



RESEARCH ARTICLE

A Behavioral Approach to Identify Barriers to Adoption of New Technology: A Case Study of Low-input Turfgrasses

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Abstract

Adopting eco-friendly technologies, such as converting lawns to alternative low-input grass species, can reduce household expenditures and mitigate negative environmental impacts at the same time. However, the rate of adoption of these technologies has not been as high as expected. This study develops a behavioral framework to identify barriers to new technology adoption by incorporating both prospect theory and present bias. We apply the framework in a choice experiment to investigate the relative importance of several factors that shape decisions associated with adoption of low-input turfgrass. We find that loss aversion plays a significant role. Though consumers exhibit present bias, long-term benefits still matter to them. Insights from the behavior model suggest that marketing and government programs that promote cost–benefit-efficient technologies should focus on eliminating or reducing potential losses caused by product failure.

Keywords: adoption of technology; behavioral economics; present bias; prospect theory

1. Introduction

Amid rising public awareness of environmental issues, eco-friendly technologies are gradually being adopted worldwide. Examples of such technologies include energy-efficient devices such as solar photo-voltaic cells, light-emitting diodes, and water-efficient washing machines and toilets. In this study, we focus on low-input turfgrass, a type of lawn grass that requires less water and fertilizer than conventional turfgrass and thus reduces environmental footprints. Sheffield and Wood (2008) predicted increasing global temperature will result in more droughts, and thus the environmental contribution of turfgrass that reduce water usage will become more crucial in the future. In addition, Gu et al. (2015) examined the long-term impact of turfgrass management practice on global warming. They concluded that turfgrass acts as a net carbon emitter and recommended reduction of fertilization as the most effective carbon mitigation approach. Given the eco-friendly features of low-input turfgrass, this study investigates the factors that impact the adoption of this relatively new technology. Previous studies that examined household's willingness to adopt eco-friendly technologies predominantly focused on the energy consumption. The adoption of turfgrass resembles energy-efficient technology adoption in the sense that consumers need to rationalize an upfront investment with delayed return under uncertainty. Despite eco-friendly technologies being seen as a “win-win” for adopters and the environment because the technologies

can reduce both adopter expenditures and negative environmental impacts, the rate of adoption of such technologies has not been as high as expected (Greene et al., 2009).

Previous studies of adoption of consumer technologies have primarily focused on two aspects: (1) evaluating the long-term benefit of adoption and (2) investigating consumers' decision-making processes when considering adopting a new technology. Studies of the long-term benefits of adoption have predominantly addressed energy use and examined how much people benefit from technology adoption and whether there has been underinvestment in energy-saving technologies. For instance, Granade et al. (2009) conducted a cost-benefit analysis of adopting an energy-efficient technology for end-users.¹ They concluded that the potential savings in terms of energy costs (\$1.2 trillion) were much larger than the required investment (\$520 million). Other studies compared energy use before and after adopting an energy-saving technology to evaluate potential cost savings. Schweitzer (2005), for example, conducted a meta-analysis of studies of weatherization assistance programs and estimated that weatherization that cost about \$2,600 could reduce natural gas use by 20%–25%, about \$260 annually. However, Allcott and Greenstone (2012) reviewed studies related to energy efficiency gaps, which refer to differences between actual and optimal levels of adoption of an energy-efficient technology. They argued that prior studies had underestimated the cost of technology adoption and, therefore, had overstated the magnitude of energy efficiency gaps.

Another body of literature has examined major factors affecting decisions about adoption of technology using behavioral economic frameworks. Technology adoption usually requires an upfront investment that only later generates returns, so understanding how households perceive the technology's future value is crucial. Several studies examined consumer perceptions of future value using the exponential discounting framework. Busse, Knittel, and Zettelmeyer (2013) found that a \$1 increase in the price of gasoline was associated with a significant increase in the market share and equilibrium price of highly fuel-efficient cars. Their estimates of implicit discount rates were low, suggesting that consumers were not myopic.

Other studies have estimated discounting factors using the exponential discounting framework and arrived at different conclusions. Allcott and Wozny (2014), for example, found that consumers equally valued a \$1 discount in future gas costs and an immediate \$0.76 discount in a vehicle purchase price. They concluded that vehicle consumers were significantly more myopic than financial market investors. Gillingham, Houde, and Van Benthem (2019) found that consumers were indifferent between a \$1 discounted future fuel cost and \$0.15–\$0.38 discounts in vehicle prices, resulting in a 4% discount rate. Their results suggest that consumers are even more myopic than identified by Allcott and Wozny (2014). Cohen, Glachant, and Söderberg (2017) also found that consumers in the United Kingdom heavily discounted future energy costs, estimating an implicit discount rate of 11%. De Groote and Verboven (2019) identified household discount factors using a program involving tradeoffs between a future household subsidy and an immediate upfront payment. They found that households heavily discounted future benefits from a new technology. For example, households were willing to pay approximately €0.5 upfront for every €1.0 of future benefit.

In addition to analyses using the exponential discounting framework, many studies have documented “present” bias in which individuals undervalue future gains or losses relative to present ones (Laibson, 1997; O'Donoghue and Rabin, 1999). Unlike exponential discounting, which analyzes discount values in two consecutive periods, models of present bias (e.g., hyperbolic discounting and quasi-hyperbolic discounting) predict how people further discount values in future periods relative to the discount value in the present period. Therefore, present bias models generalize the exponential discounting model.

Lastly, failure to adopt a new technology could be due to consumers' uncertainty regarding its effectiveness and potential downsides. Several recent studies have emphasized the importance of including consumer uncertainty perception in analyses of new technology adoption (Greene,

¹The end use is energy consumed in industrial, business, and residential settings. See report footnote 4 for more details.

2011; Heutel, 2019; Schleich et al., 2019). For instance, Greene (2011), using the expected utility framework, demonstrated that the investment required to increase car fuel economy from 28 to 35 miles per gallon should have a positive expected net present value (NPV) but also found that the investment was uninteresting to loss-averse consumers. These results potentially explain at least some underuse of energy-efficient technologies.

Tversky and Kahneman (1992) found that individual perceptions of uncertainty do not follow the expected utility framework. Prospect theory (Kahneman and Tversky, 1979) proposes that individual perceptions of uncertainty consist of four elements: (1) reference dependence, (2) loss aversion, (3) diminishing sensitivity, and (4) probability weighting (Barberis, 2013). Thus, prospect theory enhanced expected utility specifications by adding several behavior parameters and is a generalization of the expected utility model. Barberis (2013) reviewed developments in prospect theory and results of empirical studies and found that prospect theory characterizes individual uncertainty perceptions more accurately than the expected utility framework.

Our study builds on prior ones by analyzing behavior associated with adoption of a new technology by capturing consumers' degree of risk aversion associated with present bias, weighting of probabilities, and aversion to loss using prospect theory in a choice experiment. This study is most related to Heutel (2019) and Schleich et al. (2019) in the sense that it considers the effects of a comprehensive set of behavior parameters. Schleich et al. (2019) used multiple price lists with delayed returns to capture discount factors and present bias, lotteries to capture risk aversion and loss aversion, and a stated-decision survey to measure technology adoption preferences. They established a correlation between the behavioral parameters and stated decisions. Similarly, Heutel (2019) conducted multiple experiments to capture participants' behavior parameters and then analyzed correlation between those parameters and adoption of various types of energy-efficient technologies.

Our experimental design explicitly considers individuals' tradeoffs between an upfront investment and its delayed benefits under uncertainty using a choice experiment, which is different from Heutel (2019) and Schleich et al. (2019). The advantage of Heutel (2019) and Schleich et al. (2019) approach is that price lists and lotteries can be incentivized to capture participants' behavior parameters more accurately. However, their willingness to adopt technology is self-stated and thus hypothetical. In addition, these two studies intended to estimate the association between behavior parameters and consumers' willingness to adopt new technology, while the role of upfront cost was not considered. The approach in this study aimed to capture the substitution patterns between upfront costs and uncertain future returns using a choice experiment.

In addition to capturing cost–benefit tradeoffs, choice experiment allows one to investigate the relative importance of various factors in shaping consumers' technology adoption decisions. When making technology adoption decisions, consumers do not necessarily behave “rationally.” Besedeš et al. (2012), for example, showed that people use mental shortcuts (heuristics) to make complex decisions and that the heuristics shift their choices away from the “optimal rational decision.” Given that technology adoption is a complex decision that involves delayed benefit with uncertainty, participants may use mental shortcuts to simplify the complex decision. We explicitly explained to participants that the purpose of the seemingly complex choice experiment in this study is not to ask them to calculate the optimal decision; instead, we intend to characterize how consumers weigh the importance of factors with their decision heuristics. Furthermore, studies demonstrated that decision heuristics, for example, preference and risk perception, could vary by decision context (Siegrist and Árvai, 2020; Trueblood et al., 2013). Thus, choice experiment that simulates consumers' turfgrass adoption with a clearly defined decision context is more appropriate.

The present study makes several valuable contributions. In terms of theory, we incorporate parameters associated with prospect theory (reference dependence, probability weighting, risk aversion, and diminishing sensitivity) and parameters that account for quasi-hyperbolic discounting (exponential discounting and present bias) into a choice experiment to identify how those factors affect decisions about adopting the technology. To our knowledge, our study

is the first to apply such a comprehensive behavioral framework to capture household tradeoffs between the required investment and uncertain future returns in the context of technology adoption. Empirically, we develop a framework that can be easily adapted to other decisions that involve upfront investments and delayed returns under uncertainty. We also compare the results from our model to estimates from an expected utility specification with exponential discounting. We find that, as a generalization of the expected utility framework, the proposed model more accurately captures individuals' intertemporal decisions under uncertainty. Lastly, our study of adoption of low-input turfgrass sheds light on households' reasons for not adopting the technology and understanding the reasons that can improve adoption of it in the future. We present policy and marketing implications of our findings that apply to adoption of low-input turfgrass and to other new products and technologies. The objective of this study is not to prove our approach is better than the ones used in the previous studies because what model fits a data the best is often an empirical question. Rather, we propose an alternative comprehensive way to investigate people's new technology adoption behavior and shed light on how marketing and policy could encourage new technology adoption.

