Three Essays on Individual Choices and Decision Making

A DISSERTATION

SUBMITTED TO THE FACULTY OF

UNIVERSITY OF MINNESOTA

BY

Jingjing Wang

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

Adviser: Chengyan Yue

June 2019

Acknowledgements

First and foremost, I would like to express my great gratitude to my advisor, Prof. Chengyan Yue, for her guidance, encouragement, patience, and advice throughout the journey of my Ph.D. Without her unwavering support and nurturing, I would not have completed my thesis, gained research experience, and most importantly found my research interests in consumer economics and behavioral economics. I'm extremely grateful to Prof. Terrance Hurley, Prof. Metin Cakir, and Prof. Adam Rothman for being my committee members and providing helpful comments and great advice on my thesis proposal and final draft. I would also like to thank Prof. Eric Watkins and Prof. Brian Horgan for their valuable input for the survey design in the third chapter. I want to thank the staff in the department of applied economics for their support and assistance.

I would like to extend my sincere thanks to my friends in APEC program: Donghui Wang, Shuoli Zhao, Huichun Sun, Yanghao Wang, and Bixuan Sun, for listening, supporting, giving advice and leaving me many treasured memories. I would not have completed my Ph.D. without support from my families. Thanks to my mother, Ms. Yuqing Wei and my father Mr. Xin Wang, for their unconditional love and support. I greatly appreciate my mother-in-law, father-in-law, for always being there to support my study and my life. I would like to thank my husband, Bin Zang, for supporting me and encouraging me to get through difficulties during my treacherous Ph.D. journey, and in my life. Great thanks to my wonderful daughter, Zoe, for being my first reader and for all the happiness and joy she brings to my life.

Dedication

This dissertation is dedicated to my parents

for their love, support, and endless encouragement.

Abstract

Economists in different fields have been developing theoretical models and conducting experimental studies to understand how people are making decisions over various products and different domains. The first essay explores how individual choices may change over time and differ across multiple domains. This study also shows evidence for domain-specific temporal discounting and suggests that consumers are generally more impatient for health rewards but more patient for environmental rewards. The second essay aims to explore which models, the traditional temporal discounting models, or machine learning models, can better predict individuals' intertemporal choices. Results suggests that some machine learning algorithms, for example, random forest, have better prediction powers compared to the temporal discounting models. Although machine learning method sometimes suffer from overfitting problems, it may have the potential to give more accurate predictions for individual choices when the training data have enough information on individual previous choices or behaviors. The third essay examines how information framing and consumers' neighborhood attachment impact their product choices. In particular, the product we focus on is low-input turfgrass. We find the presence of environmental impact information in the choice experiment has impacts on homeowners' preferences for low-input turfgrass. We also find the homeowners' neighborhood attachment affects their lawn maintenance behavior.

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Chapter 1 Introduction

This dissertation contains three essays in the broad theme of decision-making analysis and explores individual choices and preference over time, over various goods in multiple domains, and over different attributes of a specific product. The first essay in this dissertation focuses on the consumers' intertemporal time reference over different rewards. Extensive studies in behavioral economics and psychology have investigated individual intertemporal decisions in multiple domains and tried to explain how temporal discounting affect individual judgment or choices over time. Based on experimental data, this chapter investigates the variations in individual temporal discounting for financial and non-financial (health and environmental) rewards. It is found that the estimated long-run discount rates are generally larger for health outcomes and smaller for environmental rewards. With a quasi-hyperbolic discounting model, both observed and unobserved individual heterogeneities were identified in the discount parameters. Personal characteristics, such as age, education, income, and risk perceptions, have significant impacts on time discount factors, but the impacts differ across domains. Furthermore, several nonfinancial behavioral choices are only significantly associated with present bias parameters in the corresponding domains. Individuals more patient for future environmental rewards are more willing to purchase organic, sustainable, and local products. In other words, temporal discounting are domain-specific and discount factors for monetary rewards may not provide enough predictive information for behavioral choices in nonfinancial domains.

The second essay systematically compares the model performance of temporal discounting models and supervised machine learning algorithms when predicting individuals' intertemporal choices based on known factors. Though temporal discounting models have been widely used to explain intertemporal choices for decades, some recent studies suggested that simple heuristic models may outperform traditional utility discounting models. This study uses cross-validation approach to assess the out-of-sample predictive accuracy of intertemporal choices. Results from this study suggest that ML algorithms, for instance, random forest and neural network, outperform the traditional temporal discounting models when the training and testing sets include similar subjects. However, ML algorithms suffer from overfitting problems. In particular, random forest have less accurate predictions when the testing set contains new sample with subjects totally different from those in the training set. This study demonstrates the predictive power of ML algorithms when our goal is to predict individuals' intertemporal choices based on their previous choices and background information, but the selection of best prediction method should depend on our goal of prediction and the dimension of data.

The third essay investigates homeowners' preferences for turfgrass traits and explored the framing effects and neighborhood effects on consumer preferences. Recently, there is growing concerns of environmental problems caused by excessive resources homeowners put on residential lawn. Several studies have examined the consumer preferences for residential turfgrasses; however, little is known about how homeowners may react when they were provided with information on the potential environmental consequences when making choice decisions to purchase turfgrasses. This study examines the possible framing effects and found evidence that homeowners may willing to pay more for less fertilization required turfgrass cultivars, and also willing to get lower appearance when they were presented with environmental consequences, compared to those presented with personal costs. Moreover, neighborhood attachment and neighborhood rules also have significant impacts on the preferences for the maintenance attributes.

Chapter 2 Domain-specific Temporal Discounting for Non-financial Rewards - An Experimental Analysis

2.1 Introduction

Many economic decisions involve time preferences with delayed outcomes. The tendency that individuals lower the subjective value of future outcomes is often referred to as temporal discounting. As a result of temporal discounting, a consumer might choose a smaller and more immediate reward over a larger but delayed reward (Myerson and Green 1995; Chapman and Elstein 1995). The discounted utility model assumes that people make rational tradeoffs between immediate and delayed outcomes based on a constant discount rate (Samuelson 1937). Under the time-consistent time preference assumption, individual intertemporal choices are independent of the time future outcomes occur. Recent studies revealed that instead of being a constant, temporal discount rate decreases over time. In particular, measured discount rates for longer delays are lower than those for shorter delays (Lahav, Benzion and Shavit 2011). The tendency to favor the immediate alternatives, also called impulsivity or temporal myopia, is more in line with the quasi-hyperbolic discounting model (Laibson 1997).

Studies in behavioral economics and psychology have investigated the intertemporal decisions in multiple domains. A commonly used assumption is that a single discount rate, usually elicited using financial rewards, can measure individual preference for future outcomes in different domains (Viscusi, Huber and Bell 2008; Richards and Hamilton 2012). Some research, however, has shown that the temporal discounting may vary across different domains and it is inappropriate to use one general measure of time preference for all situations (Chapman and Elstein 1995; Chapman 1996; Hardisty and Weber 2009). Domain specificity was found across financial and nonfinancial domains (Chapman 1996; Hendrickx and Nicolaij 2004). Several recent studies (Ubfal 2016; Tsukayama and Duckworth 2010) even suggested there exist good-specific discount rates, where individuals are more impatient for some goods than others.

Extensive studies tried to explain how temporal discounting affect individual judgment or choices over time. Discount factors elicited from the financial domain are often applied to explain non-financial behavioral choices. Previous studies discussed how discount factors affect individual behaviors in health domain such as smoking and drinking (Odum and Rainaud 2003; Bickel and Marsch 2001; Richards et al.1999; Harrison et al. 2010), physical activities (Kosteas 2015), and health outcomes such as obesity (Richards and Hamilton 2012; Scharff 2009; Courtemanche, Heutel and Mcalvanah 2014). Other researchers investigated temporal discounting of environmental outcomes such as deterioration in air quality, improvement in water quality and green space (Hardisty and Weber 2009; Viscusi et al. 2008; Richards and Green 2015). Environmentally friendly behaviors include more than resource conservation actions. Individuals can be eco-friendly by easily consuming locally grown products, which, compared to national-scale food, have lower life-cycle energy use and less GHG footprint (Brodt et al. 2013; Coley, Howard and Winter 2009); the external environmental benefits of organic food products and sustainably grown products (produced in environmentally friendly method) are also greatly valued by consumers (Rousseau and Vranken 2013). One of the previous studies suggested that individuals consume organic foods for both future-based benefits and present values (Gad Mohsen and Dacko 2013).

To our knowledge, only a few research investigated the differences of temporal discounting across health, environmental and financial domains. Hardisty and Weber (2009) found no significant differences in the discount parameters of financial and environmental outcomes, but health gains were discounted more than monetary and environmental gains. Their paper compared the average subjective value of the discount factor across domains and valence (gains vs. losses). A more recent study by Barile, Cullis, and Jones (2018) further confirmed the existence of both domain and valence effects of time preference with hypothetical gains and losses in these three domains. They also found that intrinsic motivation elicited from environment conservation actions have impacts on the differences between discount rates in different domains. Compared to those with lower environmental morale, people with high environmental morale are more "impatient" to take actions to conserve the environment. These previous studies, however, did not account for individual differences and the possible heterogeneity when comparing time discount factors across domains.

The main contributions of the present study to intertemporal preference literature are fourfold. First, this paper systematically investigates the discount rate of time preferences implied from three separate domains (health domain, financial domain, and environmental domain) for different time delays. Second, based on a quasi-hyperbolic discounting model, this study estimates both long-run and short-run discount factors and compares the estimated parameters across domains. Third, both observable and unobservable individual heterogeneities are controlled in our empirical model of temporal discounting in financial and non-financial domains. Furthermore, we test whether discount factors implied from nonfinancial rewards, compared to financial discount factors, have more significant correlations with the behavioral choices in the corresponding domains.

The remainder of this paper proceeds as follows. Section 1 describes the background of temporal discounting in non-financial domains. Section 2 and section 3 present the experiment method and econometric specifications. Section 4 summarizes the experimental data and discusses estimation results. Section 5 concludes.

2.2 Backgrounds

Many studies suggested that impatient individuals are more likely to be involved in impulsive behaviors which may cause poor health (e.g., obesity and smoking) (Richards and Hamilton 2012). Controlling for the concavity of the utility function, Harrison et al. (2010) found that male smokers have significantly higher discount rates than male non-smokers, but it is not necessarily true for females. Ikeda et al. (2010) suggested that BMI is positively associated with impatience and hyperbolic discounting. Atmadja et al. (2017) also found discount rate negatively related to preventive health behaviors (for example, treat their water, wash hands before eating to mitigate health threats from water pollution) in India. Other studies found that present bias plays crucial roles in explaining the relationship between time preferences and health behaviors. Using

NLSY79 data, Courtemanche et al. (2014) investigated a quasi-hyperbolic discounting model and found both long-run discount factor and present-bias predict BMI, suggesting obesity partly results from both rational intertemporal tradeoffs and time inconsistency. Richards and Hamilton (2012) also suggested that intertemporal discount function is quasi-hyperbolic in shape and found that obesity and drinking positively correlated with individual discount rates. Fang and Wang (2015) found evidence of both present bias and naivety when women are making decisions on taking mammography.

Several studies compared intertemporal time preference across health and financial domains. Chapman (1996), for example, found discount rates to be domain-specific across health and financial domains even when the utility function was taken into account. In Read and Read (2004), poor health was proven to be unrelated to discounting for monetary rewards but related to discounting of a vacation reward. Lawless et al. (2013) suggested that discount rates for health are higher than those for money for both social and private rewards. With the presence of experimental data, Bleichrodt et al. (2016) found temporal discounting for health rewards deviates more from exponential discounting compared to monetary rewards, suggesting that time preferences are domain-specific.

Environmental goods, such as air pollution and water quality, often have long-run effects on human health. The cost and benefit of most environmental goods are far away in the future, and environmentally friendly behaviors may impact multiple generations. Given that the environmental outcomes are mostly in the distant future, Weitzman (1998) argued that the discount rates applied to benefits and costs should be near zero. Several studies comparing subjects' rate of time preference also suggested that temporal discounting is less pronounced for environmental goods compared to goods in other domains, but still above zero (Gattig and Hendrickx 2007; Hendrickx and Nicolaij 2004; Richards and Green 2015). Using a utility-based choice experiment, Viscusi et al. (2008) found that the rate of time preference is more in line with hyperbolic discounting. Richards and Green (2015) compared estimates of subjects' intertemporal time preference for environmental and financial rewards and found discount functions significantly different across domains; only environmental goods are discounted in a hyperbolic pattern. Their finding suggested that empirical discount rates are different for environmental goods and financial rewards not simply because of the sign and magnitude effects but also the domain effect. Nevertheless, Ioannou and Sadeh (2016) suggested that individuals' time preferences are not significantly different across environmental and financial domains.

With the conflicting evidence on temporal discounting across domains, we seek to determine how time preference for monetary and non-monetary rewards differ by investigating the individual heterogeneity and testing for domain specificity.

2.3 Experimental Methods

Subjects in our sample were recruited through an online survey in 2015 by Qualtrics™ across the United States. To elicit an individual's time preference, we adopted the multiple price list (MPL) designed by Coller and Williams (1999), Holt and Laury (2002) and Harrison, Lau and Williams (2002). In order to compare discount factors elicited from different domains, all subjects answered two scenarios of MPLs- one financial scenario and one non-financial scenario. Subjects were randomly selected to complete one out of two scenarios of non-financial MPLs (the hypothetical rewards are square feet of park improvement for the environmental domain, or treatment with different days of relief from chronic back pain for the health domain). Although a few previous studies questioned the use of hypothetical rewards in experiment of temporal discounting and argued that individuals are more impulsive for hypothetical rewards than real rewards (Kirby 1997; Hinvest and Anderson 2010), a number of recent research suggested that hypothetical rewards can be a good proxy for real rewards in time discounting studies (Johnson and Bickel 2002; Locey, Jones and Rachlin 2011).

In the financial MPL, subjects were presented with a set of hypothetical choices between receiving a smaller reward sooner (for example $200 in 1 month) or a larger reward later (values higher than $200 in 6, 12, 18, and 24 months). One example of MPLs is shown in Table 2.1. Following the experiment protocol of Harrison, Lau and Williams (2002), each participant was presented with two future reward options instead of one "instant reward" option and one future reward option, which is to control for the front-end-delay effect (Anderson and Mellor 2008). Using the MPL approach, we expect participants to find one specific reward value they would like to receive at a delayed time when comparing to the sooner base amount (for example, $200 of financial reward) in one month, where the respondents switched from choosing the more present reward to the more delayed reward. The chosen future reward value is considered as the indifference value to the sooner reward, from which we can calculate the discount rate for the future reward. In this study, we use the indifference values of time and reward pair for statistical analysis. To control for the possible magnitude effects, we ask each subject to complete MPLs with three starting points ($150, $200, and $250).

In the environmental MPLs, subjects were given instructions to think about a situation where their local government is trying to make improvements in local parks, and they were asked to imagine themselves as a representative resident choosing between options of park improvement levels at different time frames. By suggesting that the improvement of each square feet costs a certain amount of money in the survey instruction, the environmental rewards are comparable to monetary rewards. In the environmental scenarios, each subject completed MPL questions with three starting points 30, 40, 50 square feet of park improvement, corresponding to $150, $200, $250 rewards in the financial domain.

As for MPLs in the health domain, subjects were asked to imagine that they were suffering from moderate pain or discomfort from chronic back pain. They were presented with two alternative treatments, the sooner treatment will deliver pain relief for specific days (for example 40 days) starting in one month, or pain relief for longer days starting in 6, 12, 18, and 24 months. Several studies used treatments of back pain relief as health rewards to measure the time preference in the health domain (Attema et al. 2018; Bleichrodt et al. 2016). Instead of following the experimental design to measure willingness to wait for a particular treatment as in Bleichrodt et al. (2016), we used MPLs to present different treatments with shorter or longer back pain relief and asked the subjects to choose for the indifference values for different delays. To anchor the subjects' beliefs on the non-monetary rewards, we suggested that the cost for each treatment is $150, $200, and $250 for 30, 40, 50 days of back pain relief, respectively.

