Endogenous Inertia In Complex Choices

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Abstract

Inertia is pervasive in many settings that share two features: complex products and a dynamic nature. To understand why switching is limited even in the absence of observable financial costs and to quantify the impact of policies aimed at making inertia less costly, this paper presents a theory of endogenous inertia in complex choices. Consumers' inertia is driven by the persistency of the environment and the cost of learning about the unobserved characteristics of the alternatives. The endogenous nature of inertia implies that consumers' switching depends on the choice environment and reacts to policies that change the characteristics of the choice set. The model is estimated using Medicare Part D prescription drug insurance data. Consistent with the presence of learning frictions, estimates suggest that beneficiaries are more responsive to characteristics that are easier to observe, with endogenous virtual switching costs averaging \$350.67. Using the model to simulate the impact of an Inflation Reduction Act policy to reduce overspending in this program by capping out-of-pocket costs, I find the policy leads to a 22.88% reduction in total spending and a 20% increase in switching rates. Compared to a scenario in which consumers do not optimally respond to the policy by chaning switching behavior and choices, the model predicts an additional 30% savings on average.

KEYWORDS: inertia, switching costs, Medicare Part D, rational inattention

JEL Classification:

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1 Introduction

Inertia in complex dynamic choices is ubiquitous. Most individuals face the problem of choosing a bank account or health insurance, as well as allocation decisions in retirement savings plans and mortgage refinancing. These choices are complex as it is not immediately clear what the optimal individual-specific option is: consumers need to gather information about product attributes to understand what option fits them best. These are also inherently dynamic problems, as the same choice is repeated over time in markets where buyers and sellers maintain long-term relations. It is also possible that today's selection has future repercussions too, either because of persistency in the choice environment or some preferences for the status quo; in the case of banking, for instance, it is common to pick a bank account and keep it over time.

Across all of these domains, consumers respond slowly to changes in the environment, even if the considerations that initially made a choice optimal change over time: for example, inertia has been documented in many health insurance markets (Handel 2013; Polyakova 2016), savings behavior (Madrian and Shea 2001) and mortgage refinancing (Andersen et al. 2020).

Inertia is costly: by not switching, consumers leave substantial amounts of money on the table. Some researchers have stressed how in markets for complex products, inertia and mistakes might be specific to inexperienced consumers, so that learning and experience over time lead to improvements in choices (Miravete 2003). In fact, in order to rationalize more generally a lack of switching even in the presence of substantial potential gains, the literature theorized two possible explanations.

The first explanation relies on *switching costs*, a form of consumer lock-in generated by the investments—financial or not—each consumer incurs upon purchasing a particular product, so that switching is worthwhile only when the costs of inaction are sufficiently large (Handel 2013; Farrell and Klemperer 2007). In this context, switching costs are introduced as a catch-all variable that bounds the costs from changing from the status quo, without an exact description of what investments they capture and therefore without a straightforward interpretation.

An alternative explanation for lack of switching relies instead on a different form of state dependence, namely for specific preferences for remaining with the status quo option. In this case, too, it is not always clear what the source of this preference is, and how it interacts with the choice environment.

In the case of complex choices, inertia in subsequent periods typically exacerbates choices that were poor to begin with. Apparent "mistakes" are pervasive: consumers often fail to pick the cost-minimizing option, with a significant share of customers overspending in the choice of credit cards (Agarwal, Chomsisengphet, et al. 2015), health insurance plans (Abaluck and Gruber 2011), cellular service (Grubb and Osborne 2015) and mortgage refinancing (Agarwal, Rosen, and Yao 2016); see Grubb (2015) for a review. Several competing explanations have been offered to rationalize apparent mistakes, including but not limited to costly decision making and costly search (Bernheim and Taubinsky 2018), limited consideration (Barseghyan, Molinari, and Thirkettle 2021), and preferences over non-financial attributes (Abaluck and Gruber 2011), but interestingly almost no attention has been devoted to the interaction between inertia and mistakes.

These mechanisms typically assume that search and switching costs represent an exogenous, unobservable and heterogeneous quantity possibly unrelated to the drivers of other mistakes. While some studies do examine counterfactual scenarios with different levels of switching costs, it is often unclear what kind of policy would result in this change. Finally, attributing inaction and apparent mistakes to either exogenous costs or consumer preferences implies that policy is not well suited to deal with these scenarios—in stark contrast with the flourishing of policies and regulation targeting precisely consumer mistakes and inaction, from paternalistic nudges (Thaler and Sunstein 2003) to the strategic setting of defaults (Johnson and

Goldstein 2003; Carroll et al. 2009). Relatedly, it also suggests that policies should not be able to affect inaction or what superficially look like mistakes, therefore fully discounting any impact of present or future policies.

In this paper, I ask how information acquisition about complex options interacts with inertia in dynamic problems and I propose a novel approach based on models of Rational Inattention (Sims 2003) that strives to shed light on the common drivers of mistakes and inertia. I argue that choice complexity hinders costly information acquisition, which in turns leads rational consumers to commit mistakes and, in dynamic settings, behave inertially; furthermore, these information frictions are endogenous to the choice environment, which implies that policies that change the choice environment also affect the extent of inertia and mistakes and leave room for welfare-improving interventions.

I study the interaction between information frictions and inertia in the context of prescription drug insurance for the elderly population in the United States. I examine choices in Medicare Part D, a prescription drug benefit program for Medicare enrollees that uses privately offered plans contracted by the federal government. Since its inception in 2006, Medicare Part D has been widely studied in the literature; it represents a well-known environment about which there is convincing evidence of information frictions and inertia, and which is at the center of several reforms.

There is abundant evidence that choosing a prescription drug plan within Medicare Part D is difficult for the beneficiaries enrolled in the program (Heiss, McFadden, and Winter 2006; Cummings, Rice, and Hanoch 2009; Hanoch et al. 2009). Moreover, evidence of apparent "mistakes" abounds, with beneficiaries often not choosing the plan that is cost-minimizing based on their health needs (Abaluck and Gruber 2011; Abaluck and Gruber 2016). Field experiments and survey evidence suggest that calling these choices "mistakes" is not misleading, as beneficiaries are often misinformed about the nature of the cost-minimizing option and do not understand the cost structure of the plans: when offered additional information that they can more readily absorb, beneficiaries change their choices towards cheaper options (Kling et al. 2012). In fact, supporting the interpretation that this choice environment is particularly complex for the beneficiaries that have to use it, McGarry, Maestas, and Grabowski (2018) documents that how—and how much—information is shown matters for choice. A more recent strand of research takes as input this evidence and incorporates the role of information friction to model choice in this framework, showing that there are numerous implications for welfare even in a static setting (Brown and Jeon 2023).

In fact, the choice of a health plan is repeated every year, and most beneficiaries in the program tend to remain enrolled, making this a dynamic problem in nature. Even though plan characteristics evolve over time, several papers highlighted the pervasive presence of inertia (Abaluck and Gruber 2016; Ketcham, Lucarelli, Miravete, et al. 2012; Ketcham, Lucarelli, and Powers 2015; Ketcham, Kuminoff, and Powers 2016), suggesting that there is in fact some interaction between information frictions and inertia (Heiss, McFadden, Winter, Wuppermann, et al. 2021).

In my framework, a persistent environment links information acquisition and inertia. The intuition is simple: when the characteristics of the health plans are correlated over time and the health status of the beneficiaries does not vary much, any information about the plans acquired today is also useful to inform the choice of a plan in the future. This generates a set of implications that are remarkably aligned with the observed behavior in Medicare Part D: inertia can be interpreted as the optimal response to a persistent environment; observed state-dependence reflects endogenous information acquired in the past; information acquired early on is more valuable, leading to limited learning over time. Perhaps more importantly, the model is able to rationalize inertia without introducing the additional primitive of switching costs. I consider this an attractive feature in a market where switching is as easy as clicking on a webpage, there are no financial costs associated with switching and the existing literature has estimated implied switching costs as large as \$1,700 (Miller and Yeo 2012).

In the first part of the paper, I begin by developing a quantitative dynamic theory of health insurance choice with endogenous information acquisition based on the Rational Inattention framework (Sims 1998; Sims 2003). Beneficiaries optimize choices with an infinite horizon. In each period, the utility derived from insurance plans is defined jointly by preferences and by plan formularies and cost characteristics, which vary by market but are initially unobserved by the enrollees in the program. Beneficiaries are rationally inattentive and decide how much to learn about the plan characteristics at a cost, which reflects their value of time and cognitive abilities (as well as well as the complexity of the contract). Decisions are influenced by the beliefs enrollees hold about the cost structures, which correctly reflect the distribution of possible plan characteristics across all markets. Beneficiaries are heterogeneous in their preferences, initial mistakes stem from the incomplete information under which they choose a plan, and inaction is the consequence of the persistent nature of the choice environment. The model allows beneficiaries to rationally limit their attention to a subset of available options, leading to endogenous consideration sets. I solve the problem numerically exploiting the optimality conditions and algorithm proposed in Miao and Xing (2023).

In the second part of the paper, I describe in detail the setting of prescription drug insurance in Medicare Part D and I document descriptive evidence which is consistent with the framework. I exploit an individual-level panel data from the Center for Medicare and Medicaid Services (CMS) on beneficiaries enrolled in the program between 2011 and 2017. I recover some of the descriptive features of the environment that have been discussed by the literature, including pervasive overspending and limited switching, and I document new facts about limited consideration and switching behavior. I show that, conditional on the choice in the previous period, many plans are never chosen in the data, documenting ubiquitous "zero shares" that pose an econometric challenge to standard models but can be rationalized by my frameowork. Next, I examine how switching varies across markets and time, showing great heterogeneity in switching rates even among similar individuals. I show that switching behavior is not random, but responds to characteristics of the choice set that make it more or less difficult to acquire information about the options. I examine the relationship between switching rates and the variation in out-of-pocket costs in a given market and I show that switching increases when there are greater expected savings, but decreases when the differences between the options make the choice harder. In particular, I find that the sign of the seemingly positive relationship between switching rates and variation in out-of-pocket costs is reversed when I control for the expected savings in the market.

In light of the evidence, in the third part of the paper I translate the theoretical framework into an empirical single-agent dynamic demand model with endogenous information acquisition which nests dynamic logit (Rust 1987) as a special case. I establish identification, showing that only the ratio of preferences to the cost of information is identified. I develop a feasible estimation strategy based on a Method of Simulated Moments approach and a quasi-Bayesian application of Sequential Monte Carlo and I implement it to recover preferences that are health-type specific. Results from the estimation exercise suggest that beneficiaries are more responsive to plan characteristics that are easier to observe, such as the plan premium; that beneficiaries tend to be risk averse; and that all beneficiaries value a plan quality on top and beyond of its implication on costs. The model is able to match the limited consideration observed in the data, as well as predicting inertia over time. Crucially, the model correctly predicts the differential response of switching to an increase in the within-market variance of out-of-pocket costs controlling for expected savings, matching the behavior documented in the data.

