THREE ESSAYS ON THE APPLICATION OF DISCRETE CHOICE MODELS WITH DISCRETE-CONTINUOUS HETEROGENEITY DISTRIBUTIONS

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THREE ESSAYS ON THE APPLICATION OF DISCRETE CHOICE MODELS WITH DISCRETE-CONTINUOUS HETEROGENEITY DISTRIBUTIONS

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Unobserved heterogeneity is comprehensively acknowledged as an important feature to be considered in discrete choice modeling. Over the last decade, there were abundant studies showing the great outperformance of capturing unobserved heterogeneity of Mixed-Mixed Logit(MM-MNL) models. However, most empirical researches still use mixed logit(MIXL) models or latent class(LC) models which introduced strong assumptions on distributions of marginal utility. In this dissertation, a Mixed-Mixed Logit model(MM-MNL) that assumes a non-parametric mixing distribution for marginal utility is discussed. Consequently, three empirical studies solving different transportation problems are introduced.

BIOGRAPHICAL SKETCH

Chen Wang was born in Xi'an, a historical city in China in 1989. During his childhood, Chen developed his great interest in how to construct buildings and then he performed excellent in related courses in the middle school and high school. To fulfil his dream, he went to Tsinghua University, the best university in China, and majored in civil engineering. In his senior year he changes his mind that he wanted to solve serious traffic problems which caused by tremendous fast pace of Chinese economic development.

After graduate, he decided to go to Cornell University as an M.S. /Ph.D. student in School of Civil & Environmental Engineering. He concentrated on demand study in vehicle market, developing and applying advanced econometric models. Specifically, in his master period, he paid more attention to Bayes estimators of discrete choice models as well as the related convergence issues. In 2014, he finished his M.S. degree in Cornell University and began to perusing the doctoral degree in the same department with interest in derivation and applications of advanced discrete choice models.

致我亲爱的家人们

For my beloved families

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CHAPTER 1

INTRODUCTION

Knowing and forecasting demand for differentiated products is a permanent challenge, especially in policy-making, economics and marketing researches. During recent decades, discrete choice model (DCM) has been widely utilized because of its strong explanatory power for measuring consumers' taste preferences. The seminal work by McFadden [106] introduced a multinomial logit model (MNL) which accounts for selecting a specific alternative over choice space. Despite its popularity (due to ease of interpretation and estimation), MNL does not handle unobserved heterogeneity.

Addressing unobserved preference heterogeneity is widely acknowledged in choice models with observable attributes (see Hess et al. [66], Allenby and Rossi [4], Small et al. [133, 134]), because ignoring heterogeneity may result in biased estimates and forecasts. Preference heterogeneity is usually modeled by assuming random parameter models with continuous and parametric mixing distributions (in Mixed Logit (MIXL) specifications, McFadden and Train [109]). Most applications of MIXL use univariate or multivariate normal mixing distributions. However, because the normal distribution is unbounded, an inappropriate sign for relevant parameters can be found. Moreover, with the unbounded assumption for cost coefficients, the estimates of willingness to pay (WTP) may contain implausible large numbers. Thus, Hensher and Greene [64] and Hess et al. [66] recommend bounded mixing distributions to avoid implausible extreme values. Log-normal distributions have been adopted to fix the sign of specific coefficients in many studies (e.g. Bhat [15, 16], Revelt and Train [121]). However, the heavy tail of log-normal distribution on the unbounded side may

bias the mean estimates and also imply implausible large values. Assumption of uniform (e.g. McFadden and Train [109]) or triangular distributions (e.g. Hensher and Greene [64], Hensher [63], McFadden and Train [109]) could effectively avoid problem of wrong sign and heavy tails on the correct side. However, they are usually thought too simple and restrictive for realism.

Another approach that is becoming popular is to assume a discrete mixing distribution (in Latent Class (LC) discrete choice specifications). In LC, consumers are separated into different finite classes with different fixed preference(point estimates and shares of each class are parameters). The shortcoming of LC is that the sampling variance places large impact on point estimates of each class(e.g. unexpected sign of point estimates in some classes).

Taking advantage of the fact that any distribution can be approximated arbitrarily well by an appropriate finite Gaussian mixture, a mixture of normal distributions for unobserved heterogeneity has been proposed in a model named mixed-mixed logit (MM-MNL) (Keane and Wasi [81]). MM-MNL is basically a combination of both MIXL and LC (Rossi et al. [123], Train [138], Scaccia [130], Bujosa et al. [27], Greene and Hensher [57], Keane and Wasi [81]).

Fosgerau and Hess [46] pointed the better performance of discrete normal mixtures rather than MIXL model based on both Monte Carlo simulation and empirical studies. Comparing five different models across 10 datasets that covered a wide range of products, Keane and Wasi [81] stated that MM-MNL typically outperformed the popular N-MIXL and LC models. The accuracy and complexity of MM-MIXL are determined by the number of normal components. And utilizing existed methods (such as AIC and BIC) to determine the number of normal mixture components is an appropriate approach to formulate the

models in practice.

In the following chapter, a summary of alternative discrete choice models is introduced to reveal how these models take unobserved heterogeneity into account. In addition, more details of different models are helpful for understanding the MM-MNL and making model comparison easier.

Because of the strong ability of capturing unobserved heterogeneity of MM-MNL, the application is highly motivated to achieve unbiased estimates of taste preference in empirical studies. In this dissertation, three different applications are introduced in consequent chapters 3, 4 and 5 aiming at solving important problems in transportation. The brief description of corresponding researches is displayed below.

In chapter 3, a study analyzing the willingness for improving the resiliency of New York City's transportation system after extreme whether condition is discussed. Specifically, hurricane Sandy revealed the higher-risk vulnerability to natural hazards of civil infrastructure systems in coastal megacities such as New York. Traditional sources of funding for both recovering from disasters and preventing future damages are not only limited, but also do not account for benefit transfers of the externalities induced by the provision of resilient infrastructure. In principle, property owners should be willing to pay (WTP) an amount equal to the perceived benefit, if this positive externality is internalized by them following some pricing mechanism. In this study, we analyzed the community's willingness to pay for improvements in the resiliency to extreme events of the transportation system in New York City. Choice microdata was collected for over 1500 residents of the metropolitan NYC area, while aiming at advancing the state-of-the-art in choice modeling for addressing different

attitudes toward risk. Several logit-type models were estimated and the preferred model was a discrete-continuous heterogeneity mixture that allows for the derivation of non-parametric distributions of willingness to pay. Using hypothetical scenarios of recovery, the willingness to pay as an annual for class 1 ranges from about $15 to $50, whereas for individuals who missed work and self identify as politically liberal the willingness to pay range from $120 to $775. For the mixture, the range of variation is $75-$450.

In chapter 4, a hybrid choice model with an MM-MNL kernel is derived and implemented to examine personal taste preference for cycling. According to aboveboard description, unobserved heterogeneity is comprehensively acknowledged as an important feature to be considered in discrete choice modeling. Over the last decades, the exponentially increasing number of applications showed great power of capturing unobserved heterogeneity of hybrid choice model by incorporating latent variables. However, most empirical studies of hybrid choice models used simple a standard multinomial logit kernel which introduced tremendously strong assumptions. In this study, we introduce a mixed-mixed logit model(MM-MNL) that assumes a non-parametric mixing distribution for marginal utility is proved to outperform traditional mixed logit model by many researches. Thus, we propose a hybrid choice model with a MM-MNL kernel. Consequently, the maximum simulated likelihood estimator is also derived.In the end, we also provide an empirical study on cycling decision conducted in 2013.

In chapter 5, a series of studies are introduced to examining the measurement of individual discount rates in transportation choices. Basically, users of transportation systems face economic decisions that involve cash flows in dif-

ferent points in time. In making these intertemporal choices, users tradeoff between immediate and future benefits and costs. For example, battery electric vehicles require a higher investment but offer important energy savings that may pay off. Using an appropriate discount rate, future costs are transformed into a present equivalent that can be directly compared with upfront expenses or known prices. In this project we review different methods for measuring individual discount rates that have been used in the literature to discuss, in particular, the findings of the "energy paradox" or undervaluation of future savings (making more difficult the adoption of energy efficient vehicles). We identify two main methods of treating discount rates in discrete choice models, namely endogenous and exogenous discounting. Exogenous discounting addresses some problems of the endogenous discounting method (attribute correlation, endogeneity, and imposition of rational evaluation of future costs), but lacks correct treatment of unobserved heterogeneity. We also review experimental elicitation of intertemporal preferences that accounts for heterogeneous discounting. In particular, we tested a modified version of a reward-over-time choice experiment that can be easily incorporated into transportation surveys. In addition, we compared the experimental discount rates with those obtained from a contingent valuation exercise. The continent valuation exercise not only provided a much higher mean for the discount rate (13.93% was the mean experimental discount rate, whereas the contingent valuation mean was 93.9%), but also the level of variability among respondents was unexpectedly high (6.4%-267%). At last, a follow-up discrete experiment discounting operating cost via individual discount rate shows excellent performance of exogenous discounting method.

Finally, major contributions of this dissertation are discussed together with

possible future research topics.

CHAPTER 2

ALTERNATIVE DISCRETE CHOICE MODELS

2.1 Multinomial Logit Model

In the basic multinomial logit (MNL) model (McFadden [106]), the utility function of person n choosing alternative j in specific situation t is defined by

$$U_{njt} = \beta x_{njt} + \epsilon_{njt} \tag{2.1}$$

where x_{njt} is a vector of individual n's attributes of alternative j in choice situation t and it may include alternative specific constants that contain information about unobserved attributes. β is a vector of marginal utilities of each attributes and is homogeneous across the whole sample. Error terms ϵ_{njt} are independent and identically distributed and follow the extreme value (Type I) distribution. Then the choice probabilities could be easily derived:

$$P(j|X_{nt}) = \frac{e^{\beta x_{njt}}}{\sum_{i=1}^{J} e^{\beta x_{nit}}} \tag{2.2}$$

Given the closed-form expression of choice probability, it is easy and fast to estimate MNL by maximizing the likelihood functions:

$$\ell(\mathbf{y}) = \prod_{n=1}^{N} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{e^{\beta_n x_{njt}}}{\sum_i e^{\beta_n x_{nit}}} \right)^{y_{njt}} \tag{2.3}$$

In addition, independence of irrelevant alternatives(IIA) property holds in MNL model revealing the effect of a change in x_{njt}.

2.2 Mixed Logit Models

Named by McFadden and Train [109], the mixed logit (MIXL) model is an extension of standard MNL with considering each consumer's preference as random to capture the unobserved heterogeneity. Following McFadden and Train [109], the utility to individual n from selecting alternative j on a specific choice situation t is defined by:

$$U_{njt} = \beta_n x_{njt} + \epsilon_{njt} \tag{2.4}$$

Where β_n follow the mixing distribution with full flexibility(discrete or continuous, parametric or non-parametric). For a specific individual n, the choice probability of a specific alternative also has a closed-from expression like MNL. Given the probability density function(PDF) of β_n, the likelihood function could be calculated as:

$$\ell(\mathbf{y}) = \prod_{n=1}^{N} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\int \frac{e^{\beta_n x_{njt}}}{\sum_i e^{\beta_n x_{nit}}} f(\beta_n) d\beta_n \right)^{y_{njt}} \tag{2.5}$$

Ideally, MIXL is able to approximate any random utility model with the appropriate specification of variables and mixture of distributions. However, there is no theoretical guidance on how to find the appropriate mixing distribution. The discussion in introduction chapter about mixing distributions introduces most popular assumptions.

2.3 Latent Class Models

After the theoretical discussion by Heckman and Singer [61], the latent class(LC) model has been widely used to analyze individual heterogeneity. The LC model

could be regard as a special case of MIXL model with discrete mixing distribution. In LC, consumers are classified into finite C latent classes. Following the structure of MIXL model, the β_n in LC model differ across classes but keep the same within each class. That is to say: $\beta_n = \beta_c$ with positive probability ω_{cn} for $c = 1, 2, ..., C$. Various formulations have been used for the class assignment and most applications consider a MNL model to determine individual latent class. Thus, ω_{cn} is given by choice probability of the MNL model:

$$\omega_{cn} = \frac{e^{s_n'\gamma_c}}{\sum_{c=1}^{C} e^{s_n'\gamma_c}} \tag{2.6}$$

Where s_n' is a vector of individual characteristics which determines the classification of individual n. Then given the discrete distribution of β_n, the likelihood function for the sample was shown below:

$$\ell(\mathbf{y}) = \prod_{n=1}^{N} \left[\sum_{c=1}^{C} \omega_{cn} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{e^{\beta_n x_{njt}}}{\sum_i e^{\beta_n x_{nit}}} \right)^{y_{njt}} \right] \tag{2.7}$$

One problem of implementing LC model is to determine the number of latent class. Typically, researchers would like to test different numbers of latent classes and select best models based on Bayesian information criterion (BIC) or Akaike information criterion (AIC).

2.4 Mixed-Mixed Multinomial Logit Model

Given the fact that any distribution can be approximated arbitrarily well by an appropriate finite Gaussian mixtures. The most obvious approach to enhance MIXL's ability of capturing heterogeneity is to adopt a mixture of normal distributions. This model is named mixed-mixed logit(MM-MNL) model by Keane

and Wasi [81]. MM-MNL can also be treated equivalently as an extension of the standard LC with normally distributed marginal utilities within a single class. Thus, MM-MNL has been called random parameters latent class logit model as well. Follow the utility function(equation 2.4), the marginal utility of MM-MNL with C normal mixtures is defined by (see Rossi et al. [123], Train [138], Scaccia [130], Bujosa et al. [27], Greene and Hensher [57], Keane and Wasi [81]):

$$\beta_n|\mu, \Sigma \sim \sum_{c=1}^{C} \omega_{cn}\psi(\cdot|\mu_c, \Sigma_c) \qquad (n = 1, \ldots, N) \tag{2.8}$$

where $\psi(\cdot|\mu_c, \Sigma_c)$ is multivariate normal density and ω_{cn} stand for non-negative weights for normal components c of individual n. Assuming that weights of normal components are fixed in terms of the same individual, they are determined by other individual-specific covariates Z_n using logit-type structure($\mu_c = \frac{e^{\gamma_c s_n}}{\sum_{c=1}^{C} e^{\gamma_c s_n}}$). The likelihood function of MM-MNL is given below:

$$\ell(\mathbf{y}) = \prod_{n=1}^{N} \left\{ \sum_{c=1}^{C} \omega_{cn} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\int \frac{e^{\beta_n x_{njt}}}{\sum_i e^{\beta_n x_{nit}}} f(\beta_{n|c}) d\beta_{n|c} \right]^{y_{njt}} \right\} \tag{2.9}$$

Note that if there's only one component, MM-MNL model becomes a N-MIXL model. And if $\Sigma_c = 0$, it becomes a LC model.

CHAPTER 3

ANALYZING WILLINGNESS TO IMPROVE THE RESILIENCY OF NEW YORK CITY'S TRANSPORTATION SYSTEM

3.1 Introduction: extreme weather and disruptions to transportation

New York City has one of the largest and busiest transportation systems, both in the nation and in the world. This system is vital to the everyday success of the area's economy, environment, and overall well-being (NYS 2100 Commission [116]). Any disruption to this system has far-reaching and serious ramifications. One of the largest disruptions in the system's history came in October of 2012 in the form of Hurricane Sandy. According to the National Centers for Environmental Information, Sandy was the second costliest and second deadliest tropical cyclone between 1980 and 2014, with Hurricane Katrina being first in both categories (NCEI [114]). FEMA [42] stated in their after-action report that "The storm's impact was intensified because it made landfall in the most populated region of the country—a region that includes critical infrastructure vital to the Nation's economy". The region they are referring to is the New York Metropolitan Area.

Sandy revealed some critical deficiencies in the area's transportation system, and, unfortunately, experts predict that future sea level rise and storms will exacerbate the problems caused by these deficiencies. Luckily, there are many solutions to the problem of transportation resiliency that are currently being explored, as well as many sources of funding for these solutions. By examining

the effects of Hurricane Sandy on NYC and the surrounding areas, we can see what areas need to be addressed with specific solutions and can begin to discuss how these solutions might be financed.

Several measures were taken before the storm to try and prevent damage to transportation infrastructure, including moving mobile units like trains and buses out of low-lying areas, placing sandbags and tarps at the entrances of subways and over vent to prevent flooding, and preemptively clearing debris from drains and pumps (Kaufman et al. [79]). Bus services, subway services, and commuter and regional rail train services were shut down the night before Sandy made landfall in order to allow the city time to prepare. This left many people no other option but to either walk or use a car or taxi. At the same time, many of these precautions proved successful: almost all subway and bus services were restored just a few days after the storm, and all three major airports in the area (LaGuardia, Newark, and JFK) opened within two days after the storm (Kaufman et al. [79]).

However, much damage was still done; for example, some PATH train stations were still closed weeks after the storm. Infrastructure especially in Lower Manhattan and parts of Brooklyn and Queens near the shore line was greatly affected, with tunnels and subways inundated with storm and sea water, and surface and overground transport severely damaged by high winds and torrential rain. Some sections of subway lines were closed for up to 14 months. At one time, the MTA alone estimated about five billion dollars in damage was done after Sandy passed over (MTA [112]).

Plans, such as MTA's 'Fix & Fortify', have been made to improve the resiliency of the transport infrastructure in the metro area. However, projects like

these are costly. Some of the funding comes from the state and federal government, some from the Department of Transportation. Some also comes from revenue. Shutting down the entire system not only loses revenue, but also causes a loss of money the system already has. One way the MTA, for example, makes up for a deficit is to introduce a fare hike. On March 22, 2015, commuters saw the fourth fare hike for New York City Transit up to $2.75 per ride since 2009. Citizens complained saying that the paycheck they receive stays the same even when the fares increase. However, the fare hike is intended to help solve the financial obstacles MTA faces, and to support projects such as 'Fix & Fortify' to make the system more resilient to inclement weather.