After finishing the questions of MPLs, the subjects were then asked to complete a series of questions related to their health and environmental behavioral choices and socio-demographic questions.

2.4 Empirical Model

Assume that each agent is indifferent from a sooner base amount x at time t_0 and a delayed amount y at $t_0 + t$. Based on discounted utility model, assume risk neutrality and linear utility function, the reward-time pair (x, t_0) and $(y, t_0 + t)$ are such that, for each agent i,

$$x = y(x,t)D(t) \tag{1}$$

where x and y represent the values of the sooner (in 1 month) and delayed rewards, respectively; D(t) is the discount function; and t is the time interval between the sooner and delayed rewards.

The implied discount rate (r) for each individual and each question set can be calculated using the following discount function:

$$D(t) = 1/(1+r)^t \tag{2}$$

Previous studies have questioned the exponential discounting model using experimental and field data (Frederick, Loewenstein and O'donoghue 2002; Richards and Hamilton 2012). Some study found that the implied discount rates decline over time and exhibit a present bias. In this study, we followed Laibson (1997) and employed a discount function based on the quasi-hyperbolic discounting model.[1]

$$\mathrm{D(t;\delta,\beta)} = \begin{Bmatrix} 1 & if\ t = 0 \\ \beta \exp(-\delta t) & if\ t > 0 \end{Bmatrix} \tag{3}$$

In equation (3) δ measures the long-run discount factor, and β is the short-run discount factor ($\beta < 1$ indicates the respondent have a present-biased preference). One

[1] We compared across exponential, hyperbolic and quasi-hyperbolic discounting model specifications using maximum likelihood estimation and found quasi-hyperbolic discounting model fit data in all three domains best.

focus of this study is to investigate individual differences in temporal discounting across domains, so we tested if demographic variables are correlated with discount parameters and if the demographic effects are consistent for temporal discounting choices across different domains.

To capture the individual effects, firstly we allow the long-run discount rate (δ) and present bias (β) parameters to be linear functions of observable individual characteristics. The general specification of the empirical model is as follows,

$$x_i = y_i(x,t)\beta_i \exp(-\delta_i t)\,\varepsilon_i \qquad (4)$$

where $\delta_i = \delta_0 + \sum \boldsymbol{\delta_Z}\,\boldsymbol{Z_i}$ and $\beta_i = \beta_0 + \sum \boldsymbol{\beta_Z}\,\boldsymbol{Z_i}$, δ_i and β_i are the discount parameters for each individual i, $\boldsymbol{Z}_i$ represents for demographic variables including age, gender, the presence of children in the household, marital status, education, household size, home location, and household income levels, as well as risk perception; $\boldsymbol{\delta_Z}$ and $\boldsymbol{\beta_Z}$ are the corresponding coefficients. ε_i is lognormally distributed random error. The quasi-hyperbolic model with fixed parameters was estimated using maximum likelihood regressions in Stata.

We also allow the time discount parameters to be random to capture the heterogeneity of responses that are not correlated with observable individual factors, such that $\delta_i \sim N(\boldsymbol{Z_i'}\,\boldsymbol{\delta_Z}, \sigma_\delta)$. The random parameter models were estimated using simulated maximum likelihood (SML) regression in Stata, with 100 Halton draws.[2]

[2] We have tried different numbers of Halton draws, of which draws greater than 100 generated similar estimation results.

2.5 Results and Discussions

Amongst 1000 participants who joined the online experiment, 697 completed the survey were counted as effective responses. 6 observations excluded from further analysis due to incomplete information and multiple switching points, leaving 671 observations for this study.[3]

Table 2.2 shows the summary statistics of the whole sample. The sample included 70% female and 30% male. Participants' age ranges from 18 to 80, and the average age is 46. About 59% of participants had some college or a college diploma, 26% had a high school diploma, and 15% had some graduate school education. More than half of the participants were married, and the average household size was 2 to 3 people per household. Around 30% of our sample had one or more children under age 12. Half of the sample were full-time or half-time employed. The median annual household income was between $35,000 and $50,000.

The elicited discount rates in three domains are presented in Table 2.3, with 6-month, 12-month, 18-month, and 24-month delays, respectively. The average annual discount rates for monetary rewards fall in the range of 0.642 to 0.796. Compared to financial discount rates, the discount rates for environmental improvements are lower, ranging between 0.594 and 0.776. Discount rates for health outcomes are the highest across three domains for each of the four delays, with an average between 0.929 to 1.109. Figure 2.1 also presents the patterns of implied discount rates over time across domains. Generally, participants have the highest discount rates in the health domain, followed by

[3] Responses with multiple switching point were excluded from further analysis. We expect any individual with a time-separable preference has only one switching point for each set of MPL questions (Andersen et al. 2008)

the financial and environmental domain. One consistent finding across different domains is that the discount rates are lower when the delay is longer.

With evidence that intertemporal preference is time-inconsistent for all three domains, we estimated the individual effects on long-run discount rate δ and short-run present bias parameter β based on a quasi-hyperbolic discounting function (as shown in equation 4). Controlling for the individual fixed effects, the average estimated discount rate (δ) and present bias parameters (β) for financial, health and environmental domains are (0.57, 0.89), (0.84, 0.87), and (0.53, 0.89), respectively. The regression results with individual fixed effects are presented in Table 2.4. As the first panel in Figure 2.2 suggests, the average long-run discount rates in financial domain are larger than those in environmental domain, but considerably smaller when compared to those in health domain. The distribution of present bias estimations for financial rewards suggests that the variations (standard deviation) in estimated present bias parameter are quite small, and the majority of respondents are present-biased (with $\beta < 1$). Compared to the short-run present bias parameter for monetary rewards, the present bias estimations for non-financial rewards have more variations. Around 86% and 84% of respondents exhibit present bias in environmental and health domain, respectively.

Table 2.5 presents the regression results when we allow for both observed and unobserved heterogeneities of individual effects on discount parameters. Compared to the fixed parameter models in Table 4, the log likelihood values and AICs improve significantly when the discount parameters were allowed to vary randomly based on individual differences. The standard deviations of the random parameter models are much smaller than the corresponding models in Table 2.4, indicating that there does exist some unobserved heterogeneity in discount parameters, and random parameter models can better capture the relationships between discount parameters and individual characteristics.

As suggested from the results in Table 2.4 and Table 2.5, the estimated long-run discount rates in different domains are affected by individual characteristics such as participants' age, education, income level, and employment status. Participants' age has different effects on long-run discount rates in financial and nonfinancial domains. In the financial domain, younger participants (generation X and generation Y) tend to have a higher discount rate for future monetary rewards. Previous studies also found evidence that younger adults are more impatient. They are more likely to accept a smaller sooner reward rather than a more substantial delayed reward (Steinberg et al. 2009). However, younger generations are more likely to have lower long-run discount rates for health rewards. Compared to baby boomers, long-run discount rates for health rewards are 0.24 lower for generation X (though not significant at 10% level) and 0.19 lower for generation Y (significant at 5% significance level). There is a tendency for older participants to have higher long-run discount rates in the health domain. Elders tend to be more impatient for health improvements. They prefer a sooner albeit small health reward compared to younger generations, which was also found by van der Pol and Cairns (2001).

Participants' household income and employment status have similar effects on long-run discount rates across domains. Employed participants, compared to those retired or unemployed, discount monetary rewards less. As suggested by Green et al. (1996) and Becker and Mulligan (1997), poverty increases an individual's need for immediate income more than future income. Consequently, compared to their poor counterparts, wealthier participants are more patient and discount future financial rewards less.

Compared to high school graduates, respondents with higher education have significantly lower long-run discount rates in financial and health domain, but no significant effects were found in the environmental domain. These results suggest a potential impact of individuals' education on their perceived values of monetary rewards. Previous literature found mixed results when investigating the effects of education on time preferences. While a few suggested that education has no significant impact on discount rate (Hardisty and Weber 2009), many concluded that education does impact time preference (Perez-arce 2017; Becker and Mulligan 1997). Our results provide evidence that schooling improves patience, but the educational effects vary across domains.

People with larger household size are more likely to have higher discount rates for rewards in both financial and health domain. Being married and being a female significantly decrease an individual's long-run discount rate in health domain. While the presence of children in the family decreases long-run discount rate in health domain, it increases the long-run discount rate in environmental domain. A higher willingness to take risks decreases long-run discount rates in non-financial domains (significant at 1% level for the health domain and significant at 10% for the environmental domain). This result suggests that general risk perception influence individuals' long-run time preferences for non-financial rewards. Risk-loving individuals are more likely to be patient for future health and environmental outcomes.

As for the present bias parameter, we found younger generations less present-biased (with larger β) for both financial and health rewards, but more present-biased (with smaller β) for environmental outcomes. Education has mixed effects on the present bias. More educated individuals are more present-biased for financial and environmental outcomes but less present-biased for health improvement. People with higher household income and being employed are less present-biased for health rewards. People with larger household size are more likely to be present-biased in the environmental domain but less likely to be present-biased in the health domain. The presence of children in the household is associated with a larger present bias parameter in the environmental domain. With hypothetical park improvement as the environmental rewards in our study, it is likely that respondents with children are less present-biased because they hope their children can also enjoy the environmental benefit. Risk-loving individuals are less present-biased only for rewards in health domain.

With both long-run discount rate (δ) and present bias parameter (β) estimated for each individual, we tested the correlations between discount factors and individual behavioral choices. Table 2.6 presents the pairwise correlations and coefficients presented are significant at 5% level and a single star indicates the corresponding coefficient is significant at 5% level. We are interested in finding out if non-financial behaviors are correlated with discount factors and how the correlations vary when discount factors were measured using rewards from different domains. The first panel of this table lists the pairwise correlations between individual health status/health behaviors and discount factors for respondents completed questions in both health and financial domains. The second panel presents the pairwise correlations between environmental-related attitudes/behaviors and discount factors for respondents in environmental and financial domains.

In the first panel, we found that poor health status and obesity to be positively and significantly correlated with δ in both financial and health domains. Willingness to purchase, and to pay more for organic food products are negatively correlated with δ in financial and health domains, but positively correlated with β in the health domain. One previous study also suggested that there are two subgroups of organic food consumers, one future-oriented seeking for their future health rewards and welfare, and the other present-based caring about their immediate consumption benefit (Gad Mohsen and Dacko 2013). Physical exercise, exercising for more than three times a month, are negatively correlated with long-run discount rates in both financial and health domains. Interestingly, physical exercise is found to be negatively correlated with present bias parameter (β) elicited from financial rewards, but positively correlated with β in the health domain. People who are less present-biased for health rewards tend to exercise more. These results indicate that individuals in good health, who often exercise and care about their food consumption patterns tend to have smaller long-run discount rates. The long-run discount factors measured in both financial and health domains can capture part of the correlations between health behaviors and time preferences.

Nevertheless, we found the present bias for health rewards significantly correlated with health behaviors, suggesting that some health-related behaviors are also associated with short-run self-control. Less present-biased people, who care more about future selves, tend to rate themselves as healthier and pay more attention to exercise and eating. This finding is in line with previous studies on consumers' temporal discounting behaviors in drug or alcohol use which concluded that addicted individuals might be more myopic (Ainslie 1975; Bickel et al. 1999). When making tradeoffs between current rewards (for example, gratifications from consuming unhealthful products) and future health outcomes, myopic individuals tend to ignore future outcomes.

As shown in the second panel, long-run discount rates for financial rewards are negatively correlated with environmental behaviors such as recycle and donate. Financially present-biased individuals are more likely to recycle, which may be because most of the recycling behaviors save some money immediately. However, the long-run financial discount factors are not correlated with behaviors that may only result in environmental cost or benefits in the future. Long-run environmental discount rate, on the other hand, is negatively correlated with behaviors such as willingness to purchase organic food product, willingness to pay more for sustainably grown food products, local and sustainably grown plants. In other words, those who are more patient to wait for larger future environmental improvement are willing to take environmentally friendly actions. These results, however, different from Barile et al. (2018) that people with high environmental morale is more impatient to conserve the environment.

Some mixed results were found for the present bias parameter in the environmental domain. For instance, we found β in environmental domain negatively correlated with the tendency that one will pay more for sustainable products, but positively correlated with the likelihood of purchasing bee-friendly plants and donating to some environmental organization. People who are more present-biased for environmental rewards (with lower β) are less likely to donate or buy bee-friendly plants. While most environmental-friendly behaviors may not lead to instant benefits, they may, however, be strongly associated with the long-run discount factor in the corresponding domain.

In general, long-run financial discount rates are significantly correlated with most health behaviors and some environmental behaviors, the present-biased parameters, however, are not significantly correlated with most of the individual choices. The significant correlations between health behaviors and the present bias parameters suggest that a number of health behaviors are correlated with the impulsivity. Some previous research did not find domain specificity across similar domains, for instance, for different environmental goods (Ioannou and Sadeh 2016). In this study, both the long-run discount rate and present bias parameters in nonfinancial rewards are strongly associated with behavioral choices in the corresponding domain. In short, we find evidence for domain specificity in temporal discounting for nonfinancial outcomes.

2.6 Conclusion

This paper investigates individuals' temporal discounting patterns for rewards from multiple domains. We use experimental data to test if individuals' discount parameters are related to personal characteristics and whether or not financial discount factors can be good proxies to explain non-financial behavioral choices. Applying the quasi-hyperbolic discounting model, we examine if the individual effects on discount parameters differentiate across domains. While several previous studies compared time preferences in financial, environmental, and health domains, the present study focuses on estimating and comparing time discount factors when individual specificities are controlled. Compared to discount factors for private rewards (health outcomes) and public rewards (environmental improvement), we tested whether or not financial discount factors are correlated with nonfinancial behavioral choices.

One of the most significant findings in this study is that individual time preferences are neither consistent over time, nor across domains. With our survey data, the quasi-hyperbolic discounting model can best explain intertemporal choices in all three domains. Previous research on time preference only used the discount rate for monetary rewards as a proxy to measure the time preference for environmental outcomes (Viscusi et al. 2008) and health outcomes (Richards and Hamilton 2012). Our study suggests that one universal discount rate for different domains is neither enough nor appropriate, which may potentially lead to bigger bias. The implied discount rates are generally larger for health outcomes and smaller for environmental rewards. Thus, by applying a quasi-hyperbolic discounting model, we found that the estimated long-run discount rates vary significantly across the financial and non-financial domains. Furthermore, variations in the present bias parameters in non-financial domains are more prominent compared to the financial domain.

There are both observed and unobserved individual heterogeneities in the discount parameters. Personal characteristics, such as age, education, income, and risk perceptions, have significant impacts on time discount factors, but the impacts differ across domains. In general, people with lower long-run discount rates in all three domains are wealthier, more educated, and more likely to be currently employed. Older consumers tend to have higher discount rates for health rewards while lower discount rates for financial rewards. We also found evidence that younger generations are less present-biased for financial and health rewards.

Meanwhile, long-run discount parameters for financial rewards are significantly correlated behavioral choices in most nonfinancial domains, but the present bias parameters for financial rewards are merely correlated with behavioral choices in non-monetary domains. Several behavioral choices are only significantly associated with discount parameters in the corresponding domain. In other words, temporal discounting for nonfinancial rewards are domain-specific, and discount factors for monetary rewards may not provide enough predictive information for behavioral choices in nonfinancial domains.

Previous studies estimated discount rates ranging from negative to several thousand percent per year for environmental outcomes and researchers are uncertain about which discount rate to use (Frederick, Loewenstein and O'Donoghue 2002; Weitzman 2007). Time discount rates for health outcomes also vary significantly depending on the delay of illness or health improvement, as well as the severity of the health outcomes (Chapman and Elstein 1995; Chapman 1996; Van Der Pol and Cairns 2000; Chapman 2001). Therefore, it is helpful for policymakers to understand the domain-specific temporal discounting for nonfinancial outcomes and distinguish the time discount factors for different future rewards.

Our results provide some important implications for environmental organizations, policymakers as well as individual consumers. Individuals who are less impatient for environmental rewards are more likely to make environmentally friendly choices. Educational advertisements should put greater emphasis on long-term beneficial returns of environmentally friendly behaviors. Eco-friendly behaviors can be reframed in financial terms to attract more individuals to act on long-term intentions. Promotional strategies similar to those used in LED light bulbs (providing the estimated cost and savings compared to traditional light bulbs) are also applicable for other environmentally friendly products, such as water-saving technologies/devices and energy-efficient appliances (e.g., smart home device). Meanwhile, it is critical to encourage society to build up more sustainable communities and inform the public on how environmentally positive actions can add up to significant changes for the future of the environment.