2. Background

The choice experiment in our study presents participants with an opportunity to adopt turfgrass that require less water and fertilizer than traditional turfgrass. Hard fescue (*Festuca brevipila* Tracey), chewings fescue (*Festuca rubra* L. ssp. *commutata* Gaudin), and other similar fine fescues are alternatives to conventional species such as Kentucky bluegrass (*Poa pratensis* L.) and perennial ryegrass (*Lolium perenne* L.) for temperate climates commonly found in the northern United States, where lawns typically are an important part of urban landscapes and cover large areas (Milesi et al., 2005). Kentucky bluegrass (*Poa pratensis* L.) is a winter-hardy turfgrass that requires relatively large amounts of water, fertilizer, and pesticides to meet consumers' esthetic and functional requirements.

Public pressure to reduce the amount of water and chemicals required for lawns in the United States is increasing. Previous studies have examined the factors and interventions that may impact household water conservation behavior (Addo, Thoms, and Parsons, 2018; Fielding et al., 2012; Goette, Leong, and Qian, 2019; Qaiser et al., 2011; Willis et al., 2011). Many states, including Minnesota, have recently imposed restrictions on phosphorus fertilizer (Lee and McCann, 2018), and outdoor watering restrictions are common throughout the country (Milman and Polsky, 2016). As concern about droughts associated with climate change (Sheffield and Wood, 2008) intensifies, pressure to reduce water dedicated to home lawns will likewise increase. Previous studies have established that social awareness and exposure to drought affect residents' attitudes toward water saving (Beal, Stewart, and Fielding, 2013; Knuth et al., 2018). Knuth et al. (2020) showed that plant watering requirement plays a more important role for residents of states who frequently experienced drought.

Reducing inputs required for lawns can be accomplished using various approaches, but perhaps the most effective is using alternative turfgrass species. Previous studies have demonstrated that low-input turfgrass can perform well with limited water and no fertilizer or pesticides and require less mowing (Diesburg et al., 1997; Hugie and Watkins, 2016; Watkins et al., 2011). Several studies have shown that consumers are willing to pay premium prices for certain attributes of low-input turfgrass. Yue, Hugie, and Watkins (2012) conducted a choice experiment targeting Minnesota consumers and found that they are willing to pay premiums for turfgrass that requires less irrigation, fertilization, and mowing. Similarly, Yue et al. (2017) found that consumers in the United States and Canada are willing to pay a statistically significant price premium for turfgrass that leads to less watering, fertilizer inputs, and mowing. Hugie, Yue, and Watkins (2012) conducted a conjoint analysis and found that maintenance attributes in general and irrigation requirements in particular have significant effects on consumers' willingness to purchase low-input turfgrass

seeds. Ghimire et al. (2016) found that consumers in the southern United States rank low maintenance, drought tolerance, and saline tolerance as the most desirable lawn attributes.

Despite the numerous benefits of low-input turfgrass and evidence that consumers are willing to pay a premium for those benefits, adoption of low-input turfgrass for lawns in the United States has been limited (Braun et al., 2020). All of the previously mentioned studies assumed that the alternative turfgrasses would perform as well as conventional ones and did not consider potential adoption risks. As with any new product, adoption of a new turfgrass involves uncertainty about its performance. Low-input turfgrass could be susceptible to diseases and/or weeds that would not be problematic for conventional species, for example, and consumers likely would know less about the new species' specific management requirements. Our study investigates consumer decision-making about low-input turfgrass from a behavioral perspective to shed light on factors that prevent consumers from adopting this useful technology.

3. Experiment Design

To investigate barriers to adoption of low-input turfgrass, we first convened a focus group² involving a small number of homeowners. We asked them about their turfgrass maintenance practices, the attributes of the grasses that were most important to them, and their awareness of alternative turfgrass requiring fewer inputs. We also showed participants a sample square of sod planted with a low-input turfgrass and asked them about their preferences regarding the grass and their willingness to switch to it. We found both limited adoption of the low-input turfgrass and little awareness of such grasses as an alternative for lawns. The focus group discussion revealed several prevalent concerns that potentially prevent participants from adopting low-input turfgrass: the amount of effort required to replace the entire lawn at once, uncertainty about whether the new turfgrass would survive, and whether the long-term cost and time savings would cover the initial investment cost.

We used the results of the focus group to design our choice experiment analyzing homeowners' decisions regarding adoption of low-input turfgrass. Specifically, since the effort required to completely convert a lawn to low-input turfgrass was a concern, we included three options in the choice experiment: one option replaced all of the conventional grass at once using sod and two options replaced the conventional grass gradually using overseeding. Note that the one-time full replacement option provides an immediate return on the investment while the gradual replacement options provide delayed returns. To address expressed concerns about the alternative turfgrass failing to survive, we included the probability of success for the low-input turfgrass and the additional expense required to replace it if it failed. We assumed that participants' reference points were to the status quo of conventional turfgrass and that all of their calculations of time saved, costs incurred, and potential gains would be based on their current investments in their lawns.

In the choice experiment, participants were first given an introduction to low-input turfgrass:

Low input turfgrasses are those that can provide a functional, aesthetically pleasing lawn while not needing as much maintenance (less watering, less fertilizing, fewer pesticide applications, and less mowing) as more traditional turfgrasses like Kentucky bluegrass. These low-input turfgrasses are often characterized by a combination of low-input traits such as slow vertical growth, resistance to insects and diseases, tolerance of drought, and ability to maintain quality without a lot of fertilization.

²We conducted three sessions of in-person focus group discussion with 11–14 participants in each session. Each session lasted about 90 minutes. The participants were recruited through advertisement on newspapers and socio-media. Each participant was paid \$35 to compensate their time.

The experiment administrators then explained the context of the choice experiment, which presented participants with scenarios simulating a situation in which a lawn service company provided a service converting conventional lawn grasses to low-input turfgrasses. The lawn service setting was designed to eliminate potential confusion among participants regarding the amount of effort required to make the switch. Participants then received a detailed written explanation of the choice scenarios. In each choice task, participants would be presented with three replacement options (one full replacement and two gradual replacements), and the instruction stressed that there was no “correct answer” and that their task was to determine which option provided them with the greatest overall value and worked best for their households.

Each choice scenario consisted of four options—the three replacement options (A, B, and C) and the option to opt-out and decline conversion (D). Option A represented full immediate replacement using sod and delivered returns immediately since there was no need to wait for seeds to germinate and become established. This option not only represents the most rapid way to adopt the technology but also involves the greatest upfront investment of time and money. Option B represented conversion over an intermediate length of time of 2 years using overseeding. During those two transitional years, there was a cost per year for seed and participants would begin to obtain the benefit of conversion at the beginning of the third year. Option C represented a slower overseeding conversion of 3 years, a fixed investment cost for seed, and benefits obtained at the beginning of the fourth year. As defined by prospect theory, the losses and gains from conversion and their associated probabilities are relative to the status quo, which is the participant’s current lawn, and Option D is the status quo.

Each option presented in the experiment was characterized by five attributes. The first was the upfront cost (sod, seed) per 1,000 ft², which was \$600, \$800, and \$1000 under Option A; \$300, \$400, and \$500 under Option B; and \$240, \$320, and \$400 under Option C. The second attribute was time savings of 20%, 40%, and 60% provided by low-input turfgrass during the growing season (less mowing, watering, and fertilizing). The third attribute was potential cost saved per year after completing the conversion, thanks to reduced needs for water and fertilizer, which was set at \$200, \$250, and \$300. The fourth attribute was probability of success of the new turfgrass (that it would grow as expected and require no further investment), which was set at 70%, 80%, and 90%. The fifth attribute was the additional investment required if the alternative product failed; it was set at \$150, \$175, and \$200.³ We designed the choice experiment with optimal D-efficiency.

The choice experiment was designed to capture intertemporal discounting, present bias, probability weighting, risk aversion, and loss aversion. To capture present bias, we asked participants to choose between immediate adoption with a high one-time investment cost and slower adoption with a lower per-period investment cost over multiple periods. Gradual adoption under Options B and C, which have different transition periods, was designed to capture the discounting factor. The varying probabilities of gains and losses were designed to capture probability weighting, and the varying amounts of losses and gains were designed to capture loss aversion and risk aversion.

We conducted the experiment in 2019 and used Qualtrics™, a professional survey company, to obtain a representative sample of U.S. homeowners 18 years of age or older. Interested participants were first asked a screening question: “Do you have a home lawn?” Individuals who answered yes were allowed to participate in the data-collection survey conducted prior to the choice experiment. Since the experiment design involved a 3-year transition period under Option C, the survey asked

³The levels were selected based on the inputs of horticulture scientists specialized in low-input turfgrass development and focus group discussion with home owners. We also conducted a pretest of the choice experiment with 100 participants before we ran the experiment with the full sample, and the levels were adjusted to balance the utility of each alternatives (i.e., balance the choice probability of options within each choice scenario) based on the recommendation of Huber and Zwerina (1996). This study has obtained exempt from human subject review and the study number is STUDY00000654.

participants whether they expected to live at their current residences for less than 3 years and excluded all participants who answered affirmatively. The final sample for the choice experiment consisted of 866 participants.

4. Model Setup and Estimation Strategy

To analyze the results from the choice experiment, we set up a model that incorporates both prospect theory and intertemporal choice with present bias to capture how homeowners make decisions about adopting low-input turfgrasses. Let $i = \{1, \dots, I\}$ denote homeowner i ; $j = \{0, 1, 2, 3\}$ denote opt-out Option D, Option A, Option B, and Option C, respectively, and v_{ij} the utility function of individual i choosing option j with opt-out utility normalized to 0 ($v_{i0} = 0$). Assuming that the value function of the options, u_{ij} , has the separable additive form,

$$u_{ij} = v_{ij} + \epsilon_{ij} \tag{1}$$

where u_{ij} is the value function from option j and ϵ_{ij} is the random utility error term assumed to be type-I extreme-value distributed. Thus, by McFadden (1974), the probability of individual i choosing option j can be defined as

$$s_{ij} = Pr_i \left(u_{ij} \geq \max_{k \in \{0,1,2,3\}} \{u_{ik}\} \right) = \frac{\exp(v_{ij})}{1 + \sum_{k=1}^3 \exp(v_{ik})}. \tag{2}$$

Individual i evaluates the utility from option j at a finite horizon that is assumed to be the expected duration of individual i 's residency at the current location. Let T_1 denote the length of the transition period, which is one of the predefined attributes, and T_2 denote the expected duration of residence. We directly asked participants how long they expected to live at their current addresses. The utility from option j should consist of three components: (1) utility from average time savings per period (ξ_j), (2) the net present monetary value of the investment (η_j), and (3) the alternative-specific constant term (a_j). Assuming utility takes the separable additive form,

$$v_{ij} = a_j + \omega_2 \xi_j + \omega_1 \eta_j. \tag{3}$$

In equation (3), ω_1 and ω_2 are the marginal utility from average time savings and the net present monetary value of the investment, respectively.