The damages from Sandy come at great cost for all of the areas affected. In New Jersey alone, over $3 billion in transportation-related recovery expenditures are predicted between 2012 and 2015 (Mantell et al. [104]). There were also additional, non-monetary costs. In a survey of eight different 'residence locations' including the five boroughs, New Jersey, the Northern suburbs, and Long Island, six of the eight locations reported an increase in travel time immediately after Hurricane Sandy, sometimes by as much as two and a half hours (Kaufman et al. [79]). These increased travel times correlated to an increase in the frustration levels of commuters. All of the locations surveyed reported some level of frustration due to transportation issues, with the most extreme frustration levels being experienced by those from Staten Island.

All of these factors — monetary costs due to damages from the storm, time lost due to an impaired transportation system, and increased levels of frustration — demonstrate why it is important and necessary to make the transportation system of New York City and the surrounding areas more resilient.

According to a study by Princeton and MIT researchers, there are two main contributors to increased flooding in NYC: hurricanes and other storms, and rising sea levels (Parry). Although it is difficult to predict how climate change will affect future storms, the change in sea levels can be predicted, and they are expected to rise in coming years. One estimate puts the mean annual sea level rise between 12 and 23 inches by the decade 2080 (see Climate Risk Information [32]). According to NYS 2100 Commission [116], the maximum rise could be as high as six feet in NYC and Long Island. Not only are sea levels themselves increasing, but so are their rates of change. As of now, sea level rise increases at a rate of 0.86-1.5 inches per decade; 150 years ago, these rates were as low as 0.34-0.43 inches per decade (see Climate Risk Information [32]). Because of these sea level increases, one can expect to see an increase in the number of 1-in-100 year flood occurrences. The NYC Panel on Climate Change estimates that these events could become four times as likely by 2100 in Climate Risk Information [32]. This is an issue in terms of transportation because the mean storm surge that can be produced by one of these floods (8.6 feet) is about at or above the mean elevation above sea level of NYC (10 feet of less) (Climate Risk Information [32]). This means that every flood poses a severe hazard to the transportation system. The possible effects of severe flooding on a transportation system can be seen by looking at the effects of Hurricane Sandy on the NYC transportation system and on that of the surrounding area.

3.2 Project Research Goal

The goal of this project is to provide statistical inference for the community's willingness to pay for improvements in the resiliency to extreme events of the

transportation system in New York City.This objective seeks to provide better tools for better informing planning investments to improve both resilience and security of transportation infrastructure and services.

A fundamental, specific goal is to collect microdata using a choice-experiment based specifically designed for this project. The population of interest for this study is those coastal communities in the NYC area facing increased risks of flood damage.

3.2.1 Research Plan and Methods

Traditional sources of funding for both recovering from disasters and preventing future damages are not only limited, but also do not account for benefit transfers of the externalities induced by the provision of resilient infrastructure. For instance, the construction of massive structures such as surge barriers to protect coastal urban areas provokes a positive externality on the residential value of the properties in the area. This positive externality results from lower expected damage coming from lower flood risks. In principle, property owners should be willing to pay an amount equal to the perceived benefit if this positive externality is internalized by them following some pricing mechanism. Monetizing these benefit transfers can be used as a tool not only to leverage scarce public resources, but also to achieve a socially optimal resource allocation. An essential element is then the estimation of the willingness to pay, because this measure can be exploited to determine the cost share the community is willing to cover to secure infrastructure systems as well as to receive the benefits from minimizing potential damage. To make inference on the willingness to pay for

flood risk reductions, this project adopts an approach based on discrete choice experiments by Hensher et al. [65].

3.2.2 Literature Review

Although not directly related to the goals of this project, there is a well-established literature that looks at the challenges in the catastrophe risk insurance market(see Jaffee and Russell [74], Grace et al. [49], Froot [48], Kunreuther et al. [90], Grace et al. [50], Kleindorfer and Klein [84], Kunreuther [89], Kunreuther and Michel-Kerjan [91], Kousky [86], Paudel [117]). Regarding demand-side dynamics of catastrophe risk insurance, there is strong evidence that property owners often do not fully insure their property nor do they invest in pre-event mitigation activities that can reduce losses(e.g. Kunreuther [88], Kriesel and Landry [87], Kunreuther and Pauly [92], Dixon et al. [39]). Property owners frequently do not have adequate financial resources to recover losses they do experience, and may demand relief from the government (Kunreuther and Pauly [92]). In fact, Kunreuther and Pauly [93] showed that major disasters are often followed by large, unplanned government expenditures that create major difficulties for local and state government budgets. Over-reliance on post-disaster relief from the government may create serious stress on the private insurance market (Kunreuther and Pauly [92]).

Using discrete choice theory for modeling insurance decisions by property owners has appeared as a novel avenue of research. In particular, recent studies have looked at the determination of willingness to pay for flood insurance, usually in the Netherlands (e.g. Brouwer and Akter [23], Botzen and Van Den

Bergh [21], Brouwer and Schaafsma [24]). These studies analyzed behavioral response in terms of willingness to pay (premium) for a given insurance cover, which might have an associated deductible.

In addition to the analysis of the dynamics of the catastrophe risk insurance market, there is a developing literature that looks at the role of other funding mechanism for improving resilience to floods. In particular, the following two examples analyze willingness to pay higher taxes. In Netherlands, Koetse and Brouwer [85] utilized choice experiments to compare different economic measures of the same change in welfare and to examine the effect of reference point on preferences. To this end, four experiments were designed: two measuring willingness-to-pay (WTP) and two measuring willingness-to-accept (WTA). They found a difference between WTP and WTA values and the difference was affected by flood probability. Dekker et al. [38] estimated a model for WTP for flood risk reductions that included the effects of preference certainty. They found that preference uncertainty affects the randomness of decision making and/or the tendency to choose the status quo choice(the adoption of a simplifying heuristic). In addition, they also concluded that the preference certainty has no effect on the marginal WTP.

3.3 Survey Instrument

Given the costs of recovery and infrastructure improvements, a survey was designed to explore if New Yorkers are willing to financially support investment to make the transportation system more resilient to extreme weather. After a first draft of the survey was created, a round of two focus groups was set to

pretest the instrument. After two focus groups, the final design of the survey was completed. The survey comprised the following parts:

1. Screening: to make sure the respondent was an adult living in the New York Metropolitan area.
2. Daily transportation patterns: this section asked the respondent to describe his or her daily trips in the city, including frequency of transportation modes, average commuting time, and parking preferences.
3. Past flood/evacuation experience: this section collected data about past flood and extreme weather events, including hurricanes, hurricane evacuation, and property damage.
4. Initial Sandy disruptions: this section included a filter to know whether the respondent as in New York City or other affected area when superstorm Sandy made landfall. If that was the case, then it was asked whether the respondent missed work and for how long, whether he or she was paid for the missed work-days.
5. Evacuation: if the respondent evacuated, it was registered when he or she did so. Additional questions included whether the respondent suffered any personal loss or knew someone who did.
6. Post Sandy Commute: data about patterns of disruption for the post Sandy commute was registered in this section, including days before the commute returned to normal.
7. Commute disruptions: this section collected more details about the disruptions experienced in the daily commute.
8. Other Sandy disruptions: in this section, the respondent had the opportunity to provide information about other transportation disruptions (such

as plans to leave the city; subway line closures; abnormal traffic congestion) as well as other overall impacts and inconveniences (such as difficulty getting food, loss of cellphone signal, blackouts, lack of heating).

9. General statement agreements: included data that can be used to create clusters of respondents.

10. Risks associated with extreme weather events: this section asked for an evaluation of how likely a list of extreme weather events (heat wave, heavy precipitation, storm surge, nor'easter, among others) would harm vital transportation infrastructure.

11. Responsibility: assessment of the degree of responsibility for being prepared for hurricanes.

12. Contingent valuation: this section first introduced text about the mechanisms (infrastructure improvements) that can be implemented to prevent or reduce damage to the transportation system when floods and hurricanes occur and improve system resiliency. Then there was a series of contingent valuation question to determine how much the respondents were willing to pay for project that would reduce the transportation recovery time.

13. Funding mechanisms: this section collected data about the likelihood of supporting different funding schemes (such as increased tax on vehicle sales, increase tax on gas, increased subway fares and increased parking fees).

14. Discrete choice experiment: the discrete choice experiment contained 16 hypothetical choice situations, where the respondent was presented with tables, each containing 3 different hypothetical recovery scenarios. The

scenarios varied in the percentage of the transportation system being operational 1-2 days, 3-5 days, 1 week, and 2 weeks after a highly disruptive extreme weather event (such as a superstorm at least as strong as Sandy). The first scenario represented current funding conditions. Scenarios A and B represented improvements to the first scenario, based on a hypothetical annual payment from you to support the required investments. The respondent was asked to select his or her preferred option for a random subset of 8 choice situations. More details about the discrete choice experiment are provided in section .

15. Socio-demographic data: the last section of the survey contained a set of question to gather socio-demographic characteristics of the respondents.

3.4 Data Collection and Descriptive Statistics

The data was collected in January 2015 using an online panel of 1,552 adult respondents living in the NYC metropolitan area. Tables 3.1 and 3.2 summarize the sociodemographic characteristics of the sample.

3.5 Model and Results

3.5.1 Contingent Valuation

Before the discrete choice experiment, the survey considered an open contingent valuation question, where respondents were asked to elicit their willingness to

Table 3.1: Sample Demographic Statistics

Respondent characteristics	Percentage	Respondent characteristics	Percentage
Male	44.01	Homemaker	3.67
Age from 18-24	8.25	Full-time student	3.80
Age from 25-34	19.78	Retired	1.22
Age from 35-44	17.91	Less than High School	0.32
Age from 45-54	17.78	Some High School	1.55
Age from 55-64	19.78	High School Graduate	11.79
Age from 65-74	13.14	Some College	20.30
75 years or older	3.35	Trade/technical/vocational training	3.93
Living in evacuation zones	22.81	College Graduate	34.60
Single	26.61	Some post-graduate work	5.03
In a relationship	6.38	Post-graduate degree	22.49
Married	49.42	White	77.00
Living with partner	4.83	African American	10.31
Divorced or separated	8.05	Asian	7.28
Widowed	3.54	American Indian/Alaska Native	0.45
Own pets	48.00	Native Hawaiian/other Pacific Islander	0.13
Full-time ($\geq$ 30 hours per week) job	52.45	Hispanic	11.60
Part-time/casual job	14.56		

Notes: The white, black, Hispanic and Asian percentages sum to more than 100 percent because some of the respondents have multicultural backgrounds.

pay. Considering the question of a one-time annual payment to support investments in making subway infrastructure more resilient, 81.3% of the respondents indicated that they would pay less than $1,000 (as a one-time payment). Only 3.61% would pay more than $4,000. When asked for a monthly payment, 63.23% of the respondents declared that they would pay less than $10 per month, while only 0.19% would pay more than $200. The details are shown in Figure 3.1

With the answers to the one-time payment, we estimate a tobit model which

Table 3.2: Summary statistics for household income

Income level	Personal	Household
Income $\leq \$10,000$	10.63%	4.77%
Income $> \$10,000$ and $\leq \$19,999$	6.89%	4.57%
Income $> \$20,000$ and $\leq \$29,999$	7.93%	5.67%
Income $> \$30,000$ and $\leq \$39,999$	8.96%	5.80%
Income $> \$40,000$ and $\leq \$49,999$	8.31%	7.09%
Income $> \$50,000$ and $\leq \$59,999$	9.73%	7.47%
Income $> \$60,000$ and $\leq \$69,999$	7.41%	7.93%
Income $> \$70,000$ and $\leq \$79,999$	8.96%	9.09%
Income $> \$80,000$ and $\leq \$89,999$	6.38%	6.38%
Income $> \$90,000$ and $\leq \$99,999$	6.05%	7.41%
Income $> \$100,000$ and $\leq \$149,999$	12.50%	19.14%
Income $> \$150,000$	6.25%	14.69%

is a regression for non-negative dependent variables(see results in Table 3.3). Taking into consideration that the model has a negative constant of -$220, males, young people (under 25 years), those living in evacuation zones, those with 3 or more children, non-whites, and those with a higher experience in previous evacuation are all willing to pay a significant, positive amount of money. Also note that these willingness-to-pay measure are additive for each independent variable. Frequent users of subway, and then even more frequent users of rail, appear as willing to support financially a more resilient subway system for the city. Interestingly, both suffering personal loss and surge at home have a positive amounts, but knowing someone who experienced loss or surge have negative parameters.

Table 3.3: Tobit model for Willingness to pay for improving resiliency

Variables	Estimate	S.E.	T-stat
Male	253.28	69.60	3.64
Age under 25	201.79	129.40	1.56
Lives in Evac Zone	478.27	91.03	5.25
Lives in brownstone	476.84	107.13	4.45
Married	78.07	80.09	0.97
Children: 1-2	178.30	79.33	2.25
Children: over 3	639.61	132.70	4.82
Education college	-175.04	72.64	-2.41
Income over $150,000	86.79	139.03	0.62
African American	191.78	113.48	1.69
Asian	236.93	128.15	1.85
Hispanic	236.11	105.99	2.23
Liberal	240.66	71.02	3.39
Times experienced hurricane	-28.49	10.57	-2.70
Times evacuated	151.94	47.13	3.22
Times experienced damage	54.37	43.82	1.24
Was paid for lost workdays	176.99	70.58	2.51
Experienced personal loss	135.50	88.16	1.54
Know people who experienced loss	-164.81	76.53	-2.15
Experienced surge at home	219.82	99.13	2.22
Experienced surge in neighborhood	-272.06	84.51	-3.22
Evacuated for Sandy	213.05	118.02	1.81
Used social media	334.70	80.25	4.17
Freq user: subway	207.14	82.39	2.51
Freq user: rail	478.82	125.35	3.82
Freq user: car as pass	188.16	104.83	1.79
Constant	-220.66	106.54	-2.07

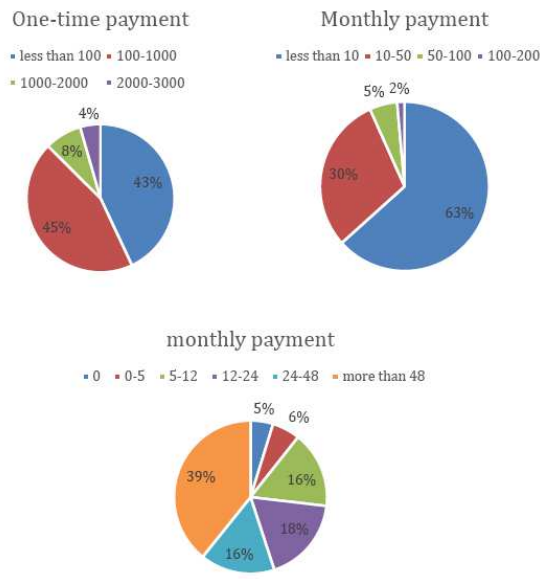


Figure 3.1: Contingent valuation, elicitation of willingness to pay for supporting investments

3.5.2 Discrete Choice Experiments

A fundamental research problem in environmental economics and engineering is to determine the consumer valuation of environmental goods and services for which there is no market price. To address this problem in this project the choice modeling approach (see McFadden [108]) for decisions under risk was adopted. Building on the theory of random utility maximization, choice modeling is more flexible than other stated-preference techniques, such as the contingent valuation method used above, because implicit prices are determined within a controlled experiment that offers better framing and scope, while easing the process of benefit transfer. In transportation, choice modeling has become the standard technique for estimating the willingness to pay for travel-time savings (used for establishing fares and tolls) and for deriving demand functions, especially in the case of new alternatives.

The stated-preference experiment was designed using a Bayesian efficient design, using the software Ngene (Rose and Bliemer [122]). Efficient designs go beyond traditional ways of determining fractional factorial designs. An efficient design maximizes the information extracted from each choice situation by minimizing asymptotic standard errors. In the case of a Bayesian design, there is the possibility of assuming prior parameters.

Experimental Design

In addition to several questions about the disruptions to daily routine experienced right after the landfall of hurricane Sandy, the online survey also contained a series of discrete choice questions about the respondents' willingness to pay to improve the recovery time of the transportation system. In the choice experiment, two hypothetical scenarios of infrastructure improvement as well as a status-quo scenario were described in terms of the percentage of the transportation system being operative 1-2 days, 3-5 days, 1 week, and 2 weeks after a highly disruptive extreme weather event. The extreme weather event was described as being at least as strong as hurricane Sandy. We will refer to these percentages as operative levels in the remainder of the report. The two scenarios of infrastructure improvement required financial support in the form of a hypothetical annual payment. The attribute levels are shown in Table 3.4.

Model estimates and inference on willingness to pay

In all models, we considered the operative levels incrementally. For example, if the operative level 1-2 days after the storm was 25%, and then increased to 35%

Table 3.4: Attributes and attribute levels for the WTP for improving resiliency experiment.

Attribute	Levels
Wingness to pay for resiliency improvement	100, 120, 250, 300, 400, 500 (in $)
Percentage of operational transportation system in 1-2 days	0%, 25%
Improvement in percentage of operational transportation system in 3-5 days	5%, 15%, 35%, 50%
Improvement in percentage of operational transportation system in 1 week	25%, 40%, 60%, 85%
Improvement in percentage of operational transportation system in 2 weeks	70%, 85%, 90%, 100%

Table 3.5: Coefficients of MNL model

Variables	Estimate	s.e.	t-stat
Annual payment	-0.00465	0.00011	-41.38
Operative level: 1-2 days	0.01944	0.00153	12.70
Inc. operative level: 3-5 days	0.01862	0.00114	16.38
Inc. operative level: 1 week	0.01525	0.00139	10.97
Inc. operative level: 2 weeks	0.01249	0.00133	9.42

for days 3-5, then we considered 25% for the first 1-2 days, and 10% for days 3-5. All estimation was performed using the gmnl package in R (Sarrias and Daziano [128]).

Base Models

The first base model that was estimated was a multinomial logit (MNL) model, which is a choice model with fixed parameters. Models with fixed parameters assume that all the individuals in the sample have the same preferences. Results of the fixed parameter estimates are shown in Table 3.5.