The long-run discount rates of health outcomes are most predominant in the three domains, which implies that consumers discount more on future health outcomes compared to outcomes in other domains. Health improvement in the future is discounted and valued so little that many individuals may not engage in preventive behaviors. Additionally, the present bias in the health domain is associated with all health-related behaviors discussed in this study. Awareness of detrimental effects of temporal myopia in one's health can help individuals fix their self-control problems and help them make better health-related decisions, such as avoiding overconsumption, eating healthy, and receiving preventive healthcare services.

One limitation of our study could be the gap between simulated experiments and real-world scenarios, where in reality people may make different choices as they do in hypothetical situations. However, previous research comparing temporal discounting of real and hypothetical monetary rewards found no differences when controlling for magnitude (Baker, Johnson and Bickel 2003; Kirby 1997). Given the cross-sectional data and the complex nature of intertemporal choices and behaviors, we cannot make conclusions on the direction of causality between time preferences and individual behaviors. However, we found evidence that temporal discounting is domain specific.

Time preferences vary significantly across financial and nonfinancial rewards, and there exist domain-specific components of time discounting behaviors. Therefore, it is useful to distinguish the discount factors across different domains.

Table 2.1. An Example of Monetary Time Preference Experiment

Payoff Alternative	Payment Option A (Receive the amount below in 1 month)	Payment Option B (Receive the amount below in 6 month)	*Annual Interest Rate* *(In percentage)*	*Annual Effective Interest Rate* *(In percentage)*	Preferred payment option (Choose A or B)
1	200	202	*2*	2.018	A or B
2	200	204	*5*	5.116	A or B
3	200	208	*10*	10.471	A or B
4	200	213	*15*	16.075	A or B
5	200	217	*20*	21.939	A or B
6	200	226	*30*	34.489	A or B
7	200	236	*40*	48.213	A or B
8	200	255	*60*	79.586	A or B
9	200	276	*80*	116.943	A or B
10	200	298	*100*	161.304	A or B
11	200	317	*116*	202.619	A or B
12	200	332	*128*	237.444	A or B
13	200	345	*139*	272.556	A or B

14	200	384	*167*	377.581	A or B

Note:

1. The reward options are in US dollars for financial domain. The MPLs for the other two domains have similar form, where the payoffs are park improvement and days of pain relief instead of dollar values.

2. The reward with one-month delay is used as the base level.

3. The columns in grey, showing the annual interest rate and annual effective interest rate, were not shown to participants.

Table 2.2. Summary Statistics of Participants' Background Characteristics (n=671)

Variable	Description of Variables	Mean	(Std. Dev.)
Age	Participant's age	46.181	(16.280)
Female	1 if female; 0 if male	0.704	(0.457)
Married	1 if participant is married; 0 otherwise	0.538	(0.499)
Children	1 if participant has one and more children under 12 years old in the household; 0 otherwise	0.291	(0.455)
High school	1 if participant has a high school diploma; 0 otherwise	0.260	(0.439)
College	1 if participant has some college experience or a college diploma; 0 otherwise	0.590	(0.492)
Graduate	1 if participant has some graduate school experience or a graduate degree; 0 otherwise	0.150	(0.357)
Household Income	Household income of participants in 2014 1 = $15,000 or under 2 = $15,001–$25,000 3= $25,001 - $35,000 4=$35,001 - $50,000 5=$50,001 - $65,000 6=$65,001 - $80,000 7=$80,001 - $100,000 8=$100,000 - $150,000 9=Over $150,000	4.330	(2.274)
Household Size	Number of people in the household	2.587	(1.381)

Employed	1 if participant is full-time or part-time employed; 0 otherwise	0.505	(0.500)
Risk Perception	General risk attitude ranging from 1 to 5, 1 most unwilling to take risks and 5 most willing to take risks	2.927	(1.162)
Poor Health status	Self-rated health status ranging from 1 to 5, 1 is excellent and 5 is poor.	3.352	(0.978)
Obese	1 if participant is obese (BMI greater than 30); 0 otherwise	0.255	(0.436)
Exercise	1 if participant take physical exercises more than three times per month; 0 otherwise.	0.694	(0.461)
Donate	1 if participant ever donated to any environmental organization; 0 otherwise.	0.195	(0.397)
Recycle	1 if participant recycle; 0 otherwise	0.866	(0.341)
Organic Purchase	1 if participant willing to purchase organic food products; 0 otherwise.	0.461	(0.499)
Organic pay more	1 if participant willing to pay more for organic food products; 0 otherwise.	0.650	(0.477)
Sustainable Purchase	1 if participant willing to purchase sustainable plants; 0 otherwise.	0.692	(0.462)
Sustainable pay more	1 if participant willing to pay more for sustainable food products; 0 otherwise.	0.489	(0.500)
Bee-friendly Purchase	1 if participant willing to purchase bee-friendly plants; 0 otherwise.	0.630	(0.483)
Local pay more	1 if participant willing to pay more for local food products; 0 otherwise.	0.593	(0.492)

Table 2.3. Elicited Discount Rates in Three Domains

	Monetary Domain		Environmental Domain		Health Domain	
Time delayed	Mean	(Standard Deviation)	Mean	(Standard Deviation)	Mean	(Standard Deviation)
6 months	0.796	(0.643)	0.776	(0.651)	1.109	(0.661)
12 months	0.695	(0.608)	0.618	(0.570)	0.976	(0.651)
18 months	0.658	(0.580)	0.613	(0.578)	0.945	(0.647)
24 months	0.642	(0.570)	0.594	(0.563)	0.929	(0.633)

Note:

1. Average annual discount rates shown in this table with standard deviations in parenthesis right to the mean levels.
2. 2. The participants were randomly chosen to make choices in MPLs of one non-financial domain (environmental or health domains), and all participants respond to financial MPLs.

Table 2.4. Estimation Results of Quasi-hyperbolic Discounting Model with Individual Effects by Domains _ with Discount Rate as a Fixed Parameter

	Financial Domain		Health Domain		Environmental Domain	
	delta	beta	delta	beta	delta	beta
Female	0.034	-0.016	-0.107	-0.142	-0.139*	-0.081*
	(0.808)	(0.849)	(1.003)	(1.411)	(1.901)	(1.805)
Generation X	0.092*	-0.027	-0.236	-0.065	-0.013	-0.020
	(1.722)	(1.162)	(1.344)	(0.386)	(0.156)	(0.386)
Generation Y	0.103*	0.026	-0.192*	0.073	-0.031	0.029
	(1.809)	(1.382)	(1.772)	(1.159)	(0.326)	(0.539)
Married	0.015	0.008	0.050	0.005	0.092	0.105
	(0.326)	(0.410)	(0.554)	(0.072)	(1.004)	(1.307)
Kids	0.092	0.003	-0.006	-0.012	0.015	-0.088
	(1.511)	(0.150)	(0.052)	(0.185)	(0.147)	(1.187)
College	-0.033	0.003	0.027	0.029	0.073	0.033
	(0.645)	(0.155)	(0.290)	(0.429)	(0.888)	(0.582)
Graduate	-0.167**	0.002	-0.222	-0.045	-0.138	-0.009
	(2.525)	(0.091)	(1.540)	(0.476)	(1.328)	(0.128)
Household Income	-0.044***	0.005	-0.011	0.022	-0.035*	-0.018
	(4.112)	(0.963)	(0.241)	(0.482)	(1.942)	(1.141)

Household Size	0.027	-0.001	0.056	0.033	-0.015	0.010
	(1.432)	(0.078)	(1.504)	(1.152)	(0.582)	(0.707)
Employed	-0.104**	-0.005	-0.189	-0.114	-0.024	0.079
	(2.276)	(0.273)	(1.013)	(0.577)	(0.320)	(1.366)
Risk attitude	0.004	0.006	-0.015	0.035	0.013	0.040
	(0.228)	(0.633)	(0.424)	(1.560)	(0.373)	(1.278)
_cons	0.662***	0.864***	1.092***	0.744***	0.729***	0.801***
	(7.820)	(22.096)	(5.911)	(5.370)	(5.369)	(9.998)
SD	0.672***		0.743***		0.681***	
	(57.673)		(50.261)		(41.980)	
AIC	1694.774		1646.690		1002.278	
Log lik.	-822.387		-798.345		-476.139	
N	8052		3924		4124	

Note:

1. Absolute t statistics in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

2. The base group is single male respondents age greater than 56 in 2015 (baby boomers) with high school education, and no kids.

Table 2.5. Estimation results of Quasi-hyperbolic Discounting Model with Individual Effects by Domains _with Discount Rate as a Random Parameter

	Financial Domain		Health Domain		Environmental Domain	
	delta	beta	delta	beta	delta	beta
Parameters						
Mean	0.761***	0.521***	1.470***	0.356***	0.863***	0.696***
	(8.614)	(12.597)	(52.962)	(28.693)	(13.190)	(20.816)
SD	0.958***		0.994***		0.934***	
	(118.236)		(83.099)		(65.344)	
Individual characteristics						
Female	0.071	0.022	-0.060***	0.043***	-0.048	-0.077***
	(1.577)	(0.998)	(4.249)	(5.047)	(0.907)	(3.421)
Generation X	0.095**	0.035	-0.124***	0.001	-0.066	-0.086**
	(2.036)	(1.335)	(9.833)	(0.190)	(1.129)	(2.383)
Generation Y	0.041	0.083***	-0.293***	0.082***	-0.057	-0.022
	(0.751)	(2.896)	(20.637)	(9.681)	(1.011)	(0.467)
Married	0.006	0.004	-0.040***	-0.030***	0.013	0.020
	(0.147)	(0.177)	(3.811)	(3.385)	(0.265)	(0.538)
Kids	0.035	-0.010	-0.079***	-0.057***	0.119*	0.080**
	(0.542)	(0.331)	(5.335)	(4.707)	(1.916)	(2.520)

College	-0.035	-0.051**	-0.001	0.008	0.060	-0.058**
	(0.612)	(2.166)	(0.096)	(1.239)	(1.392)	(2.092)
Graduate	-0.152**	-0.079***	-0.173***	0.122***	-0.091	-0.121**
	(2.211)	(2.644)	(9.989)	(8.484)	(0.870)	(2.481)
Household Income	-0.049***	-0.006	-0.018***	0.004***	-0.013	0.001
	(5.182)	(1.391)	(7.164)	(2.848)	(1.518)	(0.327)
Household Size	0.045**	0.015	0.061***	0.006**	-0.034**	-0.019***
	(2.430)	(1.280)	(19.317)	(2.342)	(2.174)	(2.828)
Employed	-0.095**	-0.011	-0.104***	0.030***	-0.081*	0.049*
	(2.151)	(0.487)	(5.135)	(4.432)	(1.834)	(1.955)
Risk attitude	-0.007	0.003	-0.081***	0.051***	-0.029*	0.003
	(0.375)	(0.314)	(16.635)	(12.351)	(1.837)	(0.388)
SD	0.148***		0.047***		0.118***	
	(11.537)		(6.700)		(4.739)	
AIC	-1674.241		-263.992		-728.051	
Log lik.	863.121		157.996		390.026	
N	8052		3924		4124	

Note: 1. Absolute t statistics in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

2. The results from random parameter models were estimated using simulated maximum likelihood regressions.

3. The base group is single male respondents age greater than 56 in 2015 (baby boomers) with high school education, and no kids.

Table 2.6. Pairwise Correlations Between Individual Behaviors/Attitudes and Discount Parameters in Different Domains

<u>Financial v.s. Health discount factors</u>

	Obese	Exercise	Willingness to Purchase Organic Products	Willingness to Pay More for Organic Products	Poor Health Status
δ_f	0.189*	-0.230**	-0.160*	-0.110*	0.2661*
δ_h	0.195*	-0.230**	-0.218*	-0.166*	0.3041*
β_f		-0.122*			
β_h	-0.198*	0.165*	0.235*	0.176*	-0.222*

<u>Financial v.s. Environmental discount factors</u>

	Recycle	Donate	Willingness to Purchase Organic Products	Willingness to Pay More for Sustainable Products	Willingness to Pay More for Local Products	Willingness to Purchase Bee-friendly Purchase	Willingness to Purchase Sustainable Products
δ_f	-0.139*	-0.110*					
δ_e			-0.126*	-0.115*	-0.101		-0.098
β_f	-0.139*						
β_e		0.104		-0.093		0.110*	

Note: This table shows the pairwise correlations of individual behaviors/attitudes and discount parameters.

Coefficients significantly different from zero at 10% level are displayed in the table and * indicate the corresponding coefficient is significantly different from zero at 5% level.

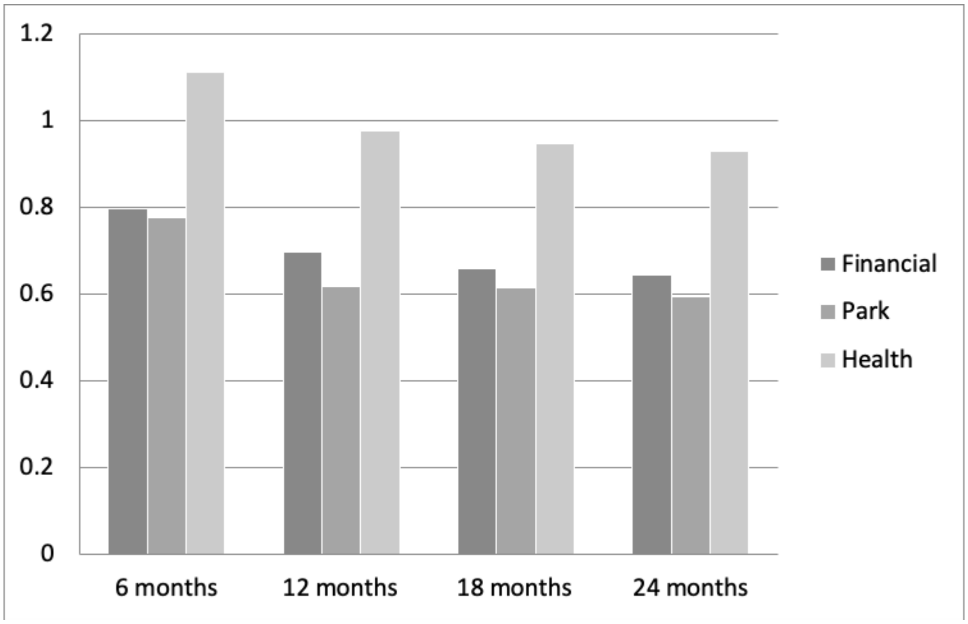

Figure 2.1. Elicited Annual Discount Rates for Different Time Delays

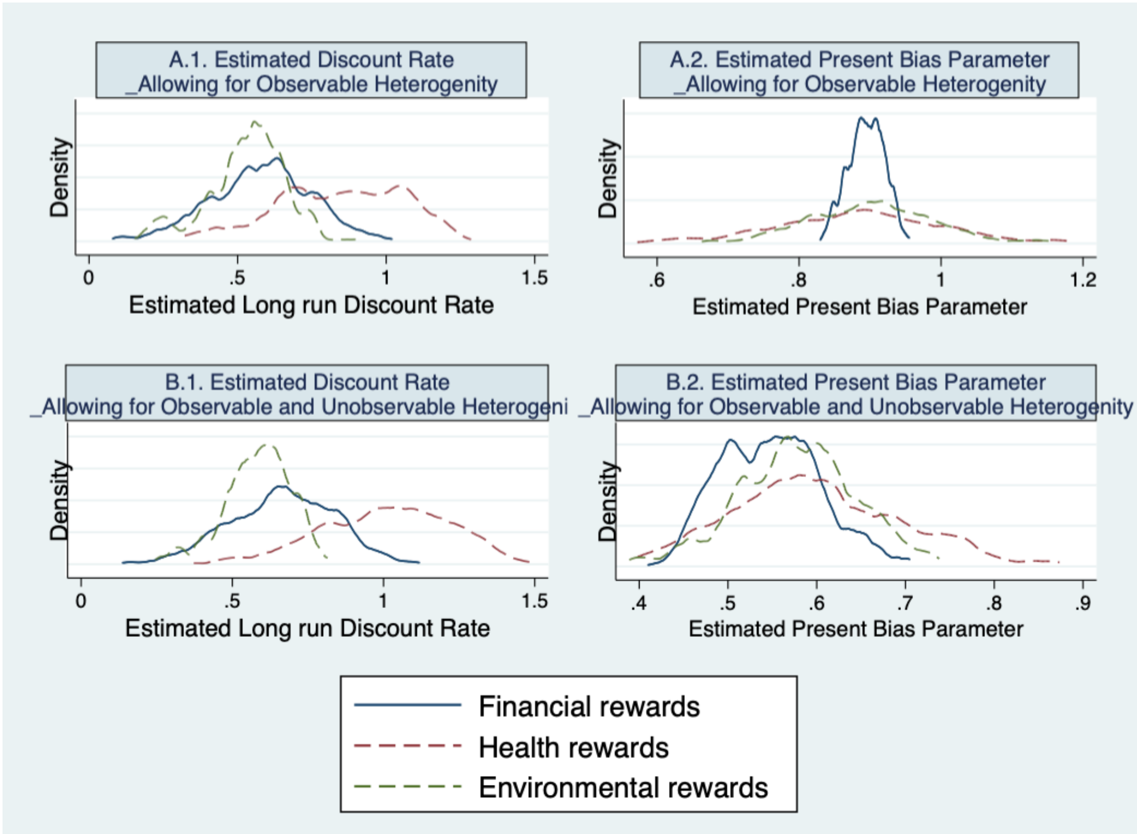

Figure 2.2. Distribution Density of Estimated Long-run Discount Rates and Short-run Present-bias Parameter

Chapter 3 Predicting Intertemporal Choices Using Machine Learning Methods

3.1 Introduction

People make decisions about future outcomes all the time. For example, when choosing between a chocolate cake today and a slimmer waist next week, we are facing a tradeoff between short-term benefits and long-term consequences. Intertemporal choices often involve tradeoffs between smaller-sooner rewards and larger-later rewards (Myerson and Green 1995). Decisions like this could affect individual health, financial outcomes, as well as the economic growth of a society (Frederick et al. 2002).

