Finite Mixture Models of Dynamic Discrete Choices with Hyperbolic Discounting in Medicare Part D

Hana Choi

1 Introduction

Large number of literature addressed non-parametric identification of dynamic discrete choice models. Hotz and Miller(1993) is the first author to explore conditional choice probabilities to identify choice-specific continuation values. Although Rust(1994a, 1994b) shows that the discount factor in dynamic discrete choice models are generically not identified, Magnac and Thesmar(2002) uses exclusion restrictions to overcome the nonidentification problem.

Growing number of papers attempted to incorporate unobserved heterogeneity into the dynamic discrete choice models. Kasahara and Shimotsu(2009) extends the scope of non-parametric identifiability of type probabilities and type-specific component distributions in finite mixture models. They find that the three important determinants of identification are the time-dimension of panel data, the number of values the covariates can take, and the heterogeneity of the response of different types to changes in the covariates. For example, in a simple case where the transition function is type-invariant, which is the case I focus in this paper, a time-dimension of T=3 is sufficient for identification, provided that the number of values the covariates can take is no smaller than the number of types and that the changes in the covariates induce sufficiently heterogeneous variations in the choice probabilities across types. Hu and Shum(2010) further extends non-parametric identification to classes of models with time-varying serially correlated unobserved state variables or agent-specific unobserved heterogeneity.

In above models where agents make decisions over time, it is assumed that individuals maximize expected future utility flows subject to an intertemporal budget constraint, thus solving a constrained utility maximization problem. In these models agents discount future utility flow exponentially over time. On the other hand, a number of studies in psychology and behavioral economics have suggested alternative models to explain behavior that is hard to be explained by the standard models. Examples of such behavior are preference reversals in intertemporal choices or under-investment in activities with apparent low cost and high expected returns. The alternative models are built on hyperbolic discounting to explain the preference reversal, where individuals choose a reward at date t over a larger one at date t+s, but revert to choosing the later reward if the two dates are shifted by an equal time period. Such choices cannot reconcile with standard models of individual optimization.

Number of empirical papers attempted to estimate dynamic models with hyperbolic discounting time preferences under parametric assumptions. These include Laibson, Repetto and Tobacman(2007), Paserman(2008), Fang and Silverman (2009). Recently Fang and Wang(2011), Mahajan and Tarozzi(2011) further extended this line of work by looking at non-parametric identification when individuals may also be naive. Mahajan and Tarozzi(2011) treat "time-consistent $\beta = 1$", "time-inconsistent naive β_n", "time-inconsistent sophisticated β_s" as unobserved types with different hyperbolic discounting factors. They identify and estimate all time-preference parameters as well as the relative weights of "time-consistent", "naive" and "sophisticated" types by (i) adding more information in the form of elicited beliefs about state occurrences and elicited responses to time preference questions and (ii) designing a product appealing to particular types of agent and offering it for sale in a field intervention. They estimate that time-inconsistent agents account for more than half of the population and that "sophisticated" inconsistent agents are considerably more present-biased than their naive counterparts.

Fang and Wang(2011) on the other hand allows for partial naivety and exploits the exclusion variables that affect only the transition probabilities of states over time but do not affect the decision-makers' static payoff functions to identify discount factors, a present-bias factor(β), an exponential discounting factor(δ) and a potential naivety parameter($\widetilde{\beta}$) as defined in O'Donoghue and Rabin(1999a). This is a condition similar to that in Magnac and Thesmar(2002). Because the exclusion variables only affect the transition of the payoff-relevant state variables, their effects on the choices in the current period inform us about the degree to which the agents discount the future and thus $\beta, \widetilde{\beta}$ and δ can be separately identified using short-panel(two periods) data.

Although the importance of unobserved heterogeneity has been emphasized in depth with standard discrete choice models, it has not been studied yet, whether the standard identification argument with unobserved heterogeneity can be applied to models with hyperbolic discounting preferences. In this paper, I show that if we have type-invariance in the transition process, along with the exclusion restrictions mentioned in Fang and Wang(2011), we can identify all three discount factors, type probabilities and type-specific component distributions in finite mixture models of dynamic discrete choices with three periods data. I would like to extend this argument to the case where we have variables that affect the decision-makers' static payoff functions, but do not affect the transition probabilities of states over time(not necessarily type-invariance in the transition process). Having this identification argument, I plan to estimate the hyperbolic discounting factors in Medicare Part D prescription drug insurance market, an ideal context for several reasons.