When assuming exponential discounting, expected utility v_{ij} should take the form

$$v_{ij} = a_j + \omega_2 \sum_{t=T_1+1}^{T_2} \beta_2^t \tau^{\gamma_2} / (T_2 - T_1) + \omega_1 \left\{ \sum_{t=T_1+1}^{T_2} \beta_1^t [\pi g^{\gamma_1} - (1 - \pi)l^{\gamma_1}] - \sum_{t=0}^{T_1} \beta_1^t c^{\gamma_1} \right\}. \tag{4}$$

In equation (4), β is the exponential discounting factor, τ is the time savings per period relative to current practice (percentage), γ_1 and γ_2 are the risk-aversion parameters, π is the probability of gain, and c_t , g_t , and l_t are the cost, potential gain, and potential loss in period t , respectively. The average present value of time saving is $\xi_j = \sum_{t=T_1+1}^{T_2} \beta_2^t \tau^{\gamma_2} / (T_2 - T_1)$, the expected total present value due to loss and gain generated by low-input turfgrass is $\sum_{t=T_1+1}^{T_2} \beta_1^t [\pi g^{\gamma_1} - (1 - \pi)l^{\gamma_1}]$, and the present value of the total cost is $\sum_{t=0}^{T_1} \beta_1^t c^{\gamma_1}$. Thus,

$$\eta_j = \sum_{t=T_1+1}^{T_2} \beta^t [\pi g^{\gamma_1} - (1 - \pi)l^{\gamma_1}] - \sum_{t=0}^{T_1} \beta^t c^{\gamma_1}.$$

To account for present bias, loss aversion, and probability weighting, the model takes the form

$$v_{ij} = a_j + \omega_2 \sum_{t=T_1+1}^{T_2} \beta_2^t \tau^{\gamma_2} / (T_2 - T_1) + \omega_1 \left\{ \sum_{t=T_1+1}^{T_2} \alpha \beta_1^t [w(\pi)g^{\gamma_1} - w(1-\pi)\lambda l^{\gamma_1}] - \sum_{t=0}^{T_1} \alpha^{1_{t>0}} \beta_1^t \lambda c^{\gamma_1} \right\}. \tag{5}$$

The difference between equations (4) and (5) is three components: the quasi-hyperbolic discounting (Laibson, 1997) parameter α used to capture present bias, the probability weighting function $w(\cdot)$, and the loss-aversion parameter λ . The functional form suggested by prospect theory is adapted from Tversky and Kahneman (1992) with the individual evaluating losses and gains according to the function $V(\cdot)$,

$$V(x) = \begin{cases} x^{\gamma_1} & \text{if } x \geq 0 \\ -\lambda(-x)^{\gamma_1} & \text{if } x < 0 \end{cases} \tag{6}$$

and the probability weighting function,

$$w(\pi) = \frac{\pi^\mu}{(\pi^\mu + (1-\pi)^\mu)^{1/\mu}}. \tag{7}$$

It is straightforward to see that equation (5) is a generalization of equation (4); that is, equation (5) becomes equation (4) when $\alpha = 1$, $\mu = 1$, and $\lambda = 1$. We assume an individual’s reference point is the status quo.

Having specified an individual’s utility and likelihood, we estimate the distribution of the parameters using Bayesian inference. The choices made by the participants are represented by $Y = \{y_1, \dots, y_I\}$, a vector in which each element represents one of the four options in a choice scenario (opt-out, A, B, and C). We are interested in estimating the cumulative distribution function of the parameters (e.g., $F(\Theta|Y)$). However, the nonlinear nature of the value function makes it difficult to solve using optimization algorithms so we use Bayesian inference instead. We assume that the prior cumulative distribution of the parameters was

$$\left\{ \begin{array}{l} \beta_1 \sim U(0, 1) \\ \beta_2 \sim U(0, 1) \\ \alpha \sim U(0, 1) \\ \mu \sim N(1, 1) \\ \lambda \sim N(3, 2) \\ \gamma_1 \sim U(0, 1) \\ \gamma_2 \sim U(0, 1) \\ \tau_1 \sim N(0, 3) \\ \tau_2 \sim N(0, 3) \\ a_j \sim N(0, 3) \end{array} \right. \tag{8}$$

where $U(\cdot, \cdot)$ refers to a uniform distribution and $N(\cdot, \cdot)$ denotes a normal distribution. By Bayes’ theorem, the distribution of the parameters is proportional to $F(Y|\Theta)F(\Theta)$. In other words,

$$F(\Theta|Y) \propto F(Y|\Theta)F(\Theta) \tag{9}$$

where $F(Y|\Theta)$ is the likelihood function and $F(\Theta)$ is the distribution of the parameters. The likelihood function $F(Y|\Theta)$ is given by

$$F(Y|\Theta) = \prod_{i \in \{1, \dots, I\}} \prod_{j \in \{0, 1, 2, 3\}} s_{ij}^{1_{\{y_i=j\}}} (1 - s_{ij})^{1_{\{y_i \neq j\}}}. \tag{10}$$

The prior probability function is given by equation (8).

The posterior distribution $F(\Theta|Y)$ is estimated using a differential-evolution Markov chain Monte Carlo (MCMC) method (ter Braak and Vrugt, 2008) and implemented using

BayesianTools in R (Hartig et al., 2019). We employed seven chains in the MCMC process, which allowed for testing of convergence. We ran each chain until the last 5,000 iterations indicated convergence. That is, until the potential scale reduction factor (PSRF) was less than 1.1 for all parameters, the convergence threshold suggested by Brooks and Gelman (1998).

5. Results

Table 1 presents summary socio-demographic statistics for the 866 participants in the choice experiment. More than half expected to live in their current residences for at least an additional 15 years. Note that we use this information for the variable T_2 in equations (4) and (5). Participants' yard sizes varied from less than 1/8 acre to more than 1 acre. We also collected the information on how much time participants spent on lawn maintenance. Our survey shows that most participants reported maintaining their lawns weekly or biweekly during growing seasons, and they spent 30 minutes to 2.5 hours each time. The median age of the participants fell in the 56–65 category and about 45% had a college degree. Most of the households (70%) were occupied by less than four people and 74% had annual household incomes of no more than \$80,000. The choice probabilities of each option by scenarios are presented in Table A2 in the Appendix.

We used the last 4,000 iterations of each Markov chain to determine the density of the parameters. We first estimated the expected utility model with constant exponential discounting, which corresponds to equation (4). Table 2 summarizes the estimation results for each parameter, including the PSRFs, maximum *a posteriori* (MAP)⁴, 2.5 percentiles, medians, and 97.5 percentiles. Figure 1 presents the distribution of the parameters. All coefficients have PSRF values less than the 1.1 convergence threshold, and we further demonstrate convergence by presenting trace plots of each iteration from the seven Markov chains in Figure A1 in the Appendix. Each trace plot connects the values of the iterations and the line represents regression of the value of the coefficient against the n th iteration. This visual representation also indicates that the last 4,000 iterations reached a steady state.

The most noticeable result from the expected utility model is the MAP-estimated discounting factor of 0.761. Figure 2 presents the estimated discounting level over 15 years. In the figure, the y -axis represents the cumulative discounting factor, β_1^t , and the x -axis represents the t th year. The exponential curve plots the discounting level over time estimated using the exponential discounting model. Figure 2 shows that monetary benefits that will occur five or more years later are discounted by more than 75%. Therefore, based on this MAP estimator, a primary barrier to adoption of a new technology is intertemporal time discounting.

To account for the other important factors identified in the focus group, we then extended the expected utility model to incorporate behavioral factors. We adapted the prospect theory model to evaluate present bias by including a quasi-hyperbolic discounting factor α , a probability weighting function $w(\cdot)$, and a loss-aversion parameter λ as in equation (5). Figure 3 presents the corresponding density functions, and Table 2 presents summary statistics for the parameter distributions.

Let M_B and M_E denote the behavior model and expected utility model, respectively. We use the Bayes factor, $\frac{Pr(Y|M_B)}{Pr(Y|M_E)}$, to compare model goodness-of-fit. The log of the Bayes factor is 49.05, which results in a Bayes factor much larger than 100; this indicates that the behavioral economic model fits the data much better than the expected utility model with exponential discounting. As Table 3 indicates, the PSRFs are all less than the 1.1 convergence threshold (see also trace plots in Figures A2 and A3 in the Appendix).

⁴MAP is an analog of maximum likelihood estimator for Bayesian Inference, which is the point estimation that maximizes posterior likelihood function.