For decades, empirical research has studied the correlations between intertemporal choices and future consequences extensively and some found time preference varies across individuals. Individuals' socio-demographics, such as education, age, gender, and income level were influential to their intertemporal decisions. For instance, Becker and Mulligan (1997) found more wealth is associated with lower rates of time preference and education lowers time preference; individuals with addictions are more likely to be impatient and present biased (T. Richards and Hamilton 2012). Studies also indicated that younger adults are more impatient (Steinberg et al. 2009). However, there remains a question of how to predict people's intertemporal decisions based on known factors. Specifically, we want to know if time preference can be predicted based on observed intertemporal choices and whether or not specific demographic characteristics can be good predictors for intertemporal discounting behaviors.

To explore these questions, we included three most widely used delayed discounting models: exponential discounting (Samuelson 1937), hyperbolic discounting model (Ainslie 1975), and quasi-hyperbolic model (Laibson 1997; Harris and Laibson 2001). Several studies compared different temporal discounting specifications and estimated the relationship between intertemporal choices and individuals' demographics. Most of these studies focus on estimating and explaining the discount factors using different functional forms and select the best-performed model using R-square or likelihood ratio test (Benhabib, Bisin and Schotter 2010; T. Richards and Hamilton 2012). But the best-fitted models vary significantly depending on different experimental data and various reward domains (Richards and Green 2015). Meanwhile, Cavagnaro et al. (2016) used adaptive design optimization (a computer-based method) to compare different temporal discounting models and found individual heterogeneity in terms of functional forms. Using cross-validation approach, Ericson et al. (2015) compared heuristics models to delayed discounting ones and suggested that heuristic models explain time-money tradeoff better than utility-discounting models.

Different from previous studies, we adopted the method of supervised machine learning (ML) to compare the model fitness and investigate which model explains more variance of intertemporal trade-off. The primary goal of supervised ML is to predict the value of an outcome variable based on a set of input variables (Athey 2017). More specifically, with the observed data divided into training and testing data sets, supervised ML learn a mapping function from the training data and the use the learned function to predict outcomes in the testing data based on corresponding input values. Machine learning techniques such as LASSO, decision trees, and support vector machines allow more flexible relationships than simple linear models and have been proven to be effective in modeling complex relationship (Varian 2014). Over the past decade, the application of data-driven model selection and causal inference by supervised ML methods have attracted growing attentions. Some researchers compared ML algorithms to conventional modeling. For instance, Bajari et al. (2015) compared linear and logit model and six ML algorithms to predict grocery store sales and introduced a combined ML model with the best predictive accuracy. Lusk (2017) compared traditional logit model and classification tree to predict a binary outcome of being a vegetarian, and they found no significant difference in the prediction accuracy across methods for both in-sample and out-of-sample data. In the temporal discounting literature, Stevens and Soh (2018) used machine learning method CART (Classification and Regression Tree) to predict heuristic similarity judgments of reward amount and delays, and they found decision tree algorithm can predict both decision outcomes and response times. However, several studies questioned the effectiveness of ML prediction for forecasting. Carbonneau, Laframboise and Vahidov (2008) used ML methods to forecast demand by at the end of a supply chain and compared these methods with traditional econometrics models, although they found neural networks and support vector machines perform best for the out-of-sample prediction, but their prediction accuracy for new data set was not significantly better than traditional models.

To the best of our knowledge, there is only one existing literature compare the prediction accuracy of machine learning algorithms with other statistical models (Arfer and Luhmann 2015). Their study is focusing on comparing the predictive accuracy of different models, including two machine learning models (random forest and support vector machine), time discounting models (exponential, hyperbolic, and quasi-hyperbolic), and several attribute-based models (difference model and trade off model). Instead of debating on the selection of models, the differences in predictive accuracy is quite small between models. They suggested that a simple difference model outperformed other models.

Our study is different from previous studies in that we systematically tested the difference in predictive powers with different time delays and with different starting reward magnitudes. We tested if different approaches of cross validation will affect the predictive powers for intertemporal choices. Last but not least, we accounted for individual differences in temporal discounting and used socio-demographics as predictors for intertemporal choices.

Specifically, we included respondents' socio-demographic variables and time delay variables as predictors (explanatory variables) in our model to investigate the role that individual characteristics and time difference played in predicting intertemporal choices. We used three ways of validations to test for the predictive accuracy across models. Aside from the commonly used 10-fold cross-validation, we systematically tested the predictive powers when the testing set is selected based on different starting values and different time delays.

The rest of this paper is structured as follows. Section 2 presents the different temporal discounting models and ML algorithms. Section 3 describes the data collection and the cross-validation method. Section 4 summarizes and discusses the prediction results. Section 5 concludes this paper.

3.2 Model Framework

3.2.1 Temporal discounting Models

In our experiment, each agent is asked to make choices between a sooner base amount \$$x$ at time t and a larger delayed reward \$$y$ at $t + \tau$. Based on discounted utility model, any future rewards $y_{t+\tau}$ can be calculated into present values in time t to compare with the sooner rewards. Assuming risk neutrality and linear utility function, the discount function can be denoted by $D(\tau)$,

$$y_t = D(\tau) y_{t+\tau}$$

A logistic function can be used to express the probability that the larger later reward will be chosen over the smaller but sooner reward:

$$P(choice = 1) = P(y_t > x_t) = P(D(\tau) y_{t+\tau} > x_t) = \frac{1}{1+\exp(-\mu(D(\tau) y_{t+\tau} - x_t))} \quad (1)$$

The discount function $D(\tau)$ represent different models we are aiming to compare and will be discussed in the following sections. And the parameter μ is a noise parameter for the logistic regression.

In the time discounting literature, there are three most commonly used time discounting functions: exponential discounting, hyperbolic discounting, and quasi-hyperbolic discounting.

Exponential Discounting

$\mathrm{D(t)}$ represents exponential discounting if

$$\mathrm{D(t)} = \mathrm{e}^{-\delta \mathrm{t}}$$

Hyperbolic Discounting

$\mathrm{D(t)}$ represents hyperbolic discounting (Mazur 1987) if

$$\mathrm{D(t)} = \frac{1}{1 + \delta \mathrm{t}}$$

where δ is the discount parameter ($\delta > 0$).

Quasi-hyperbolic Discounting

Another extensively used time discounting model is quasi-hyperbolic discounting, also called Beta-Delta model:

$$\mathrm{D(t)} = \begin{Bmatrix} 1 & if\ t = 0 \\ \beta\delta^{t} & if\ t > 0 \end{Bmatrix}$$

where β is a factor indicating present bias when $\beta < 1$, and δ is the long-run discount parameter.

Following Andersen et al. (2008) and Richards and Green (2015), we allow discount parameter δ to be a linear function of observable individual demographics.

Instead of estimating δ parameters, we estimated the fixed effects of demographic variables,

$$\hat{\delta} = \hat{\delta}_0 + \widehat{\boldsymbol{\delta}}_{\boldsymbol{z}}\boldsymbol{Z}$$

where $\hat{\delta}_0$ is the estimate of the constant and $\widehat{\boldsymbol{\delta}}_{\boldsymbol{z}}$ is a vector of estimated parameters for demographic effects; $\boldsymbol{Z}$ is a vector of demographic variables, including age, gender, marital status, education, household size, household income, and risk perception.

In the most general form, the basic model is as follows:

$$P(Choice = 1) = \frac{1}{1 + \exp(-\mu(f(Z_i, \tau)y_{t+\tau} - x_t))}$$

where $f(Z_i, t)$ represents different models mapping individual demographics and time delays to the present value in a sooner time. For the delayed discounting models, $f(\boldsymbol{Z_i}, t) = D(\boldsymbol{Z_i}, t; \delta, \beta)$ and D(.) represents different temporal discounting models. Three different model specifications for delayed discounting were estimated using non-linear least squares in Stata, we use cluster options to control for individual specific effect.

3.2.2 Logistic Regression Model

With binary choices as the dependent variable, we first used a logistic model as a base for prediction, and the model specification is as below,

$$\Pr\,(choice_i = 1|\boldsymbol{X_i}) = \frac{\exp\,(\boldsymbol{\beta X}_i)}{\sum_{j \in I} \exp\,(\boldsymbol{\beta X}_j)}$$

where is $\boldsymbol{X}_i$ is a vector of variables including magnitudes, time delays, together with individual demographic information, with associated parameters $\boldsymbol{\beta}$. The dependent variable a binary variable y indicating the choice of later larger reward.

3.2.3 Supervised Machine Learning

3.2.3.1 Linear classification through Support Vector Machine (SVM)

In supervised machine learning, classification method is often used to deal with discrete outcomes. The following supervised machine learning methods are all nonparametric algorithms. Support vector machine is a penalized method of regression, which maps the input variables onto a m-dimensional feature space using linear (or nonlinear) mapping and with a regression model $f(\boldsymbol{X})$ (Hastie, Tibshirani and Friedman 2001). The SVM minimizes

$$\min_{\beta} \sum_{i=1}^{n} V(y_i - f(\boldsymbol{X})) + \frac{\lambda}{2} |\beta|^2$$

and the loss function is:

$$V_\epsilon(r) = \begin{cases} 0 & \text{if } |y - f(\boldsymbol{X})| < \epsilon \\ |y - f(\boldsymbol{X})| - \epsilon & Otherwise \end{cases}$$

where ϵ is the tuning parameter that controls which error term to be included in the regression.

3.2.3.2 Neural Network Model

A neural network is an algorithm with a network of neurons where each neuron has many input signals representing the actives at the input (Benediktsson, Swain and Ersoy 1990; Byvatov et al. 2003). In other words, neurons are created from linear combinations of the inputs and the outcome variable is modeled as a function of these neurons. With a two-class classification the neural network model can learn a non-linear function approximation for classification $f(\boldsymbol{X})$. A decision function is determined by choosing appropriate weights for the neural network by minimizing an error function. The error function for a two class (y=1/0) classification can be written as below,

$$E = \sum_{i=1}^{n} \left(y - f(\boldsymbol{X})\right)^2$$

3.2.3.3 Random Forest

Random forest (Breiman 2001) starts from drawing bootstrap sample from the training data and grows trees by randomly selecting variable set at node level for splitting, then recursively split the explanatory variables for each terminal node of tree until reaching the minimum node size. The process is repeated across B trees to form a random forest. With binary response variables, we use random forest for classification. Let $\hat{C}_b(\boldsymbol{X})$ denote the predicted class of the *b*th random-forest tree.

$$\hat{C}_{RF}^{B}(\boldsymbol{X}) = majority\ vote\ \left\{\hat{C}_b(\boldsymbol{X})\right\}_1^B$$

where b $\in (1, B)$ and B is the number of trees

3.3 Methods

3.3.1 Data collection

The time preference experiment was conducted using the web-based Qualtrics Survey Software in 2015. Subjects in this study were randomly selected and recruited across the United States. We adopted the multiple price list (MPL) design by Coller and Williams (1999), Holt and Laury (2002) and Harrison, Lau and Williams (2002). Respondents were presented with a series of hypothetical choices between receiving a smaller monetary reward sooner or a larger reward later (for example, choose between

$200 in one month or $205 in six months). The sooner smaller rewards vary in three magnitudes ($150, $200, $250) and choices sets vary with four different delays (6-month, 12-month, 18-month, and 24-month). Table 3.1 shows the statistics for different choices pairs. With the instrument of MPL, we get a series of choice decisions for different pairs of sooner smaller and larger later rewards. The choice decision variable (coded as 1 if the later-larger reward is chosen, coded as 0 if the sooner-smaller reward is chosen) was used as the dependent variable in time discounting models and ML models. Variables such as starting values and reward delays in the MPL experiment, together with some individual sociodemographic were used as predictors for both temporal discounting model and ML models.

3.3.2 Cross-validation

Cross-validation is a widely used technique in machine learning to assess the performance of different models (Arlot and Celisse 2010; Kohavi 1995). The basic concept of this approach is to estimate a predictive model with one subset of the sample (training data set) and then test the predictive power of the model using another subset of the data (testing data or validation data). To systematically test for the prediction powers across models, four validation approaches were adopted. With multiple responses from the same subject, we first used 10-fold cross-validation for all observations. After randomly dividing responses from each subject into ten equal size subsets, the whole sample is split into ten subsets. Then, we kept one subset as the testing set and the rest nine subsample as the training set to estimate a model. To ensure that information from all observations was evaluated, this process was repeated ten times, and each observation appeared in the testing set just once. In this way, responses from the same individual may appear in both the training and testing sets. For the second and the third approaches, we did cross-validation based on the levels of starting values and time delays in our data, responses from each subject appear in both training and testing sets. With data in three magnitudes (starting values), responses with a particular starting value were used as the testing set and the rest as the training set. We repeated this process three times to make sure responses with each magnitude appear once in the testing set. Validation using time delays was similar to 4-fold cross-validation, in which observations with the same time delay appear in the testing set once. For instance, one round of this cross validation involves estimating models using choice data with 6-, 12-, and 18- month delays, and validating the analysis on the data with 24-month delays.

We also used 10-fold cross validation at the subject level. Using this technique, we first randomly split all individuals into ten subsets in the same size by subject ID. The validation approach then was repeated ten times with each subset used as the testing set just once. With this approach, subjects in the testing set were not the same as those in the training set. In other words, the testing set can be considered as an unknown data set where it does not have any demographic information of the training set.

To compare across the models, we calculated the out-of-sample prediction power for different models on testing data set and compared the prediction accuracy based on Predictive accuracy (PA), the percentage of accurately predicted outcome responses in the testing set.

3.4 Results and Discussion

Table 3.2 shows the summary statistics of our sample. The sample includes 70% of female and 30% male. Participants' age ranges from 18 to 80, and the average age is 46. About 59% of participants have some college or a college diploma, 26% have a high school diploma, and 15% have some graduate school education. More than half of the participants are married, and the average household size is 2 to 3 people per household. Half of the sample are full-time or half-time employed. The annual household income is measured in categories, where average participants have a household income between $35,000 and $65,000 in the year 2014.

