ .

I apply the fixed and random effects meta-analysis to generate a cross-study test of each of the stated hypotheses.

### 3.7.2 Results

First, I examine whether expectations of product performance of an eco-friendly product will bias the evaluations of those products.

*H1: When people expect an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

For each of the six studies, I estimate  $\beta_3$ , the interaction effect of an eco-product label and prior expectations of eco-product performance on the ratings of product performance attributes. I focus on a rating of light pleasantness for CFL versus incandescent light, and a rating of softness for toilet paper made from recycled paper versus virgin wood pulp. The meta-analysis indicates significant heterogeneity in the effect sizes with an estimated 75% of the variation arising from differences in the true effect among studies. Both the random and fixed effects models returned similar results, but the random effects model is more appropriate given the heterogeneity in the effect size across studies. The meta-analysis of H1 indicates an overall estimate of  $\beta_3 = 0.2$  ( $p = 0.001$ , Figure 3.2). This means that increasing prior expectations of eco-product performance by one standard deviation increases the ratings of product performance attributes by 20% of a standard deviation. However, it is important to note that this relationship between

expectations and perceptions holds when “perceptions” are considered to be equivalent to reported perceptions. I push the question further to test sensory perceptions and find no evidence of a relationship between expectations and sensory perceptions.

Second, I examine whether motivations for an eco-product to perform well will bias the evaluations of those products.

*H2: When people are motivated for an eco-product to perform less well than a standard version of the product, people will subjectively perceive this performance gap (even when it objectively does not exist).*

For all six studies, I estimate  $\beta_5$ , the interaction of an eco-product label and a measure of motivations for the product to perform well on the ratings of pleasantness of light and softness of toilet paper. Due to the significant heterogeneity between studies, a random effects model is used to estimate the overall effect size. The fixed effects results are also included for comparison. The meta-analysis of H2 indicates an overall estimate of  $\beta_5 = 0.076$ , but the result is not statistically significant in the random effects model ( $p = 0.143$ , Figure 3.3). Therefore, I reject H2.

Third, I examine whether expectations influence post-testing product choice and whether the effect of expectations on choice is stronger when the product is evaluated with the eco-product labels compared to when it is evaluated without the labels. The comparison of the impact of expectations in the labeled versus the blind-reveal treatments tests whether expectation-biased sensory information influences product choice.

*H3: Prior performance expectations of eco-products influence post-testing product choice through the mechanism of biased sensory perception.*

In four studies (S3-S6), I estimate  $\beta_{L1}$ , the impact of prior expectations on product choice when eco-product labels are present during the evaluation of the products. In three studies (S4-S6), I estimate  $\beta_{BR1}$ , the impact of prior expectations on product choice

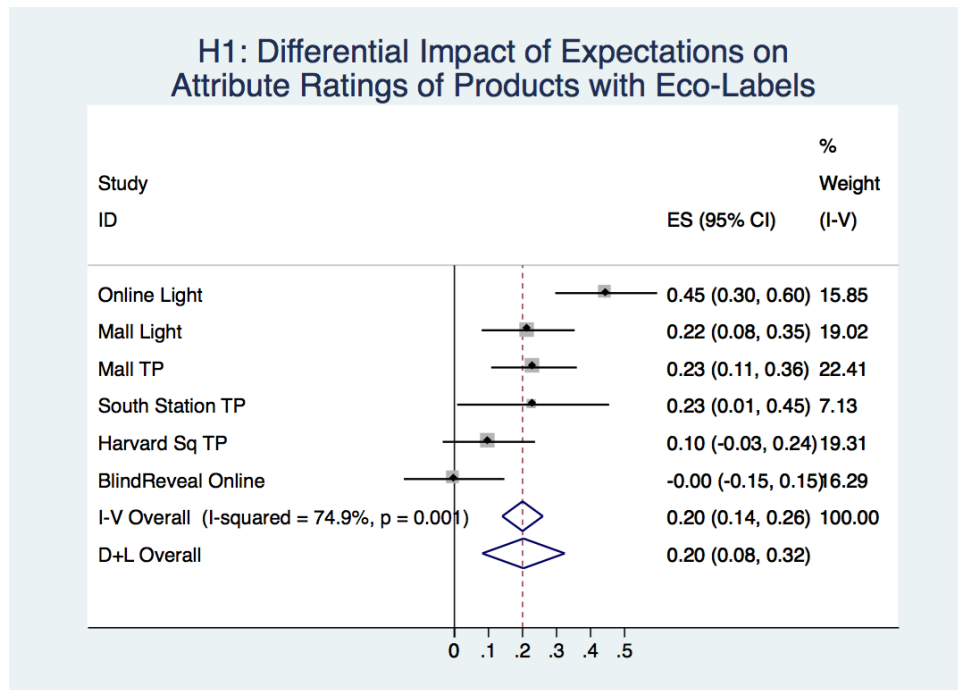


Figure 3.2: Meta-Analysis of H1: Expectations Biased Perception

when eco-product labels are absent during the evaluation of products, but revealed before product choice. This design allows me to control for the direct effect of expectations on product choice and isolate the causal pathway between expectations, sensory perception, and product choice. H3 predicts that  $\beta_{L1} > \beta_{BR1}$ .

Contrary to the predictions of H3, I find that prior expectations about eco-friendly product performance have a similar and marginally significant influence on product choice when the products are tested with or without eco-friendly labels. In the labeled treatments, I find a marginally significant overall effect of  $\hat{\beta}_{L1} = 0.146$  in the fixed effects model ( $p = 0.054$ , Figure 3.4). In the blind-reveal treatments, the effect is also marginally significant ( $\hat{\beta}_{BR1} = 0.165$ ,  $p = 0.082$ , Figure 3.5). The effects of expectations in the meta-analyses of the labeled treatments and the blind-reveal treatments are remarkably similar ( $p = 0.875$ ). Therefore, I unambiguously reject H3.

### H2: Differential Impact of Motivations on Attribute Ratings of Products with Eco-Labels

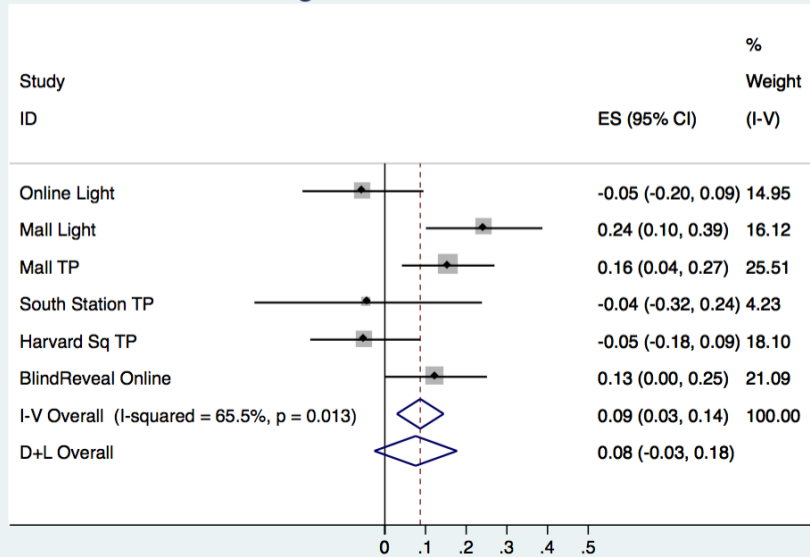


Figure 3.3: Meta-Analysis of H2: Motivation Biased Perception

### H3: Impact of Eco-Product Expectations On Eco-Product Choice Labeled Treatment

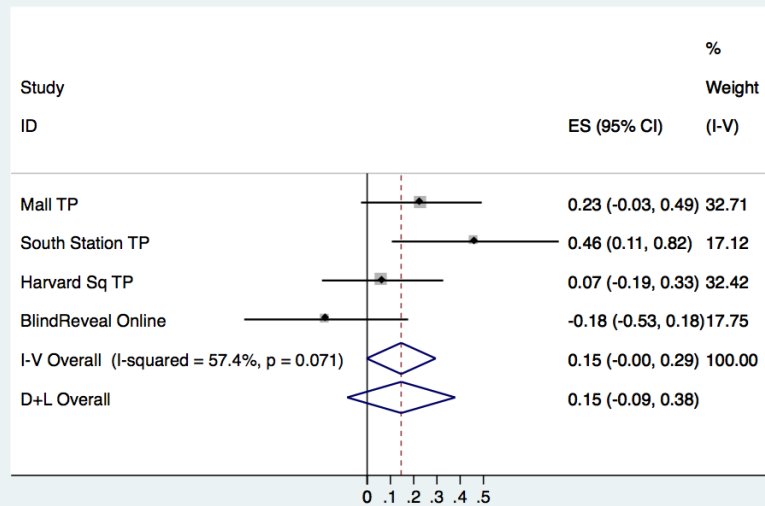


Figure 3.4: Meta-Analysis of H3, Part 1: Impact of Expectations on Product Choice in Labeled Treatment