In the fourth and final part of the paper, I exploit the empirical results to quantify the impact of a policy proposed in the 2022 Inflation Reduction Act aimed at limiting out-of-pocket costs incurred by beneficiaries to a maximum of $2,000. The stated aim of the policy is to limit rampant cost sharing in prescription drug Medicare Part D plans, essentially ensuring that beneficiaries do not overpay excessively following the choice of a high-cost plan. The cap proposed by the policy directly affects the subset of beneficiaries with an expensive health condition, but it also indirectly affects the choice environment of all beneficiaries, as it reduces the variation in unobserved expected out-of-pocket costs across all plans in a market. I compute the percentile equivalent to the cap in the distribution of out-of-pocket costs for the affected set of beneficiaries, and I simulate the impact of a policy that caps out-of-pocket costs at that percentile level for beneficiaries of each health type. Using the predictions from the model I find that such policy leads to a 22.88% reduction in total spending and a 20% increase in switching rates. Compared to a scenario in which consumers do not optimally respond to the policy by changing switching behavior and choices, the model predicts an additional 30% savings on average. I show that these savings result from beneficiaries limiting their attention to a smaller set of cheaper plans when first enrolled in the program, and from increased switching to better plans in subsequent periods. I interpret these results as evidence that the policy is effective in reducing overspending, with the model presented in this paper internalizing the behavioral response of beneficiaries to the simplied choice environment.

1.1 Related literature

This paper builds on several different literatures. The theoretical framework I exploit is based on the Rational Inattention literature pioneered by Sims 2003. The link between Rational Inattention and discrete choice problems has been formalized by Matějka and McKay (2015), and the first paper to develop a discrete-choice dynamic rational inattention model with a discrete state-space was Steiner, Stewart, and Matějka (2017); both papers exploit the so called choice-based representation of the Rational Inattention problem. The approach followed in this paper is based on the posterior-based representation of the dynamic problem suggested Miao and Xing (2023), which allows me to model the endogenous nature of inertia and to incorporate the presence of limited consideration as formalized by Caplin, Dean, and Leahy (2019). Rational Inattention has already been applied to investigate information acquisition in Medicare Part D in a static context most notably by Brown and Jeon (2023), which is the closest paper to this one. A dynamic Rational Inattention model with a continuous state-space has also been used to study migration decisions in structural work by Porcher (2020). To the best of my knowledge, this is the first paper to apply a dynamic Rational Inattention model with a discrete state-space to study an empirical problem.

This work relates to the large literature on Medicare Part D. Abaluck and Gruber (2011), Abaluck and Gruber (2016), Ketcham, Lucarelli, Miravete, et al. (2012), Ketcham, Lucarelli, and Powers (2015), Ketcham, Kuminoff, and Powers (2016), Heiss, McFadden, Winter, Wuppermann, et al. (2016), Ho, Hogan, and Scott Morton (2017), Coughlin (2019).

There is a large body of work on switching costs: Farrell and Klemperer (2007), Miller and Yeo (2012), Hortaçsu, Madanizadeh, and Puller (2017), Handel (2013), Heiss, McFadden, Winter, Wuppermann, et al. (2021), Pakes et al. (2021).

Finally, there is active reserch on limited consideration: Abaluck and Adams-Prassl (2021), Barseghyan, Molinari, and Thirkettle (2021).

2 A Model of Insurance Choice

In this section, I develop a quantitative dynamic model of insurance choice that endogenous information acquisition about the options in the choice set. I leverage results from the theoretical literature on dynamic rational inattention (Steiner, Stewart, and Matějka 2017; Miao and Xing 2023), exploiting an insight on the evolution of the contracts over time to argue that costly information acquisition can rationalize persistency in choices over time and lead to apparent inertia in the choice of insurance contracts.

I consider a consumer who chooses a plan from a set of available options. The consumer's choice is influenced by the information she has about the options in the choice set, and while the consumer can acquire information about the options in the choice set, this process comes at a cost.

The consumer's utility from a given plan does not depend on the information she has about the plan. Specifically, a consumer i at time t chooses between J_t alternatives present in market m, indexed by j. There are M markets. Following the literature (Abaluck and Gruber '11, Brown and Jeon '23), I assume that the consumer's period utility from a given plan j is given by[1]:

$$u_{ijtm} = \beta_0 \underbrace{p_{jtm}}_{\text{premium}} + \beta_1 \underbrace{c_{ijtm}}_{\mathbb{E}[OOP]} + \beta_2 \underbrace{\sigma^2_{ijtm}}_{Var(OOP)} + \beta_3 \underbrace{q_{jtm}}_{\text{quality score}} \tag{1}$$

The consumer's utility from a given plan is a function of the plan's premium, the expected out-of-pocket costs, the variance of out-of-pocket costs, and a quality score, respectively. The quality score is a measure of the quality of the plan that is directly observable to the consumer. Note that there is no taste shock associated with the plan, but that the summary statistics characterizing the distribution of out-of-pocket costs are individual-specific, as they depend on the consumer's health status.

To introduce uncertainty specifically about the plans' characteristics, I parametrize the utility function in Equation 1 as follows:

$$u(j, \theta_i, \omega_t, m; \boldsymbol{\beta}) = \beta_0 p(j, \omega^m_{tj}) + \beta_1 c(j, \theta_i, \omega^m_{tj}) + \beta_2 \sigma^2(j, \theta_i, \omega^m_{tj}) + \beta_3 q(j, \omega^m_{tj}) \tag{2}$$

The consumer's health status is captured by θ_i, which I assume be constant over time and directly observable to the consumer by the time they have to make a health plan choice. The Medicare Part D population is at least 65 years old, and this assumption captures the idea that they tend to be familiar with their conditions and the drugs they need once they enter the program. The consumer's health status is assumed to be drawn from a distribution Θ with support $\Theta \in [\underline{\theta}, \overline{\theta}]$, which is independent of the distribution of plans' characteristics.

The cost-relevant characteristics of plan j in market m in year t (other than the premium) are summarized by the function ω^m_{tj}. This mapping is constant across consumers and captures contractual provisions such as deductibles, coinsurance rates, formularies, and the thresholds governing the different phases of coverage. I can then denote with ω^m_t the mapping of all plans in a given year and market to their cost-relevant characteristics. Finally, I model ω^m_t as a random variable with discrete and finite support of cardinality Ω, whose evolution follows a First Order Markov Process with transition kernel $\Gamma(\omega^m_t, \omega^m_{t+1})$. This law of motion is known to the consumer, who can therefore form beliefs about the distribution of ω^m_t in the future.

Under this parametrization, the distributions of out-of-pocket costs are determined by the consumer's health status together with the plans' characteristics in a given year and market. I assume that, when making

[1]This utility specification is microfounded as the linearization of a CARA utility function where the underlying costs are normally distributed (Abaluck and Gruber '11).

a plan choice, the consumer is uncertain about the plans' characteristics but not about their own health, as those characteristics are imperfectly observed. This uncertainty is initially capture by the distribution of prior beliefs over the possible realizations of ω_t^m, which I denote with $\mu(\omega_t^m)$. The consumer's beliefs about the plans' characteristics are potentially updated if they decide to acquire information, which is a costly endeavor.

Consumers then face a trade-off: acquiring more information about the plans allows them to make a better choice and minimize health insurance costs, but information acquisition comes at the cost of time and effort spent collecting and analyzing data. The exact nature of this trade-off is explored in the next subsection, where I describe in detail the dynamic rational inattention problem.

2.1 Information Acquisition and the Rational Inattention Problem

The dynamic rational inattention problem quantifies the trade-off between being able to make a more informed choice resulting in lower costs and higher utility and paying the implicit costs associated with information acquisition. The statement of the problem follows Steiner, Stewart, and Matějka 2017 and Miao and Xing 2022.

Consumer i in market m starts with a prior belief $\mu_i(\omega_t^m)$ over the possible realizations of the state of the world ω_t^m. Consumers have to make two choices. First, they choose how much information to acquire about the unobserved state ω_t^m; this will induce a posterior belief about the realization of such state by combining the new information with the prior using Bayes' rule. Then, they choose a plan based on their posterior beliefs about the state.

Formally, information is acquired through signals x_t. Consumers cannot pick signals themselves, but choose instead the conditional distribution from which signals are drawn, i.e., the information structure $f_t(x_t|\omega_t^m, x^{i,t-1}; \theta_i)$. Learning strategies are unrestricted, which allows consumers to become partially informed and, more generally, does not constrain how much and what type of information is acquired. This freedom is important to capture the fact that consumers can acquire information in a variety of ways, for instance through direct experience with the plans, word of mouth, or online research.

One reason why consumers may rationally decide not to become fully informed is that information may be too costly: information structures that provide more precise information about ω_t^m are also more expensive. To formalize this idea, I define learning costs using Shannon entropy, the standard measure in the literature on rational inattention based on Sims (2003). Shannon entropy is a measure of the uncertainty associated with a random variable, and for a discrete random variable ω with distribution ν it is defined as follows:

$$H(\nu) = -\sum_{\omega} \nu(\omega) \ln \nu(\omega) \tag{3}$$

Using entropy to measure the uncertainty summarized by the belief distributions, I define the cost of information acquisition as the difference between the entropy of prior beliefs and the expected entropy of posterior beliefs based on the chosen information structure, a measure known as *conditional mutual information*:

$$\mathcal{I}(\omega^{t,m}, x_{it}|x_i^{t-1}) = H(\omega^{t,m}|x_i^{t-1}) - \mathbb{E}_{x_{it}}[H(\omega^{t,m}|x_i^{t-1}, x_{it})|x_i^{t-1}] \tag{4}$$

This definition naturally captures the idea that the cost of information acquisition is increasing in the precision of the information structure, as more precise information structures will lead to lower entropy of posterior beliefs. Learning costs are further modulated by κ, the marginal cost of acquiring information.

Once the consumer has chosen an information structure, a signal x_{it} is drawn from it. The consumer then selects a plan j_{it} by following a deterministic strategy $\sigma_t(x_{it}, x^{i,t-1}; \theta_i)$.

Combining the choices of information structure and plan strategy, the consumer's problem can be stated as follows:

$$\max_{f,\sigma} \mathbb{E}\left[\sum_{t=0}^{\infty} \delta^t \underbrace{u(j_{it}, \theta_i, \omega_t, m; \boldsymbol{\beta})}_{\text{flow utility}} - \sum_{t=0}^{\infty} \delta^t \kappa \underbrace{\mathcal{I}(\omega^t, x_{it}|x_i^{t-1})}_{\text{learning costs}}\right] \text{ s.t. } j_{it} = \sigma_t(x_{it}; \theta_i) \tag{5}$$

Importantly, at the end of each period, consumers do not observe the realization of the state of the world, i.e., the full vector of plan characteristics for each plan in the choice set. This is line with the consumer experience: the only observable at the end of one period is a draw of out-of-pocket costs associated with the plan that has been chosen, while knowing the state would pin down the full cost distribution (and would do so for every plan in the choice set).

Finally, an assumption implicit to this statement of the problem is that consumers do not use the cost realization itself to update their beliefs, sticking only to the information they have acquired previosuly, when searching for the best plan.

2.2 State-dependent Formulation and Optimal Solution

The signal-based statement of Problem (5) is rather general, but it does not offer many insights into the solution of the problem. However, it has been shown in the literature that there is no need to model explicitly the endogenous choice of information structure.

The problem can be substantially simplified by restricting attention to a special class of information structures where signals correspond directly to choices (the so called choice-based approach, see Matejka and McKay 2015, Steiner, Stewart, and Matějka 2017) or posterior beliefs (the so called posterior-based approach, see Caplin and Dean 2013, Miao and Xing 2021). Intuitively, it is suboptimal to construct an information structure where two different signal realizations lead to the same choice: the use of a convex cost function implies that combining the signals would result in the same choice strategy at a lower cost. This implies that the optimal information structure uniquely maps signals to plan choice probabilities or posterior beliefs, turning the dynamic rational inattention problem into a stochastic choice problem.