Temporal discounting models with demographic effects were estimated using nonlinear least squares. Table 3.3 shows the estimation results from one of the training data set used in 10-fold cross-validation. On average, we found some significant demographic effects on the discount factor (δ), indicating that the demographic variables have strong correlations with individual time discounting behaviors. Therefore, it is reasonable for us to use demographic variables to predict intertemporal choices. In general, we found the signs and magnitudes for demographic effects were mostly consistent across three temporal discounting models. AIC and BIC values were also listed in this table, we evaluated the fitness of model for the in-sample data by comparing these values, and we can conclude that Quasi-hyperbolic discounting model fit the randomly sampled data the best. This model comparison approach based on the model fitness has been used extensively in the temporal discounting literature. However, studies chose the best-fitted models differently, and the selection of model may vary based on their data.

Table 3.4 shows the predictive accuracy of different models with 10-fold cross-validation for the whole sample. The average predictive accuracy and the 95% confidence interval (reflecting the variability of model prediction power under different resampling) were presented in Figure 3.1. The predictive powers for the three temporal discounting were quite similar with little variations, while always outperform a simple logistic regression. The random forest algorithm outperforms other models in this situation with an average predictive accuracy score higher than 0.93. Other ML algorithms, such as linear SGD and neural network, have relatively lower predictive powers compared to temporal discounting models. These results suggest that random forest could possibly ensemble the intertemporal decision-making process better than traditional temporal discounting models when enough information of the sample characteristics is provided.

Table 3.5 presents the model comparison when the subsample for cross-validation was separated based on the starting values of sooner smaller rewards. In this approach, the random forest got the highest predictive power, followed by the neural network, and then three temporal discounting models. In Table 3.6, we also tested if the model performances differed when the training and testing sets were segmented based on time delays. Random forest algorithm still gave the best prediction. But the temporal discounting models outperform neural network algorithm. In other words, if a consumer data contains information about each individual's previous intertemporal choice pattern, then it is likely that random forest method can utilize this information to get good predictions of individual's future intertemporal choices. These findings suggests that supervised ML method can predict an individual's intertemporal choices better than traditional time preference models when responses from same subjects appears in both training and testing set, regardless of the different cross-validation methods.

ML algorithms are sometimes questioned because of the overfitting problem. To test for the predictive power of ML algorithms for new dataset, we did the 10-cross validation at subject level. As discussed in the method section, responses from each subject can only appear in the training set or testing set, but not both. In this approach, the testing data set includes individual responses whose demographic characteristics are independent of the training set. In Table 3.7, the values of predictive accuracy for temporal discounting models decrease only a little (at around 0.75) compared to the results in Table 3.4 (around 0.752), suggesting the temporal discounting model have relatively consistent prediction power for known and unknown data set. Overall, the predictive powers of ML algorithm are much smaller when the subjects in the testing set are different from the training set. ML algorithms fail to outperform the temporal discounting models when predicting intertemporal choices for new subjects. Compared to Figure 3.1, the wider confidence interval in Figure 3.4 suggested that there are more variations in prediction power when the subsamples included responses from different subjects. This is not surprising because the individuals included in the testing set were completely different from the training set. The joint distribution of intertemporal choices and individual characteristics could be unstable across different individual groups, therefore, the learned prediction function based on a training set may not suitable for a new data set. Hastie, Tibshirani and Friedman (2001) discussed the problem of instability and high variance of regression trees (such as the random forest). With resampling, different groups of individuals were left out as the testing set; the predictive error could vary a lot depending on which group of individuals were left to be predicted. Accordingly, more variations in predictive power can be found for the testing set.

3.5 Conclusion

This study compares different ML algorithms and widely used temporal discounting models in predicting individual intertemporal choice behaviors. Several cross-validation approaches were used to systematically test for the predictive power of different models.

Results suggest that when the datasets for cross validation were divided based on the magnitude of sooner-smaller rewards and different time delays, and divided randomly across all observations, ML methods, especially random forest, outperformed traditional temporal discounting models. In another word, with the validation set have similar individual information as the training set, non-linear ML algorithm treated the demographics and time delay variables as explanatory vectors and learned each individuals' intertemporal choices patterns by training; thus they can make good predictions of choices at different times for a well-studied individual.

The prediction error is largely reduced using these ML methods compared to the temporal discounting models. As discussed by Stevens and Soh (2018), ML can be used to model intertemporal choices as well as model the decision-making process. It is possible that ML method ensembled the correlations between intertemporal decision-making process and demographic characteristics in the training practices.

With the information on individuals' previous intertemporal choices, the ML model can be a reliable method to predict their future intertemporal decisions. It is possible ML learns each person’s choice pattern; therefore, the model may suffer from overfitting.

Contrarily, when the testing set and training set contains responses from different subjects, ML methods make less accurate predictions when compared to traditional temporal discounting models. Most of the ML methods fail to outperform temporal discounting models for when the subsets were randomly divided at individual level. This result suggests that demographic variables alone are only weak predictors of intertemporal decision outcomes. In other words, we can hardly predict Jonny’s intertemporal choices based on John’s previous behaviors, even though they have similar demographic backgrounds. This also suggests that ML methods can possibly give better predictions for the outcome variable if given more preference-related predictor variables portraying different individual behaviors and characteristics. It is not surprising when we consider the possible overfitting of the ML models. The predictive power for new data is usually lower because less useful information is provided on the subject level. The predictive accuracy of temporal discounting models, however, are relatively consistent no matter how the training and testing sample are divided. Therefore, we cannot easily conclude on whether ML can better predict individual intertemporal choices or not. The selection of best models should depend on our goal of prediction and the dimension of data.

Table 3.1. Statistic Summary of the Intertemporal Choice Responses for All Participants

Sooner and Smaller rewards (magnitudes) In 1 month	Delayed Time (months)	Percentage of choosing Sooner and Smaller rewards Mean	*Std. Dev.*
$150	6	42.0964%	(0.4937)
$150	12	49.9255%	(0.5000)
$150	18	53.0452%	(0.4991)
$150	24	55.2409%	(0.4973)
$200	6	55.6483%	(0.4968)
$200	12	57.8937%	(0.4938)
$200	18	58.5296%	(0.4927)
$200	24	58.4898%	(0.4928)
$250	6	52.9558%	(0.4992)
$250	12	56.9995%	(0.4951)
$250	18	58.2911%	(0.4931)
$250	24	58.5395%	(0.4927)

Note: During the time preference experiment, respondents were presented with several multiple price lists, and asked to state their choices for a series of tradeoffs with sooner smaller v.s. larger later rewards. For each pair of starting value and time delay, there are fifteen later rewards differs in magnitudes (varies from 2% to 160% larger compared to the starting values).

Table 3.2. Summary Statistics of the Participants (n=671)

Variable	Description of Variables	Mean	(Standard Deviation)
Age	Participant's age	46.131	(16.266)
Female	1 if female; 0 if male	0.705	(0.456)
Married	1 if participant is married; 0 otherwise	0.537	(0.499)
Education	Participants' education level 1 = Some high school or Less 2 = High school diploma 3= Some college 4= College diploma 5= Some graduate school 6= Graduate degree	3.447	(1.270)
Household Income	Household income of participants in 2014 1 = $15,000 or under 2 = $15,001–$25,000 3= $25,001 - $35,000 4=$35,001 - $50,000 5=$50,001 - $65,000 6=$65,001 - $80,000 7=$80,001 - $100,000 8=$100,000 - $150,000 9=Over $150,000	4.322	(2.270)
Household Size	Number of people in the household	2.589	(1.382)
Employed	1 if participant is full-time or part-time employed; 0 otherwise	0.505	(0.500)
Risk Perception	General risk attitude ranging from 1 to 5, 1 most unwilling to take risks and 5 most willing to take risks	2.931	(1.160)

Table 3.3. Estimation Results from Temporal Discounting Model using Nonlinear Least Square (NLS)

Variables	Exponential	Hyperbolic	Quasi-hyperbolic
Noise term	0.012***	0.013***	0.013***
	(27.035)	(27.572)	(25.674)
Constant	1.001***	1.273***	0.951***
	(7.454)	(4.961)	(7.299)
Female	0.077*	0.171**	0.077*
	(1.749)	(2.260)	(1.763)
Age	-0.002	-0.000	-0.002
	(1.121)	(0.017)	(1.084)
Married	0.028	0.009	0.027
	(0.593)	(0.098)	(0.573)
Education	-0.065***	-0.096***	-0.064***
	(3.726)	(3.079)	(3.709)
Household Income	-0.069***	-0.112***	-0.068***
	(6.158)	(5.266)	(6.189)
Household Size	0.069***	0.149***	0.070***
	(3.982)	(3.941)	(4.057)
Employed	-0.095**	-0.139	-0.095**
	(2.059)	(1.548)	(2.083)
Risk Perception	-0.007	-0.011	-0.007
	(0.362)	(0.300)	(0.396)
Tau			0.958***
			(54.944)
N	108702	108702	108702
AIC	119528.186	120209.955	119477.173
BIC	119624.150	120305.919	119582.733
Log likelihood	-59754.093	-60094.977	-59727.587

Note: 1. Absolute t statistics in parentheses. * $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

2. Results in this table come from estimations on 90% of the sample, one of the training sets used in 10-fold cross validation.

Table 3.4. Comparison of Model Performance under 10-fold Cross-validation

Models	Predictive Accuracy	
	Mean	S.D.
Random Forest	0.931	(0.0028)
Linear SVM	0.649	(0.0954)
Neural Network	0.749	(0.0124)
Logistic	0.718	(0.0040)
Exponential	0.752	(0.0032)
Hyperbolic	0.753	(0.0031)
Quasi-hyperbolic	0.752	(0.0035)

Table 3.5. Comparison of Model Performance under Cross-validation based on Rewards Magnitudes

Models	Predictive Accuracy	
	Mean	S.D.
Random Forest	0.825	(0.0071)
Linear SVM	0.692	(0.0578)
Neural Network	0.752	(0.0150)
Logistic	0.711	(0.0258)
Exponential	0.750	(0.0094)
Hyperbolic	0.750	(0.0073)
Quasi-hyperbolic	0.750	(0.0070)

Table 3.6. Comparison of Model Performance under Cross-validation based on Time Delays

	Predictive Accuracy	
Models	Mean	S.D.
Random Forest	0.877	(0.0278)
Linear SVM	0.689	(0.0839)
Neural Network	0.751	(0.0135)
Logistic	0.709	(0.0728)
Exponential	0.752	(0.0142)
Hyperbolic	0.752	(0.0172)
Quasi-hyperbolic	0.752	(0.0175)

Table 3.7. Comparison of Model Performance under 10-fold Cross-validation by Subjects

	Predictive Accuracy	
Models	Mean	S.D.
Random Forest	0.728	(0.0186)
Linear SVM	0.695	(0.0991)
Neural Network	0.741	(0.0255)
Logistic	0.715	(0.0155)
Exponential	0.750	(0.0116)
Hyperbolic	0.751	(0.0119)
Quasi-hyperbolic	0.750	(0.0112)

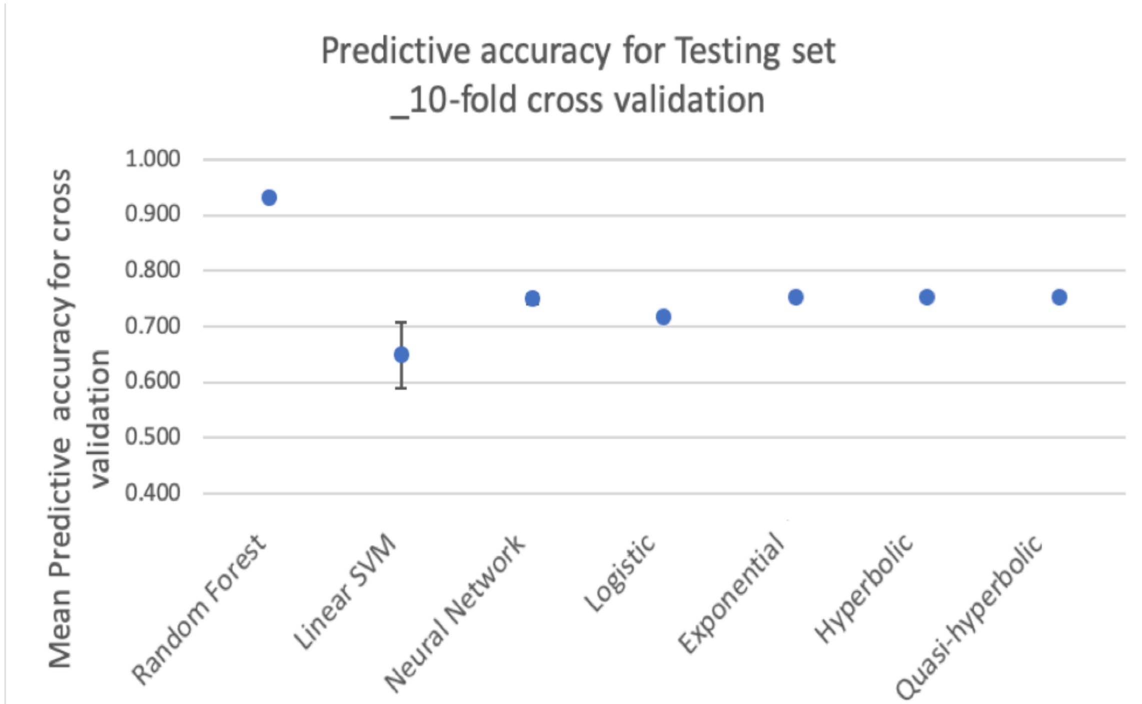

Figure 3.1. The Prediction Power of Different Models under 10-fold Cross-validation. Predictive accuracy is presented in this graph for each model. The error bars show a 95% confidence interval reflecting the variability of model prediction power under different resampling.

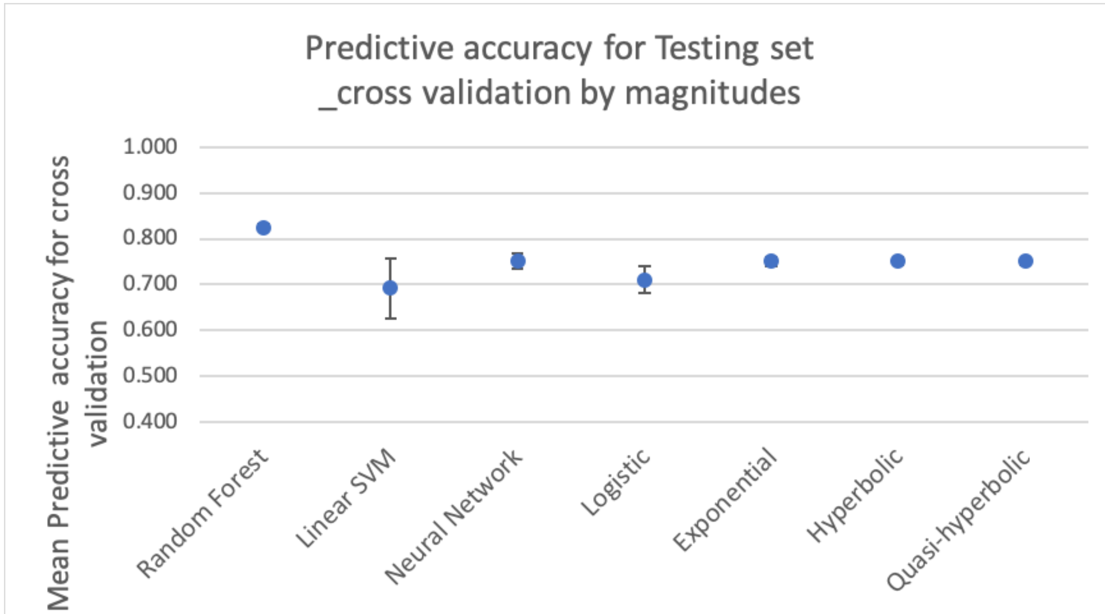

Figure 3.2. The Prediction Power of Different Models under three-fold Cross-validation by Reward Magnitudes.