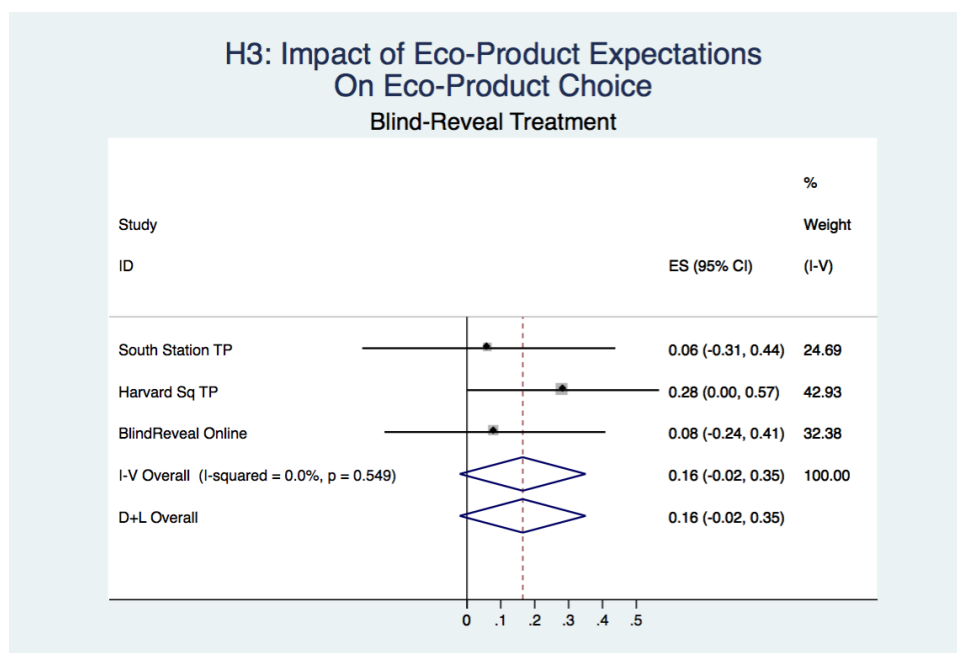


Figure 3.5: Meta-Analysis of H3, Part 2: Impact of Expectations on Product Choice in Blind-Reveal Treatment

### 3.8 Conclusions

In this manuscript, I proposed a connection between expectation biased perceptions of energy efficient products and the energy efficiency gap. I found that people who expected eco-products to perform poorly compared to regular products reported relatively poor performance and those who expected eco-products to perform better than regular products reported relatively good performance. I demonstrate that expectations influence the evaluations of products that are objectively identical except for the presence of an eco-product label. I demonstrate this effect in two very different product categories. The eco-product bias influences evaluations of light quality for energy efficient compact fluorescent lights and of toilet paper softness for toilet paper made from recycled paper. Expectations influence product evaluations and marginally influence subsequent product preference.



I also examine the role of motivation for eco-products to perform well in the reported perception of eco-product performance and find mixed results. I do consistently find that motivation for eco-products to perform well influences product choice. Motivation for eco-products to perform well are a strong predictor of ratings of eco-product quality in Studies 2 and 3, which use the same study population (suburban mall study) and a marginally significant predictor in Study 6. From these studies, I cannot draw strong conclusions about the effect of motivation on the perception of eco-products. If the underlying hypothesis is valid, then it is likely that the measure of motivation was flawed. In the final study, I modified the question to ask specifically about the importance of energy consumption and environmental impact of light bulbs and used these as proxy measures for motivation. The importance of energy consumption was a marginally significant predictor of relative performance. More specific measures of motivation for products to perform well may yield more consistent results.

To further clarify the relationship between expectations, perceptions and product choice, I explored whether having participants test the products without labels would diminish the influence of expectations on product choice. The purpose of this approach was two-fold. First, if I could determine a way to “turn off” the bias on product choice, then I could contribute to the development of strategies to optimize the market diffusion of eco-friendly products, potentially reducing the energy efficiency gap. Second, if I could show that the timing of the eco-product label changes the effect of expectations on product choice, then I could prove a causal pathway whereby expectations influence perceptual information about product attributes during the testing stage which then goes on to influence product choice. However, in these studies, I did not find evidence of this causal relationship. Instead, the studies showed that expectations influence evaluations of product attributes and expectations also influence product choices. These findings align with the predictions of Bayesian updating.

Bayes' rule predicts that prior beliefs and new information combine to form posterior beliefs. In this context, expectations about eco-product performance are prior beliefs, testing of the product provides new information, and posterior beliefs go on to inform product choice. In my original hypotheses, I hypothesized that in addition to the usual predictions of Bayesian updating of beliefs, prior beliefs were influencing the sensory information people receive while testing the product. In other words, according to this hypothesis, not only would the prior influence the posterior, but it would also influence the new sensory information gleaned through product testing.

In the first three experiments, when participants rated the pleasantness of light on a Likert scale, I assumed they were accurately representing their sensory experience. Under this assumption, the influence of prior expectations on these ratings would be evidence that prior expectations influence sensory perception. The results showed that prior expectations do indeed affect ratings of product attributes. However, the blind-reveal design took the examination a step further and attempted to definitively test whether prior expectations influenced sensory perceptions. If sensory perception was affected by the eco-bias, then removing the labels during the testing period would de-bias the sensory perception and lead to different posterior beliefs and product choices compared to when the labels were present. Revealing the labels before participants made a product choice controlled for the influence of overall product preferences and isolated the difference in perceptual information gleaned from the product testing.

By failing to show that the blind-reveal design reduces the influence of expectations on product choice, I conclude that it is unlikely that sensory perceptions differed when the product was labeled as eco-friendly, regular or if the labels were removed entirely. Instead, it is likely that the process of Bayesian updating leads individuals to combine their prior beliefs (expectations of attributes) with new information (sensory perception of attributes) to form posteriors which they report as the ratings of attributes. These

findings could have important implications for experimental methods in behavioral science.

The role of experimenter demand also merits closer examination both for the influence of expectations on eco-products and for similar studies in the behavioral science literature. When I redesigned the experiment to carefully control for experimenter demand, I found no relationship between performance expectations and evaluations of product attributes or product choice. The single study is not enough to dismiss the overall findings, especially given the theoretical grounding of the relationship, but it does cast doubt on the strength of those findings.

In conclusion, these studies suggest that the slow take-up of eco-products could be due to low expectations of the performance of eco-products which lag behind the improvements in eco-product performance. When expectations influence evaluations of product attributes, consumers require repeated positive experiences to outweigh initial negative expectations. This suggests that eco-products that improve their performance will continue to be evaluated as performing poorly even when they are objectively identical in the quality of attributes. As a result, there may be a lag in the optimal consumption of eco-friendly products.

Significant empirical evidence suggests that eco-products are underutilized. The failure to choose products that have relatively low environmental impact reduces social welfare due to environmental externalities. There is also evidence that for energy-consuming products, the failure to choose energy efficient products may also reduce the welfare of individual consumers. The energy efficiency gap describes the phenomenon that many individuals do not utilize the optimal level of energy efficient appliances, home weatherization, and energy efficient products (Jaffe and Stavins 1994a). There have been many explanations proposed and explored, but none can fully explain the gap that remains. This study points to a new possible contributing factor to the energy

efficiency gap, and may help us better understand why we have seen sluggish market take-up of eco-friendly products.

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# Appendix A

## Chapter 1 Appendix

### A.1 Supplemental Tables

Table A.1: Extensive Margin of Donations Analysis

	<i>Dependent variable:</i>		
	Non-Zero Donation to CO2 mitigation		
	(1)	(2)	(3)
Letter Treatment D.V.	0.0001 (0.143)	-0.011 (0.146)	-0.021 (0.162)
Essay Treatment D.V.	0.218 (0.146)	0.237 (0.149)	0.236* (0.143)
Baseline Climate Concern		0.468*** (0.057)	0.537*** (0.059)
Parent D.V.			0.272* (0.152)
Age (years)			0.001 (0.006)
Income (\$1000's)			0.001 (0.002)
High School D.V.			-0.425 (0.721)
Trade School D.V.			-0.437 (0.754)
Associate Degree D.V.			-0.149 (0.712)
Bachelor Degree D.V.			-0.357 (0.742)
Graduate Degree D.V.			-0.475 (0.720)
Vote Republican D.V.			-0.144 (0.152)
Vote Democrat D.V.			-0.170 (0.191)
Male D.V.			-0.187 (0.147)
White D.V.			-0.451*** (0.147)
Hispanic D.V.			0.262 (0.233)
Constant	1.258*** (0.101)	1.315*** (0.104)	1.997*** (0.683)
State Fixed Effects	No	No	Yes
Clustered Standard Errors	No	No	Yes
Observations	1,736	1,724	1,645