Market design decision significantly affect the allocation and the welfare of many markets from health insurance to school choice systems, timber auctions and 401k savings. Public policy often determines the rule of the allocation, the information available to each agent and the defaults individuals face. This paper tries to examine the consequences of default option decisions and opt-out costs (which can be interpreted as searching/switching/psychological costs) in Medicare Part D when preferences are characterized by "hyperbolic discounting"(Laibson 1997). The program is large and controversial, receiving government subsidies of about $40 billion annually and covering over 24 million people(Duggan, Healy and Scott Morton 2008). It began providing coverage in 2006, and it has been the largest change to the Medicare program since it started. Medicare Part D established a competitive health insurance exchange marketplace in which firms compete to provide prescription drug insurance plans, which is the envisioned model for the recent federal health reform.

There is an evidence that individuals display inertia in this market and are affected by program defaults(Keith 2010). In the standard economics, if the default option is arbitrarily chosen and if opting out of the default is easy, then defaults should not matter. However in practice defaults tend to be sticky even with small opt-out costs. Handel(2009) examined insurance choice the year following a large price change and found that individuals may have forgone gains of over $1500 that year to stay in their current plan. Ericson(2010) showed that substantial differences persisted on an ongoing basis between enrollees who enrolled just before and after a new health plan option was introduced at a large employer. Even though switching plans in Medicare Part D, prescription drug coverage, is probably easier than switching an entire health insurance plan, changing plans may still be difficult if individuals are considerably present-biased. In a given year, plans that have existed for a longer period of time have annual premium that are 10% or $50 higher than newly introduced plans. Despite the ease of switching in this market with the opportunity to switch plans every year during the open enrollment period, only about 10% of enrollees switched between 2006 and 2007(McFadden and Winter 2007). Ketcham, Lucarelli, Miravete and Roebuck(2010) found that this probability of an enrollee switching plans, although small, increased with the potential gain to doing so. Some authors, on the other hand, suggest that many of the enrollees face considerable opt-out costs(including searching/switching/psychological costs). Abaluck and Gruber(2009) argue that Medicare Part D enrollees have difficulty in making their initial plan choices, while Kling et al.(2009) show that enrollees may not be paying attention to their options in subsequent years, as 45% of beneficiaries in MCBS(Medicare Current Beneficiary Survey) made no observable attempt to gain information.

Identifying and estimating the structural model with unobserved heterogeneity in opt-out costs will enable us to quantify the stickiness of plan choices due to present-biased preferences. I can then analyze, with counterfactual analysis, how the default option and how the distribution of opt-out costs affect the allocation and the welfare of consumers in Medicare Part D market.

2 Model Setup

Extending the model in Fang and Wang(2011) with finite number of unobserved types, consider a decision maker who has an additively time separable intertemporal utility function. Every period, each individual makes a choice a_t from the discrete and finite alternatives set $A = \{0, 1, ..., I)$, and each individual belongs to one of M types where his/her type attribute is unknown. The probability of belonging to type m is π^m, where the π^m's are positive and sum to 1. A list of state variables are denoted by $h_t \equiv (x_t, \epsilon_t)$ where $x_t \in X$ is observable individual characteristics that may change over time, and $\epsilon_t \equiv (\epsilon_{1t}, ..., \epsilon_{At}) \in R^A$ are the vector of random preference shocks for each of the A alternatives. I assume that the time horizon is infinite with time denoted by $t = 1, 2, ...$ and impose a first-order Markov property on the conditional choice probability of a_t and denote type m's conditional choice probability by $P^m(a_t \mid x_t, x_{t-1}, \epsilon_t, \epsilon_{t-1}, a_t, a_{t-1})$

Assumption 1. Extreme Value Distribution
ϵ_t is *i.i.d* extreme value distributed.