Predictive accuracy is presented in this graph for each model. The error bars show a 95% confidence interval reflecting the variability of model prediction power under different resampling.

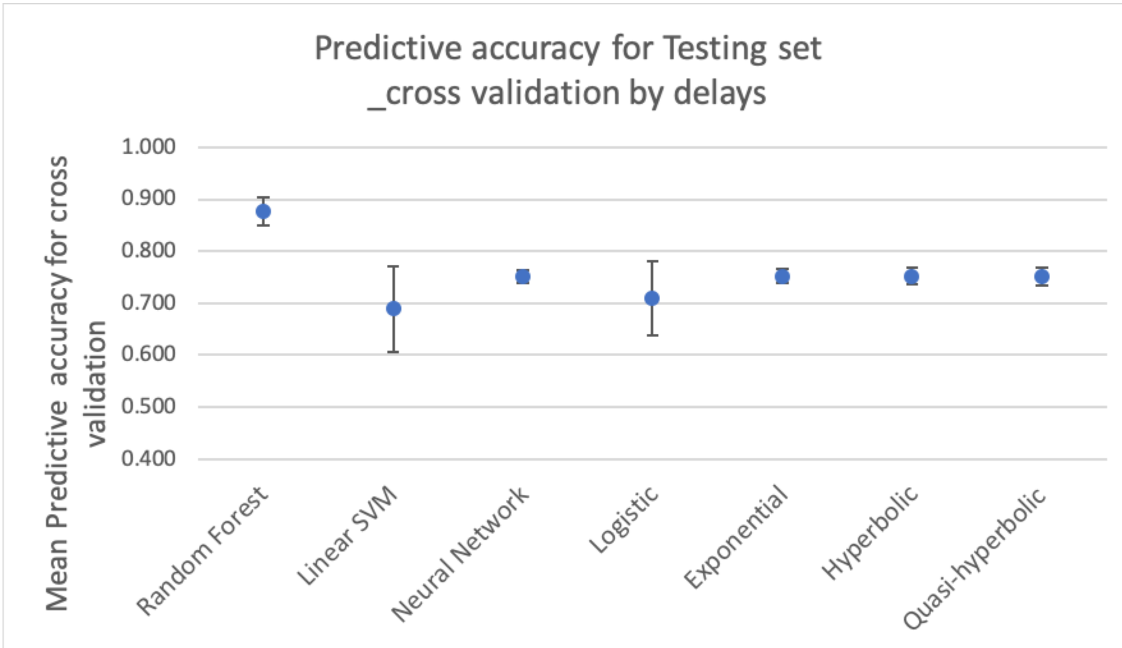

Figure 3.3. The Prediction Power of Different Models under four-fold Cross-validation by Time Delays.

Predictive accuracy is presented in this graph for each model. The error bars show a 95% confidence interval reflecting the variability of model prediction power under different resampling.

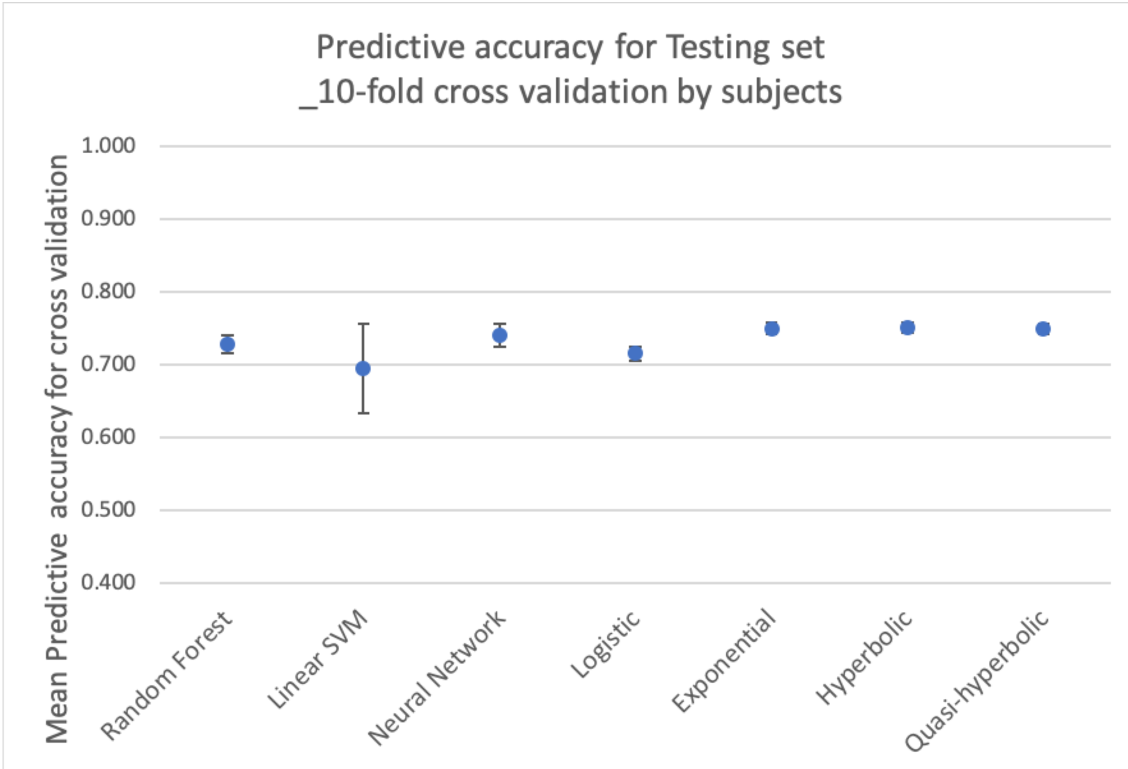

Figure 3.4. The Prediction Power of Different Models under 10-fold cross-validation Resampling by Subjects.

Predictive accuracy is presented in this graph for each model. The error bars show a 95% confidence interval reflecting the variability of model prediction power under different resampling.

Chapter 4 How Do Environment Impact Information and Neighborhood Attachment affect Consumer Choice of Low-input Turfgrasses? Evidence from Discrete Choice Experiments

4.1 Introduction

Turfgrasses, one of the essential landscape components in the United States, occupies a quarter of the total urban area and covers the surface area three times larger than any irrigate crop (Milesi et al. 2005; Yue, Hugie and Watkins 2012). Green, lush, and healthy lawns provided economic and aesthetical benefits for homeowners and the community. A well-manicured lawn also provides environmental benefits by reducing water runoff, soil erosion, protecting water conservation, and supporting local ecosystem (McPherson, Simpson and Livingston 1989; Beard and Green 1994; Krenitsky et al. 1998; Boyd and Wainger 2002; Khachatryan et al. 2017). However, there are growing concerns about how a well-maintained home lawn requires a substantial amount of resources and how improperly lawn care practice, such as over-fertilization or over-irrigation can lead to potentially harmful and adverse environmental effects (Robbins and Birkenholtz 2003; Meyer, Behe and Heilig 2001; Yue et al. 2016). According to a report from EPA, 40-60% of nitrogen from lawn fertilizers runs off-site and end up in surface and groundwater in Chesapeake Bay (U.S. EPA 2010). In light of these environmental consequences, many researchers have been advocating low-input turfgrass cultivars, that could well adapt to the local climate and require less resource and inputs (Yue et al. 2016). Others suggested that organic fertilizers can be good alternatives to sustainably keep the residential lawn healthy with less environmental consequences (Suh, Khachatryan and Guan 2016; Khachatryan et al. 2017).

Homeowners are often involved in difficult trade-offs between aesthetical benefits and environmental concerns when engaged in lawn management practice (Carrico, Fraser and Bazuin 2012). A wide array of studies suggested that consumers would like to purchase products that are environmentally friendly (Guagnano, Dietz and Stem 1994; Schlegelmilch, Bohlen and Diamantopoulos 1996; Engel and Pötschke 1998; Laroche, Bergeron and Barbaro-Forleo 2001; Hu, Woods and Bastin 2009; Yue et al. 2010). The environmental consequences from lawn care practice, however, are sometimes less obvious for the homeowners when they are making decisions and choosing turfgrass cultivars. Therefore, we are interested in examining if consumer preferences for turfgrass differ when they make choices in the presence of information about the environmental consequences compared to a situation where they only think about their personal cost and benefits. Researchers in experimental economics use similar approach to test for the framing effects, the phenomena that consumers' evaluations and choices differ based on how equivalent options are differently described (Kühberger and Gradl 2013; Levin, Schneider and Gaeth 1998).

Residential lawn can be viewed as a privately-owned public resource. It provides both private and public benefits by giving aesthetic views and green coverage for a neighborhood. While the costs to maintain a healthy lawn is fulfilled by private homeowner, the environmental costs are actually taken by all the people in the community or in the society. How people manage their lawn are not only determined by their self-utility and benefits, but also the pressure from neighborhood and communities. Many studies demonstrated the effects of neighborhood attachment and pressure on environmental-related behaviors (Farrow, Grolleau and Ibanez 2017; Maerten 2017). Individuals may behave differently when others perceive their behaviors. For instance, a recent study (Bucciol, Montinari and Piovesan 2019) showed that introducing peer pressure in waste disposal, by letting two households share the same unsorted waste bin, significantly lowers the unsorted waste production. Studies suggest that lawn maintenance practice is beyond the individual experience of the homeowner, but also an engaging way to be a positive member of a community (Carrico et al. 2012). Nielson and Smith (2005) suggested that the perceived feelings of neighbors influence individual yard maintenance; individuals may want to conform typical behaviors as others in the community to maintain a positive self-image. Applying the principal components analysis (PCA), Carrico et al. (2012) found that social pressures positively predicted fertilizer application. These social pressures may be influential when formal neighborhood organizations and lawn care regulations are in presence. Meanwhile, several studies (Leonard 2016) suggested that neighborhood condition could also affect homeowners' maintenance practice and people would like to invest in home exterior upkeep when they live in good neighborhood. Therefore, we also tested if neighborhood attachment and neighborhood rules would affect homeowners' preference for low-input turfgrasses and lawn care practice.

Several previous studies investigated homeowner preference for low-input turfgrasses and lawn maintenance. With data from a choice experiment in Minnesota, Yue et al. (2012) suggested that consumers are willing to pay premiums for low-input turfgrass cultivars which require less resource, such as less irrigation, less fertilization, and reduced mowing frequency. In a follow-up study, Yue et al. (2016) explored the heterogeneity in consumer preferences for turfgrass attributes in North America and found three segments of turfgrass consumers: “Balanced”, “Appearance Conscious”, and “Low-input conscious.” Other studies (Ghimire et al. 2014; Hugie 2012) also identified water use, mowing requirement, and drought tolerance as important turfgrass traits. Two studies investigated homeowners’ preferences for sustainable landscape management. Suh et al. (2016) found that environmental perceptions are influential factors in explaining the purchase frequencies of organic/natural fertilizers by Do-it-Yourself homeowners. Khachatryan et al. (2017) showed that homeowners are willing to pay price premiums for turfgrass fertilizer with eco-friendly attributes, such as natural and organic sources. However, none of those above-mentioned studies has explored the framing effects of the product attributes, in other words, whether or not the presence of environmental consequences information of turfgrass attributes affect consumer preferences for turfgrasses. Moreover, how neighborhood attachment and rules affect consumer preferences for turfgrass attributes is not investigated.

In this paper, we use survey data on homeowners to investigate the impact of environmental information on consumers’ preferences for resource/input needs for lawn maintenance. We tested whether there exist statistically significant differences in consumer preferences when resource-related attributes in choice experiment were described as private monetary costs or potential environmental impacts. Based on the random utility framework, we employed the commonly used mixed logit models and also adopted error component mixed logit models to account for the potential endogeneity problems for the unobservable components. Lastly, we explored the neighborhood effects (neighborhood attachments and neighborhood rules) on homeowners' preferences for turfgrass maintenance attributes and lawn appearance.

Our study contributes to the literature by examining the difference in consumer preferences for input attributes when the attributes were presented in private monetary costs and environmental impacts. Our work differs from previous studies on consumer preferences for turfgrasses in that in addition to the estimation of consumer preferences for turfgrass attributes, and we also take into account the effects of neighborhood attachment and neighborhood pressure. This provides additional insight to help the turfgrass industry better understand how lawn care practices can be a social practice, and educational information could help guide the homeowners to take more sustainable actions when maintaining their residential lawn.

4.2 Methods

4.2.1 Choice Experiment

A discrete choice experiment is a commonly used approach to research consumer preferences, and to reveal consumers' willingness to pay for particular products or services (Lancaster 1966). By asking the respondents to state their choices over various hypothetical alternatives, the choice experiment help researchers to understand the process of decision making and the relative importance of each product attribute. A choice experiment contains a series of choice scenarios, each asking participants to make choices among several alternatives with different combinations of attribute levels. Based on the consumer utility theory, rational consumers make choices to maximize the utility of a good or service from its associated attributes. With the overall utility integrated by the separated utility from each attribute, the marginal value of different attributes for various products can be evaluated by choice modeling using discrete choice data. In most cases, price is also included as an attribute in the choice experiment, which allows the nonmarket valuation of each attribute. The hypothetical choice experiments were sometimes questioned because the respondents do not pay real money when making decisions, and the choices they make are not real. However, Carlsson and Martinsson (2001) suggested that choice experiment responses are statistically indistinguishable across hypothetical and non-hypothetical (real purchasing) treatments. Moreover, Lusk and Schroeder (2004) demonstrated that the biases associated with estimated marginal WTP using hypothetical choice experiments are reduced when choice experiment questions are framed in a way that is similar to actual purchasing settings (non-hypothetical settings).

A fractional-factorial design for the choice experiment was generated using JMP® Pro 11 to achieve the highest D-efficiency. The D-efficiency of our final choice design was 87%. During the experiment, respondents were asked to complete ten choice scenarios. Each choice scenario contains three alternatives; two of them presented choices of low-input turfgrass species with varied combinations of turfgrass traits. We also included a status quo alternative representing the current traits of a home lawn. The status quo option remains the same in all ten choice scenarios.

The attribute definitions and levels in choice scenarios were listed in Table 4.1. The selection of attributes and levels was based on previous field studies and consultation to turfgrass experts. Three lawn maintenance attributes were included, representing the lawn care time, irrigation, and fertilization requirement for each specific grass option. We used relative scores for input reductions, compared to the reference condition (100%). Each of these attributes was included in the choice scenarios with four ordinal levels (0%, 25%, 50%, 75%). To examine the possible effects of neighborhood pressure on lawn appearance, we included an attribute where lawn appearance is framed in comparison with other lawns in the neighborhood. The reference level is that lawn appearance around average compared to other lawns in the neighborhood. Three levels of appearance included average (the reference level), below average, and above average. An attribute representing the usage of low-input turfgrass in the neighborhood was also included. To calculate the WTP values for turfgrass traits, we included a price attribute in each choice set at four levels, which were expressed as the amount of turfgrass seeds that could cover an area of 1,000 ft^2.The price levels were selected based on the prices of turfgrass seeds in different retail stores.[4]

[4] The price points were determined by checking the turfgrass seed price levels of different stores, including online stores; chain stores such as Home Depot, Menards, Wal-Mart, and Lowes; and local garden centers in 2019 when the survey was conducted.

In order to test the possible framing effects on the resource inputs, two versions of surveys were used. In these two versions of choice experiments, only information about two resource attributes (water use and fertilizer use) were different. For the control version (with private costs), the resource-related attributes were framed with the monetary values of water bills and fertilization costs for irrigation and fertilization requirements, respectively. For the treatment version (with public cost), the resource-related attributes were framed as gallons of waters, and the actual pounds of fertilizer applied to the lawn. Using two versions of the stated preference surveys, we aimed to test whether the consumer preferences for turfgrass attributes differ when respondents were presented with different information on the turfgrass attributes. Examples of the choice scenarios in private and public version are presented in Figure 4.1 and Figure 4.2.