Table 3.6: Coefficients of MIXL model

Variables	Estimate	s.e.	t-stat
Annual payment (mean)	-0.0272	0.0009	-30.80
Operative level: 1-2 days (mean)	0.1248	0.0031	40.26
Inc. operative level: 3-5 days (mean)	0.1003	0.0025	40.14
Inc. operative level: 1 week (mean)	0.0686	0.0023	30.00
Inc. operative level: 2 weeks (mean)	0.0501	0.0021	23.72
Annual payment (SD)	0.0254	0.0008	30.02
Operative level: 1-2 days (SD)	0.0241	0.0037	6.45
Inc. operative level: 3-5 days (SD)	0.0277	0.0023	11.98
Inc. operative level: 1 week (SD)	0.0008	0.0029	0.26
Inc. operative level: 2 weeks (SD)	0.0150	0.0019	7.83

All the parameters have the expected signs. The annual payment parameter represents the marginal utility of income and is negative, meaning that individuals value saving money. All the operative levels are positively valued. The order of the valuation is decreasing, meaning that a 1% increase in the operative level is valued higher, the faster the recovery is.

The second base model that was tried was a mixed multinomial logit model (MIXL), which is a random parameter choice model. Random parameter models allow for unobserved heterogeneity in preferences. For random parameter models with continuous heterogeneity distributions, model estimates include the population mean and the standard deviation. The standard deviation measures how preferences vary with respect to the population mean. Results of an MIXL with normally distributed parameters are presented in Table 3.6.

As with the MNL, all parameters have the expected signs and magnitudes.

The only parameter being negative is that of the mean valuation of the annual payment. The operative levels are all positive and increasing with a shorter recovery, indicating that individuals value a quicker recovery of the transportation system. All the parameters are statistically significant, with the exception of the standard deviation of the incremental operative level at 1 week. In general, this model supports the presence of important heterogeneity in preferences.

To disentangle some of the heterogeneity, a hierarchical Mixed Logit model was estimated, where some interactions with socio-demographic variables were introduced. These interactions represent determinist preference variations. Model estimates are shown in Table 3.7:

Double Mixture Models

Because MIXL imposes a very specific shape for the distribution of preferences, we also specified a double mixture model. In a discrete-continuous mixture model, there is a discrete number of clusters of individuals, and within each cluster preferences are modeled according to an MIXL. From a statistical point of view, this discrete-continuous representation of preference heterogeneity is interpreted as a Gaussian mixture. Gaussian mixtures — i.e. a combination of normal distributions — can approximate any distribution, including multimodal cases. A logit-type model with a Gaussian mixture is known in the recent choice modeling literature(Keane and Wasi [81], Greene and Hensher [57]) as Mixed-Mixed Logit (MM-MNL) model.

After preliminary tests, an MM-MNL with two discrete classes was specified. The estimates of relevant parameters are presented in Table 3.8.

As expected, the population coefficient of the annual payment is negative

Table 3.7: Coefficients of MIXL model with interaction

Variables	Estimate	s.e.	t-stat
Annual payment (mean)	-0.0255	0.0013	-20.39
Operative level: 1-2 days (mean)	0.1104	0.0048	23.04
Inc. operative level: 3-5 days (mean)	0.0848	0.0038	22.42
Inc. operative level: 1 week (mean)	0.0613	0.0038	16.26
Inc. operative level: 2 weeks (mean)	0.0457	0.0036	12.88
payment × income below $70,000	-0.0049	0.0013	-3.74
payment × male	0.0037	0.0013	2.81
oper:1-2 days × missed work	0.0205	0.0055	3.73
incoper:3-5 days × missed work	0.0221	0.0043	5.12
incoper:1week × missed work	0.0105	0.0045	2.35
incoper:2weeks × missed work	0.0059	0.0043	1.39
Annual payment (SD)	0.0250	0.0008	30.60
Operative level: 1-2 days (SD)	0.0231	0.0036	6.33
Inc. operative level: 3-5 days (SD)	0.0276	0.0022	12.55
Inc. operative level: 1 week (SD)	0.0001	0.0029	0.05
Inc. operative level: 2 weeks (SD)	0.0145	0.0019	7.54

while the other population coefficients — associated with the improvements in the transportation system — are positive. Note how whereas class 1 exhibits more heterogeneity in the payment attribute, class 2 shows more heterogeneity in the incremental improvements in the operative levels. Regarding the assignment to classes, those respondents that are **liberal** and **missed work** after Sandy, are statistically significantly more likely to belong to class 2. As we discuss below, individuals in class 2 are willing to pay more for improving recovery of the transportation system. Hispanic and Asian males with a household income greater then $70,000 are also more likely to belong to class 2, although the effect

Table 3.8: Coefficients of MM-MNL model

Variable	Estimate	SD	t-stat
Fixed coefficients			
Inc. operative level: 3-5 days	0.1054	0.0377	2.796
Inc. operative level: 1 week	0.0823	0.0301	2.734
Random coefficients			
Class 1			
Annual payment (mean)	-0.0855	0.0241	-3.548
Operative level: 1-2 days (mean)	0.0556	0.0350	1.589
Inc. operative level: 2 weeks (mean)	0.0824	0.0216	3.815
Annual payment (SD)	0.0434	0.0124	3.500
Operative level: 1-2 days (SD)	0.0975	0.0704	1.385
Inc. perative level: 2 weeks (SD)	0.0349	0.0181	1.928
Class 2			
Annual payment (mean)	-0.0111	0.0031	-3.581
Operative level: 1-2 days (mean)	0.1240	0.0394	3.147
Inc. operative level: 2 weeks (mean)	0.0590	0.0240	2.458
Annual payment (SD)	0.0078	0.0069	1.130
Operative level: 1-2 days (SD)	0.0284	0.0085	3.341
Inc. perative level: 2 weeks (SD)	0.0197	0.0064	3.078
Assigntment to class 2			
Male	0.0951	0.0658	1.445
Income below $70,000	-0.4821	0.3145	-1.533
Missed work after Sandy	0.4640	0.2088	2.222
Liberal	0.4280	0.1918	2.231
Conservative	-0.1262	0.0734	-1.719
African American	0.0956	0.4534	0.211
Asian	0.4199	0.3282	1.279
Hispanic	0.5579	0.3030	1.841

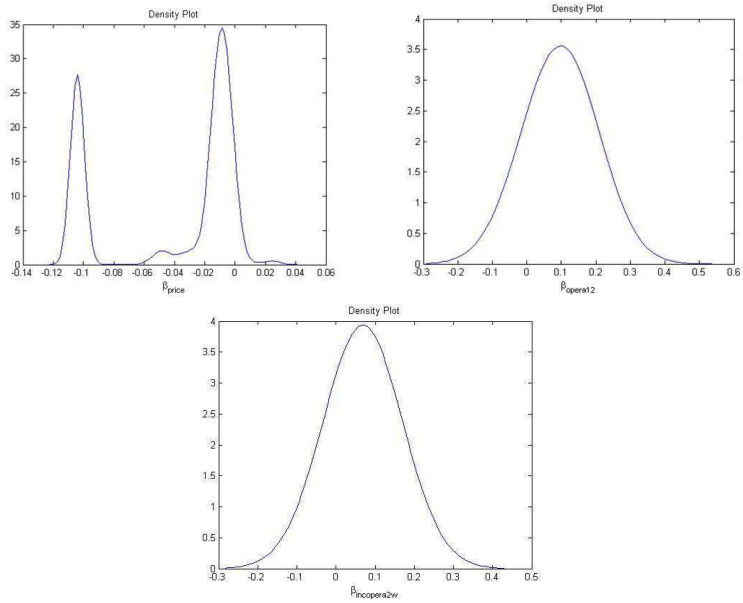


Figure 3.2: Estimated mixing densities of the random coefficients

is not significant at the 95% level.

The estimated mixing distributions for the random parameters are shown in Figure 3.2. These are based on a normal kernel function of the point estimates. The estimated mixing distributions of the marginal utility for both the recovery 1-2 days after the event ($\beta_{opera12}$) and 2 weeks after ($\beta_{incopera2w}$) are Gaussian-shaped. This result indicates that, instead of a mixture, using a normal distribution to approximate the taste variations of these two attributes would be appropriate. The estimated mixing distribution of the marginal disutility of the payment (β_{price}), instead, shows two separated peaks in correspondence with the values of the means of each component. Hence, the heterogeneity distribution of the marginal disutility for the annual payment clearly is multimodal, which would have not been revealed by using a simple normal density as mixing distribution.

To monetize the estimates, we also calculated the post-processed

Table 3.9: Summary of individual post-processed WTP

	Mixture		Class 1		Class 2	
WTP [$/percent-point]	Est.	SD	Est.	SD	Est.	SD
Operative level: 1-2 days after event	8.6377	604.44	1.1813	2.4203	14.2089	3.0806
Incremental operative level: 3-5 days	7.7826	512.22	1.5671	1.9079	12.0162	2.8634
Incremental operative level: 1 week	6.0721	457.40	1.1904	1.2859	9.6324	3.4012
Incremental operative level:	4.5678	404.62	1.0938	0.6868	6.7232	2.5661

willingness-to-pay (WTP) for each attribute (Table 3.9). Residents are willing to pay more for a faster recovery of the transportation system after an extreme weather event. Note that the willingness to pay is considerably higher for class 2, which is more likely to include individuals who missed work during superstorm Sandy. Those individuals who missed work suffered directly the impacts of Sandy and it is possible that one of the reasons to miss work was the problems in the transportation system.

To have a better idea of the derived estimates, Table 3.10 shows the total annual willingness to pay for investments in the transportation system under differing hypothetical situations. Each scenario describes different recovery times for the transportation system with respect to a hypothetical base level. The base scenario considers that the transportation system is shut down 1-2 days after a highly disruptive event; only 5% in operative 3-5 days after; one week after the system is 25% operative; and 2 weeks after the event, 70% of the system is in operation. The scenarios are ordered in increasing recovery speed. The willingness to pay for each scenario is incremental with respect to the base condition.

The willingness to pay for class 1 ranges from about $15 to $50, whereas that of class 2 ranges from $120 to $775. For the mixture, the range of variation is $75-

Table 3.10: Annual WTP for improvement

	Annual WTP ($)			Operative levels certain period after(%)			
Situation	Mixture	Class 1	Class 2	1-2 days	3-5 days	1 week	2 weeks
Base Scenario	NA	NA	NA	0	5	25	70
Situation 1	76.80	14.27	122.79	0	10	40	80
Situation 2	169.66	30.91	272.04	0	20	60	90
Situation 3	149.64	19.88	250.58	10	30	60	80
Situation 4	305.29	51.22	490.90	10	50	80	100
Situation 5	261.68	31.60	438.43	30	50	70	90
Situation 6	322.40	43.50	534.75	30	50	80	100
Situation 7	295.88	27.65	506.12	50	60	70	90
Situation 8	388.75	44.29	655.38	50	70	90	100
Situation 9	377.28	29.40	655.84	70	80	90	90
Situation 10	455.11	45.07	776.00	70	90	100	100

$450. In a contingent-valuation question, where respondents were asked how much they would pay to "support investments that would reduce the recovery time from 3 weeks to only 3 days", the average annual willingness to pay was $192, with a standard deviation of $305.

Finally, density plots for the WTP measures are shown in Figure 3.3. All 4 post-processed WTP measures are bimodal, which explains the overall large standard deviations for the mixture WTP of Table 3.9.

3.6 Conclusions

New York City is known to many as the "city that never sleeps". With over eight million citizens, it is the most populated city in the United States. The area

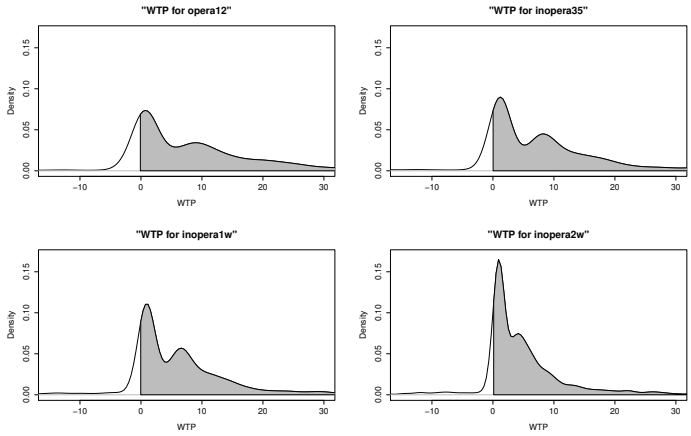


Figure 3.3: Estimated mixing densities of the willingness-to-pay measures

surrounding the city itself is known as the New York Metropolitan Area, which includes some New York State counties north of the city, parts of New Jersey, Pennsylvania, and Connecticut as a combined statistical area, or CSA. This CSA is also the most populated in the US at over 23 million people. An area with this large number of residents needs a well-built and well-maintained public transportation system. Most people living outside New York City commute to the city for both business and leisure. Not many can afford a car, or afford the extremely high prices of parking in the city. Therefore, agencies like New Jersey Transit (NJT), Port Authority of New York and New Jersey (PANYNJ), and Metropolitan Transportation Authority (MTA) have worked together to provide vital bus and rail services in the area. If these services were to cease operations for any amount of time, the entire area would come to a halt as well.

In this project, a survey was designed to collect data on the disruptions that individuals experienced during and after superstorm Sandy. 1,552 adults living in the metropolitan area of New York City participated in the online survey. For those who were in an area affected by Sandy, more then 20% experienced subway line and station closures, and limited bus service for at least one week.

30% of those affected stated that they considered superstorm Sandy a major disruption.

The empirical dataset was complemented with a unique choice experiment. In the experiment, respondents faced differing scenarios of the expected transportation system recovery after an extreme weather event (as strong as superstorm Sandy) under a hypothetical annual payment. Recovery was expressed in terms of the percentage of the system being operative in discrete times after the disruptive shock. With a nonlinear specification, the preferences with respect to both recovery and payment turned out to be heterogeneous in the sample.

Whereas some components of recovery seem to be normally distributed, payment heterogeneity is better represented by a bimodal distribution that can be reasonably approximated by a mixture of two normal distributions. The estimate of the weights of the mixture — modeled as a logit-type function of subject covariates — revealed that individuals who missed work after Sandy hit the area — which acts as a proxy for those individuals who experienced major disruptions in their routines, reducing their earnings in some cases — are more likely to pay more for improving recovery of the transportation system. A similar effect is observed for individuals who identified themselves as politically liberal.

These variables defined a specific class of residents, which we labeled as class 2. Using hypothetical scenarios of recovery, the willingness to pay as an annual for class 1 ranges from about $15 to $50, whereas that of class 2 ranges from $120 to $775. For the mixture, the range of variation is $75-$450. In a contingent-valuation question, where respondents were asked how much they would pay to "support investments that would reduce the recovery time from 3

weeks to only 3 days", the average willingness to pay was $192, with a standard deviation of $305.

CHAPTER 4

DISCRETE-CONTINUOUS MIXTURE KERNELS FOR HYBRID CHOICE MODELS

4.1 Introduction

In addition to observable attributes, hybrid choice models introduce endogenous attributes that may represent latent constructs such as attitudes or multidimensional attributes that are hard to measure in a single item (see Rungie et al. [125, 124], McFadden [107], Walker [144], Ben-Akiva et al. [10, 11]). The application of hybrid choice models has been explosive in the last five years. A sample of the most recent work includes (e.g. Mabit et al. [100], Kamargianni et al. [78], Kamargianni and Polydoropoulou [77], La Paix Puello and Geurs [94], Fernández-Heredia et al. [44], Maldonado-Hinarejos et al. [102], Motoaki and Daziano [111], Sottile et al. [135], Daziano [35], Bhat and Dubey [17].) Hybrid choice models are specified by a system of equations composed by a discrete choice kernel that represents the actual choice process, and measurement and structural equations that ensure identification of the endogenous attributes. Estimation of hybrid choice models is fairly complex when a simultaneous estimator for the system is considered. Because of the complexity and computational cost of estimation, most of the previous work considers rather strong assumptions for the discrete choice kernel. For instance, the consideration of the simple multinomial logit (MNL) model (McFadden [106]) dominates applied work. Despite its popularity (due to ease of interpretation and estimation), MNL does not handle unobserved heterogeneity. There are a few exceptions adopting more advanced discrete choice models for the kernel, such as mixed

logit model(see Maldonado-Hinarejos et al. [102]), latent class model(see Motoaki and Daziano [111]), and probit model(Bhat and Dubey [17], Kamargianni et al. [78]).

Addressing unobserved preference heterogeneity is widely acknowledged in choice models with observable attributes (see Hess et al. [66], Allenby and Rossi [4], Small et al. [133, 134]), because ignoring heterogeneity may result in biased estimates and forecasts. Preference heterogeneity is usually modeled by assuming random parameter models with continuous and parametric mixing distributions (in Mixed Logit (MIXL) specifications, McFadden and Train [109]). Most applications of MIXL use univariate or multivariate normal mixing distributions. However, because the the normal is unbounded, an inappropriate sign for relevant parameters can be found. Moreover, with the unbounded assumption for cost coefficients, the estimates of willingness to pay (WTP) may contain implausible large numbers. Thus, Hensher and Greene [64] and Hess et al. [66] recommend bounded mixing distributions to avoid implausible extreme values. Log-normal distributions have been adopted to fix the sign of specific coefficients in many studies (e.g. Bhat [15, 16], Revelt and Train [121]). However, the heavy tail of log-normal distribution on the unbounded side may bias the mean estimates and also imply implausible large values. Assumption of uniform (e.g. McFadden and Train [109]) or triangular distributions (e.g. Hensher and Greene [64], Hensher [63], McFadden and Train [109]) could effectively avoid problem of wrong sign and heavy tails on the correct side. However, they are usually thought too simple and restrictive for realism.