I present below the posterior-based formulation suggested by Miao and Xing (2023), as it leads to a tractable problem with a more general class of information costs than the choice-based formulation, and it allows for endogenous consideration sets where some plans are ignored by the consumer—a relevant feature of health insurance choice in Medicare Part D.

Define a choice rule as a sequence of state-dependent plan choice probability distributions, i.e.

$$\{s_t(j_t|\omega^t, j^{t-1}) \in \Delta(J|\Omega^t \times J^{t-1}) : \text{ all } (\omega^t, j^{t-1}), t \geq 1\}$$

Denote with $\{\mu_{t+1}(\omega^{t+1}, a^t)\}$ the joint distribution of the state and plan choice trajectories. This distribution is uniquely determined recursively by the initial distribution of prior beliefs on the state $\mu_1 \in \Delta(\Omega)$, the transition kernel of the state $\Gamma(\omega_t^m, \omega_{t+1}^m)$, and the preceding choice rule:

$$\mu_{t+1}(\omega^{t+1}, a^t) = \Gamma(\omega_t^m, \omega_{t+1}^m) s_t(j_t|\omega^t, j^{t-1}) \mu_t(\omega^t, a^{t-1}) \quad \forall t \geq 1 \tag{6}$$

We set $j_0 = \emptyset$, so that $s_1(j_1|\omega^1, j^0) = s_1(j_1|\omega^1)$ and $\mu_1(\omega^1, j^0) = \mu_1(\omega_1)$.

The joint distribution allows the computation of three objects of interest, namely the predictive distribution $\mu_t(\omega_t|j^{t-1})$ which can be interpreted as a per-period prior belief, the posterior belief distribution $\mu_t(\omega_t|j^t)$, and the distribution of a plan choice conditional on a history of plan choices $q_t(j_t|j^{t-1})$, which I call a *conditional default rule* following Steiner, Stewart, and Matějka (2017) and Miao and Xing (2023). Similarly, denote with $q_t(j_t)$ the *unconditional default rule*. Consistently with the previous convention, we set $\mu_1(\omega_1|j_0) = \mu_1(\omega_1)$ and $q_1(a_1|a_0) = q_1(a_1)$.

Predictive distributions and posteriors are linked by the following formulas:

$$\mu_t(\omega_t|j^{t-1}) = \sum_{j_t} q_t(j_t|j^{t-1})\mu_t(\omega_t|j^t), t \geq 1 \tag{7}$$

$$\mu_{t+1}(\omega_{t+1}|j^t) = \sum_{\omega_t} \Gamma(\omega_t, \omega_{t+1})\mu_t(\omega_t|j^t), t \geq 1 \tag{8}$$

These equations imply that the predictive distribution of the state in the next period is a weighted average of the posteriors over the state in the current period, where the weights are given by the transition kernel of the state. At the same time, the current predictive distribution is a weighted average of the posteriors over the state in the current period, where the weights are given by the conditional default rule.

Finally, note that using Bayes' rule it is possible to derive the plan choice rule so that the problem can be interpreted as a standard one of stochastic choices.:

$$s_t(j_t|\omega^t, j^{t-1}) = \frac{\mu_t(\omega_t|j^t)q_t(j_t|j^{t-1})}{\mu_t(\omega_t|j^{t-1})}, t \geq 1 \tag{9}$$

With this notation, the dynamic plan choice problem can be reformulated as follows:

$$\max_{(\mu_t(\omega_t|j_i^t), q_t(j_{it}|j_i^{t-1}))_{t\geq 1}} \mathbb{E}\left[\sum_{t=1}^{\infty} \delta^{t-1} u(j_{it}, \theta_i, \omega_t, m; \boldsymbol{\beta})\right] - \kappa \sum_{t=1}^{\infty} \delta^{t-1} I(\omega^t; j_{it}|j_i^{t-1}) \tag{10}$$

where the expectation is taken with respect to the joint distribution of plan choices and state realizations, $I(\omega_i^t; j_{it}|j_i^{t-1})$ is the conditional information cost in t of acquiring information j_{it} about ω_t defined as:

$$\sum_{j^{t-1}} q_{t-1}(j^{t-1}) \left[H(\mu_t(\cdot|j^{t-1})) - \sum_{j_t} q_{it}(j_t|j^{t-1})H(\mu_t(\cdot|j^t))\right], \tag{11}$$

and the unconditional default rule $q_t(j_{it})$ is calculated as:

$$q_{t-1}(a^{t-1}) = q_0(a_0) \prod_{s=1}^{t-1} q_s(a_s|a^{s-1}), q_0(a^0) \equiv 1. \tag{12}$$

This formulation of the problem uses posterior beliefs as choice variables, leaving unchanged the trade-off between maximizing expected utility and paying the learning cost to acquire information.

Miao and Xing (2023) analyze a problem more general than Problem (10) and characterize its optimal solution using two sets of necessary and sufficient conditions. The insurance plan choice is modeled as an infinite horizon problem, hence we focus on the stationary Markovian solution to the dynamic rational inattention problem with infinite horizon. This allows me to siplify many of the conditioning sets, where histories are substituted with the latest realization of the plan characteristics and latest plan choice. While the Markovian solution is not guaranteed to exist for all dynamic rational inattention problems, it constitutes an approximation to the optimal soution when the latter is not Markovian.

The necessary conditions consist of a set of Bellman equations that characterize the value function and the optimal information acquisition policy, ensuring that the consumer maximizes their expected lifetime utility accounting for the dynamics of beliefs.

The sufficient conditions are a set of inequalities that must hold for all plans in the choice set. The sufficient conditions inform what plans in the choice set belong to the consideration set, that is, what plans are worth considering for the consumer and therefore chosen with positive probability. The intuition is that the consumer will only consider plans that are sufficiently attractive: if a plan is either all around too expensive or attractive only under hypothetical plan characteristics that are *ex ante* unlikely, the consumer will not consider it.

Necessary conditions

$$s(j_t|\omega_t, j_{t-1}, \theta) = \frac{q(j_t|j_{t-1}, \theta) \exp\left(v(\omega_t, j_t)/\kappa\right)}{\sum_{\tilde{j}_t} (\tilde{j}_t|j_{t-1}, \theta) \exp\left(v(\omega_t, \tilde{j}_t)/\kappa\right)} \tag{13}$$

$$q(j_t|j_{t-1}, \theta) = \sum_{\omega_t} \mu(\omega_t|j_{t-1}) s(j_t|\omega_t, j_{t-1}) \tag{14}$$

$$v(\omega_t, j_t) = u(\omega_t, j_t) + \beta \sum_{\omega_{t+1}} \Gamma(\omega_t, \omega_{t+1}) \widetilde{V}(\omega_{t+1}, j_t) \tag{15}$$

$$\widetilde{V}(\omega_t, j_{t-1}, \theta) = \kappa \ln \sum_{j_t} q(j_t|j_{t-1}, \theta) \exp(v(\omega_t, j_t)/\kappa) \tag{16}$$

$$\mu(\omega_{t+1}, j_t, \theta) = \sum_{\omega_t, j_{t-1}} \Gamma(\omega_t, \omega_{t+1}) s(j_t|\omega_t, j_{t-1}, \theta) \mu(\omega_t, j_{t-1}, \theta) \tag{17}$$

$$\mu(\omega_t|j_{t-1}, \theta) = \frac{\mu(\omega_t, j_{t-1}, \theta)}{\mu(j_{t-1}, \theta)}\ , \ \ \mu(j_{t-1}, \theta) = \sum_{\omega_t} \mu(\omega_t, j_{t-1}, \theta) > 0 \tag{18}$$

Sufficient conditions

For all plans it must hold:

$$\sum_{\omega_t} \frac{\mu(\omega_t|j_{t-1}) \exp\left(v(\omega_t, j_t)/\kappa\right)}{\sum_{\tilde{j}_t} q(\tilde{j}_t|j_{t-1}, \theta) \exp\left(v(\omega_t, \tilde{j}_t)/\kappa\right)} \leq 1, \quad t = 1, 2, \ldots \tag{19}$$

with equality if $q(j_t|j_{t-1}) > 0$.

Practically, the problem is solved numerically following the procedure described in Miao and Xing (2023)—based itself on a variation of the Arimoto-Blahut algorithm—which consists in iterating over the necessary and sufficient conditions over all periods of time. The algorithm is reported in Appendix XXX.

3 Industry Background and Data

The model I use is well suited to analyze problems that are dynamic in nature that feature repeated, complex choices, i.e., problems where it is difficult for the decision maker to compare options and understand what is the best course of action. For this application, I focus on a well-studied market that fits this description, namely the Medicare Part D market for prescription drug insurance.

Part D represents the prescription drug benefit for the older population of Medicare enrollees, and it is provided using private plans. It was introduced in 2006 and it is divided in stand-alone plans (PDPs) and Medicare Advantage plans, which include a series of extra benefits. It is a large market: in 2023, there are more than 48 million people covered by it, totaling upward of $120 billions in costs, with 47 different providers offering 766 PDPs across 34 PDP markets. The market is highly concentrated, with the top three organizations covering 60% of enrollees. While it is possible to exit the program, the vast majority of enrollees tend to remain in the program over the years, so that they face the choice of selecting a plan every year.

The choice of a prescription drug plan is not easy. First, the notion of "best" plan depends on the plan characteristics as well as the individual's health situation and drug needs, which prevents an enrollee from using direct comparisons and evaluations between different plans available on the internet, or simply adopting the plan chosen by a relative or friend. Comparisons are further complicated by the fact that providers tend to offer products with the same names across PDP markets (e.g., Essential, Extra, or Secure plans) which have different characteristics nonetheless (e.g., different premium or benefit structure): buying the same plan in different markets would lead to different outcomes even for the very same individual.

Second, as it is often the case with insurance plans, the characteristics of the products themselves are not readily observable. While some financially relevant features are easier to retrieve, such as the contractual premium —specific to a plan and usually clearly reported on the provider's and Medicare's website—, other features are more difficult to compare and fully understand. For example, the out-of-pocket cost distribution is individual specific, as the underlying health status drives the need prescription drugs. Knowing the health status itself is not enough to recover the cost distribution, though: the cost structure is non-linear—with a deductible phase, a coverage gap, and a catastrophic phase—so that the individual needs to have a precise expectation of what drugs they will need and when during the year to be able to compute the expected cost of a plan. Leaving aside the non-trivial complexities of computing this expectation for all plans a consumer faces in a given year and market, the sheer amount of time and effort needed make learning about plans a costly and time-consuming activity.

As mentioned in the introduction, these difficulties are well-known both to the CMS and to researchers. Several surveys document how difficult the choice is from the perspectives of enrollees (Heiss et al. 2006, Cummings et al. 2009) and how this translates into mistakes in plan choices (Abaluck and Gruber 2011, 2016). Moreover, it has been shown in multiple field studies how the choice architecture can be improved to help consumers make better choices, with evidence of misinformation about plans and that how (and how much) information is shown matters for choice (Kling et al. 2012, McGarry et al. 2018).

Finally, the choice of plan is repeated every year, and plans' characteristics changes over time. This means that the optimal plan changes over time, as well as that the enrollee needs to learn about the new plans available every year and how existing plans have changed. This is a costly activity, with enrollees trying to understand how much of the information learned in the previous year can be used to make a better choice in the current year. As a result, researchers have documented how inertia and mistakes abound: less than 15% choose the lowest cost option during the first year in the program, and between 10% and 50%

switch plans every year (Brown and Jeon 2023, Heiss et al. 2021, MISSING that document why the range is so wide;). In my final sample, the average yearly switching rate is estimated at 11.51%.