Assumption 2. Utility Function
The instantaneous utilities are given by, for each $a_t \in A$,

$$u^{m*}_{a_t}(x_t, \epsilon_t) = u^m_{a_t}(x_t) + \epsilon_{a_t t}$$

where $u^m_{a_t}(x_t)$ is the deterministic component of the utility from choosing a_t at x_t and $(\epsilon_{1t}, ..., \epsilon_{At})$ has a joint distribution G, which is absolutely continuous with respect to the Lebesque measure in R^A. The instantaneous utilities do not depend on time, are independent of the lagged variable $(x_{t-1}, \epsilon_{t-1}, a_{t-1})$ conditional on (x_t, ϵ_t) and are assumed to be additively separable.

Assumption 3. Transition Function
The transition function is assumed to be common across types(type-invariant), stationary and conditionally independent.

$$\begin{aligned}
f^m(x_t, \epsilon_t \quad &\mid \quad \{x_k, \epsilon_k, a_k\}_{k=1}^{k=t-1}) > 0 \text{ for all } (x_t, \{x_k, \epsilon_k, a_k\}_{k=1}^{k=t-1}) \text{ and for all } m \\
f^m(x_t, \epsilon_t \quad &\mid \quad \{x_k, \epsilon_k, a_k\}_{k=1}^{k=t-1}) = f(x_t, \epsilon_t \mid \{x_k, \epsilon_k, a_k\}_{k=1}^{k=t-1}) \\
&= \quad f(x_t, \epsilon_t \mid x_{t-1}, \epsilon_{t-1}, a_{t-1}) = f(x_t, \epsilon_t \mid x_{t-1}, a_{t-1}) \text{ for all } m \\
&= \quad q(\epsilon_t \mid x_t) f(x_t \mid x_{t-1}, a_{t-1}) = q(\epsilon_t) f(x_t \mid x_{t-1}, a_{t-1})
\end{aligned}$$

Allowing the agents' preference to be potentially time-inconsistent(O'Donoghue and Rabin 1999a), define $(\beta - \delta)-$preferences

Definition 1 $(\beta - \delta)-$**preferences**

$(\beta - \delta)-$preferences are intertemporal preferences represented by

$$U_t^m(u_t^m, u_{t+1}^m, ...) = u_t^m + \beta \sum_{k=t+1}^{+\infty} \delta^{k-t} u_k^m$$

where $\beta \in (0,1]$ and $\delta \in (0,1]$.

The parameter δ (standard discount factor) represents time consistent discounting in the long-run, where as β (present bias factor) captures the degree of short-term impatience. $\beta < 1$ implies present-biased preferences. I will further distinguish between "naive" and "sophisticated" agents as defined in O'Donoghue and Rabin (1999a). An agent is sophisticated if the self in t correctly anticipates the future selves' present-bias $\widetilde{\beta} = \beta$. On the other hand an agent is (partially) naive if the self in every period t underestimates the present-bias of the future selves, believing that $\widetilde{\beta} \in (\beta, 1]$ ($\widetilde{\beta} = 1$ implies the agent is completely naive). Each period t, the self maximizes the current utility $U_t^m(u_t^m, u_{t+1}^m, ...)$ given the subsequent decisions of other selves. A strategy profile for all selves is $\sigma \equiv \{\sigma_t\}_{t=1}^{\infty}$ where $\sigma_t : X \times R^A \times M \to A$ for all t. For any strategy profile σ, define $\sigma_t^+ \equiv \{\sigma_k\}_{k=t}^{\infty}$ as the continuation strategy profile from period t on. The type m agent's period-t expected continuation utility for a given continuation strategy profile σ_t^+ is

$$V_t^m(x_t, \epsilon_t; \sigma_t^+) = u_{\sigma_t(x_t,\epsilon_t)}^{m*}(x_t, \epsilon_{\sigma_t(x_t,\epsilon_t)t}) + \delta E[V_{t+1}(x_{t+1}, \epsilon_{t+1}; \sigma_{t+1}^+) \mid x_t, \sigma_t(x_t, \epsilon_t)]$$

where the expectation is taken over the future state x_{t+1} and ϵ_{t+1}.