Another approach that is becoming popular is to assume a discrete mixing distribution (in Latent Class (LC) discrete choice specifications). In LC, con-

sumers are separated into different finite classes with different fixed preference(point estimates and shares of each class are parameters). The shortcoming of LC is that the sampling variance places large impact on point estimates of each class(e.g. unexpected sign of point estimates in some classes).

Taking advantage of the fact that any distribution can be approximated arbitrarily well by an appropriate finite Gaussian mixture, a mixture of normal distributions for unobserved heterogeneity has been proposed in a model named mixed-mixed logit (MM-MNL) (Keane and Wasi [81]). MM-MNL is basically a combination of both MIXL and LC (Rossi et al. [123], Train [138], Scaccia [130], Bujosa et al. [27], Greene and Hensher [57], Keane and Wasi [81])).

Fosgerau and Hess [46] pointed the better performance of discrete normal mixtures rather than MIXL model based on both Monte Carlo simulation and real dateset. Comparing five different models across 10 datasets that covers a wide range of products, Keane and Wasi [81] stated that MM-MNL typically outperform the popular N-MIXL and LC models. The accuracy and complexity of MM-MIXL is determined by the number of normal components. Therefore, instead of arbitrarily assuming parametric mixing distribution, utilizing existed methods to determine the number of normal mixture components may capture unobserved heterogeneity precisely and practical.

In this study, we introduce discrete-continuous mixture kernels for hybrid choice models to enhance its explanatory power for individual heterogeneity.

4.2 A hybrid choice model with an MM-MNL kernel

Adopting the notation of Daziano [35], the system of equations of a hybrid choice models with an MM-MNL can be written as follows:

Structural equations

$$\underset{(L\times 1)}{\mathbf{z}_n^*} = \underset{(L\times L)}{\mathbf{\Pi}}\,\mathbf{z}_n^* + \underset{(L\times M)}{\mathbf{B}}\,\underset{(M\times 1)}{\mathbf{w}_n} + \underset{(L\times 1)}{\boldsymbol{\zeta}_n}\,, \boldsymbol{\zeta}_n \sim \mathcal{N}(0, \mathbf{H}_\Psi^{-1}) \tag{4.1}$$

$$\underset{(J\times 1)}{\mathbf{U}_{tn}^*} = \underset{(J\times K)}{\mathbf{X}_{tn}}\,\underset{(K\times 1)}{\boldsymbol{\beta}_n} + \underset{(J\times L)}{\mathbf{\Gamma}}\,\underset{(L\times 1)}{\mathbf{z}_n^*} + \underset{(J\times 1)}{\boldsymbol{\nu}_{tn}}\,, \boldsymbol{\nu}_{tn} \sim EV1(0,1) \tag{4.2}$$

$$\underset{(R\times 1)}{\mathbf{I}_n^*} = \underset{(R\times 1)}{\boldsymbol{\alpha}} + \underset{(R\times L)}{\mathbf{\Lambda}}\,\underset{(L\times 1)}{\mathbf{z}_n^*} + \underset{(R\times 1)}{\boldsymbol{\varepsilon}_n}\,, \boldsymbol{\varepsilon}_n \sim \mathcal{N}(0, \mathbf{H}_\Theta^{-1}) \tag{4.3}$$

$$\boldsymbol{\beta}_n|\boldsymbol{\mu}, \mathbf{\Sigma} \sim \sum_{c=1}^{C} \omega_{cn}\phi(\cdot|\boldsymbol{\mu}_c, \mathbf{\Sigma}_c) \qquad (n = 1, \ldots, N) \tag{4.4}$$

$$\omega_{cn} = \frac{\exp(\mathbf{s}_n'\gamma_c)}{\sum_{c=1}^{C}\exp(\mathbf{s}_n'\gamma_c)} \tag{4.5}$$

Measurement equations

$$\underset{(1\times 1)}{I_{rn}} = \begin{cases} 1 & \text{if } \mu_{0_r} < I_{rn}^* \leq \mu_{1_r} \\ 2 & \text{if } \mu_{1_r} < I_{rn}^* \leq \mu_{2_r} \\ \vdots & \\ M_r & \text{if } \mu_{M_r-1} < I_{rn}^* \leq \mu_{M_r}, \end{cases} \tag{4.6}$$

$$\underset{(1\times 1)}{y_{tn}} = i \in C_n \text{ iff } U_{itn} - U_{jtn} \geq 0, \forall j \in C_n, j \neq i, \forall n \in N. \tag{4.7}$$

where $\mathbf{z}_n^*$ is vector of endogenous attributes; the matrix $\mathbf{\Pi}$ allows for the eventual presence of simultaneity; $\mathbf{B}$ is a matrix of regression parameters; and $\mathbf{H}_\Psi^{-1}$ is a full covariance matrix.

$\mathbf{U}_{tn}$ is a vector of utility functions for individual n and choice situation t; $\mathbf{X}_{tn}$ is a design matrix of exogenous attributes; and $\boldsymbol{\beta}_n$ is a vector of preference parameters; $\mathbf{\Gamma}$ is a matrix of preference parameters associated with the endogenous attributes. The preference parameters $\boldsymbol{\beta}_n$ are assumed to have a

discrete-continuous heterogeneity distribution described by equations (4.4) and (4.5). Equation (4.4) constructs a Gaussian mixture for $\boldsymbol{\beta}_n$ with C components or classes, where $\phi(\cdot|\boldsymbol{\mu}_c, \boldsymbol{\Sigma}_c)$ is the multivariate normal density, and ω_{cn} stands for non-negative weights for each normal component c (with parameters $\boldsymbol{\mu}_c$ and $\boldsymbol{\Sigma}_c$) of the mixture. A semi-parametric logit-type structure is assumed in equation (4.5) for the weights. This expression can be interpreted as the probability of individual n belonging to class c.

Equations (4.3) and (4.6) identify and measure the endogenous attributes $\mathbf{z}_n^*$ in a system of independent ordered probit models. $\mathbf{I}_n^*$ is a latent vector of R endogenous, continuous indicators; $\boldsymbol{\alpha}$ is an intercept vector and $\boldsymbol{\Lambda}$ is a matrix of factor loadings. $\boldsymbol{\varepsilon}_n$ is a vector of measurement error terms with covariance matrix $\mathbf{H}_\Theta^{-1}$. Exogenous indicators $I_{rn}, r \in 1, .., R$ are either categorical, as shown in equation (4.6), binary, or continuous. In the categorical case, $\boldsymbol{\mu}_r = (\mu_{0_r}, \ldots, \mu_{M_r})'$ is a vector of ordered-probit threshold parameters.

If $\boldsymbol{\delta}$ denotes the whole set of unknown parameters of the hybrid choice model outlined above, the likelihood of observing the choice indicators $\mathbf{y}_n = (y_{1n}, ..., y_{Tn})'$ and the exogenous indicators $\mathbf{I}_n = (I_{1n}, ..., I_{Rn})'$ can be written as:

$$\begin{aligned}\ell(\mathbf{y}, \mathbf{I}; \boldsymbol{\delta}) = \prod_{n=1}^{N} \sum_{c=1}^{C} \omega_{cn} \int_{z_n^*} \prod_{t=1}^{T} \int P_{tn|c}(i_{tn|c} \,|\mathbf{z}_n^*, \mathbf{X}_n, \boldsymbol{\theta_c})h(\boldsymbol{\theta_c})d\boldsymbol{\theta_c} \\ \prod_{r=1}^{R} f(I_{rn}|\mathbf{z}_n^*, \boldsymbol{\Lambda}, \boldsymbol{\mu}_r, \mathbf{H}_\Theta^{-1})g(\mathbf{z}_n^* \,|\mathbf{w}_n, \tilde{\mathbf{B}}, \mathbf{H}_{\tilde{\Psi}}^{-1})dz_n^*\end{aligned} \tag{4.8}$$

where $P_{tnc}(i_{tn|c} \,|\mathbf{z}_n^*, \mathbf{X}_n, \boldsymbol{\theta_c})$ is the probability of the chosen alternative of individual n in choice situation t given the preference parameters $\boldsymbol{\theta}_c$ of component c; and where $g(\mathbf{z}_n^*|\mathbf{w}_n, \tilde{\mathbf{B}}, \mathbf{H}_{\tilde{\Psi}}^{-1}) \sim \mathcal{N}((\mathbf{1}_L - \boldsymbol{\Pi})^{-1}\mathbf{B}\mathbf{w}_n, [(\mathbf{1}_L - \boldsymbol{\Pi})^{-1}]\mathbf{H}_\Psi^{-1}[(\mathbf{1}_L - \boldsymbol{\Pi})^{-1}]')$. Finally, the actual density of $f(I_{rn})$ depends on the nature of the indicator.

If I_{rn} is binary, then:

$$f(I_{rn}) = \Phi\left(\frac{\alpha_r + \boldsymbol{\lambda}_r'\mathbf{z}_n^*}{[\mathbf{H}_\Theta^{-1}]_{rr}}\right)^{I_{rn}} \left(1 - \Phi\left(\frac{\alpha_r + \boldsymbol{\lambda}_r'\mathbf{z}_n^*}{[\mathbf{H}_\Theta^{-1}]_{rr}}\right)\right)^{(1-I_{rn})}. \tag{4.9}$$

If I_{rn} is categorical, then:

$$f(I_{rn} = m) = \Phi\left(\frac{\mu_{m_r} - \boldsymbol{\lambda}_r'\mathbf{z}_n^*}{[\mathbf{H}_\Theta^{-1}]_{rr}}\right) - \Phi\left(\frac{\mu_{m-1_r} - \boldsymbol{\lambda}_r'\mathbf{z}_n^*}{[\mathbf{H}_\Theta^{-1}]_{rr}}\right) \tag{4.10}$$

with Φ being the cumulative distribution function (cdf) of a standard normal distribution, and $[\mathbf{H}_\Theta^{-1}]_{rr}$ being the r-th element of the diagonal of $\mathbf{H}_\Theta^{-1}$

If I_{rn} is continuous, then:

$$f(I_{rn}) = \frac{1}{[\mathbf{H}_\Theta^{-1}]_{rr}}\phi\left(\frac{I_{rn} - \alpha_r - \boldsymbol{\lambda}_r'\mathbf{z}_n^*}{[\mathbf{H}_\Theta^{-1}]_{rr}}\right), \tag{4.11}$$

where ϕ is the probability density function (pdf) of a standard normal distribution.

4.3 Empirical case study: cycling demand

To test empirically the estimator of a hybrid choice model with a MM-MNL kernel, we use the bicycle route choice data collected by and the structural equation model fitted in Motoaki and Daziano [111]. The data was collected in 2013 and the survey included a discrete choice experiment in which hypothetical binary route choices — with a third alternative of opting out — for bicycling were described in terms of travel time, slope (grade), presence of a bike lane, and traffic volume. In addition to the characteristics of each route, weather conditions were also presented, in terms of general conditions of the day ("sun", "rain", "snow"), temperature and expected depth of precipitation in inches for rain

Table 4.1: Attributes and attribute levels for the route choice experiment.

Attribute	Number of levels	Levels
Slope	3	0% (Flat), 3% (Moderate), 5% (Moderate), 8% (Steep), 10% (Steep)
Travel Time	3	10, 15, 20 minutes
Bike Lane	2	Yes, No
Traffic	5	Heavy, Light
Weather	3	Sun, Rain, Snow
Precipitation: Rain[a]	3	0, 0.3, 1 inches (0, 0.76, 2.54 cm)
Precipitation: Snow[a,b]	3	0, 0.5, 2 inches (0, 1.27, 5.08 cm)
Traffic	5	Heavy, Light
Temperature	3/2	25°F, 35°F, 50°F (Sample 1) / 75°F, 90°F (Sample 2)
		−4°C, 2°C, 10°C (Sample 1) / 24°C, 32°C (Sample 2)

[a] conditional on weather conditions (sun: zero chance of precipitation)

[b] only for Sample 1

and snow. The experimental attributes are presented in Table 4.1. These levels were combined using a D-efficient design with 9 choice situations(for further details about the survey, data collection, and experiment design, see Motoaki and Daziano [111]). Characteristics of the sample are presented in Table 4.2.

Using effect indicators in a Likert scale, Motoaki and Daziano [111] fitted a Multiple Indicator and Multiple Causes (MIMIC) in which three latent constructs were identified, namely (1) bicyclist status; (2) external restrictions; and (3) physical condition (see Figure 4.1).

Table 4.2: Descriptive statistics of the sample (Motoaki and Daziano [111]).

	Total N = 599		Sample 1 N_1 = 544		Sample 2 N_2 = 55	
Respondent characteristic	Total	%	Total	%	Total	%
Male	250	42%	220	40%	30	55%
Access to bike (yes=1)	323	54%	291	53%	32	58%
Advanced, confident cyclist	127	21%	110	20%	30	55%
Intermediate cyclist	195	33%	176	32%	19	35%
Cycling commute: never	497	83%	451	83%	46	84%
Cycling commute: less than once a week	32	5%	31	6%	1	2%
Cycling commute: 1-2 days a week	29	5%	31	6%	1	2%
Cycling commute: 3-4 days a week	18	3%	18	3%	0	0%
Cycling commute: 5+ days a week	15	3%	15	3%	0	0%
Commute mostly by car	66	11%	58	11%	8	15%
Commute mostly by bus	168	28%	145	27%	23	42%
Live on campus	164	27%	156	29%	8	15%
Distance to campus: within 1 mile	276	46%	253	47%	23	42%
Distance to campus: 1-5 miles	118	20%	101	19%	17	31%
Distance to campus: 5-10 miles	18	3%	13	2%	5	9%
Age: 18-22	351	59%	332	61%	19	35%
Age: 23-27	116	19%	91	17%	25	45%
Age: 28-40	78	13%	70	13%	8	15%
Age: 40+	54	9%	51	9%	3	5%
Exercise frequency: never	37	6%	37	7%	0	0%
Exercise frequency: less than once a month	34	6%	31	6%	3	5%
Exercise frequency: once a month	19	3%	19	3%	0	0%
Exercise frequency: 2-3 times a month	66	11%	59	11%	7	13%
Exercise frequency: once a week	90	15%	79	15%	11	20%
Exercise frequency: 2-3 times a week	225	38%	198	36%	27	13%
Exercise frequency: daily	128	21%	121	22%	7	13%
Undergraduate student	350	58%	335	62%	15	27%
Graduate student	184	31%	148	27%	36	65%

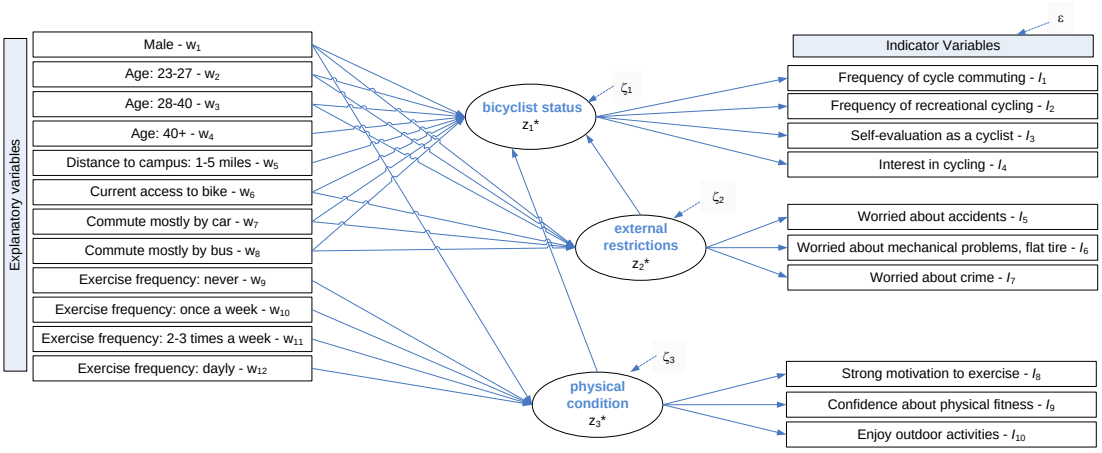


Figure 4.1: Path diagram of the MIMIC model (Motoaki and Daziano [111]).

4.3.1 Hybrid choice model estimates

There are two components in the hybrid choice model: **the MM-MNL kernel** and **the MIMIC model**. MM-MNL models require a prior specification of the number of classes. Below we present the estimates of a model with 2 classes. In this model, which is an extension for the latent class model of Motoaki and Daziano [111], class 1 is defined as base and the assignment parameters then refer to the probability of belonging to class 2. Looking at the parameters of the covariates, class 2 is more likely to be composed by males, undergraduates students, and individuals who describe themselves as beginner cyclists. Advanced cyclists, graduate students, and students living within 1.5 miles from campus are more likely to belong to class 1. Unlike the model of Motoaki and Daziano [111], where fixed parameters were considered within each class, because we adopted an MM-MNL kernel, we also estimated standard deviations for the random parameters.