3.1 Data

The main source of data I use is the Center of Medicare and Medicaid Services (CMS) Medicare Part D tables. Specifically, I exploit individual-level panel datasets that contain a 20 percent sample of all Medicare Part D beneficiaries from 2011 to 2017, initially comprising roughly 12 million unique beneficiaries. I focus the analysis on this time span as the first years after the introduction of Medicare Part D, between 2006 and 2010, featured substantially larger choice sets with twice the average number of plans in the choice sets compared to following years, hindering the application of my model.

The data contain detailed information on the set of plans available to the beneficiaries. In particular, for each plan I observe the drug formularies and all the plan characteristics potentially observable by consumers (such as premium, coverage thresholds, and provisions on deductibles), while for each individual beneficiary I observe certain demographics, what plan was chosen every year, prescription drug consumption in chronological order and the associated realized costs.

To construct an appropriate set of beneficiaries, I start by focusing on the individuals who select a Prescription Drug Insurance Plan (PDP), 43% of my initial sample. I exclude individuals who move between markets during the year, those who remain enrolled in the benefit for one year only, as well as those who drop out of the program mid-year or switch to Medicare Advantage. I also exclude individuals who are eligible for low-income subsidies, as they face a different choice set and are subject to different incentives. Finally, I exclude individuals who have employer coverage, as they are likely to have a different cost structure and different incentives. The final sample results in 1,325,113 unique individuals and 3,276,858 choice occasions.

The analysis deals with the optimality of plan choices, a concept I define following the literature. The optimal plan is the one that minimizes the total cost paid by the beneficiary, as resulting from the annual premium and the expected out-of-pocket cost for the individual. This definition naturally implies the one of "mistakes" in plan choices: a plan choice is a mistake if there exists another plan in the choice set that would have led to a lower expected total cost from an *ex ante*, full information perspective. As the annual premium is fixed and observable, I need to simulate the expected out-of-pocket cost for all plans in the choice set for each individual in the sample, where the expectation reflects all information available to the beneficiary at the time of choice.

I follow Abaluck and Gruber (2016) and Brown and Jeon (2023) to construct a measure of out-of-pocket costs based on the rational expectations assumption. I replicate the calculator in Abaluck and Gruber (2016), which takes as input the observed drug consumption of a beneficiary, applies to it a plan formulary and cost-sharing characteristics, and returns the predicted out-of-pocket cost realization under that plan choice. As in the original paper, this procedure ignores concerns of moral hazard.[2] Unlike Abaluck and Gruber (2016), who need to reconstruct the formulary from the data, I have access to the actual formularies, improving the accuracy of the prediction.

I aggregate individuals based on how similar their health statuses appear in the first month of the year, and construct a measure of expected out-of-pocket costs for each plan in the choice set as the average of the predicted out-of-pocket costs for all individuals in the group. I also compute the sample variance of the

[2]It is common in the Medicare Part D literature to ignore moral hazard concerns; see, in addition, Abaluck and Gruber (2011), Ho et al. (2017) and Brown and Jeon (2023). Futhermore, Abaluck and Gruber (2009) argues that the bias arising from the violation of this assumption would likely be small, given the average demand elasticity estimated in the literature for prescription drugs.

predicted out-of-pocket costs to construct a measure of the uncertainty associated with each plan choice. Under the assumption of normally distributed out-of-pocket costs, these two summary statistics completely pin down the distribution of out-of-pocket costs for each plan in the choice set of a given market.

Further details on the construction of the data are reported in Appendix XXX.

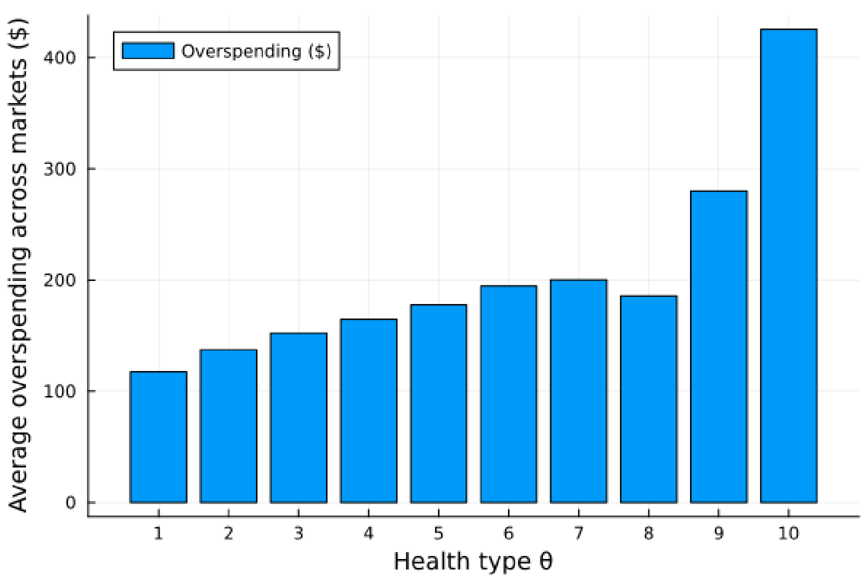
3.2 Motivating evidence

In this section, I present some descriptive evidence that motivates the use of the model presented in the previous section.

Overspending

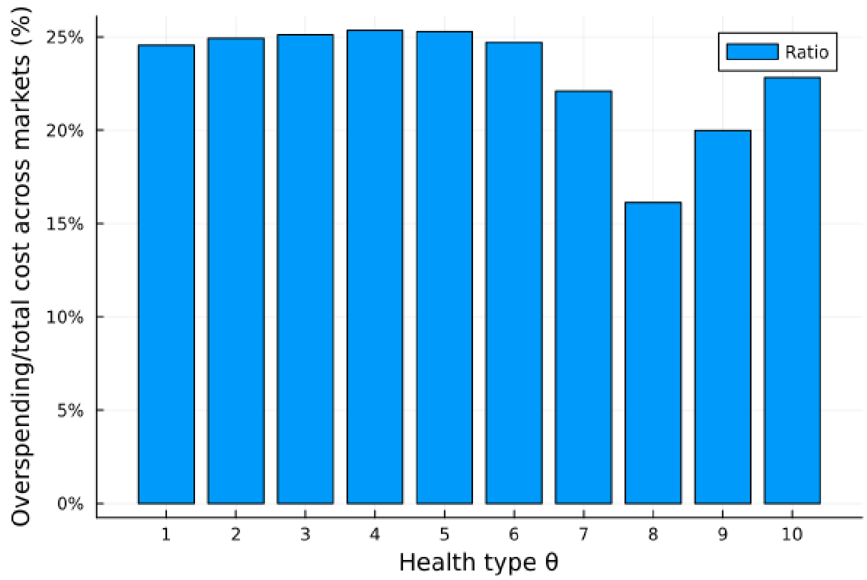
As a starting point, I start by showing the pervasive presence of suboptimal choices in my data. I construct a measure of overspending as the difference in total costs (ie, annual premium and annual expected out-of-pocket costs) between a given option and the cheapest feasible option in the choice set. Average overspending across my sample amounts to \$212.84, but this statistic masks large heterogeneity between health types and markets. Figure 1 plots the distribution of average overspending across years and regions by health type. From the figure it is clear how aveage overspending ranges from \$117.29 for the health type with lowest expected costs to \$425.30 for the health type with highest expected costs. In fact, there is great variation in overspending even *within* types. The within-type distribution across markets is reported in Appendix A Figure 12.

Figure 1: **Overspending distribution by type**



To get a better understand of how much money is at stake, Figure 2 plots the ratio of overspending to average spending by type. The figure shows that, on average, overspending amounts to 23.10% of average spending, with the ratio varying across types and ranging from 16.2% to 25.35%. This suggests that the stakes of making a mistake in plan choice are substantial for all types, and that the potential gains from switching to a better plan are large. Even in the absence of a random utility model that uses taste shocks to rationalize poor choices, this evidence points to the need to justify mistakes—in the case of my model, through the presence of learning frictions.

Figure 2: **Ratio of overspending to average spending by type**



Zero shares and limited consideration

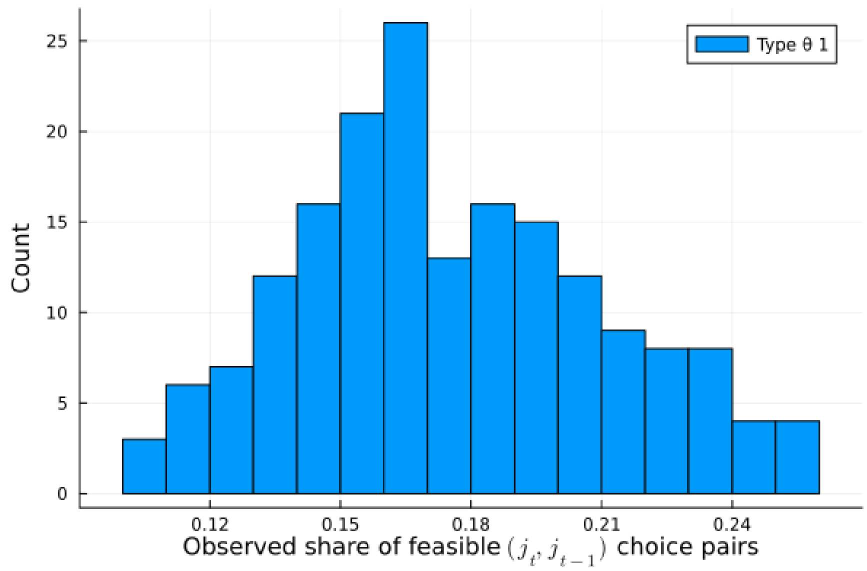
A second feature of the data that motivates the use of the model is the presence of "zero shares", that is, the fact that many feasible choices are never observed in the data. While zero shares are often treated as a data nuisance or a small sample issue, I document that in the context of Medicare Part D they represent a prominent feature of the data that warrants further inspection and needs to be rationalized by the model.

First, for each individual I construct a choice pair (j_t, j_{t-1}) detailing choices in the current and previous period. I then aggregate choice pairs across individuals by computing their distribution in a given realization of the state of the world and for a given health type. Finally, I compute the fraction of feasible choice pairs that has positive probability of being observed in the data for a given type, where feasible choice pairs are defined as those that could have been observed based on the plans available in the current and preceding period. On average in my sample, the fraction of feasible choice pairs that is effectively observed equals 18.15%, a very small number.

The average fraction of zero shares is not the result of some outlier markets, but rather a feature of the choice problem. Averaging across types within realization of the state of the world, the minimum share of observed pairs is 9.85%, while the maximum share is 29.63%. Figure 3 shows the distribution of considered choice pairs across states of the world for a given type, while Figure 13 in Appendix A reports the distribution of zero shares across markets separately for all health types.

The presence of zero shares is not due to the fact that some plans are never chosen by anyone: all plans are chosen by at least one individual in at least one state of the world. At the same time, it is hard to justify zero shares as a small sample issue. Even when ignoring the choices of beneficiaries that are enrolled in Medicare Part D for the first year, the sample on average includes more than 10,800 choice occasions per state of the world; each state has on average 16.86 feasible plans (with a minimum of 14 plans and a

Figure 3: **Distribution of observed choice pairs across ω (one type)**



maximum of 21 plans), so that on average each *choice pair* could be chosen by more than 38 beneficiaries. It is also unlikely that zero shares are due to the fact that optimal plans vary by type. I aggregate choice pairs across types and states of the world. Excluding choice pairs that are not feasible, the share of observed choice pairs equals 56.14%. This implies that, in the raw data, almost half of the feasible sequences of choices from one period to the next is never chosen by anyone.