*Note:* Logit regression. Dependent variable indicates donation > \$0. Income is a numeric variable in \$1000's. Dummy variables are included for those who vote mainly or exclusively for Democrats and Republicans. Voters who vote half Republican and half Democrat as well as those who do not vote for either party are the comparison group. Education is a categorical variable split into dummy variables and less than high school education is the comparison group. D.V. indicates binary dummy variables. Baseline climate concern is a 10 point scale measure standardized with mean=0, sd=1. Age is measured in years. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01



Table A.2: Implicit Discount Rate Analysis with Treatment Interactions

	<i>Dependent variable:</i>		
	Implicit Discount Rate		
	(1)	(2)	(3)
Letter Treatment D.V. (LT)	-0.027 (0.036)	-0.009 (0.020)	-0.277 (0.225)
Essay Treatment D.V. (ET)	-0.060 (0.037)	0.018 (0.019)	-0.245 (0.232)
Parent D.V.	0.006 (0.029)		0.025 (0.034)
Parent x LT	0.024 (0.041)		0.028 (0.041)
Parent x ET	0.103** (0.042)		0.089 (0.055)
Baseline Climate Concern		0.017 (0.014)	0.020 (0.020)
Baseline CC x LT		-0.026 (0.020)	-0.038 (0.026)
Baseline CC x ET2		-0.003 (0.019)	0.004 (0.027)
Constant	0.358*** (0.025)	0.362*** (0.014)	0.923*** (0.195)
Demographic Controls	<i>No</i>	<i>No</i>	<i>Yes</i>
Dems x Trt Interactions	<i>No</i>	<i>No</i>	<i>Yes</i>
State Fixed Effects	<i>No</i>	<i>No</i>	<i>Yes</i>
Clustered Standard Errors	<i>No</i>	<i>No</i>	<i>Yes</i>
Observations	1,701	1,700	1,623
R <sup>2</sup>	0.009	0.003	0.153

*Note:* OLS Regression. Demographic controls included where indicated are listed in Table 1.6. Demographic controls are interacted with treatment dummy variables where indicated. State-level fixed effects are not interacted with treatment dummies. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A.3: Impact of Treatment Groups on Decision Factors

<i>OLS Estimates</i>		
	Letter Treatment	Essay Treatment
Implicit Discount Rate	−0.007 (0.019)	0.017 (0.019)
Climate Concern	0.028 (0.058)	0.083 (0.058)
Legacy	0.167*** (0.050)	0.066 (0.050)
Vividness of Future	0.249*** (0.058)	0.067 (0.057)
Hindsight	−0.007 (0.058)	−0.011 (0.058)
Impact on Own Kids	0.024 (0.058)	0.048 (0.058)
Mitigation Responsibility	0.059 (0.058)	0.122** (0.058)
Hope	−0.100* (0.058)	−0.026 (0.058)
Guilt	−0.061 (0.058)	0.037 (0.058)
Efficacy of Climate Action	−0.013 (0.054)	0.026 (0.050)

*Note:* Dummy variables for the Letter and Essay treatments are regressed on the dependent variables in the lefthand column. No additional covariates are included in this specification. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A.4: Relationship Among Decision Factors, Donations and Concern

	<i>Dependent variable:</i>			
	Donation	Donation	Concern	Concern
Implicit Discount Rate	-0.208 (0.454)	-0.568 (0.477)	0.089 (0.175)	-0.179 (0.123)
Climate Concern	0.803*** (0.058)	0.876*** (0.093)	NA	NA
Legacy	1.515*** (0.168)	1.128*** (0.179)	1.161*** (0.060)	0.672*** (0.044)
Vividness of Future	0.110 (0.148)	0.121 (0.150)	0.146** (0.057)	0.118*** (0.039)
Hindsight	0.322** (0.147)	0.321** (0.149)	0.173*** (0.057)	0.116*** (0.038)
Climate Affect Kids	1.569*** (0.143)	1.131*** (0.177)	1.597*** (0.043)	0.846*** (0.041)
Mitigation Responsibility	1.580*** (0.143)	1.133*** (0.182)	1.753*** (0.039)	1.026*** (0.040)
Hope	0.437*** (0.147)	0.254* (0.150)	0.277*** (0.057)	0.191*** (0.038)
Guilt	1.346*** (0.144)	0.919*** (0.166)	1.197*** (0.049)	0.477*** (0.042)
Efficacy of Mitigation Action	1.721*** (0.161)	1.297*** (0.200)	1.897*** (0.045)	1.074*** (0.045)
Demographic Controls	No	Yes	No	Yes
Baseline Concern	No	Yes	No	Yes

*Note:* The variables listed in the lefthand column are regressed on revealed willingness to donate to climate change mitigation and reported post-treatment concern about climate change on a 1-to-10 scale. Details on demographic controls can be found in Table 1.1.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## A.2 Demographic Characteristics of Study Population

Table A.5: Demographics: Linear and Dummy Variables

Statistic	N	Mean	St. Dev.	Min	Max
age	1,713	37.781	11.759	18	76
kids	1,786	0.721	0.449	0	1
white	1,788	0.820	0.384	0	1
hisp	1,788	0.070	0.256	0	1

Table A.6: Demographics: Household Income

Household Income	Treatment Groups			
	LT	ET	C	Total
Less than \$25,000	99	114	126	339
\$25,000-\$34,999	94	101	92	287
\$35,000-\$49,999	97	109	99	305
\$50,000-\$74,999	127	136	115	378
\$75,000-\$99,999	85	83	81	249
\$100,000-\$149,999	71	49	52	172
\$150,000-\$199,999	9	10	14	33
\$200,000 or more	4	8	10	22
Total	586	610	589	1785

Table A.7: Demographics: Racial Groups

	Treatment Groups			
	LT	ET	C	Total
American Indian or Alaskan Native	15	15	11	41
Asian	33	37	30	100
Black or African American	53	48	38	139
Native Hawaiian or Other Pacific Islander	0	3	2	5
White	496	510	509	1515
Other	11	16	9	36

Note: Multiracial participants were counted in multiple racial groups.

Table A.8: Demographics: Gender

Gender	Treatment Groups			Total
	LT	ET	C	
Male	223	213	200	636
Female	361	397	386	1144
Other	1	0	3	4
Total	585	610	589	1784

Table A.9: Demographics: Highest Level of Education Completed

Level of Education	Treatment Groups			
	LT	ET	C	Total
Less than high school diploma or equivalent	3	4	4	11
High school diploma or equivalent	159	171	149	479
Trade school degree or certificate	30	32	31	93
Associate degree	91	116	102	309
Bachelors degree	216	204	201	621
Graduate degree (Masters, PhD, MD, JD, etc)	85	85	101	271
Total	584	612	588	1784

Table A.10: Demographics: Voting Preferences

	Treatment Groups			
	ET	LT	C	Total
Nearly always vote for Democrats	154	160	164	478
Vote for Democrats more often than Republicans	132	126	127	385
Half Democrats, half Republicans.	62	71	50	183
Vote for Republicans more often than for Democrats	84	86	97	267
I nearly always vote for Republicans	89	114	85	288
I will not vote for either party	25	16	16	57
I do not vote	40	38	50	128
Total	586	611	589	1786

## A.3 Survey Instruments

### A.3.1 Essay Prompts by Treatment

#### Letter Treatment

##### Pre-essay questions:

- Do you have children, grandchildren, nieces or nephews? [“Yes, I have children”, “Yes, I have grandchildren”, “I have niece(s) or nephew(s)”, “No, I do not have children, grandchildren, nieces or nephews”]
- What is the current age of your youngest child [grandchild, niece or nephew]? (in years)

##### Essay prompts for participants *with* children, grandchildren and/or nieces/nephews

- Imagine it is the year 2050. Your youngest child [grandchild, niece/nephew] is [child’s age + 35] years old, working hard, and raising a family of their own. Your child [grandchild, niece/nephew] opens the mailbox and finds a letter from you, written in the year 2015.

The letter is a message from the past and tells them what you thought about the risks and challenges of climate change and how they might affect the way your child would live their life in 2050. Tell your child [grandchild, niece/nephew] what, if any, actions on climate change you have taken already and what you will take in the next few years.

Please spend at least 5 minutes writing that letter. At the end of the survey, you will have the option of adding your letter to a long-term archive where your child [grandchild, niece/nephew] can read it in 2050.

Note: The submit button will appear after the minimum writing time of 5 minutes has elapsed.

### **Essay Prompts for Participants *without* children, grandchildren and/or nieces/nephews**

- Imagine it is the year 2050. A child born today is 35 years old, working hard, and raising a family of their own. They open a time capsule and find a letter from you, written in the year 2015.

The letter is a message from the past and tells them what you thought about the risks and challenges of climate change and how they might affect the way children in 2015 would live their lives in 2050. Tell this child what, if any, actions on climate change you have taken already and what you will take in the next few years.