Table 1. Summary statistics of participants' socio-demographic characteristics

	Frequency	Percent
Expected years live in current residency		
4~6 years	124	14.319
7~9 years	72	8.314
10~12 years	154	17.783
13~15years	40	4.619
15+ years	476	54.965
Yard size		
Less than 1/8 acre	157	18.13
City lot (1/8 acre)	169	19.52
1/4 acre	188	21.71
1/2 acre	138	15.94
1 acre	99	11.43
More than 1 acre	115	13.28
Frequency maintain your lawn		
More often than weekly	46	5.312
Weekly	300	34.642
Biweekly	185	21.363
Monthly	61	7.044
Every 2 months	17	1.963
Every 3 months	20	2.309
Less frequently than every 3 months	53	6.12
Not applicable	184	21.247
Time usually spent on lawn maintenance		
Less than 30 minutes	26	3.002
30 minutes to 59 minutes	185	21.363
1 hour to 1.49 hours	169	19.515
1.5 hours to 1.99 hours	113	13.048
2 hours to 2.49 hours	97	11.201
2.5 hours to 3 hours	48	5.543
More than 3 hours	44	5.081
Not applicable	184	21.2471
How much spent on lawn, past 12 months		
Less than \$100	192	22.171
\$100-\$199	160	18.476
\$200-\$299	112	12.933
\$300-\$399	66	7.621

(Continued)

Table 1. (Continued)

	Frequency	Percent
\$400–\$499	37	4.273
\$500–\$599	32	3.695
\$600–\$699	12	1.386
\$700–\$799	11	1.270
\$800–\$899	4	0.462
\$900–\$1,000	7	0.808
More than \$1,000	9	1.039
I don't know	40	4.619
Not applicable	184	21.247
Age		
18~25	11	1.27
26~35	59	6.81
36~45	104	12.01
46~55	144	16.63
56~65	244	28.18
65+	304	35.10
Gender		
Female	684	78.98
Male	182	21.02
Education		
Some high school or less	22	2.54
High school diploma	190	21.94
Some college	267	30.83
College diploma	155	17.90
Some graduate school	30	3.46
Graduate degree and above	202	23.33
Household size		
1	182	21.02
2	403	46.54
3	122	14.09
4	93	10.74
5	39	4.50
6	18	2.08
7	5	0.58
8+	4	0.46
Household income		
\$15,000 or under	60	6.93
\$15,001–\$25,000	95	10.97

(Continued)

Table 1. (Continued)

	Frequency	Percent
\$25,001–\$35,000	88	10.16
\$35,001–\$50,000	171	19.75
\$50,001–\$65,000	133	15.36
\$65,001–\$80,000	100	11.55
\$80,001–\$100,000	97	11.20
\$100,001–\$150,000	89	10.28
\$150,001–\$200,000	23	2.66
\$200,001 and over	10	1.16
Employment		
Full-time employed	237	27.37
Part-time employed	107	12.36
Retired	384	44.34
Unemployed	138	15.94

Notes: Participants answered “not applicable” for frequency, time, and cost on lawn maintained were those who hired lawn services. Our survey asked if participants maintained their lawn on their own, and those who answered “yes” were directed to answer the questions related to their maintenance practices.

The results from the behavioral economic model are somewhat different from the ones from the expected utility model. First, we find that participants exhibit strong present bias; the quasi-hyperbolic discounting factor α has a MAP of 0.73 so all future values are discounted by 73% relative to present values. In addition to present bias, we find virtually no long-term discounting over time. Participants' exponential discounting factors, β_1 and β_2 , are very close to 1. Figure 2 presents the level of discounting estimated using the behavioral model. After a 73% discount in year 1, discounting remains virtually unchanged thereafter. Therefore, we find, based on the behavioral model, that consumers tend to heavily discount future values (a 73% discount rate) but that long-term benefits still play a significant role in their decisions. For example, consider a simplified case in which, at current period $t = 0$, the technology requires a \$1,000 upfront investment and potential returns of \$200 per period over 15 periods. In this case, the investment, when considering only the upfront cost, total benefit over time, and discounting factor, would be unprofitable based on estimates from exponential discounting. The NPV would be $\$826.23 - \$1,000.00 = -\$173.77$. However, when using the behavioral model, the NPV is $\$2,327.02 - \$1,000.00 = \$1,327.02$, making it an attractive investment.

Additionally, the behavioral model suggests that loss aversion is likely to be the primary barrier to adoption of low-input turfgrass rather than heavy discounting of future benefits. As the MAP of λ indicates, the absolute loss is valued almost six times more than the gain, suggesting that a warranty that would prevent losses should the new turfgrass fail to grow could be an effective way to promote adoption. Table 4 shows the results of simulating the impact of a warranty based on the ten choice scenarios, presenting observed probabilities of choosing to opt out and the simulated opt-out probability when a warranty covers potential losses. We find that provision of a warranty prominently boosted the likelihood that consumers would choose some form of lawn conversion rather than opting out.

Currently, the market does not offer service plans that assist homeowners in gradually switching to low-input turfgrasses. We simulated the market response to a program that resulted in time savings of 30% relative to current practices and required a one-time upfront cost

Table 2. Coefficient summary statistics, exponential discounting model

	PSRF	MAP	2.50%	Median	97.50%
β_1	1.037	0.761	0.723	0.760	0.795
β_2	1.029	0.959	0.930	0.951	0.972
γ_1	1.010	0.391	0.300	0.413	0.529
γ_2	1.026	0.994	0.749	0.948	0.997
τ_1	1.025	2.552	2.239	2.653	3.090
τ_2	1.039	1.050	0.843	1.119	1.413
a_1	1.030	-0.229	0.001	-0.219	-0.473
a_2	1.048	0.637	0.992	0.658	0.337
a_3	1.045	1.228	1.637	1.249	0.880

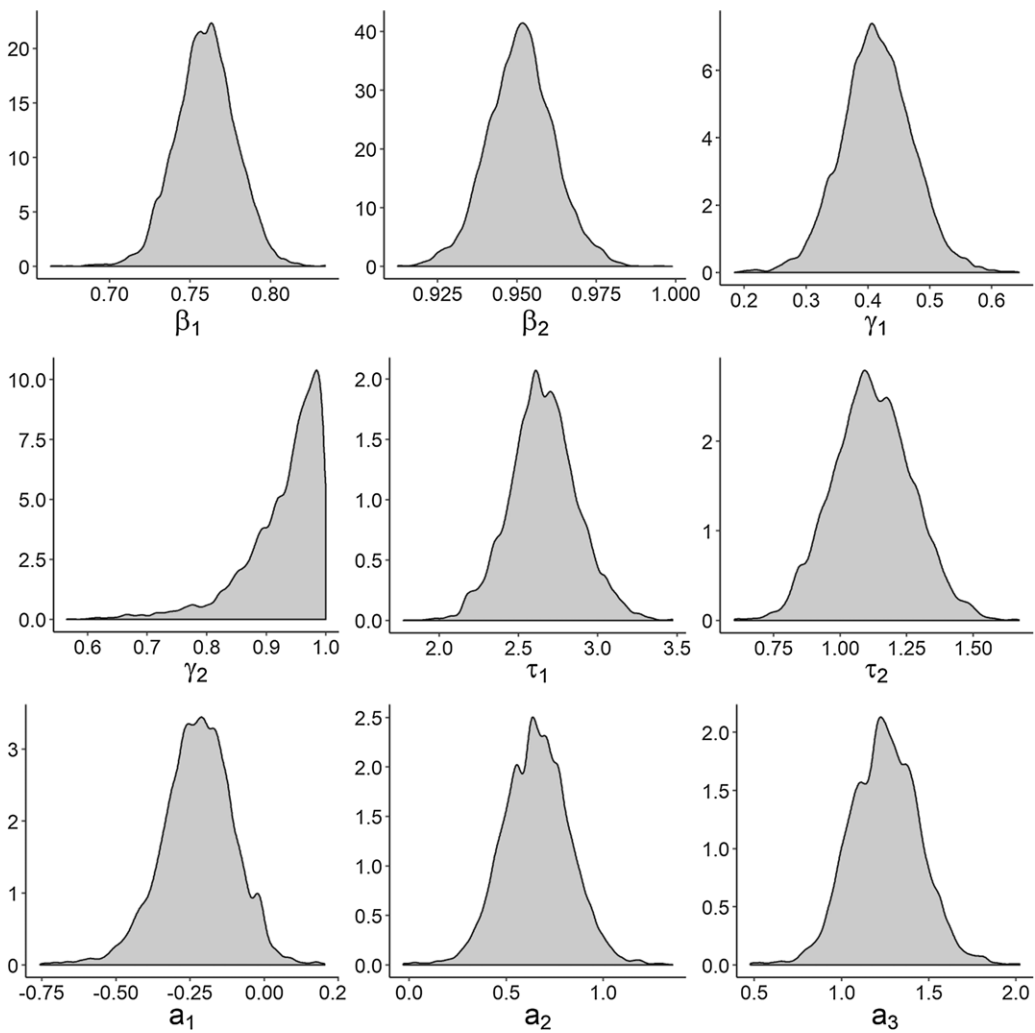


Figure 1. Distribution of parameters, traditional exponential discounting model.