Table 4.3: Point estimates for the MM-MNL kernel

Class 1				Class 2			
Attribute	Est.	S.E.	T-stat	Attribute	Est.	S.E.	T-stat
Bike***	4.076	0.507	8.045	Bike	1.137	0.930	1.223
Time*	-0.037	0.017	-2.173	Time***	-0.102	0.016	-6.434
Time × BS***	0.035	0.005	6.926	Time × BS***	-0.024	0.007	-3.528
Slope***	-0.384	70.026	-14.962	Slope***	-0.266	0.022	-12.187
Slope × PC*	0.022	0.011	2.001	Slope × PC***	0.040	0.010	4.135
BikeLane***	0.736	0.112	6.597	BikeLane***	0.701	0.095	7.354
Traffic***	-1.216	0.117	-10.383	Traffic***	-1.489	0.115	-12.994
Rainfall***	-1.804	0.260	-6.938	Rainfall***	-1.832	0.508	-3.608
Snowdepth***	-4.948	0.461	-10.722	Snowdepth***	-1.832	0.197	-9.307
Temp < 75° F ***	-0.038	0.009	-4.090	Temp < 75° F ***	0.237	0.034	7.013
Temp ≥ 75° F ***	-0.035	0.005	-6.577	Temp ≥ 75° F ***	0.090	0.016	5.484
sd.Bike***	1.220	0.194	6.282	sd.Bike	0.269	0.687	0.3915
sd.Time	0.005	0.028	0.171	sd.Time***	0.116	0.015	7.843
sd.Time × BS***	0.010	0.016	0.581	sd.Time × BS*	0.022	0.010	2.251
sd.Slope***	0.168	0.022	7.766	sd.Slope***	0.138	0.020	7.067
sd.Slope × PC	0.009	0.034	0.255	sd.Slope × PC	0.006	0.031	0.185
sd.BikeLane***	0.711	0.181	3.938	sd.BikeLane***	0.849	0.157	5.394
sd.Traffic	0.060	0.473	0.126	sd.Traffic***	1.053	0.153	6.889
sd.Rainfall**	1.446	0.442	3.273	sd.Rainfall	0.919	1.076	0.8541
sd.Snowdepth***	3.489	0.426	8.1885	sd.Snowdepth	0.329	0.359	0.916
sd.Temp < 75° F	0.014	0.008	1.811	sd.Temp < 75° F ***	0.086	0.011	7.801
sd.Temp ≥ 75° F**	0.016	0.006	2.663	sd.Temp ≥ 75° F*	0.022	0.011	1.982
Estimation statistics				Class assignment(class 1 as baseline)			
Log-likelihood	-3802.5			Intercept***	-0.704	0.119	-5.938
No. observations	5391			Male***	0.739	0.080	9.269
No. iterations	160			Undergrad***	0.992	0.093	10.683
AIC	7706.93			Miles_1 **	-0.265	0.081	-3.267
BIC	8043.15			Miles_1_5 ***	-0.566	0.123	-4.599
				Beginner ***	0.929	0.111	8.407
				Advanced ***	-0.451	0.085	-5.275

Table 4.4: MIMIC component estimates(I).

Measurement Equation: λ (R squared)	Estimate	s.e.	t-stat	p-value	LB 95% CI	UB 95% CI
Bicycle Status	Reliability: 0.755 (α), 0.765 (ω)					
Frequency of cycle commuting (0.803)	1.000					
Frequency of recreational cycling (0.449)	0.661	0.051	12.893	0.000	0.561	0.761
Self-evaluation as a cyclist (0.661)	0.861	0.056	15.329	0.000	0.751	0.971
Interest in cycling (0.501)	0.711	0.050	14.277	0.000	0.613	0.809
External Restrictions	Reliability: 0.728 (α), 0.733 (ω)					
Worried about accidents (0.544)	1.000					
Worried about mechanical problems (0.518)	0.975	0.057	17.071	0.000	0.863	1.087
Worried about crime (0.453)	0.908	0.055	16.486	0.000	0.800	1.016
Physical Condition	Reliability: 0.778 (α), 0.780 (ω)					
Strong motivation to exercise (0.834)	1.000					
Confidence about physical fitness (0.722)	0.898	0.005	17.880	0.000	0.800	0.996
Enjoy outdoor activities (0.436)	0.644	0.036	17.685	0.000	0.573	0.715
p-value (Chi-square)	0.000					
Comparative Fit Index (CFI)	0.941					
Tucker-Lewis Index (TLI)	0.927					
Root Mean Square Error of Approximation	0.057					
p-value RMSEA $\leq$ 0.05	0.049					

For both classes, longer travel time, deeper slope and heavy traffic prevent people from cycling in general. On the other hand, the presence of a bike lane makes cycling and a specific route more attractive. Weather affects both routs and hence precipitation in both forms (rain and snow) makes cycling less attractive. All these effects are corroborated by the correct signs of the parameters. In addition, the positive point estimates of the interaction of slope and the latent physical condition show that people with better physical conditions

Table 4.5: MIMIC component estimates(II).

Measurement Equation: λ (R squared)	Estimate	s.e.	t-stat	p-value	LB 95% CI	UB 95% CI
Bicycle Status (0.578)						
Male	0.355	0.090	3.927	0.000	0.179	0.531
Age: 23-27	0.341	0.120	2.842	0.004	0.106	0.576
Age: 28-40	0.488	0.147	3.318	0.001	0.200	0.776
Age: 40+	0.455	0.164	2.771	0.006	0.134	0.776
Distance to campus: 1-5 miles	0.278	0.121	2.306	0.021	0.041	0.515
Latent Physical Condition	0.211	0.046	4.609	0.000	0.121	0.301
Latent External Restrictions	−0.427	0.062	−6.919	0.000	−0.549	−0.305
Access to bike	0.989	0.102	9.692	0.000	0.789	1.189
Commute mostly by car	−0.389	0.135	−2.872	0.004	−0.654	−0.124
Commute mostly by bus	−0.239	0.098	−2.435	0.015	−0.431	−0.047
External Restrictions (0.105)						
Male	−0.306	0.074	−4.122	0.000	−0.451	−0.161
Age: 23-27	−0.204	0.105	−1.950	0.051	−0.410	0.002
Age: 28-40	−0.295	0.123	−2.404	0.016	−0.536	−0.054
Access to bike	−0.213	0.074	−2.884	0.004	−0.358	−0.068
Commute mostly by car	0.173	0.118	1.471	0.141	−0.058	0.404
Commute mostly by bus	0.174	0.084	2.068	0.039	0.009	0.339
Physical Condition (0.426)						
Male	0.195	0.088	2.222	0.026	0.023	0.367
Exercise frequency: never	−0.535	0.185	−2.888	0.004	−0.898	−0.172
Exercise frequency: once a week	0.568	0.147	3.863	0.000	0.280	0.856
Exercise frequency: 2-3 times a week	1.155	0.126	9.137	0.000	0.908	1.402
Exercise frequency: daily	1.889	0.145	13.015	0.000	1.605	2.173

are less sensitive to the effects of slopes, as expected. The opposite sign for the interaction between travel time an the latent bicyclist status shows a different effect for the two classes. From the point estimates of the class assignment mode, more advanced cyclists are possibly classified in the first class. Thus for an advanced cyclist, an increase in their bicyclist status – which summarizes the cycling skills of the individual – reduces the negative effect of travel time (i.e. experienced cyclist are less sensitive to travel time). On the other hand, for beginners, an increase in their skills seems to put more weight on travel time. The point estimates of MM-MNL kernel are displayed in Table 4.3.

Table 4.4 and Table 4.5 summarize the causal relationships and measurement of the latent variables.Gender, age, commute distance, access to bike, an indicator for commuting mostly by car, another indicator for commuting mostly by bus, physical condition, and external restrictions significantly influence individual's bicyclist status. For instance, fit men who live 1-5 miles from campus and have access to a bike have a higher bicyclist status. Higher external restrictions and mostly commuting by motorized modes decrease the score of the latent bicycle status. Finally, in our data males are expected to have better physical condition than women and for them it is more apparent to explain the relationship between physical condition and frequency of exercising.

4.4 Conclusions

In the past few years, hybrid choice models have been dominating applications of discrete choice analysis, due to the flexibility of these models in incorporating endogenous attributes, including subjective factor such as personal attitudes,

and multidimensional attributes that are hard to characterize as a single item. The estimation of hybrid choice models is complex, but the improvement of computer hardware makes hybrid choice is associated with important reductions in computational cost. However, most recent studies still use a multinomial logit as the choice kernel of the hybrid model.

Preference heterogeneity is comprehensively acknowledged as an important feature to be considered in discrete choice modeling. The consequences of neglecting or inappropriate handling unobserved heterogeneity include biased estimates which may mislead policymakers. Given the advantages of flexible heterogeneity distribution, in this paper we propose a hybrid choice model with a discrete-continuous heterogeneity distribution for the random parameters. A maximum simulated likelihood estimator was derived and used for this hybrid choice model with an MM-MNL kernel.

We also provide an empirical case study on cycling route decisions. The adoption of the Gaussian mixture for the choice kernel introduces more flexibility to the hybrid choice model and enhances the model fit. As expected, travel time, slope and heavy traffic impose negative impact on cycling decision, whereas ownership of a bike and the presence of bike lanes on the road encourage people to ride a bike. We also find that individual's latent attributes influence the choice probability. People with better physical conditions are less sensitive to slope. The latent bicyclist status influences sensitivity to travel time in the opposite direction for 2 classes.

There are several possible avenues for further improvement. Perhaps the most interesting topic is the estimation process of the model. The frequentist estimator of the hybrid choice model requires optimization of the simulated

likelihood function which is time consuming. Weak identification is another challenge for the frequentist estimator. Without the requirement of maximization, Bayes estimators may be an attractive approach for hybrid choice models with flexible heterogeneity distributions. Thus, the next step following this research may include derivation of Bayes estimators for hybrid choice model with an MM-MNL kernel.

CHAPTER 5

ON THE PROBLEM OF MEASURING DISCOUNT RATES IN INTERTEMPORAL TRANSPORTATION CHOICES

5.1 Introduction

Users of transportation systems face economic decisions that involve timing differences such as purchasing a monthly or annual public transportation pass (versus single tickets). Vehicle ownership is another clear example of a decision that involves different timing of costs and benefits. In effect, cars are durable goods that are bought for use in future trips. In making intertemporal economic choices, users tradeoff between immediate and future costs. In the case of vehicle choice, purchase price is the known present value of the investment. Future expenses include fuel expenditures, costs of regular maintenance, parking permits, insurance, etc. The evaluation of these tradeoffs between costs and benefits at different points in time requires the use of a **discount rate**. The discount rate, which reveals an individual's current willingness to pay for future money, is thus a key index for understanding intertemporal transportation choices. Moreover, transportation and energy policymakers need estimates of discount rates. On the one hand, discount rate estimates are needed to forecast the impact of market penetration and use of new technologies that offer lower operating costs at a higher investment. On the other hand, discounting estimates also inform regulations such as subsidies and conservation programs. In perfect market conditions, the discount rate can be regarded as the **market interest rate**. However, given market imperfections caused by transaction costs and incompleteness of the intertemporal market, evaluation of individual discount

rates becomes challenging.

Although standard and hedonic regressions can be used to determine discount rates used by individuals in their intertemporal decisions, discrete choice models (McFadden [106]) offer a structural approach to the problem of estimating individual discounting. Seminal work on the problem of estimating individual discount rates with discrete choice models includes Hausman [60], Lave and Train [96], and the technical reports cited in Train [137]. In addition, excellent and relatively recent literature reviews are provided by Frederick et al. [47] and Cameron and Gerdes [30]. Hausman [60] was interested in modeling purchase behavior of energy-intensive durable goods — he modeled the specific choice of room air conditioners. Proposing a method that we will identify in this paper as "endogenous discounting", Hausman [60] concluded that individuals discounted expected operating costs using a 25% annual rate. The author described this estimate as being substantial especially when compared with those rates usually used in engineering life-cycle analysis. In his survey paper, Train [137] reviewed ranges of discount rates for several energy-intensive durable goods such as heating systems, refrigerators, and automobiles from several studies including Hausman [60], Lave and Train [96]. Train [137] discussed the specific impact of socioeconomic characteristics on discount rate estimates, as well as the wide range of variation observed in empirical work. Frederick et al. [47] distinguished time discounting from time preference and emphasized that groupwise differences in discount rates were large. The authors also identified limitations of Samuelson [126] discounted-utility model — which has dominated research — and discussed advantages of alternative formula such as the hyperbolic discount function proposed by Loewenstein and Prelec [99]. A more recent paper by Cameron and Gerdes [30] summarized early models of time preferences pay-

ing more attention on the description of field experiments as well as an update of structural analysis using random utility maximization models.

As it can be inferred from the paragraph above, the problem of time preferences is particularly relevant to understand the adoption of energy efficiency in general. In the specific case of transportation decisions, consumers make choices realizing that energy efficient vehicles offer important savings in fuel cost at a higher purchase price. Energy efficient vehicles include standard gasoline cars with improved fuel economy (above 40 MPG), hybrids, and ultra-low-emission cars (plug-in electric and hybrids, with fuel economy of about 100 MPGe). If consumers have high discount rates when buying future energy savings, energy efficient vehicles are perceived as less attractive; consequently, cheaper, less efficient cars will be preferred. The phenomenon that consumers and firms are strangely reluctant to invest in energy-efficient projects or goods that payoff the investment via energy savings is named "energy paradox" (neglect of private profitability) or "energy efficiency gap" (neglect of social desirability) in the energy economics literature (Jaffe and Stavins [72]). From a time preference perspective, the presence of an energy paradox is linked to unexpectedly high discount rates. The energy policy consequence is that broad adoption of highly efficient technologies requires special tools such as subsidies, taxes, standards, and labeling.

Jaffe and Stavins [72] examined the microeconomic foundations that explained the energy paradox in incorporating energy-saving technology in new residential construction as well as retrofitting. The authors attributed the paradox to three main dimensions, namely **market failure** (imperfect or asymmetric information or both, principal-agent problems, externalities and average cost-

pricing in energy markets, liquidity constraints in capital markets, research and development spillovers in innovation markets), **behavioral bias** (bounded rationality and heuristic decision-making, myopia, inattentiveness, inertia, biased beliefs, loss aversion, reference-dependent preferences), and **model misspecification** (omission of relevant attributes, observed and unobserved heterogeneity). Reviewing recent studies on the energy paradox (eg. Jaffe and Stavins [72, 73], Howarth and Sanstad [70]), Greene et al. [56] identified the following eight factors to explain the market failure in the automotive market: (a) principal-agent problems (moral hazard, split incentives), (b) asymmetric information (adverse selection), (c) imperfect information, (d) transaction costs (hassle factor), (e) bounded rationality, (f) lack of skills to perform the necessary calculations for correct discounting, (g) external costs, and (h) consumer myopia.

Expanding on Jaffe and Stavins [72], several resource and energy economists have added to the debate about the energy paradox (Newell and Siikamäki [115], Allcott and Greenstone [2], Ansar and Sparks [5], Van Soest and Bulte [142], DeCanio [37], Hassett and Metcalf [59] , to name just a few). DeCanio [37] analyzed the response by firms to energy-saving investment using a set of regressions. According to the coefficient estimates, the author concluded that organizational and institutional characteristics of the firm had greater effect in explaining energy-efficiency investments than economic factors. Hassett and Metcalf [59] derived a stochastic model and forecasted the discount rate via simulations to argue in favor of rational cost minimizing behavior by consumers. **Investment irreversibility** (sunk costs) and **volatility** were used to explain higher rates (energy paradox explained as an **option value** of delaying the investment decision). Simulations led to a four times higher hurdle

rate, whereas the actual discount rate was quite similar to the contemporary observed interest rate. In contrast, Sanstad et al. [127] — using the same model and data — criticized the conclusions of Hassett and Metcalf [59] in that their work used lower risk-adjusted discount rates than those observed in reality. However, the study of Ansar and Sparks [5] supported Hassett and Metcalf [59] by extending the stochastic model to incorporate innovation temporal effects (learning and experience).

In sum, high internal rates of return are expected for consumers investing in energy efficiency, either because of market imperfections, behavioral irregularities, option values (rational delay), or a combination of all these factors. For planning transportation energy policy, a true understanding of how to measure and model subjective discounting is needed (cf. Greene [54]). In this paper, we revisit the problem of time preferences in transportation choices and summarize the (sometimes competing) multidisciplinary avenues of research that analyze discounted operating costs. We note that although the energy paradox has been addressed in vehicle choice models since their inception, the subject has been surprisingly absent in the explosive transportation research interest in the adoption of electric vehicles (cf. Daziano and Chiew [36]). To account for the differing explanations behind the energy paradox, we propose to follow the work of Newell and Siikamäki [115] in water heaters and combine a random utility maximization model with exogenous discounting. As we elaborate in the paper, exogenous discounting assumes a given rate for the calculation of the present value of future costs or benefits. In the proposed approach the discount rate is exogenous to the discrete choice model, but an individual estimate is determined within the same survey according to a field experiment that elicits time preferences — unlike most applications in economics where a market

interest rate is used for exogenous discounting.

We overview first how to represent intertemporal choice in discrete choice models (Section 5.2). In particular we describe the utility specification when assuming either an endogenous (Section 5.2.1) or exogenous (Section 5.2.2) discount rate. Our review has a specific focus on vehicle purchase decisions. Then, we describe lab or field experiments that can be used to reveal subjective discounting (Section 5.3). In Section 5.4, a field experiment is analyzed as case study to discuss how to incorporate subjective discounting data in a transportation survey. Finally, Section 5.5 concludes and provides insights for further research.

5.2 Discrete choice and the intertemporal consumption problem

In random utility maximization models, consumers are assumed to make decisions among mutually exclusive alternatives that are characterized by observable attributes. An intertemporal economic choice problem involves a tradeoff between purchase price (known present equivalent of the investment) and the present value of future costs. If PVFC_{in} represents the present value of future costs of alternative i and individual n, then choice is determined by maximizing the indirect conditional utility:

$$U_{in} = \beta_p \text{price}_{in} + \beta_{\text{PVFC}} \text{PVFC}_{in} + \mathbf{x}'_{in}\boldsymbol{\beta}_x + \varepsilon_{in}, \tag{5.1}$$

Where U_{in} is the utility function for alternative i and individual n (and con-

sumers choose the alternative with largest utility); price_{in} is the purchase price of alternative i; $\mathbf{x}_{in}$ represents the vector of attributes other than costs; β_p and β_{PVFC} represent marginal utility of purchase price and present value of future costs which could be estimated; $\mathbf{x}_{in}$ is other attributes with impact on decision in vehicle consumption and $\boldsymbol{\beta}_x$ represents the marginal utility of each attributes. ε_{in} is the error term absorbing other unobserved attributes.

If L_{in} is expected length of time that the household will own the alternative, then

$$\text{PVFC}_{in} = \sum_{t=1}^{L_{in}} \frac{\mathbb{E}(fc_{int})}{(1+r)^t}, \tag{5.2}$$

Where $\mathbb{E}(fc_{int})$ is the expected value of the future (operating) cost at time t, and r is the discount (interest) rate.