Please spend at least 5 minutes writing that letter. At the end of the survey, you will have the option of adding your letter to a long-term archive where a child born in 2015 can read it in 2050.

Note: The submit button will appear after the minimum writing time of 5 minutes has elapsed.

### **Essay Treatment**

#### **Essay prompt**

- Please spend at least 5 minutes writing about the risks and challenges of climate change. Reflect on what you already know and what you might like to learn more about.

Note: The submit button will appear after the minimum writing time of 5 minutes has elapsed.

### **Control**

#### **Essay prompt**

- Please spend at least 5 minutes writing about your daily routine in the morning after you wake up and in the evening hours before you go to bed.

Note: The submit button will appear after the minimum writing time of 5 minutes has elapsed.

### **A.3.2 Donation**

- We will be randomly selecting 1 out of every 100 participants to receive a bonus of \$20.

You have the option to donate part or all of your bonus to Trees for the Future, a non-profit that plants trees that remove carbon dioxide from the atmosphere which helps reduce climate change. You can check out the organization at their website: <http://www.treesforthefuture.org/>.

Below, choose how much of the \$20 bonus you would like to donate to Trees for the Future and how much you would like to keep for yourself if you win the bonus. [“\$20 for Trees for the Future; \$0 for myself”, “\$19 for Trees for the Future; \$1 for myself” ,..., “\$1 for Trees for the Future; \$19 for myself”, “\$0 for Trees for the Future; \$20 for myself”]

### A.3.3 Time Discounting

- Now, we will ask you a series of questions where you will choose between two options. Option 1 will have an amount of money to be awarded as a bonus one month from today. Option 2 will have an amount of money awarded as a bonus four months from today.

You will make 14 of these choices with different amounts of money.

One of the MTurk workers who completes this survey will be randomly selected. Then, one of the 14 choices will be randomly selected. If that person chose Option 1, then they will receive the Option 1 bonus in one month. If that person chose Option 2, then they will receive the Option 2 bonus in four months.

Before making your choices over the bonus payments, you will take a short 3 question quiz to be sure that you understand these instructions. You must get all 3 questions correct, but you will have 3 chances to correctly answer the quiz.

- How many people in this survey will receive an MTurk bonus in the amount of one of their choices? [“None”, “1”, “2”, “3”]
- If you are the selected person, how will your bonus be chosen? [“1 of your 14 choices will be randomly selected and rewarded”, “An average of your 14 choices will be rewarded”, “The study administrator will choose whichever choice she thinks is best”]
- Do each of my choices have an equal chance of being implemented as a MTurk bonus payment? [“Yes”, “No”]

**By random assignment, the following choices were given in either ascending order or descending order:**

- Would you rather have \$100.00 in one month or \$101.00 in four months?
- Would you rather have \$100.00 in one month or \$102.50 in four months?
- Would you rather have \$100.00 in one month or \$105.00 in four months?



- Would you rather have \$100.00 in one month or \$107.50 in four months?
- Would you rather have \$100.00 in one month or \$110.00 in four months?
- Would you rather have \$100.00 in one month or \$110.00 in four months?
- Would you rather have \$100.00 in one month or \$115.00 in four months?
- Would you rather have \$100.00 in one month or \$120.00 in four months?
- Would you rather have \$100.00 in one month or \$130.00 in four months?
- Would you rather have \$100.00 in one month or \$140.00 in four months?
- Would you rather have \$100.00 in one month or \$150.00 in four months?
- Would you rather have \$100.00 in one month or \$175.00 in four months?
- Would you rather have \$100.00 in one month or \$200.00 in four months?
- Would you rather have \$100.00 in one month or \$250.00 in four months?
- Would you rather have \$100.00 in one month or \$300.00 in four months?

#### A.3.4 Decision Factor Questions

Legacy Motive Questions (Replication of survey instruments from Zaval et al. 2015)

- It is important to me to leave a positive legacy. [1-6 scale: End-points labeled “1 (Not at all)” and “10 (A great amount)”]
- It is important for me to leave a positive mark on society. [1-6 scale: End-points labeled “1 (Not at all)” and “10 (A great amount)”]
- I care about what future generations think of me. [1-6 scale: End-points labeled “1 (Not at all)” and “10 (A great amount)”]
- I feel hopeful about the future. [1-6 scale: End-points labeled “1 (Not at all)” and “10 (A great amount)”]
- On a scale of 1 to 10, how easily does life in the year 2050 come to mind? [1-10 scale: End-points labeled “1 (Not at all easily)” and “10 (Very easily)”]
- On a scale of 1 to 10, how easily can you look back on your actions with the benefit of hindsight? [1-10 scale: End-points labeled “1 (Not at all easily)” and “10 (Very easily)”]
- On a scale of 1 to 10, how concerned are you about climate change? [1-10 scale: End-points labeled “1 (Not at all concerned)” and “10 (Extremely concerned)”]

- On a scale of 1 to 10, how likely is it that climate change will negatively affect your own child? [1-10 scale: End-points labeled “1 (Very Unlikely)” and “10 (Very Likely)”]
- Rate the extent to which you agree or disagree with the following statement: The actions the entire world takes as a whole can make a difference for climate change. [“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
- Rate the extent to which you agree or disagree with the following statement: Taking action to help reduce climate change is part of my responsibility as a person who cares about the welfare of others. [“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
- Rate the extent to which you agree or disagree with the following statement: I feel guilty about my role in contributing to climate change. [“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]

## Appendix B

# Chapter 2 Appendix

### **B.1 Supplemental Tables**

### **B.2 Sensitivity Analyses**

Markets	$\gamma$	Mean $ \bar{\gamma}_{t+1} - \bar{\gamma}_t $	Var $ \bar{\gamma}_{t+1} - \bar{\gamma}_t $	$\sigma_m^2$	Range
Annual NOx	142.60	17.61	786.87	5.52	2011-2011
CAIR Annual NOx	369.63	72.72	39,406.23	106.61	2008-2014
CAIR Ozone Seasonal NOx	280.19	33.92	3,544.42	12.65	2007-2014
Connecticut Class I REC	40.27	1.66	5.87	0.15	2007-2014
CSAPR Annual NOx	221.18	54.67	2,339.10	10.58	2014-2015
CSAPR Group 1 SO2	177.89	72.38	7,408.75	41.65	2014-2015
CSAPR Seasonal NOx	226.04	53.77	2,058.21	9.11	2014-2015
DC Solar REC	393.53	9.99	270.29	0.69	2011-2014
Delaware Existing REC	1.47	0.04	0.02	0.01	2009-2014
EUA Futures	9.96	1.04	6.15	0.62	2006-2016
Group 1 SO2	121.42	27.06	814.47	6.71	2011-2011
Illinois Wind	10.57	1.30	3.50	0.33	2009-2010
Maine Existing REC	0.24	0.02	0	0.01	2009-2014
Maryland SREC	239.17	8.11	101.56	0.42	2009-2014
Massachusetts C.I. REC	44.14	1.68	4.14	0.09	2009-2014
Michigan REC	2.09	0.14	0.08	0.04	2012-2014
Nat'l Green-E Wind REC	3.63	0.49	0.18	0.05	2007-2007
New Hampshire C.I REC	41.80	1.23	5.50	0.13	2009-2014
New Jersey SRECS	376.83	21.71	4,398.16	11.67	2007-2011
Ohio Adj-State Non-Solar	5.84	0.69	2.28	0.39	2010-2014
Ohio Adj-State Solar	98.57	7.94	280.11	2.84	2010-2014
Ozone Seasonal NOx	164.43	44.65	5,749.32	34.97	2011-2011
Pennsylvania SREC	124.32	13.26	595.47	4.79	2009-2014
Pennsylvania Tier I REC	6.85	0.70	0.85	0.12	2009-2014
Rhode Island Existing REC	0.97	0.03	0.01	0.01	2009-2014
Rhode Island New REC	47.79	1.39	6.25	0.13	2009-2014
SO2	130.80	12.69	715.46	5.47	2007-2009
Texas Rec	2.27	0.21	0.17	0.08	2007-2014
WECC Wind Green-E REC	4.10	0.38	0.24	0.06	2007-2007

Table B.1: A subset of pollution allowance markets with average allowance prices, mean change in monthly average prices, variance of the change in monthly average prices, and monthly variance scaled by the average allowance price, and range of years represented in the data.