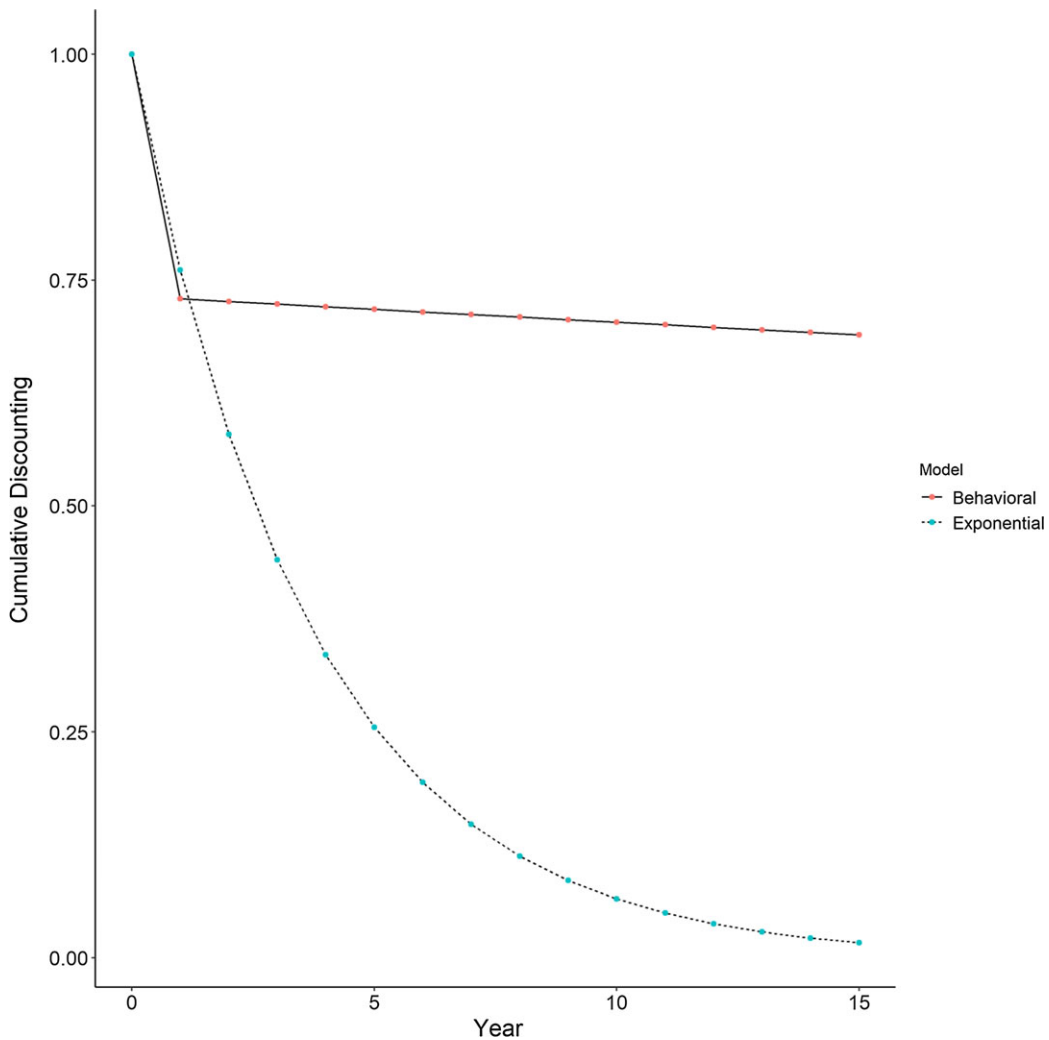


Figure 2. Effect of intertemporal time discounting.

of \$1,000 to replace the existing lawn. We also simulated potential gains and losses relative to current practice ranging from \$0 to \$500.

We conducted a robustness check of the claim that (1) consumers are moderately myopic in the sense that they exhibit present bias that discounts all future values but the exponential discounting values are small and (2) consumers show strong loss aversion by deriving estimates of the same parameters (PSRF, MAP, 2.5 percentile, median, and 97.5 percentile) for sub-samples of participants. The sub-samples were based on age (younger than 65, 65 or older), education (a college degree, no college degree), income (\$50,000 or less, more than \$50,000), and gender (male, female). The results are shown in Table A1 in the Appendix.

The results in Appendix Table A1 support the robustness of the behavioral model with the full sample. We find that the exponential discounting factor is very close to 1 for all subgroups and that future value discounting is generated primarily by present bias. The robustness check shows, for example, that male participants, participants who had obtained a college degree, and participants whose incomes exceeded \$50,000 discounted all future values by 60%–65% relative to

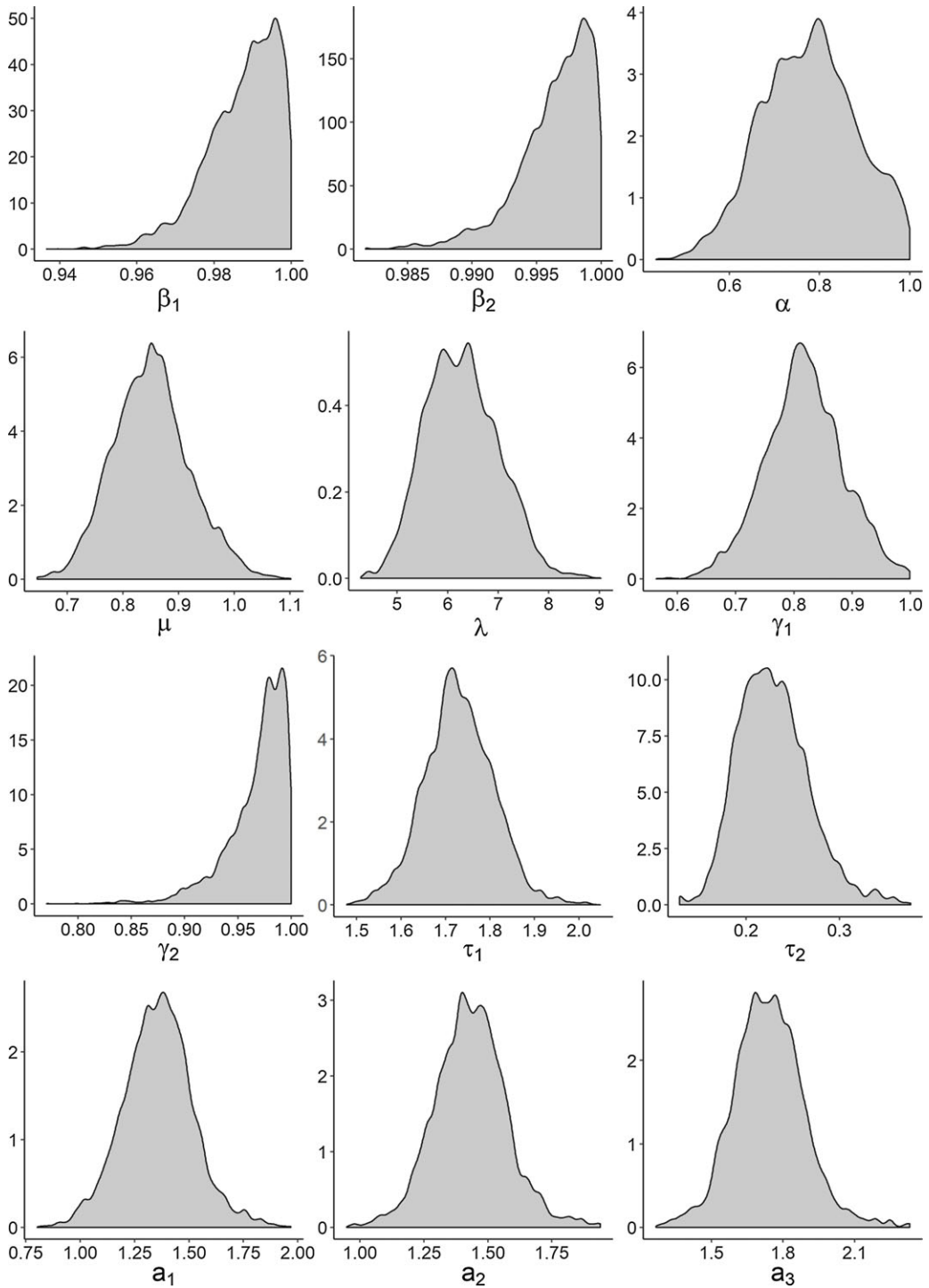


Figure 3. Distribution of parameters, behavioral model.

Table 3. Coefficient summary statistics, behavioral model

	PSRF	MAP	2.50%	Median	97.50%
β_1	1.027	0.996	0.965	0.989	0.999
β_2	1.034	0.999	0.989	0.997	1.000
α	1.017	0.732	0.577	0.779	0.975
μ	1.011	0.830	0.724	0.849	0.994
λ	1.011	5.932	4.983	6.252	7.715
γ_1	1.024	0.813	0.683	0.816	0.947
γ_2	1.029	0.990	0.896	0.976	0.999
τ_1	1.047	1.760	1.578	1.727	1.884
τ_2	1.033	0.227	0.166	0.226	0.315
a_1	1.046	1.272	1.691	1.360	1.035
a_2	1.052	1.331	1.725	1.431	1.158
a_3	1.057	1.633	2.063	1.735	1.451

Table 4. Simulated effect of warranty

Scenario	Observed opt-out probability	Predicted opt-out probability with warranty	Percentage decrease in opt-out probability
1	19.96%	8.01%	59.87%
2	15.83%	6.40%	59.58%
3	9.97%	5.17%	48.18%
4	16.14%	6.21%	61.56%
5	20.29%	7.13%	64.87%
6	17.02%	6.20%	63.57%
7	21.45%	8.80%	58.95%
8	16.59%	6.58%	60.34%
9	12.03%	4.72%	60.76%
10	19.55%	8.97%	54.13%

Notes: Scenario refers to the choice experiment scenarios in which participants were asked to make choices about switching to low-input turfgrass.

present values. The present bias discounts for the other subgroups were smaller. The robustness check further supports the results for the whole sample in terms of loss aversion as the parameters are greater than 4 for all subgroups.

We further analyzed how homeowners valued time saved on maintenance with low-input turf-grasses, which require less mowing. We measured the monetary value of time savings using willingness to pay (WTP), which reflects a homeowner’s tradeoff between a one unit of (discounted) average maintenance time saving and a one unit of monetary cost. The monetary cost would be constant under linear utility. However, because of the nonlinearity of utility in our model, WTP in this case is a nonlinear function of time savings and cost:

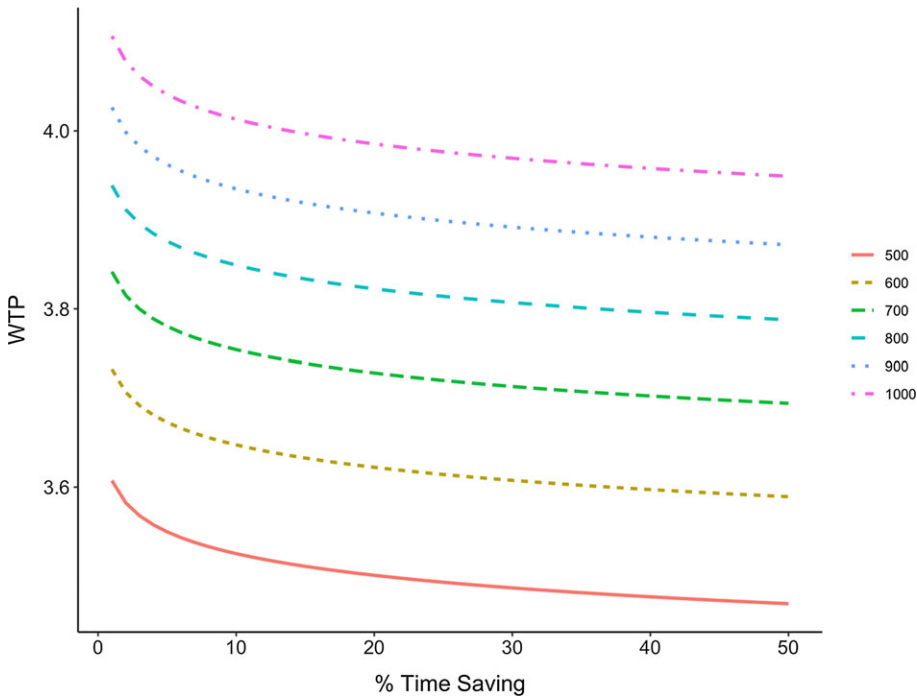


Figure 4. Simulated willingness to pay for time savings, one-time investment rapid adoption.