Definition 2 Perceived continuation strategy profile
The perceived continuation strategy profile for a naive agent is a strategy profile $\widetilde{\sigma} \equiv \{\widetilde{\sigma}_t\}_{t=1}^{\infty}$ such that

$$\widetilde{\sigma}_t(x_t, \epsilon_t) = \arg\max_{a_t \in A} \left\{ u_{a_t}^*(x_t, \epsilon_{a_t,t}) + \widetilde{\beta}\delta E[V_{t+1}(x_{t+1}, \epsilon_{t+1}; \widetilde{\sigma}_{t+1}^+) \mid x_t, a_t] \right\}$$

where $\widetilde{\sigma}_{t+1}^+ \equiv \{\widetilde{\sigma}_k\}_{k=t+1}^{\infty}$ is what a naive agent perceives as the future selves' strategy, and not what will actually be played in the observed data.

Definition 3 Perception-perfect strategy profile
The perception-perfect strategy profile for a naive agent is a strategy profile $\sigma^* \equiv \{\sigma_t^*\}_{t=1}^{\infty}$ such that

$$\sigma_t^*(x_t, \epsilon_t) = \arg\max_{a_t \in A} \left\{ u_{a_t}^*(x_t, \epsilon_{a_t,t}) + \beta\delta E[V_{t+1}(x_{t+1}, \epsilon_{t+1}; \widetilde{\sigma}_{t+1}^+) \mid x_t, a_t] \right\}$$

where σ^* is what will be observed in he data and this is the best response of the current self given the perceived continuation strategy profile of the future selves.

Assmption4. (Stationarity)

The observed choices are assumed to be generated from stationary perception-perfect strategy profile of the infinite horizon dynamic game with agents having $(\beta - \delta)-$preferences.

Now let's define the two value functions W and Z. The deterministic component of the current choice-specific value function for type m agent is,

$$W^m_{a_t}(x_t) = u^m_{a_t}(x_t) + \beta\delta \sum_{x_{t+1}\in X} V^m(x_{t+1}) f(x_{t+1} \mid x_t, a_t)$$
$$\text{where } V^m(x_{t+1}) \equiv E_\epsilon V^m(x_{t+1}, \epsilon_{t+1}; \widetilde{\sigma}^m)$$

On the other hand, we can also define the choice-specific value function of the next-period self as perceived by the type m current self, $Z^m_{a_t}(x_t)$ as

$$Z^m_{a_t}(x_t) = u^m_{a_t}(x_t) + \widetilde{\beta}\delta \sum_{x_{t+1}\in X} V^m(x_{t+1}) f(x_{t+1} \mid x_t, a_t)$$

With these notations, we will derive the choice probability functions that are observed in the data. The current period type m decision maker will play the perception-perfect strategy profile $\sigma^{m*}_t(x_t, \epsilon_t)$ if and only if

$$\sigma^{m*}_t(x_t, \epsilon_t) = \arg\max_{a_t\in A} \left\{ W^m_{a_t}(x_t) + \epsilon_{a_t t} \right\}$$

Thus the type m current-period self's equilibrium choice probability of action a_t given state variable x_t is

$$P^m(a_t \mid x_t) = \Pr\left[W^m_{a_t}(x_t) + \epsilon_{a_t t} > \arg\max_{j\in A} \{W^m_j(x_t) + \epsilon_{jt}\} \right] = \frac{\exp\left[W^m_{a_t}(x_t)\right]}{\sum_{j=0}^{A} \exp\left[W^m_j(x_t)\right]} \tag{1}$$

If this choice probability is observed in the data, we can follow the identification argument in Fang and Wang(2011), but since type m is unobservable, we cannot directly observe $P^m(a_t \mid x_t)$.