After the choice scenario questions, respondents answered questions about their socio-demographic backgrounds, lawn-maintenance habits, environmental beliefs, neighborhood connections, and neighborhood rules. This choice experiment was conducted using an online survey instrument in 2019. Participants in this study were randomly selected across the United States and recruited by a professional survey company, Qualtrics™. To understand consumer preferences for those who would purchase turfgrass seeds, this study only recruited homeowners with residential lawns.

4.2.2 Econometric Models

The choice experiment is modeled based on random utility theory (McFadden 1986), that individual's utility is decomposed into a deterministic component, and a random component which captures unobserved taste variations (Lusk et al.2003; Ouma et al.2007; Tonsor et al.2009). The random utility model used in our study is described using equation (1):

$$\begin{aligned} U_{ijt} &= ASC + U_i(\boldsymbol{X}_{jt}) \\ &= ASC + V_i(\boldsymbol{X}_{jt}) \quad + \quad \varepsilon_{ijt} \end{aligned} \tag{1}$$

This standard specification shows the utility that individual i ($i = 1,2,\ldots,$ N) selects among options of turfgrass seeds, including two low-input turfgrass options (j =A, B) and a status quo ($j = SQ$) with zero cost. In this study, each individual needs to make choices for *t* ($t = 1,2,\ldots,10$) choice scenarios. $\boldsymbol{X}_{jt}$ is a vector of observed attribute levels for option j in choice scenario t. $V_i(\boldsymbol{X}_{jt})$ denotes the individual utility from the turfgrass attributes, and ε_{ijt} is the random term that is independently and identically distributed.

We used random parameter logit model, also called mixed logit model, has been widely used to analyze choice experiment data due its flexibility and ability to control for taste variations in the observable component in the utility function (Train 2009). Compared to the conditional logit model, a mixed logit model is more flexible and does not require the independence of irrelevant alternatives (IIA) assumption to hold (McFadden and Train 2000; Revelt and Train 1998). To capture heterogeneity in consumer preference, mixed logit model allows parameters of turfgrass attributes to vary randomly and captures the correlation patterns for responses from same respondent (Train 2009).

With a status quo option in our choice design, it is possible that that the error structure patterns are similar among changing alternatives, but not correlated with the status quo option (Spencer-cotton, Kragt and Burton 2018; Scarpa, Willis and Acutt 2007). To capture the systematic effect of the status quo option, an alternative specific constant (ASC) was included in the model, which equals one for the status quo option and zero otherwise. We adopted an error component mixed logit model (Scarpa et al. 2007) to address the possible correlated error structure, which allows the error component to vary across different alternatives. The utility function of our model becomes,

$$U_{ijt} = \begin{cases} ASC + \quad V_i(\boldsymbol{X}_{(\boldsymbol{sq})\boldsymbol{t}}) \quad +\varepsilon_{ij} \quad , & j = \quad status\ quo \quad ; \\ \quad V_i(\boldsymbol{X}_{\boldsymbol{jt}}) \quad +\mu_{ijt} + \varepsilon_{ij}, & j = \quad alternative\ A\ or\ B \end{cases} \tag{2}$$

In the error component mixed logit model, the random error term ε_{ijt} in the previous function is specified into two parts, μ_{ijt} is the error component ($\mu_{ijt} = 0$ for status quo) and ε_{ij} is the unobserved error component. The choice model included six attributes as below:

$$V_i(\boldsymbol{X}_{\boldsymbol{jt}}) = \beta_{price} price_{ijt} + \beta_1 time_{ijt} + \beta_2 water_{ijt} + \beta_3 fertilizer_{ijt}$$
$$+ \beta_4 appearance_{ijt} + \beta_5 neighborusage_{ijt}$$

Although consistent parameter estimations can be generated from the mixed logit model and error component model generate, it is not easy to get implications and make direct comparisons based on these estimates (Train 2009). Therefore, we calculate the WTP estimates based on the estimated parameters from both models, and the confidence intervals are estimated using the Delta method.

$$WTP_k = -\frac{\beta_k}{\beta_{price}} \tag{3}$$

We first estimated the consumer preferences and willingness to pay for each attribute using the full sample. To directly evaluate the differences in consumer preferences between two versions of survey, we used the pooled model and added interactions of public (dummy variable equals one for public version, otherwise for private version) and turfgrass attributes in the choice model. The error component mixed logit model was estimated using hierarchical Bayesian estimation (RSGHB package) in R software.

4.3 Results and Discussions

Table 4.2 presents the summary statistics for respondents in two samples. A total of 1020 respondents finished the online survey and passed all the quality checks. Half of the respondents finished the private version survey, and the other half completed the public version survey. The average age was around 50 for private version sample, and 47 for public version sample. 76% of both samples were females. Around 16% of the respondents had some post-graduate education, more than half had some college education or a college diploma, and the rest 25% have high school diploma or less education. Half of our sample were married. The median household income in 2018 is around $50,000, which is generally lower than the national median. More than half of participants, 56% of the private sample and 64% of the public sample, had pets that played on the lawn. Around 37% of the private sample and 43% of the public sample have at least one child in the household. The average household size was two to three people.

4.3.1 Estimation results and WTP estimates

To start with, we did the estimation for all the responses, with pooled data from both private and public versions. Table 4.3 presents the estimation results for both mixed logit model and error component mixed logit model that include an ASC and turfgrass attributes. The coefficient estimates for most turfgrass attributes were significantly different from zero and similar across different models. As expected, the coefficients for price were negative, indicating that individual's utility from purchasing turfgrass seeds decreases as the price increases. The coefficient for ASC was significantly negative for both private and public version samples, suggesting that there is a preference for low-input turfgrass traits compared to status quo option. For both versions, all attributes except for neighborhood low-input grass usage were positive and significant. Homeowners were willing to pay more for turfgrass cultivars which require less inputs such as less lawn care time, less water and less fertilizers. Meanwhile, they were willing to pay more for a relatively better lawn appearance in the neighborhood. On average, consumers were indifferent to the adaptation rate of low-input grasses in the neighborhood. In other words, homeowners generally don't care about what kind of turf species their neighbors are using, nor were they willing to pay extras to have more of their neighbors convert to low-input turfgrasses. For both mixed logit model and error component mixed logit, the standard deviations for all turfgrass attributes were significant, indicating that there exists individual heterogeneity in the turf seeds preferences. Moreover, the significant standard deviation of the error component suggested that the patterns of error component across the low-input turf alternatives were correlated and different from the status quo alternatives, which gives us further support to adopt the error component model to control for the correlated errors.

Based on the estimates from mixed logit and error component mixed logit model, we calculated the marginal willingness to pay (WTP) estimates for each of the turfgrass attribute and the ASC using equation (3). Table 4.4 presents the WTP estimates and 95% confidence intervals. In general, the WTP estimates from mixed logit model (MXL) and error component mixed logit model (EC_MXL) were quite similar. Note that the attributes in the choice experiments were in ordinal levels but coded as continuous variable in the regression, we need to multiply the average WTP estimates by the reduction percentage to get the corresponding WTP estimates at different levels. On average, consumers were willing to pay the highest premiums for turfgrass cultivars that could save water. Compared to the reference level of 4 times watering per week, homeowners would like to pay around \$11.4 premiums for turfgrass species requiring twice watering each week (a 50% reduction compared to status quo alternative) and pay \$17.1 for turf cultivars need watering once a week (75% reduction in water use). These results are mostly consistent with findings from the previous literature (Yue et al. 2016; Yue et al. 2012; Hugie et al. 2012). Homeowners are concerned about the voluminous water usage on their residential lawn and they would like to pay price premiums to get turf species with better tolerance of water stress. Lawn care time is also an influential factor when consumers are purchasing turfgrass seeds. Respondents were willing to pay around \$4.5 for 2 hours of lawn care time saved during growing season. Consumers were willing to pay \$4.1, \$8.3, and \$ 12.4 per square feet to get turf grass that requires three times, two times, and one time of fertilization each year, respectively. Yue et al. (2016) also indicated that consumers are willing to pay more for turfgrass species that require less mowing and less fertilization.

4.3.2 Testing for the framing effects

In order to test for the framing effects, we estimated the models using pooled data with integrations between the public survey version and the turfgrass attributes. By introducing interaction terms of turfgrass traits and public version dummy variable, we systematically tested whether consumers' preferences for each turfgrass traits were affected by the framing of the two choice experiments. Results are shown in Table 4.5. Results from mixed logit model suggested that respondents were willing to pay price premiums for cultivars that require less fertilizer when presented with environmental impact information. Furthermore, when thinking about the environmental consequences, homeowners were willing to sacrifice the overall lawn appearance. Results from the error component model suggested that the respondents in public version were willing to pay more to reduce water use.

4.3.3 Neighborhood Effects

We also tested the possible neighborhood effects by estimating the pooled model with the interactions between the neighborhood attachment, neighborhood rules and turfgrass attributes. To capture the neighborhood effects in multiple dimensions, a series of questions about homeowners' attitudes toward neighborhood connections, community lawn care perceptions and neighborhood rules were asked. Considering the model complexity of adding more than ten variables in the regression, we used facto analysis to generate two factors similar to Carrico et al. (2012): neighborhood attachment and neighborhood rules. The factor analysis results and the statistics of variables were listed in Table 4.6. The Cronbach's Alpha was used to measure the reliability of the factor analysis. The Cronbach's alpha ranges from 0 to 1, with value close to 1 indicating variables' consistent measure of the same concept. The Cronbach's Alpha values were 0.91 and 0.87, respectively, indicating excellent consistency of the questions used to generate the two factors. Neighborhood attachment was a measure indicating that an individual has good emotional connections with other neighbors and has positive perspectives on the overall lawn maintenance practices of the community. Neighborhood rules was a factor representing the strictness of written and unwritten lawn maintenance rules in the community.

The results from these specifications, incorporating neighborhood effects on attributes in the error component models, were presented in Table 4.7. Neighborhood attachments have positive effects on time reduction and appearance attributes. It is possible that homeowners who are more attached with other members in the neighborhood would like to trust other people in the community and think about the overall utility of the community or the society when making decisions. As a result, they would like to invest in turfgrass species which require less inputs to avoid some possible adverse environmental consequences. Meanwhile, the neighborhood rules have significantly positive effects on the lawn appearance, but negative impacts on the water reduction, and fertilization reduction attribute. This appears to indicate that some homeowners may have little choices but to follow the written or unwritten rules to maintain their home lawn. With the presence of neighborhood pressure, either from the community rules or from a close watch of neighbors, homeowners tend to care less about the input reductions when maintaining residential lawns. These results are consistent with some previous research (Nielson and Smith 2005; Carrico et al. 2012; Fraser, Bazuin and Hornberger 2016). Neighborhood rules can enforce the social norms of lawn care and influence lawn care behaviors. In this case, homeowners tend to have a greater commitment to maintaining beautiful lawns by applying excessive water and fertilizer.

4.4 Conclusion

In this study, we considered how attribute framing in a choice experiment influence consumers' preference for low-input turfgrass. Results from this study provide evidence that different attribute descriptions in choice experiment affect consumers preferences. By applying several specifications of random utility model, we demonstrate that the presence of information about environmental problems resulted from lawn irrigation and fertilization have significant impacts on consumer preferences for turfgrass traits. Our results also indicate that neighborhood attachment and neighborhood rules, strongly affected how consumers choose turfgrass seeds, and how they would like to manage their home lawn.

We adopted an error component mixed logit model, together with the commonly used mixed logit model to estimate the homeowners' preferences for different turfgrass attributes. The results from error component mixed logit model are mostly consistent with what we got from the mixed logit model. Results show that, people were willing to pay price premiums for low-input turfgrass which may help them save lawn care time, and resources (water, fertilizer). Although, homeowners had little or no incentives to pay extras to get similar turfgrasses as their neighbors, they did care about their lawn appearance in the neighborhood. On average, homeowners would like to pay around $12 per 1000 square feet for turfgrass seeds that could make their home lawn appears above the average in the neighborhood.

Homeowners were likely to pay more for turfgrass cultivars requiring fewer resources and care less about the lawn appearance when they think about the potential environmental consequences of lawn care. This suggests that attributes framing in the choices experiment may influence the evaluations of consumer preferences and the welfare estimation. The preference structure in our sample reflected that turfgrass consumers may care more about the environment and adopt more sustainable behaviors when the potential environmental consequences were presented to them.

Overall, strong neighborhood attachments and neighborhood rules make homeowners care more about lawn appearance. They would like to maintain home lawn with good appearance to convey a positive self-image. Consumers with stronger attachment to the community were willing to pay more to reduce lawn care time and resources they put in their yard. Homeowners with good neighborhood connections think of themselves as members of the community, and it is possible that they believe other members could also maintain their home lawn properly. Therefore, they take into account the overall utility of the community or the society when deciding how to maintain and what to put on their lawn. With strict neighborhood rules, homeowners need to follow certain rules to fulfill the expectations from other members in the community. Sometimes homeowners are required to keep their residential lawn below certain height by the community, and a close watch from other neighbors also makes it inevitable to maintain the home lawn more than they may need, with more resources put in the yard. With the reinforcement of neighborhood pressure, it is hard for homeowners to reduce inputs on their home lawn. Therefore, it is important to raise the awareness of possible drawbacks to maintaining the perfect residential lawn with extensive inputs and resources. The social norms on lawn care in American is not easy to change, however, educational programs can be promoted to change individual attitudes and tastes (Zhang et al. 2015). Public should be able to get easy access to learn about the potentials of low-input turfgrass cultivars and sustainable lawn care practices, and the environmental benefits of limiting the use of chemicals and reducing water runoffs. It is possible that university extensions and homeowner associations can play crucial roles in promoting the notions of sustainable lawn management.

Findings from the present study provided empirical support for the promotion of low-input turfgrasses. Low-input turfgrass marketers can attract turfgrass consumers by emphasizing the features of input reductions. Although the social pressure may negatively affect the low-input turfgrass adaptation and willingness to pay, stronger neighborhood attachment makes homeowners to manage their lawns more responsibly. Moreover, turfgrass consumers were willing to pay more for fertilizer reduction when given information about the environmental consequences. Therefore, educational programs and campaigns could be developed to improve consumers’ perceptions on the benefits of properly maintained home lawn and sustainable lawn care practices to themselves, the community, as well as the whole society.

Table 4.1. Attributes and Attributes Levels in the Choice Experiment for a 0.25 acres Lawn

Attributes	Definition	Levels	Descriptions
Time	Lawn care time during growing season	Reduce 0%	(Around 8 hours of lawn maintenance each month)[a]
		Reduce 25%	(Around 6 hours of lawn maintenance each month)
		Reduce 50%	(Around 4 hours of lawn maintenance each month)
		Reduce 75%	(Around 2 hours of lawn maintenance each month)
Water	Water Use during growing season	Reduce 0%	($80 water bill each month (watering 4 times a week)[a]
		Reduce 25%	($60 water bill each month (watering 3 times a week)
		Reduce 50%	($40 water bill each month (watering 2 times a week)
		Reduce 75%	($20 water bill each month (watering once a week)
Water (public version)	Water Use during growing season	Reduce 0%	(Around 20,000 gallons of water each month (watering 4 times a week)[a]
		Reduce 25%	(Around 15,000 gallons of water each month (watering 3 times a week)
		Reduce 50%	(Around 10,000 gallons of water each month (watering 2 times a week)
		Reduce 75%	(Around 5,000 gallons of water each month (watering once a week)
Fertilizer	Fertilizer and Pesticides Use per year	Reduce 0%	($60 of fertilizer and pesticides (4 applications)[a]
		Reduce 25%	($45 of fertilizer and pesticides (3 applications)
		Reduce 50%	($30 of fertilizer and pesticides (2 applications)

		Reduce 75%	($15 of fertilizer and pesticides (one application)
Fertilizer (public version)	Fertilizer and Pesticides Use per year	Reduce 0%	(40 lbs fertilizer/pesticides (4 applications)[a]
		Reduce 25%	(30 lbs fertilizer/pesticides (3 applications)
		Reduce 50%	(20 lbs fertilizer/pesticides (2 applications)
		Reduce 75%	(10 lbs or less fertilizer/pesticides (1 application)
Appearance	The overall lawn appearance	Average	(The overall appearance of your lawn is around average in your neighborhood)[a]
		Above average	(The overall appearance of your lawn is above average in your neighborhood)
		Below average	(The overall appearance of your lawn is below average in your neighborhood)
Neighboruse	Neighborhood Usage of Low-input Turfgrass	0%	(No neighbors in your community have converted residential lawn to low-input grasses)[a]
		25%	(25% neighbors in your community have converted residential lawns to low-input grasses)
		50%	(50% neighbors in your community have converted residential lawns to low-input grasses)
		75%	(75% neighbors in your community have converted residential lawns to low-input grasses)

Price	$ per 1000 square feet of seeds	0	(price per 1000 sqft of low-input turfgrass seeds) [a]
		5	(price per 1000 sqft of low-input turfgrass seeds)
		10	(price per 1000 sqft of low-input turfgrass seeds)
		15	(price per 1000 sqft of low-input turfgrass seeds)
		20	(price per 1000 sqft of low-input turfgrass seeds)

Note: Superscript [a] indicate status quo value.