$$\frac{\partial v_{ij} / \partial \tau}{\partial v_{ij} / \partial c} = \frac{\omega_2 \gamma_2 \sum_{t=T_1+1}^{T_2} \alpha \beta_2^t \tau^{\gamma_2-1} / (T_2 - T_1)}{\omega_1 \gamma_1 \sum_{t=0}^{T_1} \alpha^{1_t > 0} \beta_1^t \lambda c^{\gamma_1-1}} \tag{11}$$

Figure 4 plots participants’ WTP for time savings for different levels of investment and average time savings for the scenarios in which they made one-time upfront investments and completely converted their lawns to low-input turfgrass. Because of decreasing marginal sensitivity, additional WTP to further decrease maintenance time increases the percent maintenance time savings. The simulated WTP values range from \$3.50 to \$4.10 for a 1% increase in time savings.

The probability weighting parameter μ has a MAP of 0.830. In Figure 5, the bold red line plots the estimated probability weighting function and the 45-degree line represents $\mu = 1$. The figure shows that homeowners’ subjective perceptions of probability diverge only slightly from the 45-degree line.

6. Discussion and Conclusions

Technologies such as fuel-efficient cars, solar photo-voltaic panels, and low-input turfgrasses for lawns are cost-effective ways to improve the health of consumers and the environment. Despite their many benefits, however, many of these technologies have failed to take hold in the market with actual adoption rates far below the economically efficient level (Greene et al., 2009). Technology adoption typically requires an upfront expense in exchange for long-term future returns, so it is crucial to understand how consumers weigh such intertemporal costs and benefits. Additionally, new technologies, by definition, are not yet proven and can fail to deliver the expected benefits. And, as outlined in the introduction, numerous studies have shown that consumers do not necessarily behave according to predictions by expected utility frameworks. Consequently, to promote adoption of environmentally friendly technologies, we must consider

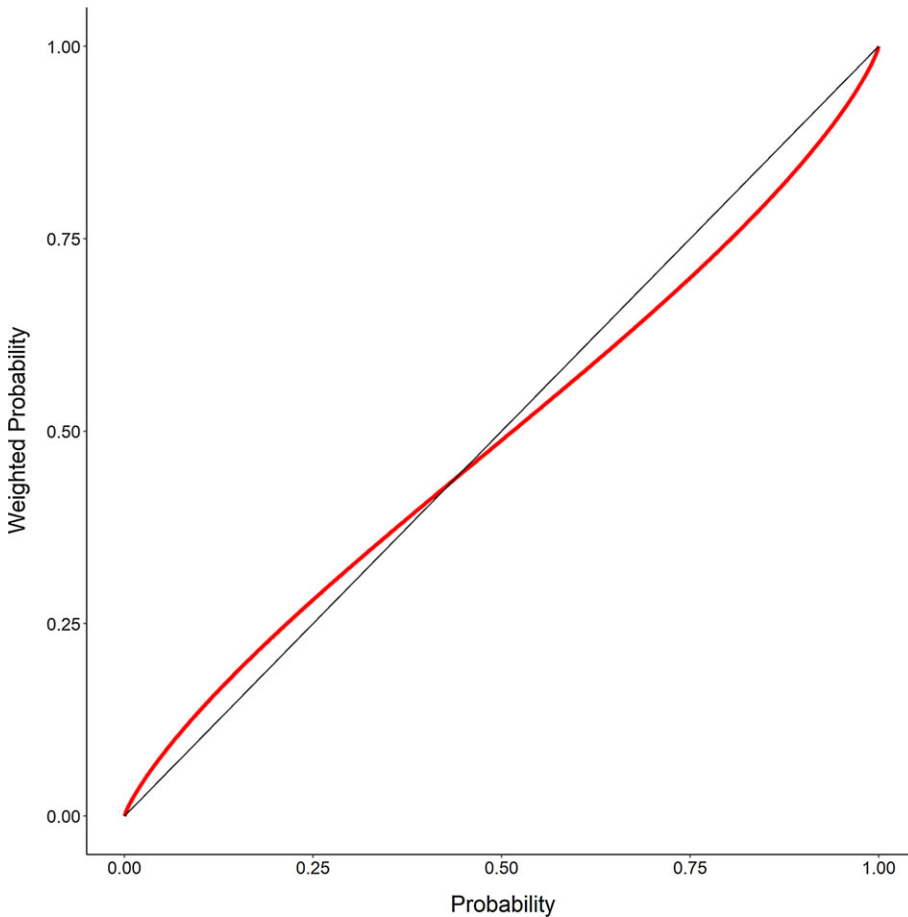


Figure 5. Probability weighting function.

alternative models such as prospect theory. We designed a choice experiment that simulated consumer decision-making and explicitly accounted for tradeoffs between an upfront investment cost and potential future gains and losses under uncertainty and present bias.

The empirical results of this study lead to two important conclusions. First, though households' decisions are influenced by present bias, the long-term benefits of a new technology still matter. The results of our behavior model suggest that, after taking present bias (73%) into account, participants' long-term discounting of future values is moderate. Those results directly contradict the results from the non-behavioral exponential discounting model, which showed that consumers discounted future values at 76.1% per year. We therefore find that estimation using only exponential discounting is misleading and overstates consumers' present-bias myopia.

The second important conclusion is that loss aversion plays a significant role in rates of technology adoption. We find that consumers weigh a loss almost six times more than the same amount of gain. Our estimates are higher than those of earlier studies (Liu, 2012; Tanaka, Camerer, and Nguyen, 2010; Tversky and Kahneman, 1992) that mostly evaluated participant responses to small investments in lotteries. Our results suggest that consumers, when making complex decisions, weigh potential losses more heavily than when they make simpler decisions. Consumers' strong loss aversion combined with the fact that turfgrass is a relative new product result in consumers' overestimation of adoption cost and reduced adoption incentives. Low-input

turfgrasses not only save consumers' expenditures on home lawns but also benefit the environment due to the low water, fertilizer, and pesticide use. Consumers' reluctance in adoption will likely result in losses in both private welfare and social welfare.

The insights generated by our behavioral model suggest that marketing efforts and government programs designed to promote new technologies should focus on eliminating or reducing barriers associated with potential losses. A warranty that would cover all or part of the cost of investing in a new technology that fails, for example, could significantly increase adoption of the technology.

Additionally, approaches such as warranties could be much less costly in the long run than reducing the amount of the upfront investment. Consider a \$1,000 investment at $t = 0$ that saves \$300 per period, has a probability of success of 90% over 15 periods, and requires only \$350 to repair problems that have a 10% probability of occurring. We can simplify the scenario further by assuming that all consumers are risk neutral and setting the probability weighting parameter at 1. This investment would not be profitable since $\sum_{t=1}^{15} 0.732^{1(t>1)} * 0.996^{t-1} (300 * 0.9 - 5.932 * (1 - 0.9) * 350) = 725.80$ and would require a subsidy (to reduce of the upfront payment) of \$274.20 to break even. This simple example is in line with the argument by Greene (2011) that a profitable investment in a new technology can be perceived as unprofitable by loss-averse consumers. However, the investment in this example can be made attractive to those consumers by providing a warranty that covers as little as \$40 of the repair cost: $\sum_{t=1}^{15} 0.732^{1(t>1)} * 0.996^{t-1} (300 * 0.9 - 5.932 * (1 - 0.9) * (350 - 40)) = 1001.88$. The warranty would induce an expected cost much lower than \$274.20 ($\$40 * 16 * 0.1 = \64) without discounting. We, therefore, find that policies designed to reduce gaps between economically optimal technology adoption rates and actual adoption rates should focus on mitigating consumer uncertainty rather than reducing the upfront cost through rebates and subsidies.

The potential limitation of our approach is that in the context of technology adoption, particularly when the technology is expensive or not widely available on the market, it is difficult to incentivize choice experiments with actual purchase (Lusk, Norwood, and Pruitt, 2006) or draw binding scenarios (Yue and Tong, 2009). Thus, our choice experiment-based approach is potentially subject to hypothetical bias. However, a recent meta-analysis by Penn and Hu (2018) found that a choice experiment effectively mitigates hypothetical bias.

Also, this study primarily focused on capturing consumers' rationales in intertemporal cost-benefit evaluation when making technology adoption decisions. There are likely other factors at play when it comes to the adoption of low-input turfgrass. For instance, consumers' preference for the esthetic features of turfgrass, the perceived effort in switching to new turfgrass, and the availability of low-input turfgrass in local stores could also affect the adoption of low-input turfgrass. Residual factors associated with consumers' preferences, such as esthetic features and perceived effort, should be captured by the alternative constant term as a whole in our model, while market factors, such as availability, are likely not captured by our experiment design.

The choice experiment design in this study will not capture all the barriers preventing the adoption of low-input turfgrass. There are various factors that can potentially affect consumers' decision-making, for instance, financial literacy (Boogen et al., 2021; Brent and Ward, 2018) and numeracy (Peters et al., 2006). However, insights into consumer's cost-benefit tradeoffs under uncertainty should be helpful in policy and marketing strategy designs.

Data Availability Statement. The data were collected by the authors. The data will be made available upon reader request.

Author Contributions. Conceptualization, C. Y., Y. L., and E. W.; methodology, C. Y. and Y. L.; formal analysis, Y. L. and C. Y.; data curation, C. Y.; writing—original draft, Y. L.; writing—review and editing, C. Y., E. W., A. P., and R. B.; supervision, C. Y.; funding acquisition, E. W., C. Y., A. B., and R. B.