3 Identification

What we observe in the data is

$$P(\{a_t, x_t\}^T_{t=1}) = \sum_{m=1}^{M} \pi^m p^{*m}(x_1, a_1) \prod_{t=2}^{T} f(x_t \mid x_{t-1}, a_{t-1}) P^m(a_t \mid x_t)$$

where $p^{*m}(x_1, a_1)$ is the initial distribution of (x_1, a_1).Since $f(x_t \mid x_{t-1}, a_{t-1})$ is nonparametrically identified directly from the observed data, we may assume that the transition function is known. Dividing $P^m(\{a_t, x_t\}_{t=1}^T)$ by $f(x_t \mid x_{t-1}, a_{t-1})$, we define

$$\widetilde{P}(\{a_t, x_t\}_{t=1}^T) = \frac{P(\{a_t, x_t\}_{t=1}^T)}{\prod_{t=2}^T f(x_t \mid x_{t-1}, a_{t-1})} = \sum_{m=1}^M \pi^m p^{*m}(x_1, a_1) \prod_{t=2}^T P^m(a_t \mid x_t)$$

Let $I = (i_1, ..., i_l)$ be a subset of the time indices where $1 \leq l \leq T$ and $1 \leq i_1 < ... < i_l \leq T$. Exploiting the idea in Kasahara and Shimotsu(2009), we define the lower-dimensional submodels as

$$\begin{aligned}
\widetilde{P}(\{a_{i_s}, x_{i_s}\}_{i_s \in I}) &= \sum_{m=1}^M \pi^m p^{*m}(x_1, a_1) \prod_{s=2}^l P^m(a_{i_s} \mid x_{i_s}) \text{ when } \{1\} \in I \\
\widetilde{P}(\{a_{i_s}, x_{i_s}\}_{i_s \in I}) &= \sum_{m=1}^M \pi^m \prod_{s=2}^l P^m(a_{i_s} \mid x_{i_s}) \text{ when } \{1\} \notin I
\end{aligned}$$

If we have sufficient variation in each type's response patterns to the variation of the covariate $(x_1, ...x_T)$, above lower-dimensional submodels imply different restrictions on the type probabilities and conditional choice probabilities. Consider the simple case where $A = \{0, 1\}$ and define for $\xi \in X$,

$$\lambda_\xi^{*m} = p^{*m}((x_1, a_1) = (\xi, 1)) \text{ and } \lambda_\xi^m = P^m(a = 1 \mid x = \xi)$$

Let ξ_j, j=1,...M-1 and k be elements of X. The type-specific distribution functions and type probabilities can be defined as(which can be analogously defined when $|A| \geq 3$)

$$\underset{(M \times M)}{L} = \begin{matrix} 1 & \lambda_{\xi_1}^{*1} & ... & \lambda_{\xi_{M-1}}^{*1} \\ ... & ... & ... & ... \\ 1 & \lambda_{\xi_1}^{*M} & ... & \lambda_{\xi_{M-1}}^{*M} \end{matrix}$$

Assumption 5 Exclusion Restriction
There exist state variable $x_1 \in X$ and $x_2 \in X$ with $x_1 \neq x_2$, such that
1. for all $a \in A$, $u_a(x_1) = u_a(x_2)$
2. for some $a \in A$, $f(x_{t+1} \mid x_t = x_1, a) \neq f(x_{t+1} \mid x_t = x_2, a)$

Proposition 1
Suppose that Assumptions 1-5 hold and assume $T \geq 3$.Suppose further that there exist some $\{\xi_1, ...\xi_{M-1}\}$ such that L is nonsingular and that there exists $k \in X$ such that $\lambda_k^{*m} > 0$ for all m and $\lambda_k^{*m} \neq \lambda_k^{*n}$ for any $m \neq n$. Then $\{\pi^m, \{\lambda_\xi^{*m}, \lambda_\xi^m\}_{\xi \in X}, \}_{m=1}^M$ is uniquely determined from $\{\widetilde{P}(\{a_t, x_t\}_{t=1}^3) : \{a_t, x_t\}_{t=1}^3 \in (A \times X)\}$. Also $\{(\delta, \beta, \widetilde{\beta}), u_a^m(\xi), Z_a^m(\xi'), V_a^m(\xi') : a \in A, \xi \in X, \xi' \in X\}$ are separately identified.