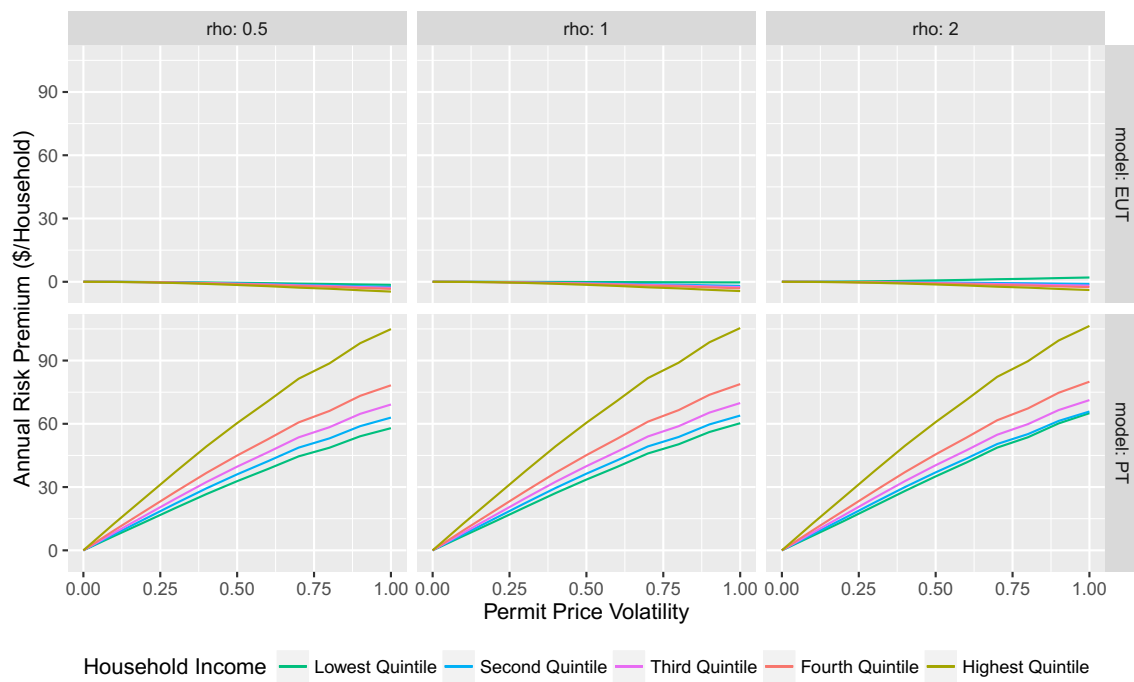


Figure B.1: Risk Aversion Sensitivity Analysis: Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\rho$ . Fixed parameter values:  $\epsilon_g = 0.13$ ,  $\eta_g = 0.3$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$ ,  $SCC = \$36/\text{metric ton of CO}_2$ .

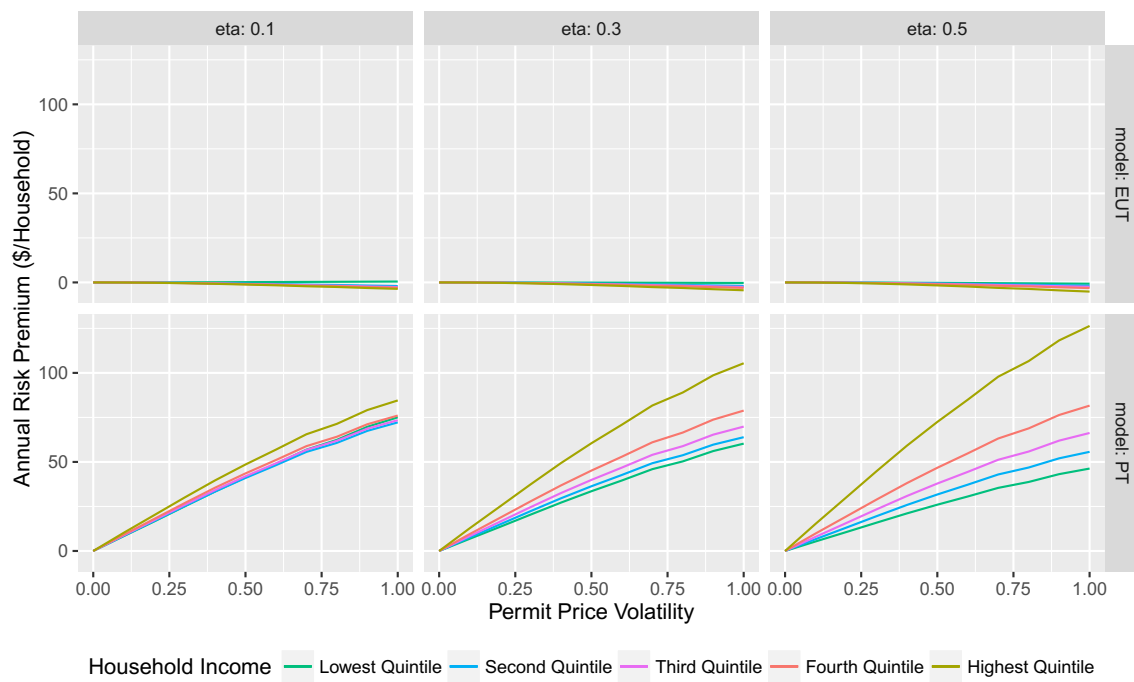


Figure B.2: Income Elasticity Sensitivity Analysis: Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\eta_g$ . Fixed parameter values:  $\epsilon_g = 0.13$ ,  $\rho = 1$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$ ,  $SCC = \$36/\text{metric ton of CO}_2$ .

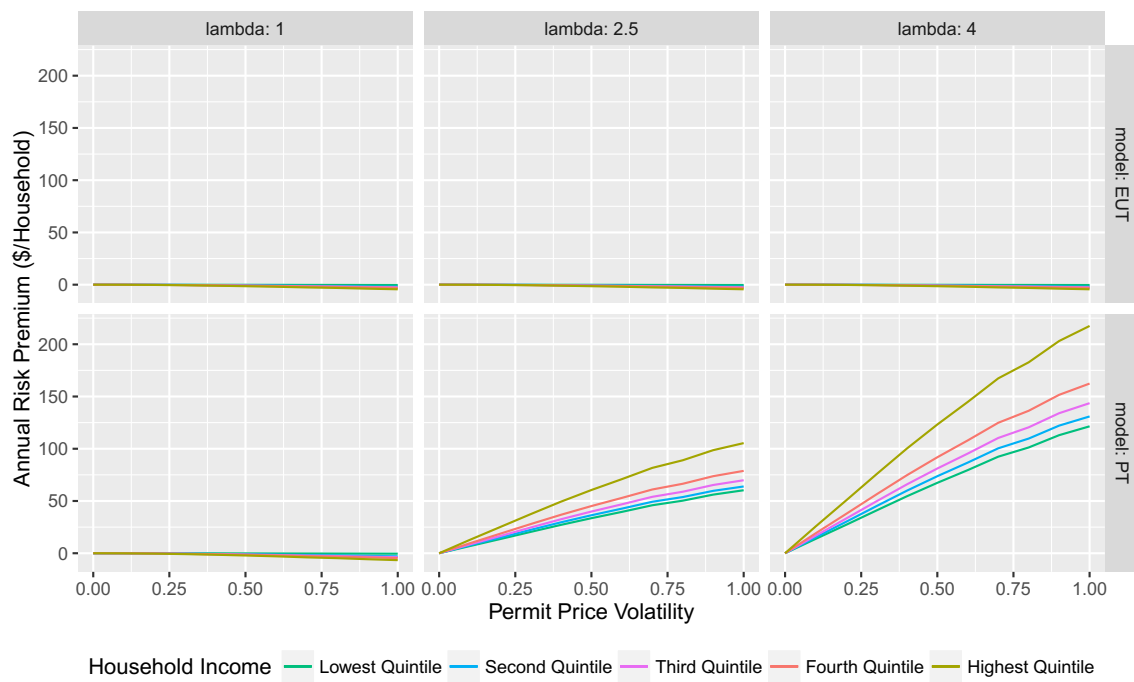


Figure B.3: Loss Aversion Sensitivity Analysis: Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\lambda$ . Fixed parameter values:  $\epsilon_g = 0.13$ ,  $\eta_g = 0.3$ ,  $\rho = 1$ ,  $\phi = 0.5$ ,  $SCC = \$36/\text{metric ton of CO}_2$ .