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Competing Interest Statement. None.

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Appendix

A.1. Choice Experiment Design

In the choice experiment design, the only attribute depending on the alternatives is the per-period cost. The other attributes—percentage time savings, potential loss or gain, and the probability of gain—do not depend on the alternative label. Each alternative’s per period cost was set to have three levels, that is, high, medium, and low. However, since options A, B, and C have different transition periods, we set different cost values for high, medium, and low to reflect the real-world situations and avoid the case where one option dominates all other options (for example, the option of switching to low-input grass all at once with the lowest cost is not realistic and such an option would dominate other options). With the assumption of risk neutral and probability weighting parameter as 1, the choice experiment design is not much different from the conventional choice experiment design. We explain the design process in detail as follows.

The choice experiment design was based on the optimization of D-efficiency. Since the D-efficiency design for discrete choice is nonlinear, we need to assume the parameter initial values. We assume that consumers are risk neutral and that the probability weighting parameter equals 1. Then, equations (4) and (5) in the paper collapse to an additive form of

$$U_j = b_{1j}\tau_j + b_{2j}c_j + b_{3j}p_jg_j - b_{4j}l_j - b_{5j}p_lj$$

In the above equation, j is the index of options. Here are the factors in the design: τ is the time savings, c is the cost, p is the probability of gain, g is the potential gain value, and l is the potential loss value. Given the above linear form of the utility function, the design is not much different from a conventional choice experiment design.

Each factor has three levels (high, medium, low), and Options A, B, and C always correspond to transition periods 0 years, 2 years, and 3 years, respectively. Without prior information, we assumed that there is no difference in participants’ preferences for Options A, B, and C or the factor levels. We then assigned a prior guess to each of the parameters in the above equation as the initial value. Lastly, the design was determined by maximizing D-efficiency, i.e.,

$$[|\Omega|^{1/K}]^{-1}$$

where K is the number of parameters in the model, and Ω is the variance–covariance matrix. The D-efficiency maximization was implemented via Stata command “dcreate.” The final design consists of 1 block of 10 scenarios.

Table A1. Coefficient summary statistics, behavioral model by age, education, gender, and income subgroups

	PSRF	MAP	2.50%	Median	97.50%
Sample: Age ≥ 65					
β_1	1.077	0.948	0.893	0.947	0.988
β_2	1.096	0.995	0.984	0.995	1.000
α	1.053	0.862	0.495	0.755	0.963
μ	1.029	1.002	0.780	1.029	1.319
λ	1.073	5.044	4.189	5.000	6.162
γ_1	1.052	0.869	0.595	0.807	0.978
γ_2	1.038	0.979	0.814	0.948	0.996
τ_1	1.079	1.603	1.460	1.695	1.954
τ_2	1.067	0.310	0.238	0.317	0.438
α_1	1.058	-1.173	-1.755	-1.152	-0.732
α_2	1.027	-1.239	-1.744	-1.174	-0.756
α_3	1.021	-1.483	-2.040	-1.426	-0.958
Sample: Age < 65					
β_1	1.081	0.997	0.976	0.991	0.999
β_2	1.052	0.998	0.979	0.994	1.000

(Continued)

Table A1. (Continued)

	PSRF	MAP	2.50%	Median	97.50%
α	1.036	0.736	0.538	0.765	0.949
μ	1.019	0.753	0.648	0.746	0.873
λ	1.065	5.908	4.398	5.427	6.572
γ_1	1.039	0.763	0.594	0.732	0.864
γ_2	1.043	0.977	0.889	0.948	0.996
τ_1	1.060	1.768	1.657	1.822	2.036
τ_2	1.055	0.254	0.184	0.260	0.369
a_1	1.076	-1.610	-1.933	-1.497	-1.132
a_2	1.077	-1.714	-1.952	-1.666	-1.325
a_3	1.077	-2.076	-2.315	-2.031	-1.668
Sample: Some college and below					
β_1	1.047	0.994	0.976	0.991	0.999
β_2	1.071	0.999	0.980	0.994	1.000
α	1.086	0.976	0.580	0.825	0.987
μ	1.032	0.653	0.602	0.714	0.850
λ	1.052	5.482	4.656	5.568	6.855
γ_1	1.068	0.751	0.639	0.799	0.937
γ_2	1.095	0.981	0.886	0.951	0.997
τ_1	1.093	1.753	1.596	1.804	2.045
τ_2	1.022	0.209	0.214	0.261	0.324
a_1	1.092	-1.192	-1.767	-1.340	-1.016
a_2	1.080	-1.362	-1.774	-1.416	-1.101
a_3	1.079	-1.725	-2.147	-1.747	-1.411
Sample: College degree and higher					
β_1	1.016	0.965	0.905	0.958	0.992
β_2	1.060	0.998	0.986	0.996	1.000
A	1.066	0.646	0.385	0.635	0.903
μ	1.074	0.930	0.780	1.018	1.316
λ	1.055	4.384	3.862	4.943	6.059
γ_1	1.015	0.697	0.478	0.684	0.870
γ_2	1.045	0.961	0.886	0.957	0.998
τ_1	1.023	1.729	1.533	1.717	1.959
τ_2	1.060	0.344	0.230	0.335	0.478
a_1	1.096	-1.425	-2.053	-1.557	-1.111
a_2	1.086	-1.563	-2.190	-1.695	-1.308
a_3	1.075	-1.862	-2.534	-1.995	-1.596
Sample: Female					

(Continued)

Table A1. (Continued)

	PSRF	MAP	2.50%	Median	97.50%
β_1	1.043	1.000	0.965	0.989	1.000
β_2	1.049	0.998	0.986	0.995	1.000
α	1.029	0.835	0.643	0.839	0.980
μ	1.026	0.760	0.702	0.794	0.896
λ	1.045	6.519	5.353	6.274	7.455
γ_1	1.052	0.857	0.735	0.841	0.953
γ_2	1.027	0.971	0.874	0.963	0.998
τ_1	1.083	1.735	1.572	1.736	1.908
τ_2	1.070	0.211	0.175	0.220	0.274
a_1	1.048	-1.384	-1.695	-1.329	-0.955
a_2	1.044	-1.482	-1.791	-1.441	-1.107
a_3	1.044	-1.839	-2.178	-1.783	-1.440
Sample: Male					
β_1	1.099	0.977	0.931	0.971	0.998
β_2	1.054	0.996	0.971	0.992	1.000
α	1.094	0.606	0.389	0.603	0.909
μ	1.054	0.970	0.696	0.950	1.245
λ	1.075	4.573	3.156	4.232	5.360
γ_1	1.054	0.722	0.463	0.681	0.913
γ_2	1.021	0.970	0.819	0.932	0.996
τ_1	1.050	1.791	1.564	1.820	2.166
τ_2	1.083	0.366	0.241	0.371	0.503
a_1	1.028	-1.531	-2.038	-1.381	-0.721
a_2	1.043	-1.488	-1.989	-1.367	-0.821
a_3	1.055	-1.639	-2.254	-1.541	-1.006
Sample: Income \leq \$50,000					
β_1	1.041	0.965	0.943	0.970	0.995
β_2	1.042	0.998	0.982	0.995	1.000
α	1.036	0.890	0.678	0.870	0.996
μ	1.043	0.684	0.620	0.722	0.871
λ	1.076	5.305	4.257	5.589	7.041
γ_1	1.046	0.664	0.543	0.674	0.814
γ_2	1.037	0.982	0.878	0.961	0.998
τ_1	1.059	1.689	1.536	1.768	2.030
τ_2	1.078	0.264	0.179	0.244	0.313
a_1	1.076	-1.499	-1.886	-1.388	-0.842
a_2	1.089	-1.680	-2.014	-1.560	-1.056

(Continued)

Table A1. (Continued)

	PSRF	MAP	2.50%	Median	97.50%
a_3	1.098	-2.153	-2.498	-2.001	-1.499
Sample: Income > \$50,000					
β_1	1.031	0.981	0.967	0.985	0.997
β_2	1.064	0.998	0.987	0.995	1.000
α	1.030	0.599	0.367	0.628	0.870
μ	1.062	0.871	0.762	0.935	1.178
λ	1.049	5.338	4.378	5.585	7.145
γ_1	1.037	0.768	0.612	0.816	0.966
γ_2	1.031	0.990	0.807	0.952	0.998
τ_1	1.079	1.748	1.644	1.779	1.934
τ_2	1.043	0.298	0.213	0.294	0.444
a_1	1.068	-1.521	-1.903	-1.513	-1.146
a_2	1.052	-1.549	-1.871	-1.523	-1.186
a_3	1.055	-1.779	-2.081	-1.739	-1.381

Table A2. Distribution of choices by scenarios

	Opt-out	A	B	C
Scenario 1	13.74%	29.91%	13.28%	43.07%
Scenario 2	12.59%	22.63%	36.26%	28.52%
Scenario 3	10.62%	16.17%	24.13%	49.08%
Scenario 4	15.01%	21.02%	23.33%	40.65%
Scenario 5	16.97%	20.90%	41.80%	20.32%
Scenario 6	17.78%	25.06%	34.53%	22.63%
Scenario 7	20.67%	16.40%	33.37%	29.56%
Scenario 8	15.01%	12.70%	18.48%	53.81%
Scenario 9	12.70%	19.52%	39.26%	28.52%
Scenario 10	16.97%	9.58%	17.44%	56.00%