Proof) The first result comes directly from Kasahara and Shimotsu(2009) Proposition 1. Once we recover $P^m(a_{i_s} \mid x_{i_s})$,it is straight forward that $W^m_{a_t}(x_t)$ can be recovered from equation(1). Normalizing $u^m_0(\xi) = 0$ for all $m \in M$, the argument of Fang and Wang(2011) can be analogously applied for each type m under assumptions 1-5, and enable us to identify $\{(\delta, \beta, \widetilde{\beta}), u^m_a(\xi), Z^m_a(\xi^{'}), V^m_a(\xi^{'}) : a \in A, \xi \in X, \xi' \in X\}$.

4 Empirical Study

4.1 Background on Medicare Part D

Medicare Part D offers prescription drug insurance for seniors over the age of 65 and order. The basic structure described below is regarding Standalone PDPs, which is different from other sources of coverage, for example Medicare Advantage HMOs or employer/union sponsored PDPs. Firms provide a menu of plans at certain prices which do not vary by age or health status, and firms must accept all individuals who choose a given plan.

Standard enrollees must initially make an active choice to enroll in Medicare Part D. The insurance plans are annual contracts. Once they are enrolled, individuals observe the new prices during an open enrollment period (November to December) and they can easily switch plans. However if they take no action, the default is to stay with their current plan.

A large share of the enrollees are Low income subsidy(LIS) recipients(52% of PDP enrollees in 2006). Medicare beneficiaries become eligible for at least a partial form of the LIS if they pass an asset test, (less than \$11010 in 2009) and their incomes are below 150 percent of the federal poverty level. The subsidy benefit varies with income and assets, and the full LIS beneficiaries receive a premium subsidy equal to "benchmark" b in that state(in average \$32/month in 2006). Default options play important role in the LIS program. First the initial enrollment is automatic, if the respondents do not choose a plan actively within the enrollment period, they are automatically enrolled into a randomly chosen plan with a premium below the benchmark. Second a plan is automatically switched if the premium of this plan was below the benchmark in the previous year, but becomes above the benchmark this year. LIS subsidy recipients are automatically switched to a different plan with premium below the benchmark, unless they take active action to stay in their current plan and pay the difference $\{p - b\}$.

4.2 Data

The Medicare Current Beneficiary Survey(MCBS) is a longitudinal survey conducted by the Center for Medicare and Medicaid Services(CMS). Each respondent of the sample is surveyed three times a year and followed for multiple years, mostly 3 years or longer. Each respondent answers questions about demographics, insurance plan choice, insurance fee schedule (premium and deductible). Further self-reported health status and objective measures including functional status and chronic conditions are recorded, which can be used to estimate the transition function. At the end of the year, respondents provide information on medical expenditure including charge and payment information of prescription or refill. Part of the Medicare Current Beneficiary Survey is Beneficiary Knowledge and Needs survey, where the effort or the magnitude of searching for plans is surveyed in detail. For example the respondent is asked whether they read the booklet for Medicare, whether they compared the plans through internet.

4.3 Empirical Specification

For simplicity, I assume that once an individual chooses "No Insurance", then this person does not come back to Medicare Part D insurance program. I will relax this assumption in the future. In the beginning of the period, the agent acquires information about the current states $\{x_t, \epsilon_t\}$. x_t include demographics, subjective/objective health status and current insurance plan characteristics. An opt-out cost θ is independently drawn from a known finite support $\{\theta_1, \theta_2, ...\theta_M; \theta_1 < \theta_2 < ... < \theta_M\}$ with type probability $\{\pi_1, \pi_2, ...\pi_M\}$. The type is unobservable to the econometrician. The agent chooses an action among three options: $a = 0$ "No Insurance", $a = 1$ "Stay in the Current Insurance Plan", $a = 2$ "Switch to New Insurance Plan".

Keith (2010) finds an evidence that firms raise prices on existing enrollees "stuck in place," while introducing new, inexpensive plans to attract enrollees entering the market. To incorporate this key feature, I assume that the premiums for current, and new insurance plans are exogenously drawn from different distributions. The premium for a new insurance plan is drawn from a known distribution $h(p^{switch})$ where $p^{switch} \in [0, b]$. On the other hand, the premium for a current insurance plan is drawn from a known distribution $h'(p^{stay})$, $p^{stay} \in [p^*, \infty]$ with last year premium p^*. If the person is standard enrollee, opt-out cost θ is paid only when switching to a new insurance plan. For a LIS recipient, if $p^{switch} < b$, then the opt-out cost θ is paid when switching to a new insurance plan. If $p^{stay} > b$, then the opt-out cost is paid when staying in the current plan, due to the automatic switching default.