Taken together, I interpret these facts as suggesting that the presence of zero shares is not due to the fact that some plans are never chosen in small samples, but rather that the choice problem is complex and that individuals decide not to consider all feasible options when making a choice. Unlike frameworks that are forced to drop alternatives with zero observed share from the sample, the model I use seamlessly integrates this feature of the data and rationalizes it as the result of learning frictions.

Inertia and limited switching

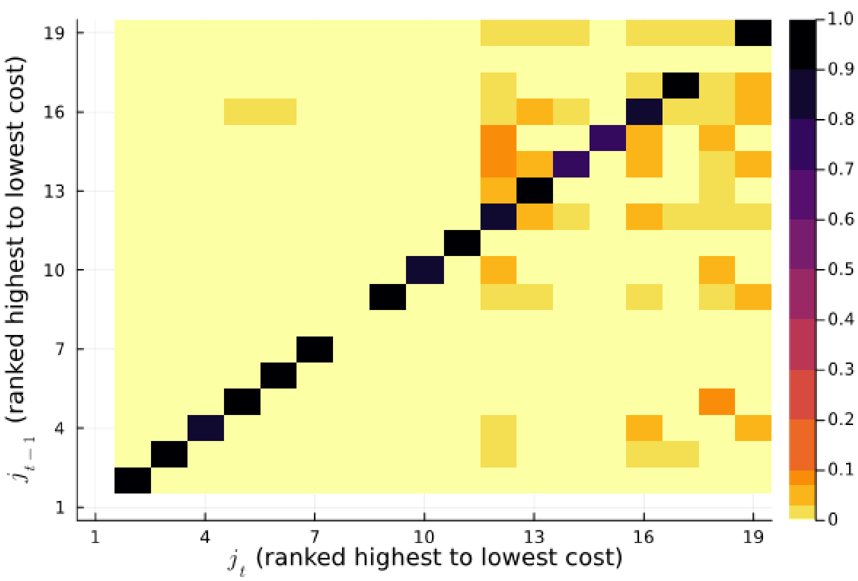
A crucial feature of the data the model aims at reconciling is limited switching over time. On average througout my sample, only 11.51% of beneficiaries changes plan from one year to the next, even though the initial choices are often suboptimal and imply substantial overspending. As it was the case with overspending and limited consideration, switching behavior varies across types and markets; the within-type distribution across markets is reported in Appendix A Figure 14.

Interestingly, switching is also highly hetereogenous within markets for individuals of the same type. As an example, Figure 4 plots a heatmap of switching rates across feasible plans in a given realization of the state of the world (corresponding to the Upper Midwest and Northern Plains region between the years 2016–2017). Since this plot is limited to beneficiaries of a single type that share the same expected out-of-pocket costs, I rank all plans in the choice set based on expected total cost, from highest (option number 1) to lowest cost (option number 19).

A few features of the data are worth noting. As expected, most beneficiaries remain in the same plan from one year to the next, with the diagonal of the heatmap being the most populated. As documented, a majority of choice pairs have zero probability of being observed in the data and are denoted by the light yellow color.

Assuming stable preferences from one year to the next, one would expect to see switching in the lower triangle of the figure, where beneficiaries switch to a cheaper plan. Although most switching is concentrated in this area, there are also some beneficiaries who switch to a more expensive plan, with the heatmap being populated in the upper triangle, suggesting some confusion on the part of beneficiaries. In the absence of any friction, one should expect every beneficiary in this set to choose option number 19. Exogenous switching costs might prevent this choice, as the cost of switching to the cheapest plan might be higher than the expected savings. However, by revealed preference, switching costs cannot exceed the smallest expected savings from switching to a cheaper plan. In this example, revealed preference suggests that switching costs should not exceed the savings from choosing option 12 instead of option 2, so that financial savings alone do not justify the observed switching behavior. Finally, one more source of heterogeneity that looks puzzling through the lens of a standard exogenous switching cost model is the role played by the choice in the previous period. The model presented in this paper rationalizes this behavior as the previous choice symbolizes a different learning path: individuals that have chosen differently in the past have also acquired different information about the plans available in the market, and this information drives the choice in the current period too.

Figure 4: **Heterogenous switching for one type (example: Upper Midwest, 2017)**



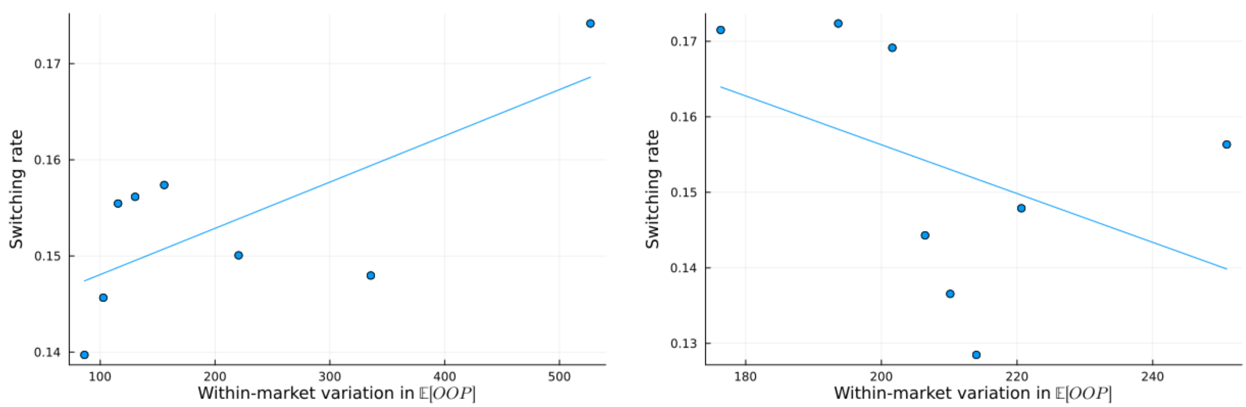
Finally, I document that switching is not only limited and heterogenous, but also that it is not random in ways that matter for policy.

The fact that switching rates depend on some features of the choice set, such as the number and characteristics of the plan available in the choice set, had already been pointed out by Ketcham, Lucarelli, and Powers (2015). In this regard, Figure 5a is a binned scatterplot that graphs the relationship between switching and the standard deviation of expected out-of-pocket costs in a given realization of the state of the world across all markets and all types. Threlationshipe figure shows a positive relationship: on average, beneficiaries who face more variation in out-of-pocket costs in their choice set are more likely to switch. This is naturally consistent with the idea that beneficiaries are more likely to switch when they face a larger potential gain from switching. In fact, this relationship is particurlarly relevant given the policy this paper set out to analyze: capping out-of-pocket costs would mechanically reduce the variation in out-of-pocket costs, and this would seem to lead to a reduction in switching rates, worsening inertia in this market.

To further investigate this relationship, Figure 5b uses the Partitioned Regression Theorem to plot the same relationship while controlling for the *range* in expected out-of-pocket costs in a given realization of the state of the world, where the range is defined as the difference between maximum and minimum feasible out-of-pocket costs. The relationship suddenly becomes negative: beneficiaries become less likely to switch when the variation in out-of-pocket costs increases, controlling for the range. I interpret this change as follows. In the raw data, switching seems to be positively associated with the amount of variation in out-of-pocket costs because the range in out-of-pocket costs is strongly positively associated with their variation; of course, a larger range signals larger potential gains from switching. However, once one fixes the potential gains from switching by controlling for the range, the relationship between switching and variation in out-of-pocket costs becomes negative. This is consistent with the idea that variation in out-of-pocket costs is a source of confusion for beneficiaries, and that they are less likely to switch when they face a more complex choice problem. This has surpising implications for policy: capping out-of-pocket costs does not necessarily lead to a reduction in switching. In fact, the final effect depends on whether the reduction in variation in out-of-pocket costs is large enough to offset the reduction in the range.

Figure 5: **Relationship between switching and variation in $\mathbb{E}[OOP]$ in the data**

(a) Raw data (b) Controlling for $\mathbb{E}[OOP]$ range



I quantify this relationship by means of a linear regression in Table 1. The coefficients on variation in out-of-pocket costs and their range are both statistically significant, validating the visual inspection.

I conclude by showing how a dynamic rational inattention model can recover this particular feature of the data. Generating fake data based on the original sample, Figures 6a and 6b repeat the same exercise using predicted switching rates. The model is able to replicate the relationship observed in the raw data and controlling for the range, suggesting it is a good starting point to analyze the impact of the policy I set out to study.

Table 1: **Regression of switching and variation in $\mathbb{E}[OOP]$ in the data**

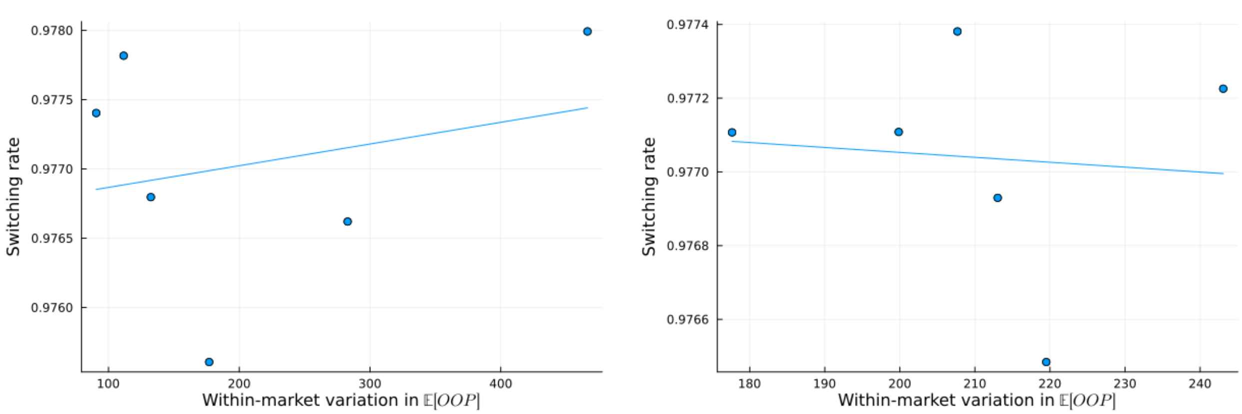
	Switching rate	
	(1)	(2)
(Intercept)	0.143***	0.146***
	(0.003)	(0.003)
$std(\mathbb{E}[OOP])$	0.005***	-0.025***
	(0.001)	(0.007)
$range(\mathbb{E}[OOP])$		0.008***
		(0.002)
Model	OLS	OLS
N	1,800	1,800
R^2	0.012	0.021

*Notes: Standard deviation and range of out-of-pocket costs are expressed in hundreds of dollars. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Figure 6: **Predicted relationship between switching and variation in $\mathbb{E}[OOP]$**

(a) Raw data

(b) Controlling for $\mathbb{E}[OOP]$ range



4 Empirical Strategy

This section details how I translate the theoretical model into an an empirical discrete state-space discrete choice model, with a focus on identification and estimation.