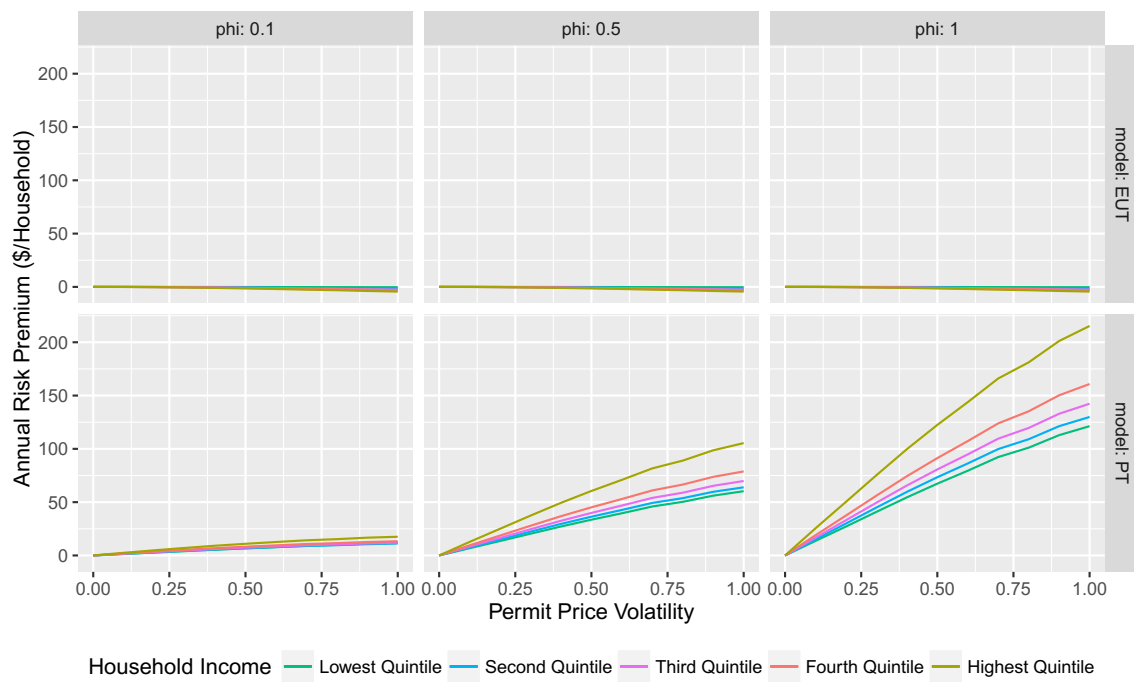


Figure B.4: Gain-Loss Utility Weighting Sensitivity Analysis: Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\phi$ . Fixed parameter values:  $\epsilon_g = 0.13$ ,  $\eta_g = 0.3$ ,  $\rho = 1$ ,  $\lambda = 2.5$ ,  $SCC = \$36/\text{metric ton of CO}_2$ .



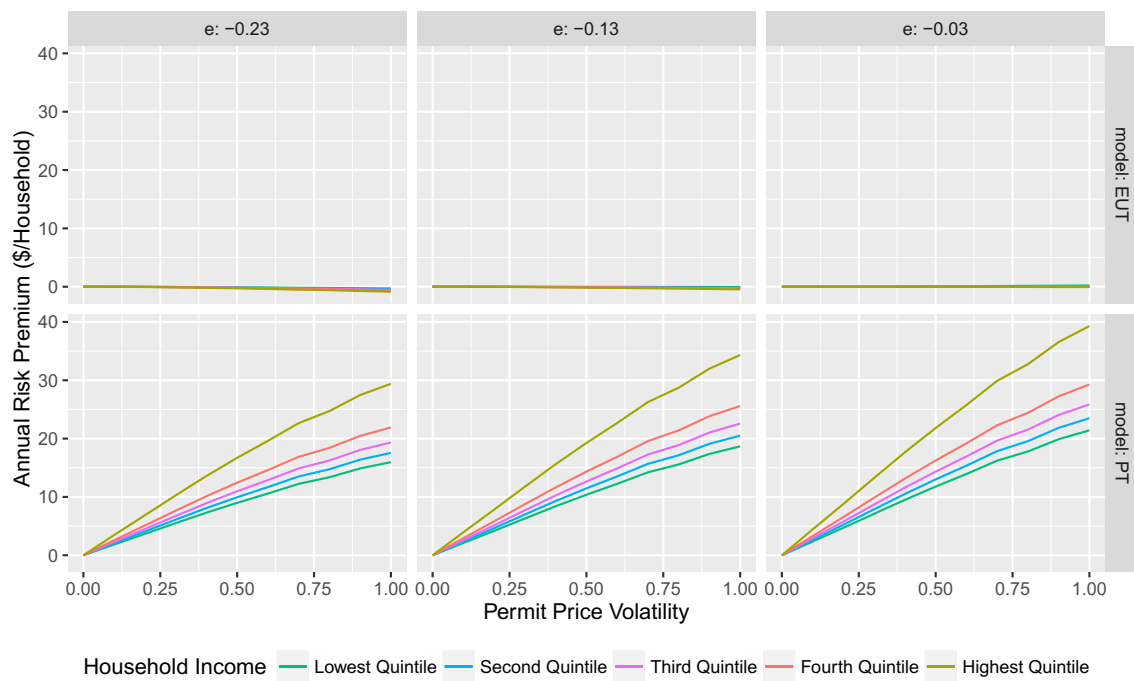


Figure B.5: Carbon Price Sensitivity (SCC=\$11): Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\epsilon_g$ . Fixed parameter values:  $\eta_g = 0.3$ ,  $\rho = 1$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$

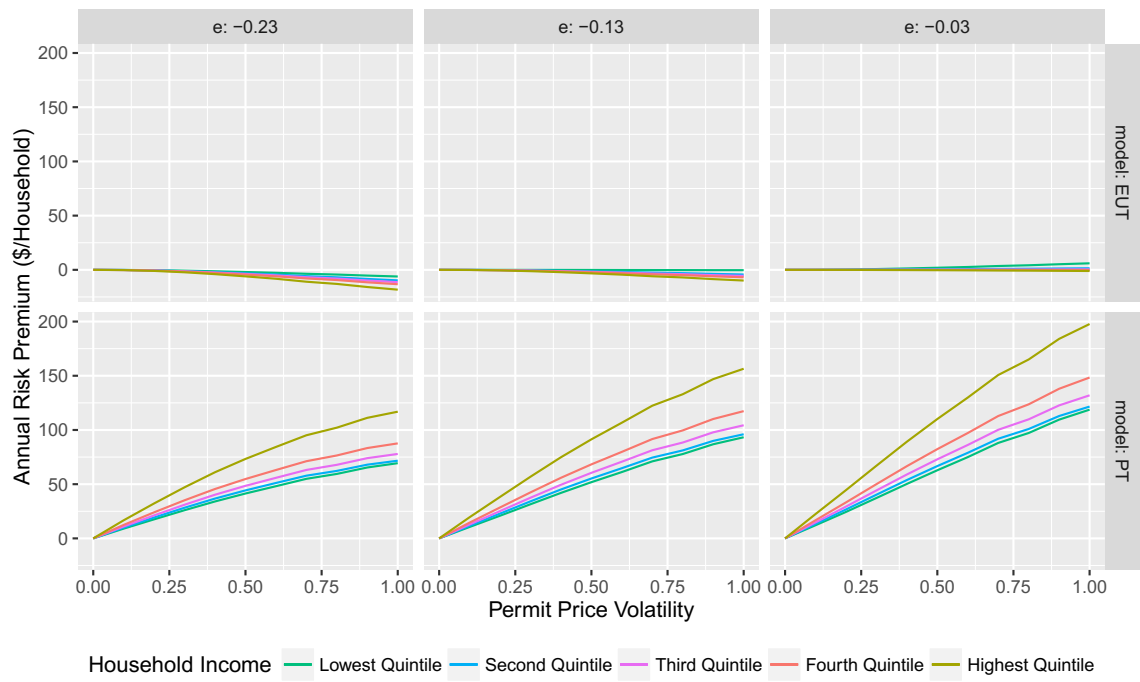


Figure B.6: Carbon Price Sensitivity (SCC=\$56): Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\epsilon_g$ . Fixed parameter values:  $\eta_g = 0.3$ ,  $\rho = 1$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$