Note that for a *rational individual* and under perfect market conditions, following the microeconomic derivation of the consumer problem with a discrete choice, $\beta_p = \beta_{\text{PFVC}} = -\alpha$, where α is the marginal utility of income.

The derivation of PVFC_{in} requires knowing the discount rate r. Even if we assume that individuals know how to discount future cash flows, the researcher may not have access to that information. If r is not known by the researcher, then *endogenous discounting* models can be used where r is determined within the model. If r is known, then *exogenous discounting* can be used.

5.2.1 Endogenous discounting

If r is not known, then it can be treated as an additional parameter in the model. Following Hausman [60] and Train [137], if L in equation 5.2 is large enough and

appreciation in fuel prices is ignored, then the *capitalized worth* approximation can be used:

$$\text{PVFC}_{in} \approx \frac{fc_{in}}{r}, \tag{5.3}$$

Where fc_{in} is a uniform (monthly or annual) equivalent of the nonuniform $\mathbb{E}(fc_{int})$. Using the capitalized worth approximation in the utility function (eq. 5.1) and defining β_{fc} as the parameter of the uniform equivalent fc_{in}, it is possible to see that $\beta_{fc} = \beta_{\text{PVFC}}/r$. As a result, for a rational consumer ($\beta_p = \beta_{\text{PVFC}}$):

$$r = \frac{\beta_p}{\beta_{fc}} = \frac{1}{\text{WTP}_{fc}}, \tag{5.4}$$

Where WTP_{fc} is the willingness to pay for marginal savings in fuel cost.

As a result, implicit discount rates can be easily derived from the estimates of discrete choice models where a time-uniform fc_{in} is considered. High implicit discount rates provide evidence in favor of individuals preferring current savings, and consequently paying less attention to future costs (i.e. the energy paradox mentioned in the introduction). A low implicit discount rate means that individuals are willing to pay more for buying an alternative that will exhibit savings in the future.

The concept of discounted operating costs has been taken into account in vehicle choice models since their inception (Lave and Train [96], Cardell and Dunbar [31], Beggs and Cardell [7], Boyd and Mellman [22], Manski and Sherman [103], Beggs et al. [8], Sherman [132], Train and Lohrer [139]). Greene [54] and Helfand and Wolverton [62] provide excellent reviews, including the original review paper of Train [137] where the methodology of endogenous discounting

Table 5.1: Endogenously determined implicit discount rate of select vehicle choice applications

Reference	Data type	Model	Implicit discount rate
Boyd and Mellman [22]	Aggregate	Mixed Logit & Logit	6% (Logit) 2% (Mixed Logit)
Cardell and Dunbar [31]	Aggregate	Mixed Logit	25%
Manski and Sherman [103]	Disaggregate	Multinomial Logit	6%-18% (urban; one-vehicle)
Beggs et al. [8]	Disaggregate	Ordered Logit	25%-35%(normalized)
Train and Lohrer [139] *	Disaggregate	Multinomial Logit	5%-12%
Berkovec and Rust [13] *	Disaggregate	Nested Logit	3%-5%
McCarthy [105] *	Disaggregate	Multinomial Logit	13.6%(10K VMT; $40K income)
Brownstone et al. [25] *	Disaggregate	Nested Logit	-2.7%-40.5%
Kavalec [80] *	Disaggregate	Mixed Logit	7% (10,000 VMT)
Brownstone et al. [26] *	Disaggregate	Mixed Logit	5.3%(MMNL) 6.1%(MNL)
McFadden and Train [109] *	Disaggregate	Mixed Logit	5.0%(MMNL) 6.0%(MNL)
Ewing and Sarigöllü [41] *	Disaggregate	Multinomial Logit	19.2%(Base) 20%(Full)
Batley and Toner [6] *	Disaggregate	Nested Logit	9%-10%
Horne et al. [69] *	Disaggregate	Multinomial Logit	23.5%
Dasgupta et al. [34]	Aggregate	Nested Logit	15.2%
Potoglou and Kanaroglou [119] *	Disaggregate	Nested Logit	18.9%-44.7%
Cambridge Econometrics [29]	Disaggregate	Mixed Logit	6%-19%
Musti et al. [113]	Disaggregate	Multinomial Logit	102%(10,000 VMT)
Lloro [97]	Disaggregate	Multinomial Logit	-9.61%-9.13%
Hess et al. [67] *	Disaggregate	Cross-nested Logit	47%

* Discount rate not reported in the original paper

is formally introduced in the transportation literature. Despite the history of interest in discounted fuel costs, the problem of the energy paradox is surprisingly absent in a large number of recent studies coming from transportation engineering analysis of the adoption of electric vehicles and alternative fuels — a theme

that has experienced an explosion in recent years due to the reintroduction and low diffusion of battery electric vehicles. In Table 5.1 we summarize select vehicle choice research using random utility maximization models. In the case that the authors did not analyze discount rates, we derived values directly from the model estimates (these cases are identified in the table with a star). When a study considered the operating cost attribute as an expense per distance (i.e. cost per mile), actual or a hypothesized vehicle miles traveled (VMT) is used to obtain fc_{in}.

As noted in previous reviews (see Greene [53], Train [137], Greene [54]), the point estimates of the implicit discount rates are not only generally higher than market interest rates, but the level of variability between and within studies is remarkable. Different choice contexts and data collection methods may explain in part the observed differences.

5.2.2 Exogenous discounting

Endogenous discounting models assume that $\beta_p = \beta_{\text{PVFC}}$, and myopic consumers are characterized by implicit discount rates that are (much) higher than market interest rates. However, the presence of market failures may explain myopic discounting in the sense that β_p and β_{PVFC} may be different.

There are several market failures that have been associated with energy efficient products. In fact, energy efficient durable goods in general come in the form of high technology products, and are thus faced to barriers of adoption and diffusion. Furthermore, there are peer and social network effects. For example, broad adoption usually happens after reaching minimum market share thresh-

olds. Additionally, Jaffe et al. [71] claimed that an individual's willingness to pay for new technology relies on other users' attitudes. In sum, no matter how compelling or attractive a radically new energy-efficient technology seems to be, it may diffuse gradually due to higher production costs and uncertainties about performance and market success. Another critical reason for market failure of new technologies addressed by Jaffe et al. [71] is incomplete and asymmetrical information. In the specific case of the vehicle market, automakers possess a better position than outsiders so that consumers become skeptical about alleged future monetary savings. Moreover, recent studies by Allcott [1], Turrentine and Kurani [141], Larrick and Soll [95] show that most consumers are not capable of rationally discounting fuel savings given relatively low gasoline price. As a result, buying an ultra-low-emission vehicle is regarded by consumers as an asymmetric investment with associated uncertainties and subjective risks. Furthermore, due to energy costs being highly correlated to capital cost,Allcott and Wozny [3] discuss that cross-sectional discrete choice estimators produce biased discount rates when calculated from the endogenous discounting method. A similar issue is reported by Gramlich [51], who look at the effect of the correlation between fuel economy and other automobile attributes such as horsepower. According to Gramlich [51] and Allcott and Wozny [3] the consideration by the researcher of an exogenous discount rate in the derivation of $PVFC_{in}$ reduces this correlation. In addition, from an economic equilibrium perspective discount rates should reflect market interest rates.

Aiming at working with an exogenous discount rates, some authors (for example, Allcott and Wozny [3] and Newell and Siikamäki [115]) in the energy economics literature have proposed to work with variants of the following util-

ity specification in willingness-to-pay space (Train and Weeks [140]):

$$U_{in} = \beta_p \left[\text{price}_{in} + \gamma_{\text{PVFC}}\text{PVFC}_{in} - \mathbf{x}'_{in}\boldsymbol{\omega}_x\right] + \varepsilon_{in}, \tag{5.5}$$

Where γ_{PVFC} is the willingness to pay for marginal savings in the present value of lifecycle costs and $\boldsymbol{\omega}_x$ is the willingness to pay for marginally improving the other attributes. As before, for a rational consumer $\gamma_{\text{PVFC}} = 1$. If $\gamma_{\text{PVFC}} < 1$, then there is evidence for myopic consumption and $\gamma_{\text{PVFC}} > 1$ reveals that consumers overvalue fuel costs.

Using aggregated U.S. data of all registered used vehicles from 1999 to 2008, Allcott and Wozny [3] assumed market stationarity for a simplified dynamic discrete model – excluding uncorrelated vehicle attributes – to estimate demand for energy efficiency. The authors specified utility as follows:

$$U_{int} = \beta_p \left[\text{price}_{int} - I_i + \gamma_{\text{PVFC}}\text{PVFC}_{itn}\right] + \tilde{\psi}_i + \tilde{\xi}_{it} + \varepsilon_{int} \tag{5.6}$$

Where I_n is income of individual n; price_{int} represents the price of vehicle i in year t; PVFC_{itn} is the present value of future gasoline costs as evaluated at time t; $-\beta_p$ is the marginal utility of money; $\tilde{\psi}_i$ and $\tilde{\xi}_{it}$ measures consumers' unobserved utility of using vehicle i over its lifetime; and ε_{int} is the idiosyncratic error term. The expected future gasoline costs at time t were calculated as the product of forecasted gasoline prices, expected vehicle miles traveled, fuel economy, and probability that the vehicle was still working. Several discount rates were tested by the authors to calculate PVFC_{itn} leading to differing estimates of γ_{PVFC}. For instance, using 5% discount rate — which corresponds to the average interest rate in the automotive market in the period considered for the analysis — a point estimate of $\hat{\gamma}_{\text{PVFC}} = 0.76$ was obtained. The null hypothesis $H_0 : \gamma_{\text{PVFC}} = 1$ was rejected, proving the existence of myopic consumption in the automotive

market. Furthermore, the author could not reject the null hypothesis when a 15% discount rate was adopted.

Based upon the model BLP model (Berry et al. [14]), Sawhill [129] specified the following utility function with random parameters to capture consumer heterogeneity:

$$U_{in} = \beta_{p,n}\left[\text{price}_{in} + \gamma_{\text{PVFC},n}\text{PVFC}_{in}\right] + \mathbf{x}'_{in}\boldsymbol{\beta}_n + \xi_i + \varepsilon_{in}. \tag{5.7}$$

Detailed data from the *Automotive News Market Data Book* and list prices were used for determining price_{in}. To ensure accurate evaluation of PVFC_{in}, Sawhill [129] obtained adjusted data from EPA for fuel economy and forecasted future gasoline price by historical gasoline price data via time-series models. Meanwhile, annual vehicle miles traveled and the expected life of vehicles were estimated using different household data. Assuming that the discount rate was 5%, Sawhill [129] estimated a model with and without consumer heterogeneity. For the simple model with fixed parameters, $\hat{\gamma}_{\text{PVFC}} = 0.62$ indicated the undervaluation of future gasoline costs. In contrast, results of the random parameter model implied that consumers overvalued energy savings ($\hat{\gamma}_{\text{PVFC}} = 1.39$ with a 90,000 lifetime mileage and $\hat{\gamma}_{\text{PVFC}} = 1.31$ with 110,000 lifetime mileage).

5.3 Experiments for elucidating individual discount rates

In experimental economics and psychology both laboratory and field experiments are widely used for elucidating individual discount rates. The fundamental design of the experiment is a binary choice between an $\$x$ sooner payment (or "smaller, immediate reward", see Kirby et al. [83]) and an $\$(x + y)$ delayed

payment ("larger, delayed reward"), where x is the base (actual monetary) reward and y reflects the discount rate. Given the importance of discount rate in economics, a huge amount of experiments have been implemented in practice (selected applications are summarized in Table 5.2). Based on similar binary choice designs, different reward amounts and time horizons result in divergent discount rates ranging from 2% (McLeish and Oxoby [110]) to around 1000% (Holcomb and Nelson [68]). These differences may be explained in part by the experimental sampling process. First, most sample sizes have been rather small (most are under 200). In addition, subjects participating in the experiments are mostly college undergraduate students or first year master's students. Despite potential flaws in the sampling process, controlled experiments still appear as an effective approach to elicit heterogeneous discount rates.

In a work that has become seminal, Coller and Williams [33] organized the series of binary choices into a Multiple Price List (MPL) that corresponds to an increasing order of interest rates. In addition to the (actually paid) monetary reward amounts, a group of respondents was also shown the implied nominal and effective interest rates. The authors obtained a median discount rate of 15%-17.5% for the group with the additional information, and a median of 17.5%-20% for the group without information regarding the implied rates. In addition, an ordered logit model was estimated to evaluate the sensitivity of the individual discount rate to socio-demographics. Due to a significant correlation with race and income level, the authors suggest that discount rates should be regarded as an individual characteristic. Following Coller and Williams [33], Harrison et al. [58] conducted another field experiment in Denmark and obtained an average discount rate of 28.1%. According to the studies summarized in Table 5.2, the major determinants of discounting heterogeneity can be described as (a)

Time horizon (Thaler [136], Benzion et al. [12], Holcomb and Nelson [68], Pender [118], Cairns and van Der Pol [28], Read and Read [120]); (b) Money magnitude or reward size (see Benzion et al. [12], Holcomb and Nelson [68], Green et al. [52], Bocquého et al. [18]); (c) Income level (Coller and Williams [33], Wahlund and Gunnarsson [143], Mahajna et al. [101], Warner and Pleeter [145]); and (d) Education level (Harrison et al. [58], Warner and Pleeter [145]). The effect of gender, mood or age are also widely discussed in the literature.

The study of Warner and Pleeter [145] provided another approach to individual discount rates. Instead of using laboratory experiments, Warner and Pleeter [145] derived discount rates from large scale real choices. The military drawdown program provided two mutually exclusive alternatives, namely Voluntary Separation Incentives (VSI) and Selective Separation Benefit (SSB) corresponding to annually future payments and a present lump-sum payment, respectively. The data was collected as the revealed intertemporal choice of over 65,000 people. The results ranged from 0% to 57.2% according to different subjects' groups and model used. Socio-demographics, especially income and education level placed a significant impact on the individual discount rate.

Exploiting a unique approach that combines choice modeling with experimental discount rates, Newell and Siikamäki [115] examined consumers' response to energy efficiency labeling on water heaters. Within a discrete choice experiment, subjects were required to examine 12 different labeling treatments that were customized by fuel type. Attributes such as potential fuel cost, capital cost and green house gas emissions were determined according to actual product characteristics. A mixed logit model in willingness to pay space was estimated with a random parameter version of the specification shown in eq.

Author	Year	Subjects	Rewards	Payment delays	Discount rate	Major determinant
Thaler [136]	1981	Not specified	$15— $3,000	3 months— 10 years	120%—219%	Delay between two payments Sign effect
Loewenstein [98]	1988	105 students	$5—$7	3 or 4 weeks	96%	
Benzion et al. [12]	1989	282 students	$40,$200,$1,000 and $5,000	0.5,1,2 and 4 years	Average 21.3%	Delay between two payments Size of cashflow Loss or gain
Holcomb and Nelson [68]	1992	101 students	$5 and $17	1 day, 1 week and 2 weeks	Around 1000%	Delay between two payments Amount of base money
Shelley [131]	1993	74 students	$40,$200,$1,000 and $5,000	0.5,1,2 and 4 years	10.7% —20.0%	Receipts or payments
Pender [118]	1996	96 (origin) 76 (follow-up)	10kg rice	7,12,19 and 24 months	26%—119%	Time frame effects Wealth
Wahlund and Gunnarsson [143]	1996	1,000 households	SEK 10,000	1 months or 1 year	Average 108%(1 month) average 39%(1 year)	Household's economic situation Financial knowledge
Green et al. [52]	1997	24 students	$100,$2,000,$25,000 or $100,000	3 or 6 months 1,2,5,10 or 20 years	20%—98%	Amount of the reward
Cairns and Van der Pol [28]	1997	103 residents in Scotland	500	2,4,5,6,8,12,14,15, 16,17,18,19 years	13.5%—41.4%	Delay between two payments
Coller and Williams [33]	1999	199 students	$500	2 months	15%-20%	Informing discount rate Parents/household income
Warner and Pleeter [145]	2001	over 65,000	Lump-sum of annuity	Twice the member's year of service	0%—57.2%	Earnings Education level
Harrison et al. [58]	2002	268 Danes	$100	6,12,24 or 36 months	Average 28.1%	Length of education Retirement Unemployment
Read and Read [120]	2004	123 people in UK	600 or 1200	1,2,3 or 10 years	50%—90%	Delay between two payments Age
McLeish and Oxoby [110]	2007	86 students	$40 or $100	3 or 5 weeks	2%—10% Mood	Gender
Mahajna et al. [101]	2008	86 bank customers	5,000 or 20,000 NIS	6 or 24 months	10%—48% (Arabs) 6%—18% (Jews)	Different groups Income
Bocquého et al. [18]	2013	107 farmers	€148—€800	1,2 or 3 years	13.6%	Amount of the reward

Table 5.2: Selected literatures of elucidating individual discount rate

5.5 for the exogenous discounting method:

$$U_{in} = \beta_{p,n}\left[\text{price}_{in} + \gamma_{\text{PVFC},n}\text{PVFC}_{in} - \mathbf{x}'_{in}\boldsymbol{\omega}_{x,n}\right] + \varepsilon_{in}. \tag{5.8}$$

However, instead of just using exogenous discounting with a uniform 5% discount rate as in Allcott and Wozny [3] and Sawhill [129], Newell and Siikamäki [115] included in the survey a version of the MPL field experiment of Coller and Williams [33], as explained above, to elicit individual discount rates. In contrast with rational consumption guided by information labeling using the heterogeneous individual discount rate, the uniform discount rate resulted in a one-third undervaluation of fuel efficiency.

5.4 Experimental Case Studies

Aiming at understanding how to best implement the time preference elicitation method of Coller and Williams [33], and expanding on Newell and Siikamäki [115], we designed a customized web survey where participants manifested their intertemporal preferences. We modified the Multiple Price List (MPL) method of Coller and Williams [33] (explained in the previous section) in that only one binary choice was shown to participants at a time. In addition, because the scenarios are displayed at an increasing interest rate, the experiment ended as soon as a respondent accepted the delayed reward. The underlying assumption to skip the following scenarios is transitivity in intertemporal preferences. We tested this sequential experiment in a focus group and we observed a better understanding of the exercise compared to the case where all delayed rewards are presented simultaneously. In particular, in the simultaneous MPL experiment we detected random and intransitive responses as well as a tendency to

choose the largest reward amount.