I expand the definition of the utility function specified while describing the model to include type-specific preferences. Specifically, beneficiary i choosing plan j in year t has the following utility function:

$$u^i(j, \theta_i, \omega_t, m; \boldsymbol{\beta}) = \beta_0^i + \beta_1^i p(j, \omega_{tj}^m) + \beta_2^i c(j, \theta_i, \omega_{tj}^m) + \beta_3^i \sigma^2(j, \theta_i, \omega_{tj}^m) + \beta_4^i q(j, \omega_{tj}^m) \tag{20}$$

where

$$\beta_h^i = \sum_{k=1}^{10} \beta_{h,k} \mathbf{1}\{k = i\} \quad \forall h = 0, \dots, 4$$

and where $p(j, \omega_{tj}^m)$ is the premium, $c(j, \theta_i, \omega_{tj}^m)$ is expected out-of-pocket costs, $\sigma^2(j, \theta_i, \omega_{tj}^m)$ is the variance of out-of-pocket costs, and $q(j, \omega_{tj}^m)$ is the plan quality as measured by CMS star ratings.

This formulation exploits the observed heterogeneity in beneficiaries' health types to allow for different preferences across types. I do not incorporate any taste shock, as in this model the familiar stochastic nature of choices follows from the information acquisition process.

Bringing a dynamic model with endogenous information to the data requires a proper definition of a few primitives: choice sets, products, states of the world, and timing of the choices.

To conceptualize choice sets, I exploit the CMS definition of 34 market regions, but exclude from the analysis regions that do not belong to the contiguous United States—namely Alaska, Hawaii, Puerto Rico and the U.S. Virgin Islands. I exclude these four regions as they are substantially different from the remaining 30 in terms of number of plans offered, types of plans, and number of beneficiaries. I then define the choice set of each individual as the set of year-specific products available that year in the market region where the individual resides.

A product, which is a PDP plan, is identified only through its name. The name of a plan—usually a combination of the name of the provider and the name of the option itself—is unique within a market region but tipically repeated across regions and across years. Using my definition, one needs to know the chosen product, the market region of the beneficiary, and the year in which the product was chosen to pin down the characteristics of a specific plan.

This definition of a product is similar to the one implictly used in Brown and Jeon (2023), but it is substantially looser than the one implemented by CMS, which identifies a plan through a combination of its contract identifier, plan benefit identifier and segment, so that a product identifier is specific to a given region and year. This distinction is important: a plan might have the same name but substantially different financial characteristics in different regions or different years. In practice, I use this loose definition to capture the notion that, from the perspective of a beneficiary, it is hard to distinguish between plans with the same name but different characteristics prior to researching the specifics of those plans: an individual might intuitively assume that the plan named "Company X Essential" chosen in 2011 in New York by their relative is the same as a plan named "Company X Essential" chosen in 2011 in Florida by another acquaintance, or chosen in 2012 in New York by another person, even though this is often not the case. From a model perspective, this definition allows me to observe the same product across different choice sets, with different underlying characteristics.

I restrict attention to the 46 products that are offered across all market regions in any given year, and I group the remaining products into a single product, product 0, which I conceptualize as the "outside option". Only a small subset of products are continuosly offered throughout the time span of my sample, but I retain all products as long as they are offered in all regions at least once, resulting in a total of 47 products.

The choice share of the outside option is on average 41.84%. While on aggregate this share is substantial, over the sample 147 products are categorized as outside option, with a small individual share. The majority of these products is region-specific (for instance, they usually include the name of the region as part of their branded name). As a comparison, following the CMS definition across my panel the 46 named products correspond to 1,079 plan-year-region combinations, while the outside option comprises 1,017 plan-year-region combinations.

Having defined a choice set and the products it includes, I further define a realization of the state of the world as the vector of cost characteristics for each product in the choice set of a given region and year. The state of the world captures the mapping between the contractual characteristics of the plans in the choice set and the ensuing cost distributions for a given individual.

For each product, I project the cost structure resulting from the contractual characteristics of the plan onto the individual's health type, exploiting three summary statistics that completely pin down the cost distribution: monthly premium, expected out-of-poket costs, and the variance of out-of-pocket costs. In practice, while some products have the same contractual structure across regions, no two choice sets have the same cost structure across regions and years; my panel of 30 regions and seven years hence results in 210 feasible different realizations of the state of the world for each health type. As a state of the world realization uniquely maps to a region-year pair for any given health type, and beneficiaries have to choose a plan in a given region-year pair, I sometimes refer to the states of the world as markets. This unique mapping between states of the world and regions-years makes redundant the time dimension of choice sets.

Whenever a product is not part of the choice set in a given state of the world, I assume that its utility is negative infinity. This assumption guarantees that the predicted probability of choosing a product that is not part of the choice set is zero.

Figure 8 shows the extent of variation in total cost associated with a given plan across space and time. Each faded line in the plot represents the total cost of one plan for a beneficiary of given type. The bold line represents the average total cost across all plans over time (for a given type). Given the previous definition of states of the world, each tick on the horizantal axis separates the 30 regions that constitute one year of observations; not all lines span the full sample of 210 states of the world, as few plans are offered throughout the entire sample. The plot shows that the variation in total cost is substantial even within a specific year.

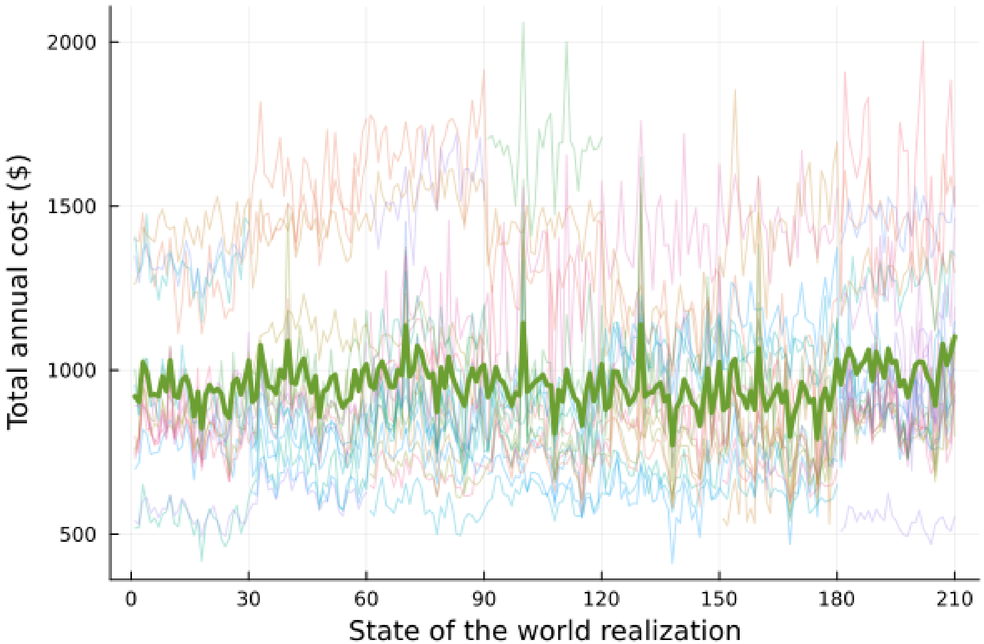
Finally, to model the dynamics of the individual problem I assume that for each beneficiary the first period is the first year in which they are enrolled in the program, and I follow them over time. Sample selection is further detailed in the Data section and in the Appendix.

4.1 Identification

Identification of the model is mainly concerned with recovering the parameters of the utility function, $\boldsymbol{\beta}$, up to a scaling factor defined by the marginal learning cost, κ. In fact, absent functional form restrictions and convincing variation in the demand for attention, in this class of models the learning cost is not separately identifiable from preferences.[3] One should stress that the fact that the cost of attention is not separately identified in a model with endogenous learning is not cause for despair. First, the counterfactual discussed

[3] Brown and Jeon (2023) makes a series of distributional assumptions and provides a parametric identification argument for the learning cost in a static model.

Figure 7: **Variation in cost characteristics across ω**



in this paper is not concerned with a policy that acts directly on learning costs, but rather with a policy that impacts learning through modifications of the choice set characteristics; in fact, it is not even clear how one would empirically quantify *ex-ante* a policy that reduces or increases the marginal cost of information κ. Second, even if the level of the learning cost is not separately identified, changes in learning costs are identified under the innocuous assumption of stable preferences. For instance, one could exploit choices before and after a policy that provides more information to the beneficiaries—such as the introduction of Medicare Plan Finder, or through a field experiment that purposefully summarizes plan characteristics for specific individual types—to identify the impact of a policy that reduces the cost of attention for all types by the same amount by estimating the model on the before- and after-sample and taking the ratio of the coefficients.

The first obstacle for identification is that beliefs are not directly observable in the data. In particular, while the problem structure governs the evolution of beliefs over time and conditional choice probabilities are revealing about the underlying information acquisition process, the model is silent regarding the prior beliefs with which beneficiaries enter the program, which are taken as a primitive. I address this issue by assuming that the prior beliefs are identical across individuals and that they are identified from the data. Specifically, I assume that the subjective prior belief associated with any given state of the world coincides with the objective empirical distribution of that state across all of my sample. This assumption can be interpreted as saying that plan characteristics are set by the organizations on the supply side, and that beneficiaries prior beliefs only depend on the actual distribution of plan characteristics that are ever realized in the sample. This is consistent with the idea that, when beneficiaries enter the program for the first time, they are unlikely to have specific beliefs about what plans are available and their characteristics. I formalize this assumption as follows:

Assumption 4.1 (Prior beliefs). *Beliefs are defined over the observed discrete state space in my sample:*

$$\mu_{it} \in \Delta(\{1, 2, \ldots, \Omega\})$$

Furthermore, the prior belief distribution is identical across individuals

$$\mu_{it} = \mu_t = (\mu_t(\omega))_{\omega \in \{1,2,\ldots,\Omega\}}$$

and is identified from the empirical distribution of the state space.

A second complication for identification lies in recovering the transition kernel for the underlying Markov process $\Gamma(\omega_t, \omega_{t+1})$ when in my sample each state of the world is realized only once. Morever, while the plan contractual characteristics are unique for a given region-year pair, those characteristics carry different implications depending on the health type of a beneficiary.

To make progress on these issues, I make two simplifying assumptions. First, I assume that beneficiaries only know the transition process for people of their own health type, that is, beneficiaries project the underlying unique evolution process for the plan characteristics onto their own health type. This assumption is quite natural, as the problem of each beneficiary only depend on the evolution of the state for a person of their own health type (given that health types are assumed constant). Second, I assume that the transition process is defined over a summary statistic of the actual realized state of the world, namely the standard deviation of the vector of out-of-pocket costs in a given region-year pair. This assumption captures the fact that the variation in expected out-of-pocket costs across regions and years is the main characteristic of interest for beneficiaries, and that the evolution of this summary statistic is informative about the evolution of the underlying state of the world. I formalize these assumptions as follows:

Assumption 4.2 (Markov transition kernel). *The Markov transition kernel for the state variable* $\Gamma(\omega_t, \omega_{t+1})$ *is defined over the standard deviation of expected out-of-pocket costs in a state of the world. Beneficiaries project the evolution process of the state variable over their health type; each beneficiary is assumed to know the transition kernel specific to their health type,* $\Gamma(\omega_t, \omega_{t+1}; \theta_i)$.

One last assumption concerns conditional choice probabilities (CCPs). By construction, plan j_t is assumed to be observable across different realizations of the state of the world ω_t with different underlying characteristics. It follows that type-specific conditional choice probabilities $s(j_t|j_{t-1}, \omega_t; \theta_i)$ are identified by looking at product choices across different realizations of the state of the world ω_t for a given type θ_i.