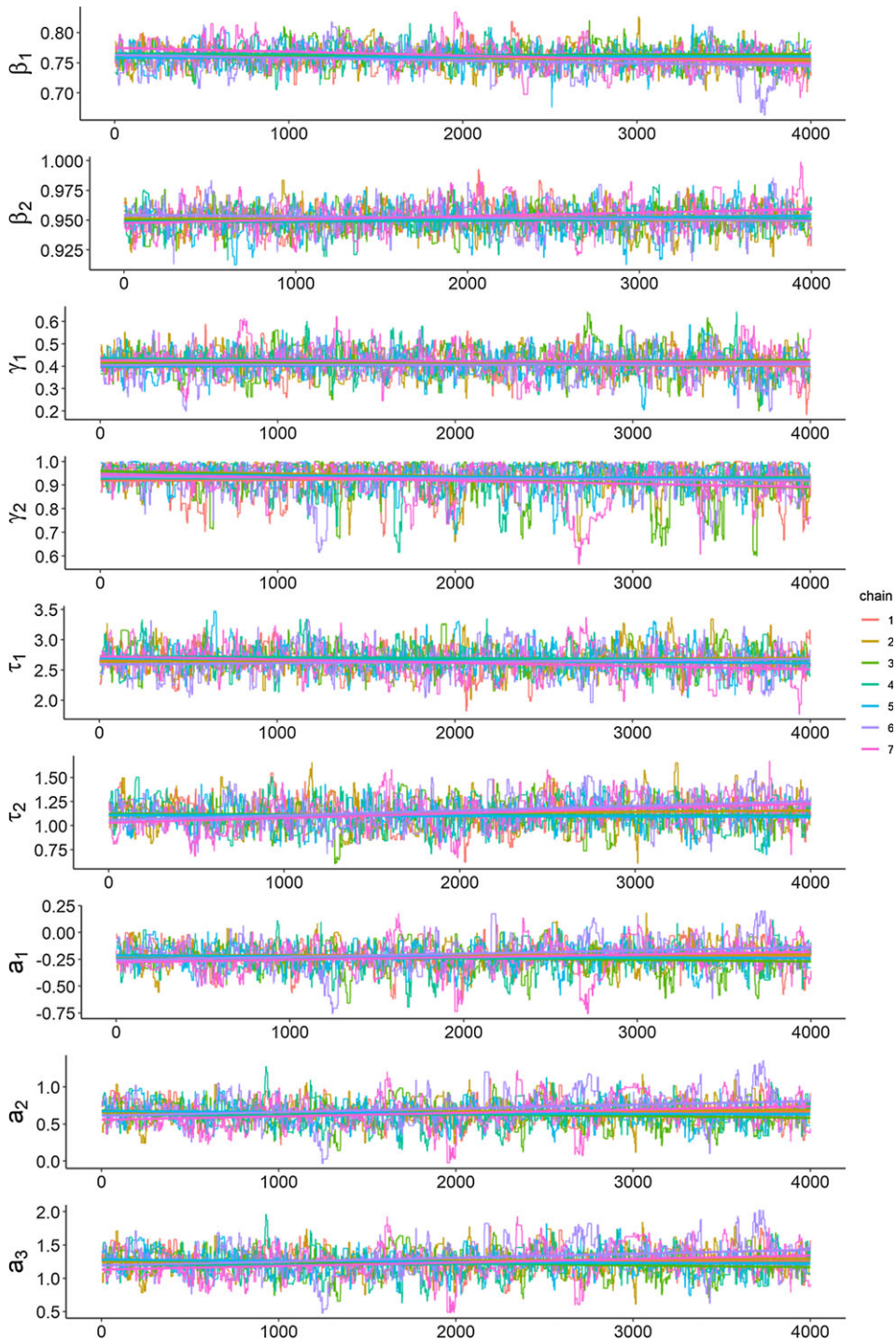


Figure A1. Trace plot of iterations, traditional exponential discounting model.

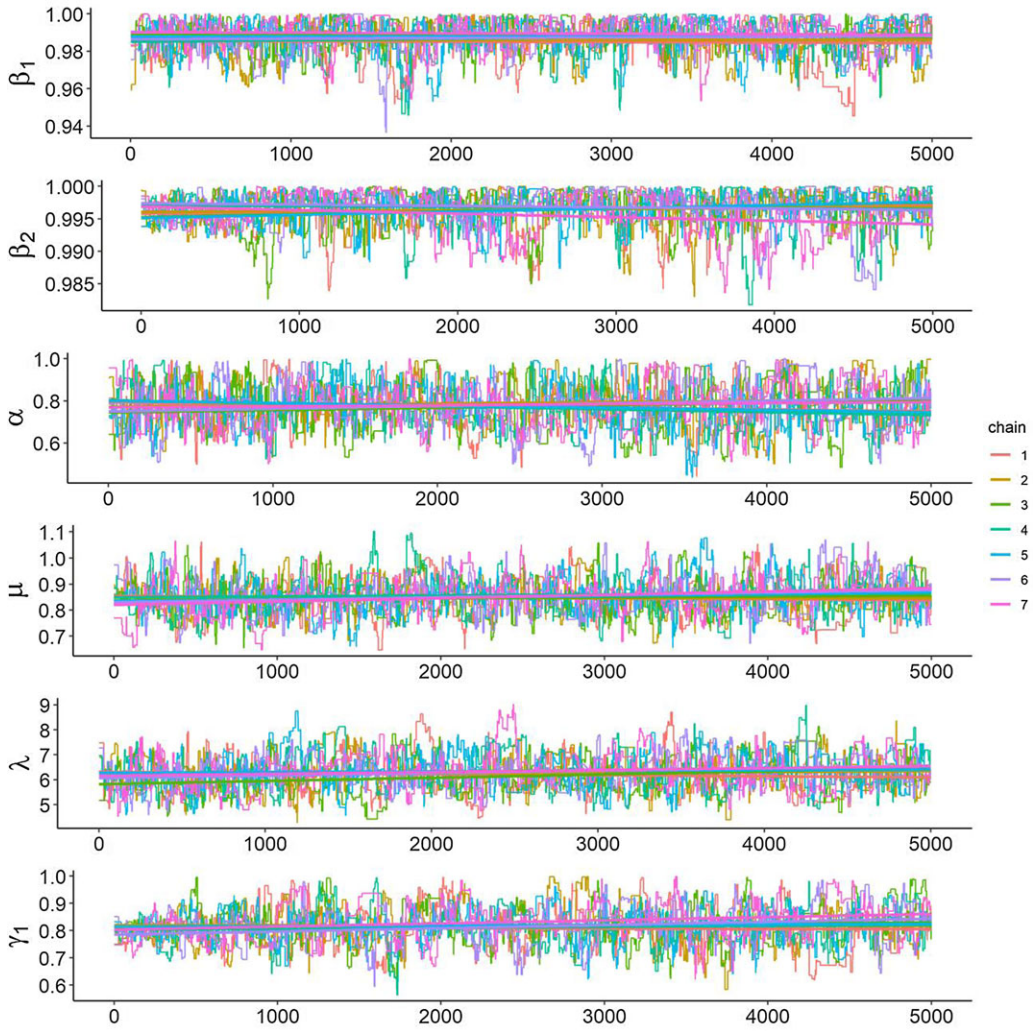


Figure A2. Trace plot of iterations, behavioral model.

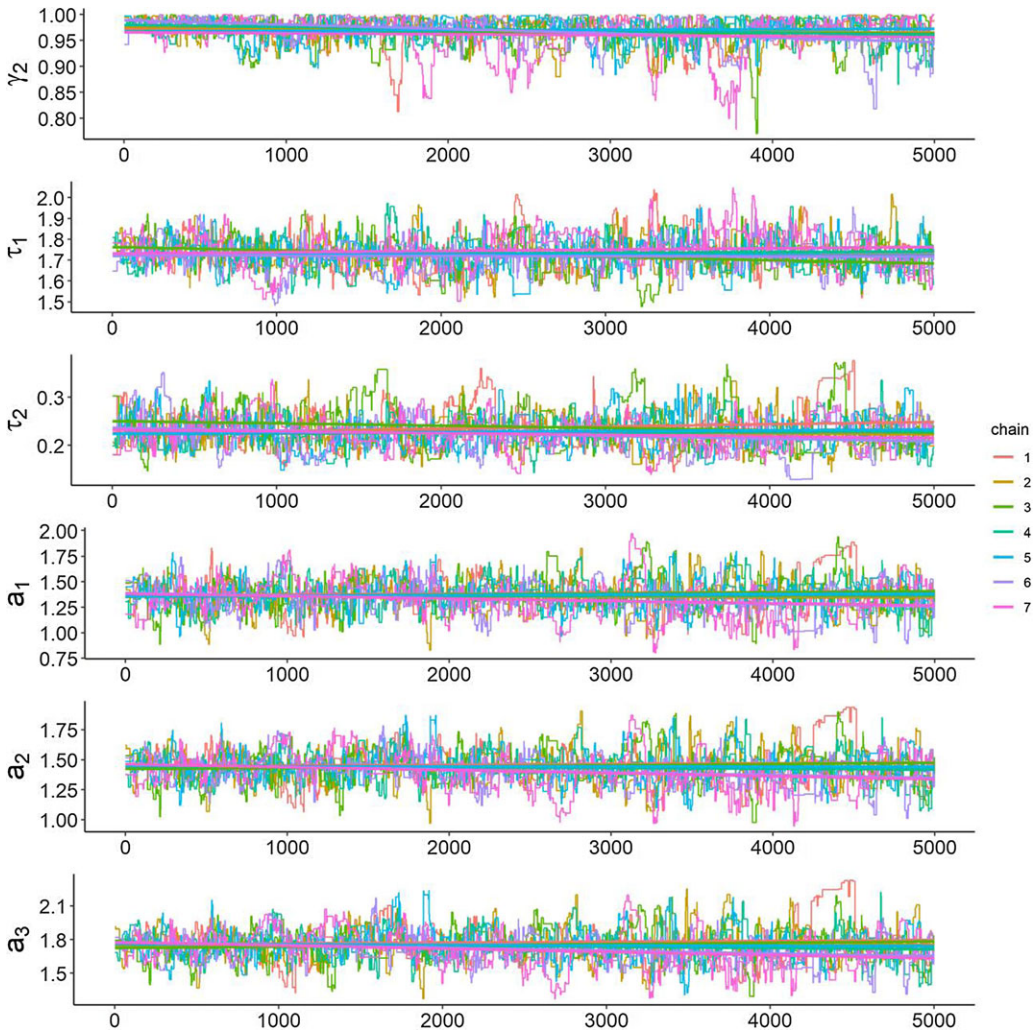


Figure A3. Trace plot of iterations, behavioral model (continued).

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