In our experiment we opted for a horizon of two months for the delayed reward. As recommended in the literature (Coller and Williams [33], Newell and Siikamäki [115]), to avoid immediacy bias in the elicitation of intertemporal preferences, instead of using an immediate reward the "sooner" payment was offered "at the end of the current month" (and consequently the delay for the larger reward was two months after the end of the current month). The immediacy bias (or present effect) appears as inconsistent preferences for the present, resulting in an unexpectedly high discount rates.

Based on the focus group experience, we also decided not to present the underlying discount rate. People are unaware of the concept of subjective discount rate, but are familiar with interest rates. Providing rate information may impose a psychological hint on participants that we wanted to avoid.

Figure 5.1 presents a screenshot of the experiment description, as well as one of the specific binary choice scenario. 8 scenarios were implemented with increasing interested rates (2%, 5%, 10%, 15%, 20%, 25%, 30%, and 35%). As explained above, the MPL experiment stopped when the respondent accepted the delayed reward (option 2).

5.4.1 First Experiment

In October 2013 an invitation was sent to 93 individuals enrolled to participate in an experimental economics panel at Cornell University. 91 participants agreed to respond our survey (97.85% response rate). The participants were

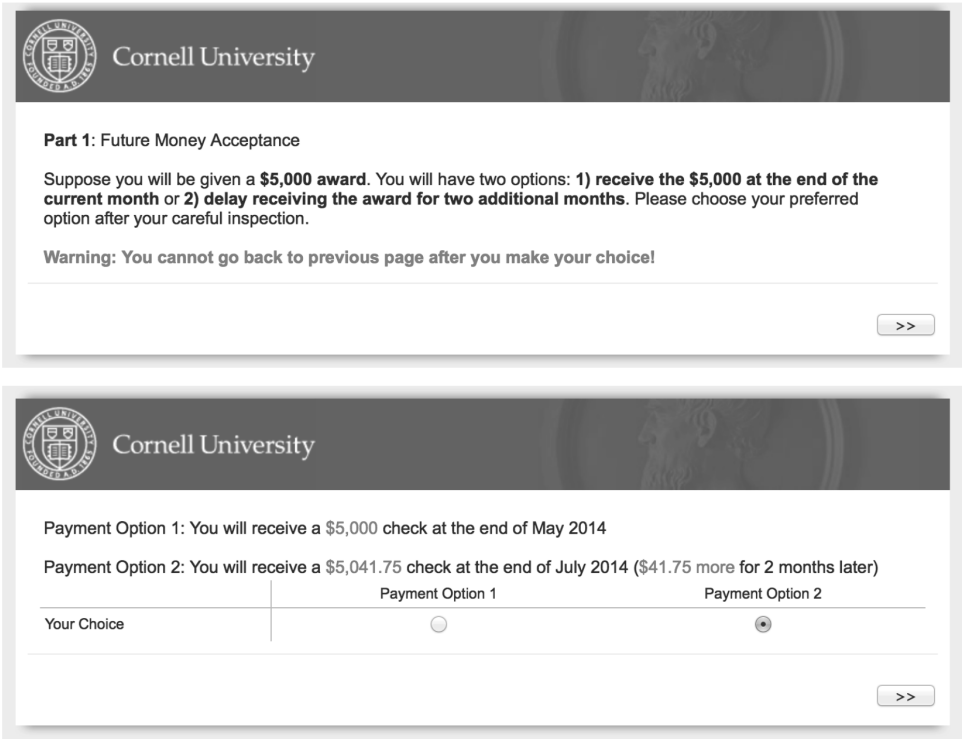


Figure 5.1: Screenshots of the experiment description and one scenario of binary choice

separated into three groups. All groups completed first a section about socio-demographics. Each group answered the subsequent sections of the survey in a scrambled order. The experiment followed a 2×2 between-subjects design in which the initial reward was randomly manipulated ($1,000 or $5,000). Table 5.3 display the selected summary statistics of the survey. A section of the survey collected information about credit history (whether respondents currently have or have had a loan) and self-reported credit rating. Note that both the credit rating and monthly expense level are categorical variables. There are 5 levels (from 1 to 5) of credit reflecting level of excellent, good, fair, poor and very poor. Meanwhile, the monthly expense has been divided into 12 categories in order of amount of money from no more than $ 500 to more than $12,000.

Table 5.3: Summary of partial data from the questionnaire

Variable	Mean	Standard Deviation
Age	20.89	2.791
Height (inches)	66.77	3.446
Weight (pounds)	143.35	29.233
Credit rating (categorical)	1.64	0.692
Monthly expense level (categorical)	2.41	1.461
Individual discount rate	12.28%	0.112

According to the MPL experiment results, the mean of the individual discount rate is 12.28% over the whole sample. The relatively high standard deviation reflects extraordinary difference among individuals. To clarify this heterogeneity, we made the initial hypothesis that people with loan experience would be more at ease comparing money at different points in time. To test this hypothesis, we divided the participants into four groups based on the manipulated initial reward and the subjects' responses to loan history. Figure 5.2 shows how the amount of initial reward influences individual discount rates even across different conditions of loan history. For subjects who have experienced a loan, the average individual discount rate decreases from 18.47% to 8.06% (a decrease of 53.56%) when the initial reward goes from $1,000 to $5,000, while the average individual discount rate for the other group falls from 12.93% to 7.69% (a decrease of 40.53%).

Table 5.4 presents estimates of an ordered logistic regression assuming a censored and ordinal dependent variable. In the ordered logistic regression y_n^* is the latent individual discount rate, which is measured by the threshold of future money acceptance. For example, if the subject refuse to accept the delayed

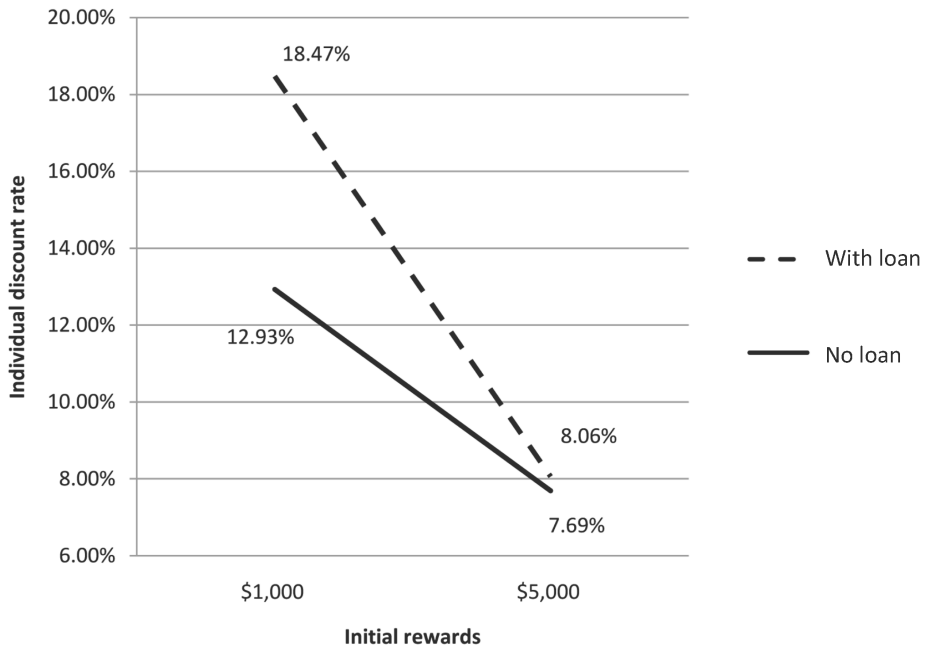


Figure 5.2: The effect of initial rewards amount and loan history on individual discount rate

reward at the 2% level but accepted the 5% discounting, then the true individual discount rate is manifested to fall between 2% and 5%. The coefficients in Table 5.4 were estimated separately using the maximum likelihood estimator for three different sub samples, namely: all subjects, group 1 (with loan history) and group 2 (no loan history). Results of the χ^2 test suggest good fit of all these three models.

Results based on all subjects indicate that the amount of initial reward, age, whether monthly expenses are below $500, from $500 to $1,000 and from $1,000 to $2,000 significantly influence the individual discount rate. Consistent with previous studies, individual discount rates decrease when the amount of the initial reward increases (an already evident result from Figure 5.2). However, age stimulates the growth of the individual discount rate in contrast with re-

Table 5.4: Estimates of coefficients in different groups

Independent variable	All subjects	Group 1	Group 2
Loan history dummy	-0.104	NA	NA
Amount of initial rewards(10^{-4})	-7.346*	-1.258*	-0.295*
Age	0.156*	0.196*	-0.198
Gender (female)	-0.429	0.457	-1.919*
Height(10^{-2})	6.952	5.315	5.211
Weight(10^{-3})	-5.272	-3.591	2.578
Monthly expense under $500	2.723*	2.262*	1.042
Monthly expense between $500 and $1,000	2.522*	2.416*	0.961*
Monthly expense between $1,000 and $2,000	2.123*	2.310	1.051
Monthly expense between $2,000 and $3,000	1.371	1.509	NA
Log-likelihood	-167.11	-99.07	-58.08
Prob¿χ^2	0.019	0.023	0.017
Pseudo ρ^2	0.056	0.083	0.082
Number of subjects	91	59	32

* Statistical significant at the 95% confidence level. (p-value<0.05.)

sults by Warner and Pleeter [145]. In addition, relative low monthly expenses contribute to higher discount rates, a result that can be easily understood as lower expenses reflect either lower income or a personal conservative attitude toward money.

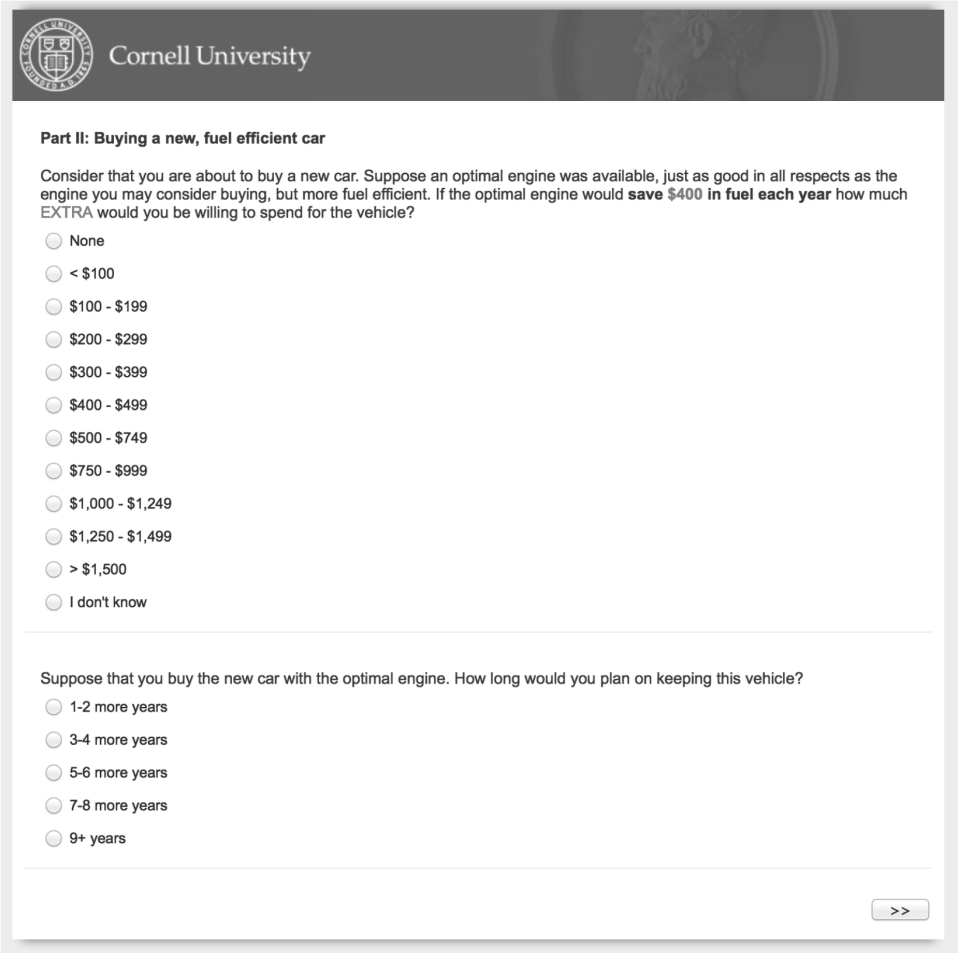
Within group 1, the amount of the initial reward, age, and monthly expenses are still the most relevant factors explaining differences in the individual discount rates. For group 2, the amount of initial reward is still significant and has the expected negative sign. In this group, males appear as having higher discount rates than females (the effect of gender was not significant for the other

two groups), and monthly expenses between $500 and $1,000 is the only range that appears to have an impact. (Note that in group 2, no subject reported a monthly expense higher than $2,000.) To control for regressors with no explanatory power we checked that personal height and weight had no impact on the subjective discount rate. Interestingly, whether a person had ever experienced a loan had no distinct impact on the determination of the individual discount rate.

A second wave of the study was conducted in May 2014. 75 participants (junior and senior college students at Cornell) answered the follow-up study. The elicited discount rate from our version of the MPL experiment had a mean of 13.93% (cf. 12.28% in the previous group) and a standard deviation of 0.121.

In addition to the MPL experiment, in the new survey we added a contingent valuation question from Greene et al. [55] about future fuel savings in the context of vehicle choice. In particular, we asked for the additional amount of money participants were willing to pay for an alternative fuel vehicle that could save fuel costs in $400 annually (Figure 5.3). To have an idea of the evaluation horizon, the expected holding time of the vehicle was also included in the survey. The purpose was to test whether the implied discount rate from this direct contingent valuation measure of vehicle energy efficiency was consistent with the MPL discounting.

Given the stated willingness to pay for fuel savings, expected ownership length of the vehicle, and the derived present value of fuel savings, implicit discount rates were calculated according to Eq. 5.2. These results were then compared with the MPL elicited discount rate. As shown in Table 5.5, the discount rate calculated from the contingent valuation exercise not only exhibit a much



Cornell University

Part II: Buying a new, fuel efficient car

Consider that you are about to buy a new car. Suppose an optimal engine was available, just as good in all respects as the engine you may consider buying, but more fuel efficient. If the optimal engine would **save $400 in fuel each year** how much EXTRA would you be willing to spend for the vehicle?

- None
- < $100
- $100 - $199
- $200 - $299
- $300 - $399
- $400 - $499
- $500 - $749
- $750 - $999
- $1,000 - $1,249
- $1,250 - $1,499
- > $1,500
- I don't know

Suppose that you buy the new car with the optimal engine. How long would you plan on keeping this vehicle?

- 1-2 more years
- 3-4 more years
- 5-6 more years
- 7-8 more years
- 9+ years

>>

Figure 5.3: Willingness to pay for fuel savings (see Greene et al. [55] for the contingent valuation question)

higher mean than the MPL rate (93.9% versus 13.93%), but also a much greater level of variability. The mean of γ_{PVFC} being 0.41 for the contingent valuation discounting indicates a high undervaluation of fuel economy.

We recognize limitations of our field experiment, especially those associated with the very particular characteristics of the sample in terms of size and composition. However, our results provide evidence in favor of the use of the MPL method for elicitation of discounting. When examining the energy paradox in transportation decisions combined with exogenous discounting, our recom-

Table 5.5: Discount rate from binary choice experiment versus that from the contingent valuation exercise

Name	Range	Mean	Standard Deviation
Elicited individual discount rate	2%—25%	13.93%	0.121
Calculated individual discount rate	6.4%—267%	93.9%	0.930
γ	0.0075—4.72	0.41	0.700

mendation is to embed the MPL experiment into a traditional survey of vehicle choice to derive subjective discount rates that can be used to calculate the present value of future fuel costs.

5.4.2 Second Experiment

In 2014, a larger data collection effort was performed over a sample of COMPLETENUMBER of individuals living across the US. Table 5.6 summarizes the main characteristics of the sample. In this survey, in addition to the MPL experiment, the survey also contained a discrete choice experiment of energy-efficient vehicle purchases. The choice experiment considered a decision among an internal combustion vehicle, and three different levels of electrification and hybridization: regular hybrid, plug-in hybrid, and battery electric cars. The experiment attributes were purchase price, monthly operating cost, and driving range.

In all models, purchase prices of vehicles were transformed to have the unit of $1,000 to adjust the magnitude of the coefficients. Operating costs were discounted to the net present value using individual discount rates measured in the

Table 5.6: Sample Demographic Statistics

Respondent characteristics	Percentage	Respondent characteristics	Percentage
Male	50.31	Lives in the west	18.02
Married	55.82	Lives in midwest	23.90
Completed college	52.07	Lives in northeast	21.4
Single family home	75.84	Have no child	33.92
Apartment	17.27	Have one child	20.65
Own house	70.34	Have two children	24.66
Student	1.00	Have three children	12.52
White	86.36	Have four children or more	8.27
African American	8.01	30 years old or younger	10.89
Hispanic	7.01	Age from 31 - 40	21.78
Asian	2.63	Age from 41 - 50	18.27
Conservative	41.80	Age from 51 - 60	27.03
Liberal	22.28	Age from 60 -70	17.15
		71 years old or older	4.88

Notes: The white, African American, Hispanic and Asian percentages sum to more than 100 percent because some of the respondents have multicultural backgrounds.

MPL experiment. We also used the logarithm of the driving range based on the assumption that the marginal utility of driving range decreases as the allowed distance increases. The summary of the attributes for estimation are shown in Table 5.7. All Model estimations were performed using the gmnl package in R (see Sarrias and Daziano [128]).

Base Models

A mixed multinomial logit (MIXL) model with normally distributed coefficients was estimated first. The results are presented in Table 5.8.