Assumption 4.3 (Conditional choice probabilities). *Conditional choice probabilities* $s(j_t|j_{t-1}, \omega_t; \theta_i)$ *are identifiable from the data as the same plan with different underlying financial characteristics is observable across different realization of the states of the world.*

The remaining part of this section also relies on two more, fairly standard, assumptions, namely that the discount factor δ is known and that the per-period utility from choosing $j_t = 0$ is normalized to zero across all states and types: $u(j_t, \omega_t; \theta_i) = 0$.

The first identification result is based off the Hotz and Miller (1993) estimation scheme and applies whenever all choice probabilities are interior. In Markovian dynamic discrete choice models without unobserved state variables, the Hotz-Miller approach exploits the fact that the Markov probabilities can be recovered directly directly from the data. I show that the same is true in the dynamic rational inattention problem with the prior assumptions.

Proposition 4.1 (Non-parametric identification with interior shares)**.** *Under Assumptions 4.1, 4.2 and 4.3, and if additionally all conditional choice probabilities $s(j_t|j_{t-1}, \omega_t; \theta_i)$ are interior, preferences $\boldsymbol{\beta}$ are non-parametrically identified up to a scaling factor defined by the marginal learning cost κ.*

Proof. See Appendix. □

In the context of prescription drug insurance choice in Medicare Part D several choice probabilities are not interior, the Hotz-Miller inversion argument does not carry through as the mapping between probabilities and choice-specific value functions is not well defined, hence the non-parametric identification result does not apply. In static analyses, the standard approach has been to drop plans with very few or zero enrolless in a given market;[4] however, the pervasive nature of zero shares in this dynamic analysis makes it impossible to drop options with zero shares or ignore the issue. In fact, the view in this paper is that there is some valuable information in observing that some plans are never chosen with positive probability: those options tend to look suboptimal from an *ex-ante* perspective, either because of their intrinsic characteristics or because of the lack of information about them. Ignoring the existence of zero shares would lead to discarding this information.

In the literature more generally, zero-valued market shares have often been dealt with usign ad-hoc practices like dropping the troubling observations or slightly perturbing them to transform the zero into a small, positive quantity. Novel threats to identification that come from these ad-hoc approaches have been highlighted recently, suggesting new ways to proceed in estimation. Two recent proposals consider identificaton and estimation with zero shares when these zero shares are generated by exogenous limited consideration (Dube, Hortacsu and Joo 2021) and where zero-shares are treated as a data issue but it is reasonable to assume a lower bound on expected sales (Gandhi, Lu and Shi 2022). These approaches are not well suited for applications to this dynamic problem. Dube, Hortacsu and Joo 2021 relies on instruments shifting exogenous "consideration" probabilities; in this context, consideration probabilities are endogenous and fully determined by learning costs, preferences and beliefs. Gandhi, Lu and Shi 2022 treats zero shares as a mere data issue to maintain consistency with the use of a random utility discrete choice model; in this context, zero-valued market shares are not a nuisance, but rather an informative feature of the data.

In the context of dynamic rational inattention models, one can still obtain parametric identification in the presence of zero-valued market shares. They key condition for identification is that the cardinality of the set of parameters to be identified is smaller than the number of positive CCPs.

Proposition 4.2 (Parametric identification with corner shares)**.** *For any given type θ_i, let $\bar{N}$ be the number of plan and state of the world realizations such that $s(j_t|j_{t-1}, \omega_t^m; \theta_i) > 0$. Then, if $\bar{N}$ is greater than the number of parameters to be identified, preferences $\boldsymbol{\beta}$ are parametrically identified up to a scaling factor defined by the marginal learning cost κ.*

Proof. See Appendix. □

As in many choice situations where options are characterized by prices, one could worry about the possible endogeneity of a plan's premium or the cost structure itself. In the specific context of Medicare Part D, as already argued in Brown and Jeon (2023) and previous work by Ho et al. (2017), this concern is somewhat attenuated by the fact that insurers are limited in their capacity to set product characteristics. Plans offered by each organization have to be approved by CMS and be actuarially equivalent to the standard benefit design, or exceed that standard. While it is still possible to manipulate the cost structure of the plan, it

[4] See, for instance, Abaluck and Gruber (2016) and Brown and Jeon (2023) .

is likely that the vast majority of choice-relevant cost characteristics are captured by the out-of-pocket cost measure. In future work, one could introduce a richer set of plan characteristics and organization fixed effects to control for the possible endogeneity of other non-cost characteristics; for instance, one could control for the number of pharmacies in the plan's network or exploit organization fixed effects to take into account geographical differences in the network structure of different plans.

Finally, expected out-of-pocket costs by construction rule out moral hazard on the patients' side. Although this reflects a standard approach in the literature, to the extent that patients' consumption is shaped by the specific plan chosen, one might be concerned about measurement error. Future work should explore alternatives to the calculator employed in this paper to measure expected out-of-pocket costs.

4.2 Estimation

The model presented in 10 implies a multinomial distribution over the plans in the choice set. Given the assumptions on the prior belief distribution, the utility function specification and the specific learning cost function adopted, we obtain a fully parametric econometric model over observables characeterized by Miao and Xing (2023) necessary and sufficient optimality conditions.

Notwithstanding access to individual-level panel data, a maximum likelihood estimator could have practical implementation issues because of the pervasive corner solutions the model generates: whenever the optimal solution ecompasses choice probabilities with zero probability mass, a criterion function based on the log-likelihood would not be well defined. These issues might arise also during the optimization routine, irrespective of whether at the optimum the solution is characterized by choice probabilities with zero mass. For these reasons, I do not employ a nested-fixed point algorithm used in standard single-agent dynamic discrete choice problems (Rust 1987), but develop a Simulated Method of Moments (SMM) estimator instead, with a criterion function that remains well defined even when the optimal solution features corner shares.

The SMM estimator is used to recover preferences up to the learning cost scaling factor, i.e. $\boldsymbol{\beta}/\kappa$. In order to simulate choice probabilities in the SMM estimator, one needs to calibrate in advance a few primitives—namely, the discount factor and the distribution of prior beliefs—as well as estimate the Markov transition kernel, which is done using a non-parametric estimator. The non-parametric estimator is based on the method of moments, where the moments match the observed transition frequencies. The remaining portion of this section is devoted to describing the estimation procedure in detail.

4.3 Prior beliefs and Markov kernel estimation

Prior beliefs μ are calibrated using the empirical distribution of the 210 states of the world $\mu(\omega)$. In practice, no state of the world is observed twice, which induces a uniform distribution where each realization has prior probability 1/210.

The estimation of the Markov transition kernel Γ is more convoluted, as no state of the world is observed twice. I project the transition process onto health types, and I estimate separate Markov transition kernels that are type-dependent. As a preliminary step, I summarize each realization of the state of the world (a multivariate vector of cost characteristics describing each plan in a region-year pair) computing the standard deviation of out-of-pocket costs for all plans in that state, denoted by $\bar{\omega}_t$. I then discretize this summary statistic into standardized bins. Next, I estimate a reduced Markov transition kernel $\gamma(\bar{\omega}_t, \bar{\omega}_{t+1}; \theta_i)$ for each health type using the method of moments, matching the observed transition frequencies between bins in two subsequent years. Finally, I use the estimated reduced Markov transition kernel to estimate the full Markov transition kernel $\Gamma(\omega_t, \omega_{t+1}; \theta_i)$ using the following procedure. For each pair of states of the world ω_t and ω_{t+1}, I compute the summary statistic $\bar{\omega}_t$ and $\bar{\omega}_{t+1}$, and I assign the probability of transitioning from ω_t to ω_{t+1} as the probability of transitioning from the bin corresponding to $\bar{\omega}_t$ to the bin corresponding to $\bar{\omega}_{t+1}$ in the reduced Markov transition kernel $\gamma(\bar{\omega}_t, \bar{\omega}_{t+1}; \theta_i)$. As the full transition kernel includes many more states of the world than the reduced transition kernel, this procedure results in a Markov transition kernel that is not stochastic. I normalize the rows of the estimated Markov transition kernel to sum to one.

4.4 Method of Simulated Moments estimation

Denote by $\boldsymbol{\beta}$ the set of parameters describing preferences and by κ the marginal learning cost. Given these parameters, jointly with the assumptions on prior beliefs and the Markov transition kernel, the model specifies conditional choice probabilities and default rules over the plans in the choice set. Given the Markovian solution, there are two periods that are relevant for estimation purposes: time $t = 1$ (the first period where a beneficiary is enrolled in the program and is observed choosing $j_{t=1}$) and time $t > 1$ (any subsequent period, such that the conditioning choice j_{t-1} is well-defined). Denote with $Y \in \{0, 1\}^J$ the random vector of choices for a generic individual, where the j^{th} element Y_j is equal to one if plan j is chosen, and zero otherwise. The model predicts (making explicit the dependency on the parameters) the following stationary default rule choice probability distribution, conditional on the choice made in the previous period and the health type of the individual:

$$Y_{j,t}|j_{t-1}, \theta \sim q(j_t|j_{t-1}, \theta_i; \boldsymbol{\beta}, \kappa) \tag{21}$$

Similarly, for the first period an individual is enrolled in the program, the model predicts the following default rule choice probability distribution, conditional on the health type of the individual:

$$Y_{j,1}|\theta_i \sim q(j_1|\theta_i; \boldsymbol{\beta}, \kappa) \tag{22}$$

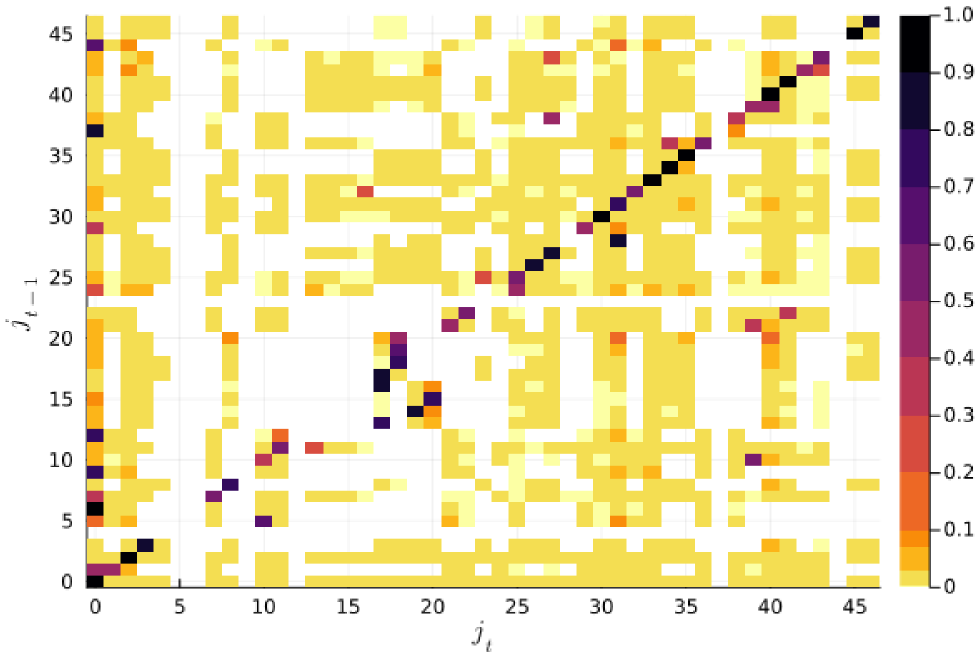
In the context of this paper the realization ω_t is observed by the econometrician, and one could use both default rule and CCP distributions to construct moments conditions. As the parametrization of preferences only uses a limited number of parameters, the estimator is based off the default rules only in order to limit the number of moments and avoid the many-moments problem.