Homeowners in the experiment were first asked about their lawn size, then they were randomly chosen to finish the private or public version choice experiments.

The magnitudes of lawn care time, water use (water bills) and fertilizer use (fertilizer cost) described in the choice attributes differ across respondents depending on homeowners' lot sizes.

Table 4.2. Respondents' Descriptive Statistic

		Private Survey Version (N=510)		**Public Survey Version (N=510)**		**Total (N=1020)**	
Variables	Description of Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	Participants' age	49.575	(15.415)	47.312	(15.233)	48.443	(15.366)
Female	1 if female; 0 if male	0.759	(0.428)	0.763	(0.425)	0.761	(0.427)
Education	The highest level of education						
	1 = High school diploma or less;	0.261	(0.439)	0.247	(0.431)	0.254	(0.435)
	2 = Some college or college diploma;	0.545	(0.498)	0.590	(0.492)	0.568	(0.495)
	3 = Some graduate school or graduate degree	0.165	(0.371)	0.147	(0.354)	0.156	(0.363)
Married	1 if participants are married; 0 otherwise	0.518	(0.500)	0.502	(0.500)	0.510	(0.500)
Child	1 if participants have child in the household; 0 otherwise	0.367	(0.482)	0.425	(0.494)	0.396	(0.489)
Pets	1 if participants have pets play on the lawn; 0 otherwise	0.565	(0.496)	0.637	(0.481)	0.601	(0.490)
Household Income	Participants' household income in 2018.	4.324	(2.232)	4.525	(2.241)	4.425	(2.239)

	1 = $15,000 or under; 2 = $15,001–$25,000; 3= $25,001 - $35,000; 4=$35,001 - $50,000; 5=$50,001 - $65,000; 6=$65,001 - $80,000; 7=$80,001 - $100,000; 8=$100,000 - $150,000; 9=Over $150,000						
Household Size	Number of people in the household	2.576	(1.367)	2.694	(1.449)	2.635	(1.409)
Lot size	Average lot size	3.357	(1.860)	3.439	(1.795)	3.398	(1.829)
Current lawn appearance	Self-rated home lawn appearance (from 1-5 indicating lower 10% to top 10% in the neighborhood).	3.282	(1.049)	3.296	(0.983)	3.289	(1.016)
Neighborhood attachment	A scale generated by factor analysis based on several questions related to homeowners' neighborhood connections and attitudes toward the community. Higher value indicates stronger social attachment.	0.012	(0.963)	-0.012	(0.933)	0.000	(0.948)

Neighborhood rules	A scale generated by factor analysis based on several questions relating to the strictness of written and unwritten rules on lawn care expectation in the neighborhood, and if the neighbors have a close watch on each other's lawn. Higher values indicate strict rules.	-0.027	(0.953)	0.027	(0.955)	0.000	(0.955)

Table 4.3. Estimation Results from the Mixed Logit model and the Error Component Mixed Logit Model on Pooled Data (n=1020)

Variables	MXL			EC_MXL		
	Mean		S.D.	Mean		S.D.
ASC	-0.579	***	(0.070)	-0.672	***	(0.079)
Price	-0.035	***	(0.005)	-0.039	***	(0.005)
Time Saving	0.628	***	(0.089)	0.636	***	(0.096)
Water Saving	0.798	***	(0.092)	0.883	***	(0.106)
Fertilizer Saving	0.579	***	(0.075)	0.633	***	(0.085)
Appearance	0.439	***	(0.029)	0.472	***	(0.034)
Neighboruse	-0.067		(0.071)	-0.078		(0.072)
Standard Deviation						
s.d. Price	0.085	***	(0.005)	0.073	***	(0.006)
s.d. Time Saving	1.777	***	(0.103)	1.339	***	(0.089)
s.d. Water Saving	1.910	***	(0.112)	1.518	***	(0.102)
s.d. Fertilizer Saving	-1.370	***	(0.090)	1.169	***	(0.067)
s.d. Appearance	0.566	***	(0.037)	0.512	***	(0.034)
s.d. Neighboruse	1.009	***	(0.109)	1.065	***	(0.060)
s.d. error component				1.192	***	(0.073)
Log lik.	-9467.696			-7306.195		

Note: Standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

For simplicity, MXL refers to mixed logit model, and EC_MXL refers to error component mixed logit model.

Table 4.4. WTP Estimates from the Mixed Logit Model and Error Component Mixed Logit Model for the Pooled Sample (n=1020)

	MXL						EC_MXL					
Attributes	Mean	95% Confidence Interval					Mean	95% Confidence Interval				
ASC	-16.543	(	-21.636	,	-11.450	)	-17.219	(	-22.291	,	-12.147	)
Time	17.943	(	12.003	,	23.882	)	16.308	(	10.885	,	21.730	)
Water Saving	22.800	(	15.915	,	29.685	)	22.641	(	15.909	,	29.373	)
Fertilizer Saving	16.543	(	11.295	,	21.791	)	16.231	(	11.144	,	21.317	)
Appearance	12.543	(	9.295	,	15.790	)	12.103	(	9.054	,	15.151	)
Neighboruse^{ns}	-1.914	(	-5.281	,	1.453	)	-1.995	(	-5.068	,	1.078	)

Note: Superscript ^{ns} indicate the WTP estimate is not significant at the 10% level.

For simplicity, MXL refers to mixed logit model, and EC_MXL refers to error component mixed logit model.

Attributes (except for the lawn appearance) were coded as ordinal variables (from 0 to 0.75) in the model, we need to multiply the estimated WTP from this table by the corresponding percentage levels to get the WTP estimates for each attribute level.

Table 4.5. Estimation Results from the Error Component Mixed Effect Model with Framing (Public Survey Version) Interactions (n=1020)

Variables	MXL			EC_MXL1		
	Mean		S.D.	Mean		S.D.
ASC	-0.581	***	(0.070)	-0.650	***	(0.068)
Price	-0.035	***	(0.005)	-0.039	***	(0.005)
Time	0.592	***	(0.119)	0.668	***	(0.092)
Water Saving	0.873	***	(0.126)	0.883	***	(0.101)
Fertilizer Saving	0.447	***	(0.101)	0.618	***	(0.084)
Appearance	0.505	***	(0.041)	0.475	***	(0.032)
Neighboruse	-0.051		(0.097)	-0.064		(0.074)
<u>*Interactions*</u>						
Public* Time	0.071		(0.157)	0.188		(0.157)
Public* Water	-0.148		(0.173)	0.145	**	(0.073)
Public* Fertilizer	0.263	*	(0.138)	-0.131		(0.153)
Public* Appearance	-0.132	**	(0.057)	0.177		(0.188)
Public* Neighboruse	-0.037		(0.132)	-0.357	***	(0.145)
Log lik.	-9463.158			-7308.432		

Note: Standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

For simplicity, MXL refers to mixed logit model, and EC_MXL refers to error component mixed logit model.

Public is a dummy variable, Public=1 if the survey frames the water use in gallons and fertilizer use in pounds, and present the information about environmental impacts of water use and fertilizer use, 0 otherwise.

Table 4.6. Factor analysis for neighborhood attachment and neighborhood rules

Variables	Statements of Likert Scale Questions	Mean	Median	Correlations with the corresponding factor	Uniqueness
Factor1_Neighborhoood attachment					
nbattach1	I feel like a member of this neighborhood.	5.313	6	0.549	0.698
nbattach2	This neighborhood helps me fulfill my needs.	4.487	4	0.513	0.736
nbattach3	I have a good bond with others in this neighborhood.	4.879	5	0.472	0.777
nbattach4	It is very pleasing to have healthy and green landscaping in our neighborhood.	5.938	6	0.786	0.382
nbattach5	Well-maintained landscaping in my community enhances the quality of my life.	5.430	6	0.787	0.381
nbattach6	I believe I have a personal responsibility to keep my lawn well maintained.	5.743	6	0.791	0.374
nbattach7	Most of the people I know keep their home lawn well maintained.	5.522	6	0.653	0.573
nbattach8	Nicely maintained home lawn will benefit the residents in the community.	5.644	6	0.806	0.351
nbattach9	My home lawn will look nicer if my neighbors maintain their lawn routinely.	5.172	5	0.555	0.692

The Cronbach's Alpha for neighborhood attachment factor analysis: 0.870

Factor 2 Neighborhood rules					
nbrules1	The written rules about how a yard should be kept are very strict in this neighborhood	3.334	3	0.859	0.263
nbrules2	The unwritten expectations about how a yard should be kept are very strict in this neighborhood.	3.665	4	0.827	0.316
nbrules3	People in my neighborhood keep a very close watch on how people maintain their yards.	3.931	4	0.776	0.398
nbrules4	The yard care rules and expectations are vigorously enforced in my neighborhood.	3.231	3	0.892	0.205
The Cronbach's Alpha for neighborhood rules factor analysis: 0.91					

Note: The variables nbattch1-10 and nbrules1-4 comes from questions of Likert scales asking respondents to disagree/agree with the statements described in the table, with a range of 1 to 7, where 1 = Strongly Disagree and 7 = Strongly Agree.

The Cronbach's Alpha measures the reliability of a set of scales. The Cronbach's alpha ranges from 0 to 1, with value close to 1 indicating variables' consistent measure of the same concept.

Table 4.7.Estimation Results from the Error Component Mixed Effect Model with Neighborhood Effects (n=1020)

	EC_MXL2		
Variables	Mean		S.D.
ASC	-0.665	***	(0.060)
Price	-0.040	***	(0.006)
Time	0.666	***	(0.099)
Water	0.894	***	(0.098)
Fertilization	0.621	***	(0.088)
Appearance	0.475	***	(0.034)
Neighboruse	-0.083		(0.068)
Interactions			
Appearance*Neighborhood attachment	0.655	***	(0.133)
Time*Neighborhood attachment	0.364		(0.244)
Water*Neighborhood attachment	0.678	***	(0.070)
Fertilizer*Neighborhood attachment	0.191		(0.127)
Appearance*Neighborhood rules	0.627	***	(0.063)
Time*Neighborhood rules	-0.372	***	(0.068)
Water*Neighborhood rules	-0.649	***	(0.192)
Fertilizer*Neighborhood rules	-0.661	***	(0.125)
Log. Lik	-7326.988		

Note: Standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

For simplicity, EC_MXL refers to error component mixed logit model.

Public is a dummy variable, Public=1 if the survey frames the water use in gallons and fertilizer use in pounds, and present the information about environmental impacts of water use and fertilizer use, 0 otherwise.

Instructions:

For the following questions, you will be asked to choose from different options of turfgrass seeds. For each scenario, there will be TWO options simulating a situation in which you BUY turfgrass seeds for your home lawn. Please read the label which describes seed cost and how the seed you purchase affects lawn maintenance time, lawn watering requirement, and lawn fertilizer requirement. Note that the maintenance attributes (lawn care time, water use, and fertilizer use) are calculated based on your home lawn size.

Please choose which turfgrass you would prefer to purchase (only ONE, either option A or option B) or (you may choose "the current situation" if you would not purchase either).

Scenario 1

Attribute	**Current Situation**	**Low-input Turfgrass A**	**Low-input Turfgrass B**
Lawn care time during growing season	**Reduce 0%** (Around 6 hours of lawn maintenance each month)	**Reduce 25%** (Around 4.5 hours of lawn maintenance each month)	**Reduce 50%** (Around 3 hours of lawn maintenance each month)
Water use during growing season	**Reduce 0%** ($40 water bill each month (watering 4 times a week))	**Reduce 0%** ($40 water bill each month (watering 4 times a week))	**Reduce 25%** ($30 water bill each month (watering 3 times a week))
Fertilizer & pesticide use per year	**Reduce 0%** ($30 of fertilizer/pesticides applied (4 total applications))	**Reduce 25%** ($22.5 of fertilizer/pesticides applied (3 total applications))	**Reduce 50%** ($15 of fertilizer/pesticides applied (2 total applications))
Overall Appearance	**Average** (Lawn appearance around average in your neighborhood)	**Average** (Lawn appearance around average in your neighborhood)	**Below average** (Lawn appearance below average in your neighborhood)
Neighborhood low-input grass usage	**0%** (No neighbors in your community have converted residential lawn to low-input turfgrasses)	**25%** (25% neighbors in your community have converted residential lawns to low-input grasses)	**50%** (50% neighbors in your community have converted residential lawns to low-input grasses)
Price ($ to seed 1000 square feet of lawn)	**$0**	**$15**	**$10**
	I would choose the Current Situation	**I would choose Low-input Turfgrass A**	**I would choose Low-input Turfgrass B**

Figure 4.1. A Choice Scenario Example for the Private Version Choice Experiment

Instructions:

Properly maintained turfgrasses provide environmental benefits such as soil erosion and water runoff control, water quality protection, and microclimate moderation.

However, with limited water availability and droughts in many regions, the water usage of lawn irrigation (up to 67% of residential water consumption in some hot climate areas) has become a major environmental concern. Previous research has suggested that a certain amount of active ingredients that people put on their lawns through fertilizers and pesticides can run off-site to surface and ground water. Excessive lawn fertilization has resulted in some negative environmental consequences such as water pollution and aquatic ecosystem deterioration.

For the following questions, you will be asked to choose from different options of turfgrass seeds. For each scenario, there will be TWO options simulating a situation in which you BUY turfgrass seeds for your home lawn. Please read the label which describes seed cost and how the seed you purchase affects lawn maintenance time, lawn watering requirement, and lawn fertilizer requirement. Note that the maintenance attributes (lawn care time, water use, and fertilizer use) are calculated based on your home lawn size.

Please choose which turfgrass you would prefer to purchase (only ONE, either option A or option B) or (you may choose "the current situation" if you would not purchase either).

Scenario 1

Attribute	**Current Situation**	**Low-input Turfgrass A**	**Low-input Turfgrass B**
Lawn care time during growing season	**Reduce 0%** (Around 6 hours of lawn maintenance each month)	**Reduce 25%** (Around 4.5 hours of lawn maintenance each month)	**Reduce 50%** (Around 3 hours of lawn maintenance each month)
Water use during growing season	**Reduce 0%** (Around 10,000 gallons of water each month (watering 4 times a week))	**Reduce 0%** (Around 10,000 gallons of water each month (watering 4 times a week))	**Reduce 25%** (Around 7,500 gallons of water each month (watering 3 times a week))
Fertilizer & pesticide use per year	**Reduce 0%** (20 lbs fertilizer/pesticides applied (4 total applications))	**Reduce 25%** (15 lbs fertilizer/pesticides applied (3 total applications))	**Reduce 50%** (10 lbs fertilizer/pesticides applied (2 total applications))
Overall Appearance	**Average** (Lawn appearance around average in your neighborhood)	**Average** (Lawn appearance around average in your neighborhood)	**Below average** (Lawn appearance below average in your neighborhood)
Neighborhood low-input grass usage	**0%** (No neighbors in your community have converted residential lawn to low-input turfgrasses)	**25%** (25% neighbors in your community have converted residential lawns to low-input grasses)	**50%** (50% neighbors in your community have converted residential lawns to low-input grasses)
Price ($ to seed 1000 square feet of lawn)	**$0**	**$15**	**$10**
	I would choose the Current Situation	**I would choose Low-input Turfgrass A**	**I would choose Low-input Turfgrass B**

Figure 4.2. A Choice Scenario Example for the Public Version Choice Experiment

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