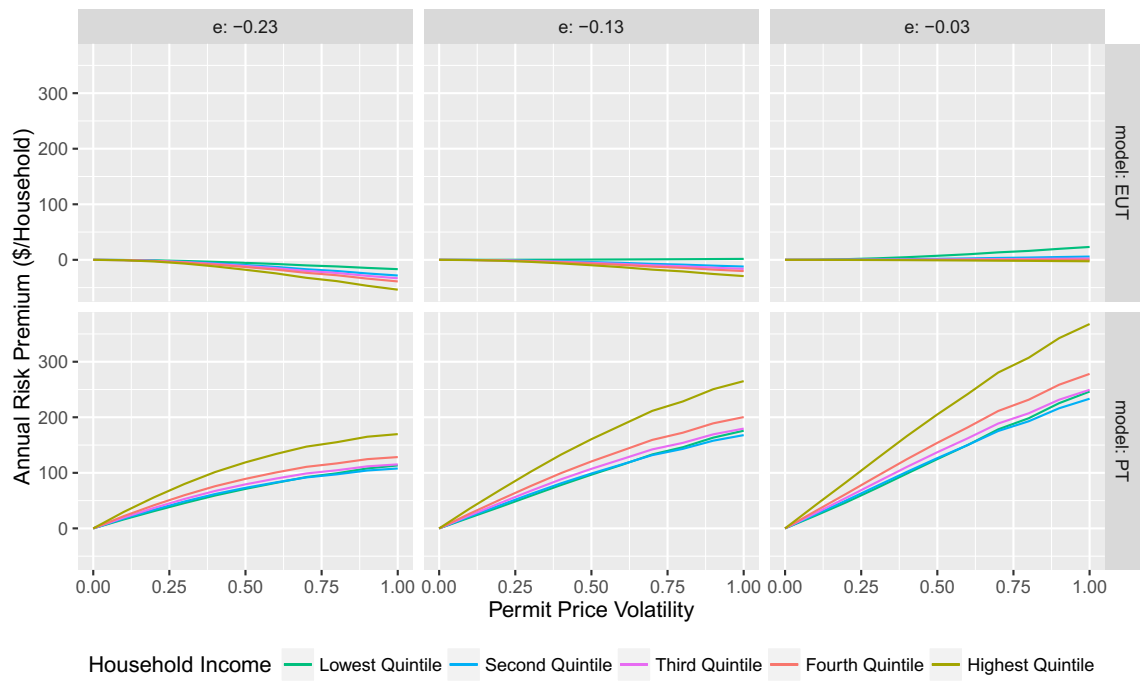


Figure B.7: Carbon Price Sensitivity (SCC=\$105): Estimated annual price risk premiums by income quintile for increasing levels of price volatility and under three different values of  $\epsilon_g$ . Fixed parameter values:  $\eta_g = 0.3$ ,  $\rho = 1$ ,  $\lambda = 2.5$ ,  $\phi = 0.5$

# Appendix C

## Chapter 3 Appendix

### C.1 Study Population Characteristics

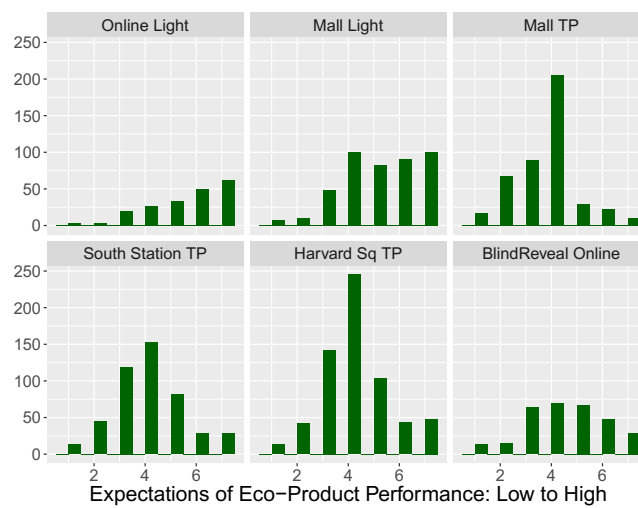


Figure C.1: Expectations about relative performance of the eco-product in the study compared to the non-eco-friendly counterpart. Higher ratings correspond to higher relative expectations for eco-products.

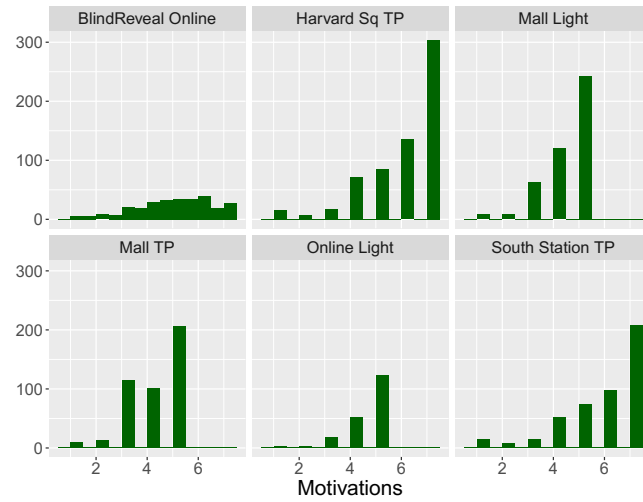


Figure C.2: Motivations for the eco-product in the study to perform well. Higher ratings correspond to higher levels of motivation for eco-products to perform as well or better than regular products.

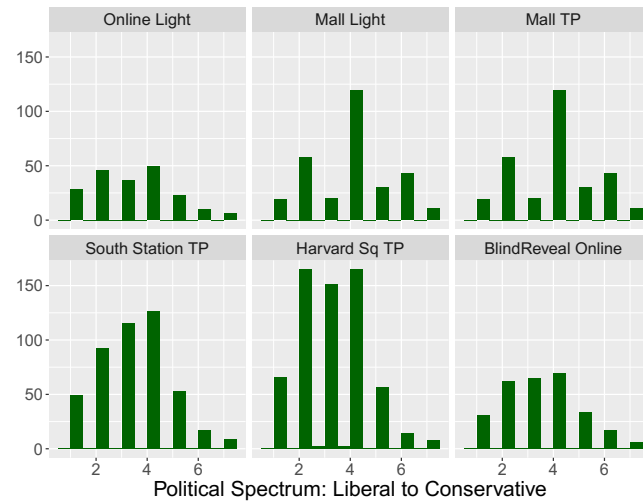


Figure C.3: Political preferences on a liberal/conservative scale. Higher ratings indicate more conservative political preferences

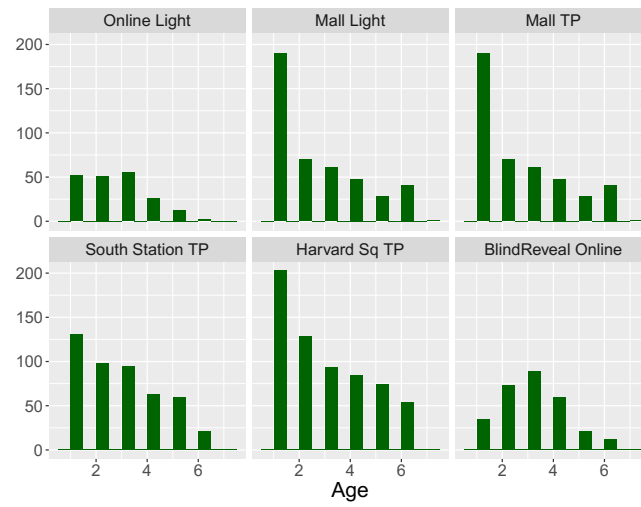


Figure C.4: Age of participants. Values from 1 to 6 correspond to the following age bins: 18-24, 25-30, 31-40, 41-50, 51-60, 61+.

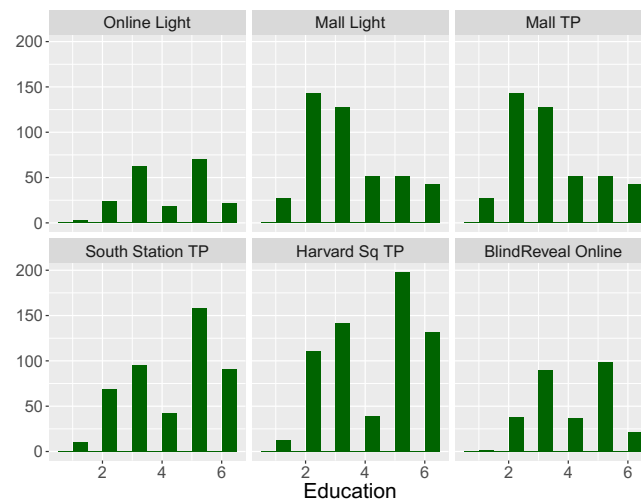


Figure C.5: Highest level of education completed by participants. Values from 1 to 6 correspond to the following responses: 1: Less than high school, 2: High school degree or equivalent (e.g. GED), 3: Some college but no degree, 4: Associate degree, 5: Bachelor degree, 6: Graduate degree.

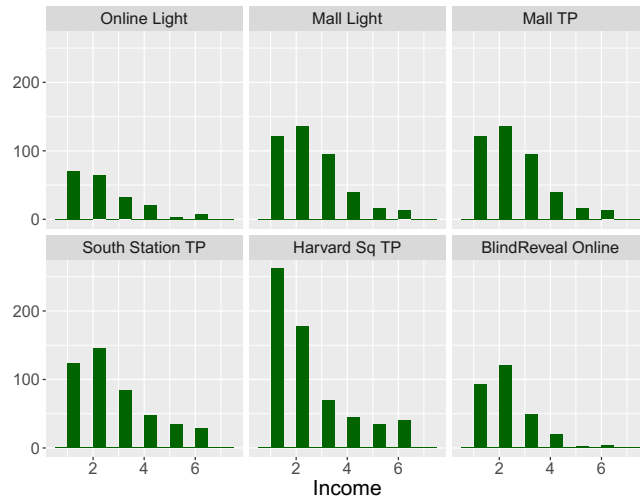


Figure C.6: Household income of participants. Values of 1 to 6 correspond to the following income bins: \$0 - \$29,999, \$30,000 - \$59,999, \$60,000 - \$89,999, \$90,000 - \$119,999, \$120,000 - \$150,999, \$160,000 or more.