5 Further Study

First I want to extend the scope of the identification result to the case where we have variables that affect the decision-makers' static payoff functions, but do not affect the transition probabilities of states over time with type-specific transition process. For example, the opt-out cost variable in our model is a variable that affects the static payoff, but do not affect the transition probabilities. Second, I need to obtain the MCBS data for 2006(the initial year of Medicare Part D)-2010 from CMS to exercise the empirical analysis. I am in the process of obtaining this data, and I expect to receive it before 2012 Spring semester starts. With the data, I will elaborate the empirical specifications and implement estimation. Because of the unobserved heterogeneity, I will need new techniques for estimation. Arcidiacono and Miller(2010) recently developed the estimation method where they adapt the expectation-maximization(EM) algorithm to incorporate unobserved heterogeneity into conditional choice probability(CCP) estimators of dynamic discrete choice problems where the unobserved heterogeneity is either time-invariant or follow a Markov chain. I am studying this method to extend it to my model with hyperbolic discounting.

6 Reference

[1] Archidiacono, Peter, and Robert A. Miller(2010), "CCP Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity" Working Paper

[2] Duggan, Mark, Patrick Healy, and Fiona Scott Morton (2008). "Providing Prescription Drug Coverage to the Elderly: America's Experiment with Medicare Part D." Journal of Economic Perspectives 22:69-92.

[3] Fang, Hanming, and Dan Silverman (2009). "Time-inconsistency and Welfare Program Participatio. Evidence from the NLSY." International Economic Review, Vol.50, No.4, 1043-1076.

[4] Fang, Hanming, and Yang Wang (2009). "Estimating Dynamic Discrete Choice Models with Hyperbolic Discounting with an Application to Mammography Decisions", NBER Working Paper.

[5] Hotz, Joseph, and Robert Miller (1993). "Conditional Choice Probabilities and Estimation of Dynamic Models" Review of Economic Studies, 60, 497-529.

[6] Hu, Yingyao, and Matthew, Shum(2010). "Nonparametric Identification of Dynamic Models with Unobserved State Variables"

[7] Kasahara, H., and K. Shimotsu (2009). "Nonparametric Identification of Finite Mixture Models of Dynamic Discrete Choices." Econometrica, 77(1), 2009, 135-175.

[8] Keith M. Ericson(2010). "Market Design when Firms Interact with Inertial Consumers: Evidence from Medicare Part D". Job Market Paper.

[9] Magnac, T., and D. Thesmar (2002). "Identifying Dynamic Discrete Decision Processes." Econometrica, 20(2), 801-816.

[10] Mahajan, Aprajit and Alessandro Tarozzi (2010). "Time Inconsistency, Expectations and Technology Adoption: The Case of Insecticide Treated Nets." Working Paper

[11] Laibson, David(1997). "Golden Eggs and Hyperbolic Discounting." Quarterly Journal of Economics, 112(2), 443-477.

[12] Laibson, David, Andrea Repetto, and Jeremy Tobacman (2007). "Estimating Discount Functions with Consumption Choices Over the Lifecycle." Working paper.

[13] O'Donoghue, T., and M. Rabin(1999a). "Doing It Now or Later." The American Economic Review, 89(1), 103-124.

[14] Paserman, M. Daniele (2008). "Job Search and Hyperbolic Discounting: Structural Estimation and Policy Evaluation." Economic Journal, 118(531), 1418-1452.

[15] Rust, John(1994a). "Estimation of Dynamic Structural Models, Problems and Prospects: Discrete Decision Processes," in Christopher Sims and J.J. Laffont, eds., Proceedings of the 6th World Congress of the Econometric Society. Cambridge University Press.

[16] Rust, John(1994b). "Structural Estimation of Markov Decision Processes," in Robert Engle and Daniel McFadden eds., Handbook of Econometrics, Vol. IV. Amsterdam: North-Holland.