Table 5.7: Summary statistics for attributes

Attribute	Min	Max	Mean	Median	Standard deviation
Price($ 1,000)	15.50	39.50	25.22	25.00	6.75
Present value of operating cost(PVOC)	0.10	71.71	4.37	2.78	5.25
Logarithm of driving range(LDR)	2.71	6.38	5.12	5.61	1.33

Table 5.8: Coefficients of MIXL model

Variables	Estimate	S.E.	T-stat
Electric:(intercept)	0.2183	0.1543	1.41
Hybrid:(intercept)	1.1614	0.0859	13.52
Plug-in hybrid:(intercept)	2.4106	0.2380	10.13
Price(Mean)	-0.1915	0.0080	-23.95
Present value of operating cost(Mean)	-0.2917	0.0120	-24.30
logarithm of driving range(Mean)	0.7881	0.0811	9.72
Price(S.D.)	0.1930	0.0079	24.45
Present value of operating cost(S.D.)	1.0305	0.0281	36.70
logarithm of driving range(S.D.)	0.7151	0.0310	23.07

Most point estimates of the MIXL model are statistically significant with an exception of the constant term of electric vehicles and all coefficients have expected signs and magnitudes. Whereas higher purchase price and operating cost place negative influence on choosing a specific vehicle, the increase in driving range makes a car more attractive. The large estimates of standard deviation reveals the presence of large preference heterogeneity among the sample.

The latent class model(LC) assumes a discrete distribution for the coefficients. The point estimates are shown in Table 5.9 and Table 5.10. Although the LC model was estimated simultaneously, I would like to discuss the latent

Table 5.9: Coefficients of latent class assignment model

Variable	Estimate	S.E.	T-stat
Assigntment to class 2			
Intercept	-0.3676	0.2310	-1.59
Number of vehicle owned	0.6844	0.0637	10.74
Number of children	-0.0448	0.0206	-2.18
Current owner of hybrid vehicles	1.5270	0.2454	6.23
Male	0.0769	0.0561	1.37
Married	0.1374	0.0597	2.30
Completed college	0.3419	0.0579	5.91
Single family home	0.2645	0.1097	2.41
Apartment	-0.0495	0.1329	-0.37
Own house	-0.3945	0.0743	-5.31
Student	0.9566	0.3103	3.08
White	-0.3996	0.1768	-2.26
African American	-0.3130	0.2009	-1.56
Hispanic	0.2794	0.1190	2.35
Asian	0.3057	0.2597	1.18
Conservative	-0.3853	0.0633	-6.09
Liberal	0.1525	0.0763	2.00
Lives in the west	0.0847	0.0807	1.05
Lives in midwest	0.3705	0.0742	4.99
Lives in northeast	0.1568	0.0760	2.06

class assignment model first.

In the class assignment model, we set class 1 as baseline and the marginal utilities reveals the preference difference compared with class 1. That is to say a positive coefficient of a certain attribute indicates its preference to class 2. For example, in our experiment, the more vehicles own currently by a certain individual, the larger probability of this person being classified in the second class.

Table 5.10: Coefficients of LC model

Variable	Estimate	S.E.	T-stat
Class 1			
Electric:(intercept)	-1.8612	0.5045	-3.69
Hybrid:(intercept)	-0.4579	0.1528	-3.00
Plug-in hybrid:(intercept)	-0.4423	0.8499	-0.52
Price	-0.2177	0.0182	-11.97
Present value of operating cost	-0.0734	0.0120	-6.13
logarithm of driving range	0.5684	0.3088	1.84
Class 2			
Electric:(intercept)	1.4485	0.1528	9.48
Hybrid:(intercept)	1.8879	0.1026	18.40
Plug-in hybrid:(intercept)	2.3718	0.2102	11.28
Price	-0.0753	0.0056	-13.38
Present value of operating cost	-0.0755	0.0160	-4.71
logarithm of driving range	0.1972	0.0661	2.98
Assigntment to class 2			

On the other hand, house owners are more likely in the first latent class. According to Table 5.9, several attributes are statistically significant. Perhaps ownership of hybrid vehicles, whether a student and the number of vehicle owned have the largest impact on class assignment (have relatively large magnitude).

In the second class, both point estimates for mean and standard deviation of marginal utilities are significant. While in the first class, estimates of the logarithm of driving range as well as the intercept for the plug-in hybrid vehicle are not significantly different from zero. In both classes, purchase price and net present value of operating cost have negative signs as expected and in class 2, the logarithm of driving range has a positive impact on vehicle selection.

Double Mixture Models

Because MIXL imposes a very specific shape for the distribution of preference heterogeneity, we also specified a double mixture model. In a discrete-continuous mixture model, there is a discrete number of clusters of individuals, and within each cluster preferences are modeled according to an MIXL. From a statistical point of view, this discrete-continuous representation of preference heterogeneity is interpreted as a Gaussian mixture. Gaussian mixtures — i.e. a combination of normal distributions — can approximate any distribution, including multimodal cases. A logit-type model with a Gaussian mixture is known in the recent choice modeling literature as Mixed-Mixed Logit (MM-MNL) model (Keane and Wasi [81], Greene and Hensher [57]).

After preliminary tests, an MM-MNL with two discrete classes was specified in terms of BIC. The estimates of relevant parameters are presented in Table 5.11 and Table 5.12.

Similar with the LC specification, in the class assignment model of MM-MNL model, we still set class 1 as baseline. From Table 5.9, we could conclude that results coincide with the LC specification given same directions and similar magnitude of coefficients. Ownership of hybrid vehicles, whether a student and the number of vehicle owned all still have the largest impact on class assignment (have relatively large magnitude). In addition, the average significance level here is higher than that in LC. Therefore, utilizing MM-MNL structure helps to individual classification in this case.

As expected, in both classes, all attributes have reasonable signs and appropriate magnitude. All estimates except mean and standard deviation of inter-

Table 5.11: Coefficients of MM-MNL model

Variable	Estimate	S.E.	T-stat
Class 1			
Electric:intercept(Mean)	-27.0141	6.0069	-4.50
Hybrid:intercept(Mean)	1.1597	0.6877	1.69
Plug-in hybrid:intercept(Mean)	3.2056	2.1910	1.46
Price(Mean)	-1.4340	0.2155	-6.65
Present value of operating cost(Mean)	-0.6518	0.1408	-4.63
logarithm of driving range(Mean)	2.7393	0.8592	3.19
Electric:intercept(S.D.)	6.2296	2.8654	2.17
Hybrid:intercept(S.D.)	0.8045	0.5300	1.52
Plug-in hybrid:intercept(S.D.)	0.2137	0.6006	0.36
Price(S.D.)	0.7818	0.1196	6.54
Present value of operating cost(S.D.)	1.9996	0.2951	6.78
logarithm of driving range(S.D.)	1.3738	0.2480	5.54
Class 2			
Electric:intercept(Mean)	1.1348	0.2517	4.51
Hybrid:intercept(Mean)	1.9153	0.1556	12.31
Plug-in hybrid:intercept(Mean)	2.9178	0.2898	10.07
Price(Mean)	-0.1253	0.0108	-11.60
Present value of operating cost(Mean)	-0.0681	0.0238	-2.86
logarithm of driving range(Mean)	0.3727	0.0937	3.98
Electric:intercept(S.D.)	2.0039	0.1685	11.89
Hybrid:intercept(S.D.)	1.4979	0.1388	10.79
Plug-in hybrid:intercept(S.D.)	0.9284	0.2160	4.30
Price(S.D.)	0.1169	0.0107	10.93
Present value of operating cost(S.D.)	0.3595	0.0389	9.23
logarithm of driving range(S.D.)	0.3740	0.0630	5.94

Table 5.12: Coefficients of latent class assignment model within MM-MNL model

Variable	Estimate	S.E.	T-stat
Assigntment to class 2			
Intercept	0.0573	0.3020	0.19
Number of vehicle owned	0.9996	0.0848	11.79
Number of children	-0.1402	0.0255	-5.50
Current owner of hybrid vehicles	1.3679	0.2756	4.96
Male	-0.0510	0.0687	-0.74
Married	0.0136	0.0730	0.19
Completed college	0.5948	0.0720	8.26
Single family home	-0.0755	0.1399	-0.54
Apartment	-0.8233	0.1678	-4.91
Own house	-0.6261	0.0976	-6.41
Student	1.2767	0.4210	3.03
White	-0.1840	0.2351	-0.78
African American	0.0748	0.2653	0.28
Hispanic	0.3938	0.1538	2.56
Asian	0.4705	0.3364	1.40
Conservative	-0.4850	0.0787	-6.16
Liberal	-0.3321	0.0923	-3.60
Lives in the west	0.1231	0.1008	1.22
Lives in midwest	0.6243	0.0912	6.85
Lives in northeast	0.0154	0.0912	0.17

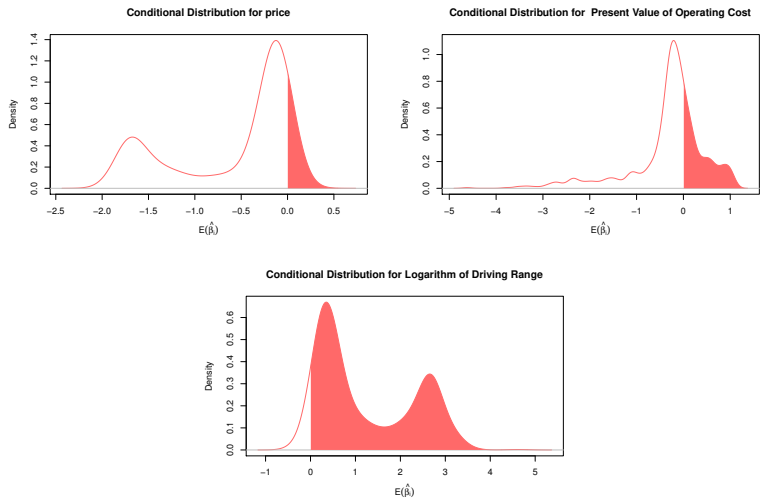


Figure 5.4: Conditional distribution for coefficient of the double mixture model)

cepts are statistically significant. To better understand the results, the density plot of coefficients in the whole sample is provided in Figure 5.4.

5.5 Conclusions

The individual discount rate is one of the most important concepts in evaluating economic decisions that involve intertemporal preferences. In the specific case of adoption of energy efficient technologies, estimates of individual discount rates are required to forecast market penetration and to evaluate the potential impact of these technologies on energy conservation. Despite energy policy efforts (subsidies for purchase, tax credits, information programs), firms and households seem reluctant to invest in energy-saving products or technologies. For example, in the automotive market, higher preferences for current consumption help to explain the slow diffusion of electric vehicles. In fact, undervaluation of operating costs — meaning that consumers would not adopt electric cars even if the savings payoff the higher purchase price — is a clear example of the energy paradox in transportation.

Measuring individual discount rates has been comprehensively discussed by social scientists, who also have elaborated explanations (market failures, behavioral bias, model specification) for the sometimes implausibly high discount rates obtained in practice. In the discrete choice literature — discrete choice is a structural approach widely applied in the analysis of travel behavior — we have identified two main methods of treating discount rates. What distinguishes the two methods is whether the discount rate is determined within or outside the discrete choice model. When endogenous discounting is used, point estimates of the implicit discount rate are derived from the inverse of the willingness to pay for operating cost savings. The use of endogenous discounting — which is the dominant approach in choice modeling — is straightforward as it only requires estimates of the marginal utility of income and that of fuel

cost. However, some energy economists have criticized endogenous discounting as it assumes rational evaluation of future costs (the marginal utility of up front costs is assumed to be equal to the marginal utility of the present value of future costs). In addition, attribute correlation and endogeneity — both represent relevant problem in vehicle choice, where most instrumental attributes are correlated, and quality is correlated with price — potentially produce bias in the estimation of endogenous discount rates. These researchers propose to use exogenous discounting, where the discount rate is actually known and usually is taken as a market interest rate that reflects opportunity costs. It is important to mention that despite the fact that endogenous discounting has been used to derive discount rates since the first applications of discrete choice to model vehicle purchase decisions, there is a surprising lack of analysis of the valuation of the present value of energy savings in recent transportation engineering applications looking at adoption of battery electric vehicles and alternative fuels. To the best of our knowledge, the use of exogenous discounting — and in general the acknowledgment of the energy paradox — is reserved to the economics literature.

In addition to direct treatment of discount rates, we also reviewed laboratory and field experiments for elucidating individual discount rates. In particular, the method of Coller and Williams [33] — supported by Harrison et al. [58] and Newell and Siikamäki [115] — emerges as a good alternative to derive discount rates that account for individual heterogeneity. In fact, incorrect treatment of unobserved heterogeneity is a criticism that can be made against the exogenous discounting method. The opportunity cost of money is not the same for every consumer, as can be expected from different access to credit and marginal utility of income. In addition, irreversibility of the decision to buy energy-efficient

in durable goods and uncertainties regarding future energy costs can explain divergence from market interest rates. Following Newell and Siikamäki [115], to address the lack of heterogeneity in exogenous discounting, we propose to use a variant of the method of Coller and Williams [33] as an integral part of a vehicle choice survey. The individual discount rate from the sequence of binary choice experiments between a sooner-but-lower and a delayed-but-higher reward can be combined with the choice data to specify a utility function that exploits heterogeneous, exogenous discounting.

In this paper we tested the method of Coller and Williams [33] in experimental session using a web survey. In particular, using an ordered logistic regression to analyze the responses to the survey, we noticed that the highest education level significantly affected the resulting discount rate. The more advance the education level of subjects, the higher the undervaluation of the future is. If the experiment is planned to be used in a vehicle choice context, our recommendation is that the initial reward represent an average of the premium for better fuel economy.

We also compared the discount rates derived from the experimental elicitation with those obtained from a contingent valuation exercise where the context was the willingness to pay as premium for future fuel savings (from Greene et al. [55]). The continent valuation exercise not only provided a much higher mean for the discount rate (13.08% was the mean experimental discount rate, whereas the contingent valuation mean was 41.9%), but also the level of variability among respondents was high (the range of the continent valuation discount rate was 3.1%-397%, versus 2%-35% in the experimental case).

In terms of future research, as there is no current application of exogenous

discounting combined with experimental elicitation of the discount rate to analyze disaggregate vehicle choice data, the next step is to design a survey with such combinations and test a model with the collected combined data.

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CHAPTER 6

CONCLUSION

Preference heterogeneity is comprehensively acknowledged as an important feature to be considered in discrete choice modeling. The consequences of neglecting or inappropriate handling unobserved heterogeneity include biased estimates which may mislead policymakers. In this dissertation, alternative discrete choice models are discussed and compared. Given the advantages of flexible heterogeneity distribution, we recommend a discrete-continuous heterogeneity distribution for the random parameters.

We also provide three empirical applications of MM-MNL models analyzing willingness to improving the resiliency, cycling route decisions and intertemporal consumption problem.

In the study analyzing the willingness for improving the resiliency of New York City's transportation system after extreme whether condition, a survey was designed to collect data on the disruptions that individuals experienced during and after superstorm Sandy. 1,552 adults living in the metropolitan area of New York City participated in the online survey. The empirical dataset was complemented with a unique choice experiment. Whereas some components of recovery seem to be normally distributed, payment heterogeneity is better represented by a bimodal distribution that can be reasonably approximated by a mixture of two normal distributions. Using hypothetical scenarios of recovery, the willingness to pay as an annual for class 1 ranges from about $15 to $50, whereas that of class 2 ranges from $120 to $775. For the mixture, the range of variation is $75-$450. In a contingent-valuation question, where respondents were asked how much they would pay to "support investments that would

reduce the recovery time from 3 weeks to only 3 days", the average willingness to pay was $192, with a standard deviation of $305.

In the second application, we propose a hybrid choice model with a discrete-continuous heterogeneity distribution for the random parameters. A maximum simulated likelihood estimator is derived and used for this hybrid choice model with an MM-MNL kernel. The adoption of the Gaussian mixture for the choice kernel introduces more flexibility to the hybrid choice model and enhances the model fit. As expected, travel time, slope and heavy traffic impose negative impact on cycling decision, whereas ownership of a bike and the presence of bike lanes on the road encourage people to ride a bike. We also find that individual's latent attributes influence the choice probability. People with better physical conditions are less sensitive to slope. The latent bicyclist status influences sensitivity to travel time in the opposite direction for 2 classes.

The individual discount rate is one of the most important concepts in evaluating economic decisions that involve intertemporal preferences. In the specific case of adoption of energy efficient technologies, estimates of individual discount rates are required to forecast market penetration and to evaluate the potential impact of these technologies on energy conservation. In this paper we tested the method of Coller and Williams [33] in experimental session using a web survey. In particular, using an ordered logistic regression to analyze the responses to the survey, we noticed that the highest education level significantly affected the resulting discount rate. The more advance the education level of subjects, the higher the undervaluation of the future is. If the experiment is planned to be used in a vehicle choice context, our recommendation is that the initial reward represent an average of the premium for better fuel economy. We

also compared the discount rates derived from the experimental elicitation with those obtained from a contingent valuation exercise where the context was the willingness to pay as premium for future fuel savings (from Greene et al. [55]). The continent valuation exercise not only provided a much higher mean for the discount rate (13.08% was the mean experimental discount rate, whereas the contingent valuation mean was 41.9%), but also the level of variability among respondents was high (the range of the continent valuation discount rate was 3.1%-397%, versus 2%-35% in the experimental case). Finally, a follow-up application of exogenous discounting combined with experimental elicitation of the discount rate to analyze disaggregate vehicle choice data.

There are several possible avenues for further improvement. Perhaps the most interesting topic is the estimation process of the MM-MNL model. The frequentist estimator requires optimization of the simulated likelihood function which is time consuming. Weak identification is another challenge for the frequentist estimator. Without the requirement of maximization, Bayes estimators may be an attractive approach for MM-MNL models. Thus, the next step following this research may include derivation and applications of Bayes estimators for MM-MNL models.

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