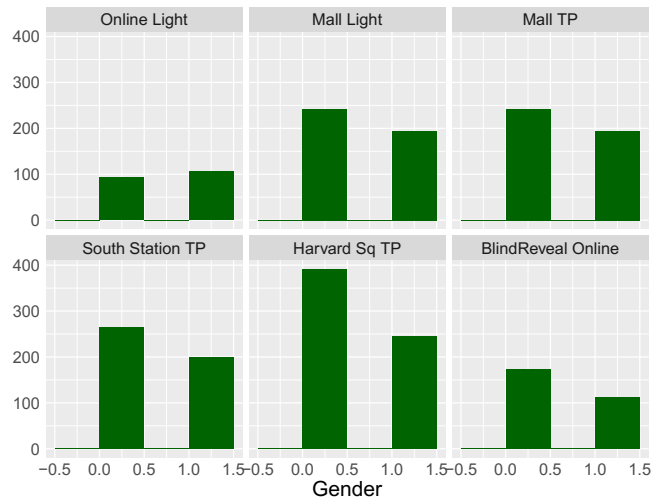


Figure C.7: Gender of participants. Value of 0 indicates female, value of 1 indicates male.

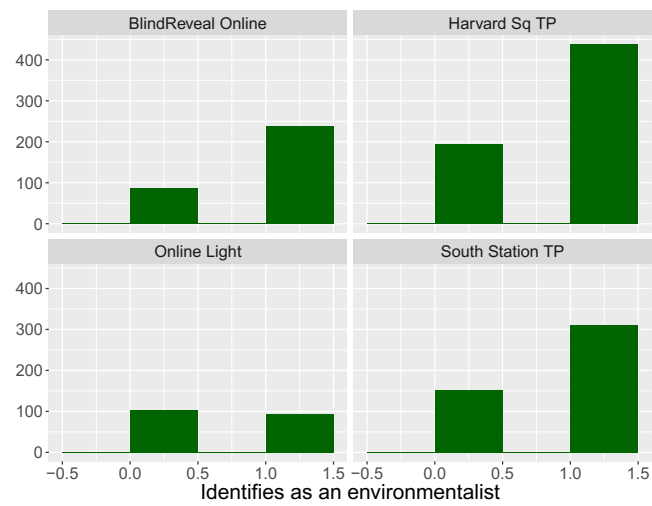


Figure C.8: Participants who identified as an environmentalists. Value of 1 indicates they identify as an environmentalist.



## C.2 Survey Instruments

### C.2.1 Study 1: Perception of Energy Efficient Lighting (Online)

**Prior expectations of light performance:** In general, how do you expect energy efficient compact fluorescent light bulbs to perform in comparison to standard incandescent light bulbs?

- 7-point numeric scale: 1 labeled “Much worse”, 7 labeled “Much better”

**Motivation for CFLs to perform well:** If energy efficient compact fluorescent light bulbs performed better than incandescents, how happy would you be?

- 5-point numeric scale: 1 labeled Very Unhappy, 5 labeled Very Happy

**Light pleasantness:** On a scale of 1 to 6, how pleasant is the light from the energy efficient compact fluorescent light bulb [incandescent bulb]?

- 6-point numeric scale: 1 labeled Not at all Pleasant, 6 labeled Very Pleasant

### C.2.2 Study 2: Reported Perception of Energy Efficient Lighting (Field)

**Prior expectations of light performance:** In general, compared to standard incandescent light bulbs do you expect energy efficient compact fluorescent light bulbs to perform worse, about the same, or better?

- 7 choices labeled as: Much Worse, Worse, Somewhat Worse, About the Same, Somewhat Better, Better, Much Better

**Motivation for CFLs to perform well:** If energy efficient compact fluorescent light bulbs performed as well as or better than incandescents, how happy would you be?

- 5-point numeric scale: 1 labeled Not at all Happy, 5 labeled Very Happy

**Light pleasantness:** On a scale of 1 to 6, how pleasant is the light from the energy efficient compact fluorescent light bulb [incandescent bulb]?

- 6-point numeric scale: 1 labeled Not at all Pleasant, 5 labeled Very Pleasant

### C.2.3 Study 3: Reported Perception of Eco-Friendly Toilet Paper

**Prior expectations of toilet paper performance:** In general, do you expect toilet paper made from recycled paper to perform worse than, about the same as, or better than regular toilet paper?

- 7 choices: Much Worse, Worse, Somewhat Worse, About the Same, Somewhat Better, Better, Much Better

**Motivation for toilet paper made from recycled paper to perform well:** If toilet paper made from recycled paper performed as well as or better than regular toilet paper, how happy would you be?

- 5-point numeric scale: 1 labeled Not at all Happy, 5 labeled Very Happy

**Toilet paper softness:** "On a scale of 1 to 6, how soft is the toilet paper made from recycled paper [regular toilet paper]?"

- 6-point numeric scale: 1 labeled Not at all Soft, 5 labeled Very Soft

**Toilet paper strength:** "On a scale of 1 to 6, how strong is the toilet paper made from recycled paper [regular toilet paper]?"

- 6-point numeric scale: 1 labeled Not at all Strong, 5 labeled Very Strong

#### C.2.4 Study 4: Sensory Perception of Eco-Friendly Toilet Paper

**Prior expectations of toilet paper performance:** In general, how do you expect toilet paper made from recycled paper to perform in comparison to regular toilet paper?"

- 7-point numeric scale: 1 labeled "Much Worse," 7 labeled "Much Better"

**Motivation for toilet paper made from recycled paper to perform well:** If toilet paper made from recycled toilet paper performed better than regular toilet paper, how happy would you be?

- 7-point numeric scale: 1 labeled Not at all Happy, 7 labeled Very Happy

**Toilet paper softness:** "On a scale of 1 to 7, how soft is the toilet paper made from recycled paper [regular toilet paper]?"

- 7-point numeric scale: 1 labeled Not at all Soft, 7 labeled Very Soft

#### C.2.5 Study 5: Sensory Perception of Eco-Friendly Toilet Paper

**Prior expectations of toilet paper performance:** In general, how do you expect toilet paper made from recycled paper to perform in comparison to regular toilet paper?"

- 7-point numeric scale: 1 labeled "Much Worse," 7 labeled "Much Better"

**Motivation for toilet paper made from recycled paper to perform well:** If toilet paper made from recycled toilet paper performed better than regular toilet paper, how happy would you be?

- 7-point numeric scale: 1 labeled Not at all Happy, 7 labeled Very Happy

**Toilet paper softness:** "On a scale of 1 to 7, how soft is the toilet paper made from recycled paper [regular toilet paper]?"

- 7-point numeric scale: 1 labeled Not at all Soft, 7 labeled Very Soft

**Joint Evaluation:** “Which toilet paper do you think is softer?”

- Toilet paper A, made from recycled paper [regular toilet paper].
- Toilet paper B, the regular toilet paper [made from recycled paper].

## C.2.6 Study 6: Sensory Perception of Energy Efficient Lighting

**Prior expectations of CFL light performance:** “Considering only light quality (brightness, color, etc), on a scale from 1 to 7, how do you expect energy efficient compact fluorescent light (CFL) bulbs to perform in comparison to standard incandescent light bulbs? Remember, if you do not know what to expect about the relative performance, just give your best guess.”

- 7-point numeric scale: 1 labeled “(Energy efficient compact fluorescent light bulbs are much worse than standard incandescent light bulbs)”, 4 labeled “(Energy efficient compact fluorescent light bulbs are about the same as standard incandescent light bulbs), and 7 labeled “7 (Energy efficient compact fluorescent light bulbs are much better than standard incandescent light bulbs)”

**Pleasantness of light** “On a scale of 1 to 7, how pleasant does the light from the GE Reveal [Energy Efficient Compact Fluorescent/Standard Incandescent] light bulb appear to be?”

- 7-point numeric scale: 1 labeled “(Not at all Pleasant)”, 7 labeled “(Very Pleasant)”

**Light bulb choice** “Which package of light bulbs would you prefer for your own household? (Keep in mind that you may actually win the light bulb you choose!)”

- “GE Reveal Standard Incandescent (4-pack)” or “GE Reveal Energy Efficient Compact Fluorescent Light Bulb (2-pack)”

**Motivations for energy efficient light to perform well** “When you are deciding whether or not to purchase a light bulb, how much does the energy consumption of the light bulb weigh in your decision?”

- 7-point numeric scale: 1 labeled “(Energy consumption is not important)” and 7 labeled “(Energy consumption is very important)”

“When you are deciding whether or not to purchase a light bulb, how much does the environmental impact of the light bulb weigh in your decision?”

- 7-point numeric scale: 1 labeled “(Environmental impact is not important)” and 7 labeled “(Environmental impact is very important)”