There are 47 plans in the choice set. However, not all plans are present in every state of the world, nor did they exist throughout the sample period. This makes it empirically impossible to observe the choice of a product conditional on the *previous* choice of another product that was, in fact, introduced later. Specifically, out of the $2,209 (= 47 \times 47)$ hypothetical moment conditions, only 1,117 are actually feasible. Importantly, some of these feasible moment conditions are still not observed in the data, as some plans are never chosen in the sample by a given type. These latter moment conditions are informative, as the model will predict zero shares to match the empirical counterpart. As I also include the first period choice in the moment conditions, the total number of moment conditions is $1,117 + 47 = 1,164$.

A graphical rendition of the variation in choice probabilities I use for estimation is reported in Figure 8. The figure shows the choice probabilities for a given health type, conditional on the previous choice, for periods $t > 1$. One can see how choice probabilities are highly heterogeneous across plans. Blanks indicate pairs that are not feasible, while the lightest yellow is used to color pairs that empirically have zero probability of being observed.

The orthagonality conditions read:

Figure 8: **Choice probabilities for a given health type, conditional on previous choice**



$$\mathbb{E}[Y_j | j_{t-1}, \theta_i] = q(j_t | j_{t-1}, \theta_i; \boldsymbol{\beta}, \kappa) \quad \forall j \in 1, \ldots, J \tag{23}$$

I limit the conditioning set to the health type θ_i by working with the implied joint distribution $p(j_t, j_{t-1})$ instead of the conditional distribution $q(j_t|j_{t-1})$, i.e., I take expectations to obtain the following moment conditions:

$$\mathbb{E}[Y_j, j_{t-1} | \theta_i] = p(j_t, j_{t-1} | \theta_i; \boldsymbol{\beta}, \kappa) \quad \forall j \in 1, \ldots, J \tag{24}$$

As there is no overlap in regressors across type, estimation is performed separately by type. Stacking over possible plans j define:

$$g(Y, j_{t-1}, \theta_i, \boldsymbol{\beta}, \kappa) := Y - p(\cdot, j_{t-1} | \theta_i; \boldsymbol{\beta}, \kappa) \tag{25}$$

with which one can construct the following conditional moment conditions:

$$\mathbb{E}[g(Y, j_{t-1}, \theta_i; \boldsymbol{\beta}, \kappa) | \theta_i] = \mathbf{0} \tag{26}$$

For the first period an individual is enrolled in the program, I observe no previous choice, hence I use the following unconditional moment conditions:

$$\mathbb{E}[Y - q(\cdot | \theta_i; \boldsymbol{\beta}, \kappa)] = \mathbf{0} \tag{27}$$

Let observations on individuals be indexed by i and time periods be indexed by t from 2011 to 2017, resulting in a sample size of n observations. The criterion function to be maximized by a Simulated Method of Moments estimator is then given by:

$$Q_n(\boldsymbol{\beta},\kappa|\theta_i) = -\frac{1}{2}\left(\frac{1}{n}\sum_{it} g(Y_{it}, j, \theta_i; \boldsymbol{\beta}, \kappa)\right)^{\top} \hat{W} \left(\frac{1}{n}\sum_{it} g(Y_{it}, j, \theta_i; \boldsymbol{\beta}, \kappa)\right) \tag{28}$$

where $\hat{W}$ is a consistent estimator of the optimal weighting matrix $W(\theta)$.

4.5 Sequential Monte Carlo estimation

Csaba (2019) highlights how zero-valued market shares hinder the application of gradient based optimization techniques in empirical models based on the Rational Inattention framework, advocating the use of gradient-free quasi-Bayesian estimators. Given the SMM criterion function Q_n and a prior over the parameters, Π, one can form the quasi-posterior as:

$$\pi(\boldsymbol{\beta},\kappa) \propto e^{nQ_n(\boldsymbol{\beta},\kappa|\theta_i)}\Pi(\boldsymbol{\beta},\kappa) \tag{29}$$

Following Chernozhukov and Hong (2003), I assume a flat prior over the parameters. I then exploit an adaptive Sequential Monte Carlo (SMC) algorithm to sequentially sample from the approximation of the quasi-posterior, following Herbst and Schorfheide (2014) and Chen et al. (2018) .

Adaptive Sequential Monte Carlo works by propagating clouds of draws from a sequence of tempered distributions that approximate the quasi-posterior. Tempering implies that inital draws are from a prior distribution, successive iterations incorporate more information from the criterion, and the final distribution maps the quasi-posterior itself. While iterating over successive approximations, the algorithm discards particle draws with relatively low mass and duplicates those with relatively high mass in order to avoid particle impoverishment. At the end of each iteration, particles are mutated by a Markov Chain Monte Carlo step to further explore the parameter space in areas with relatively high mass. As the problem is computationally demanding, initial particle draws are taken from the preliminart estimates obtained maximizing the objective function using a Nelder-Mead algorithm, and the standard SMC procedure is corrected to account for this following Chen et al. (2018).

The algorithm is adaptive in that the acceptance rate in the MCMC step is tuned sequentially to target a given rate. The use of a large cloud of draws and the adapative nature of the MCMC step make this algorithm particularly well suited to deal with multi-modal quasi-posteriors.

SMC has a number of tuning parameters; I implement the algorithm with the following parametrization. Given only the ratio $\boldsymbol{\beta}/\kappa$ is identified, I fix $\kappa = 1$ to identify $\boldsymbol{\beta}$.

I specify an independent $N(0, 100^2)$ prior distribution on each parameter. Let $\mathcal{N}_n = N(\hat{\boldsymbol{\beta}}, 10^2 I)$ denote a multivariate Normal distribution where $\hat{\boldsymbol{\beta}}$ are the parameter estimates I obtain from optimizing the first stage SMM criterion function using a Nelder-Mead algorithm, and furthermore denote with $\mathcal{N}_n(\boldsymbol{\beta})$ the $N(\hat{\boldsymbol{\beta}}, 10^2 I)$ density evaluated at $\boldsymbol{\beta}$.

I initialize the algorithm with a sample of $B = 1,000$ draws $\boldsymbol{\beta}^{(1)}, \ldots, \boldsymbol{\beta}^{(B)} \sim \mathcal{N}_n$, where the number of particles has been chosen for computational tractability. Let $\phi_1, \ldots, \phi_J$ be an increasing sequence with $\phi_1 = 0$ and $\phi_J = 1$. Set initial particle weights $w_1^b = 1$ for $b = 1, \ldots, B$. I then iterate over the following steps for $j = 2, \ldots, J$.

1. **Correction.** Update in parallel particle weights computing

$$v_j^b = (e^{nQ_n(\boldsymbol{\beta}_{j-1}^b,\kappa)}\Pi(\boldsymbol{\beta}_{j-1}^b)/\mathcal{N}_n(\boldsymbol{\beta}_{j-1}^b))^{(\phi_j-\phi_{j-1})}$$

and

$$w_j^b = (v_j^b w_{j-1}^b) / \left(\frac{1}{B} \sum_{b=1}^{B} v_j^b w_{j-1}^b \right)$$

2. **Selection.** Start by computing the effective sample size $ESS_j = B / \left(\frac{1}{B} \sum_{b=1}^{B} (w_j^b)^2 \right)$. Then:

   (a) If $ESS_j > \frac{B}{2}$: do not resample the draws and set $\tilde{\boldsymbol{\beta}}_j^b = \boldsymbol{\beta}_{j-1}^b$ for $b = 1, \ldots, B$

   (b) If $ESS_j \leq \frac{B}{2}$: draw in parallel an i.i.d. sample $\tilde{\boldsymbol{\beta}}_j^1, \ldots, \tilde{\boldsymbol{\beta}}_j^B$ from a multinomial distribution with support $\boldsymbol{\beta}_{j-1}^1, \ldots, \boldsymbol{\beta}_{j-1}^B$ and weights $w_j^1, \ldots, w_j^B$. Then, reset weights to $w_j^b = 1$ for $b = 1, \ldots, B$.

3. **Mutation.** Run in parallel B separate and independent MCMC chains of length K using the random-walk Metropolis-Hastings algorithm initialized at each $\tilde{\boldsymbol{\beta}}_j^1, \ldots, \tilde{\boldsymbol{\beta}}_j^B$ for the tempered quasi-posterior $\pi_j(\boldsymbol{\beta}, \kappa | \text{Data}, \theta) \propto (e^{nQ_n(\boldsymbol{\beta}, \kappa | \theta)} \Pi(\boldsymbol{\beta}))^{\phi_j} \mathcal{N}_n(\boldsymbol{\beta})^{1-\phi_j}$ and let $\boldsymbol{\beta}_j^b$ be the final draw of the bth chain.

At the end of the algorithm, one obtains a sample of B draws $\boldsymbol{\beta}_J^1, \ldots, \boldsymbol{\beta}_J^B$. I use this sample to compute the posterior mean and confidence set for the parameters of interest.

I take $\phi_j = \left(\frac{j-1}{J-1} \right)^{\lambda}$, where $\lambda = 2.5$. λ is a tuning parameter that governs how quickly information from the criterion is incorporated into the approximation of the quasi-posterior: setting too small a λ would result in severe and immediate particle impoverishment, not allowing the algorithm to properly explore some areas of the parameter space. I follow the advice in Herbst and Schorfheide (2014) and increase λ starting from $\lambda = 1.1$ until ESS_2 corresponds to roughly 80% of initial draws B.

I set $J = 100$ and use $K = 1$ Monte Carlo steps for computational reasons.

In the mutation step, the proposal distribution for the random-walk Metropolis-Hastings is a mixture distribution defined as follows:

$$\boldsymbol{\beta}_j^b \sim 0.9N(\tilde{\boldsymbol{\beta}}_{j-1}^b, \sigma_j^2 \Sigma_{j-1}) + 0.1N(\tilde{\boldsymbol{\beta}}_{j-1}^b, \sigma_j^2 diag(\Sigma_{j-1}))$$

where σ_j is chosen adaptively to target an acceptance rate ≈ 0.30 by setting $\sigma_2 = 1$ and

$$\sigma_j = \sigma_{j-1} \left(0.95 + 0.10 \frac{e^{16(A_{j-1} - 0.30)}}{1 + e^{16(A_{j-1} - 0.30)}} \right)$$

for $j > 2$, where A_{j-1} is the acceptance rate from the previous iteration. Σ_{j-1} is the covariance of the $\boldsymbol{\beta}$ draws from iteration $j - 1$.

The algorithm has been implemented in Julia programming language and optimized for parallel computing using multithreading.

4.6 Estimation Results

Table 2 reports parameter estimates for all types. Across most types, the coefficient on premium is substantially larger than the coefficient on expected out-of-pocket costs, even though they enter the utility function in a similar fashion. This result is consistent with the idea that consumers are more responsive to characteristics that are easier to observe and captures the fact that a plan's premium tends to be more salient than its out-of-pocket costs, which are only realized after the consumer has chosen a plan. A similar result (in a static model) is found in Brown and Jeon (2023), although in this case there is no a priori restriction differentiating information acquisition between premium and out-of-pocket costs.

The coefficient on the standard deviation of out-of-pocket costs is negative across most type, indicating that consumers tend to be risk-averse. For the two health-types with higher expenditure the coefficient is estimated to be positive, suggesting these types display a risk-loving behavior. Finally, the coefficient on quality is positive throughout, suggesting that consumers value positively a plan quality as measured by CMS.

Table 2: **Parameter Estimates (normalizing $\kappa = 1$)**

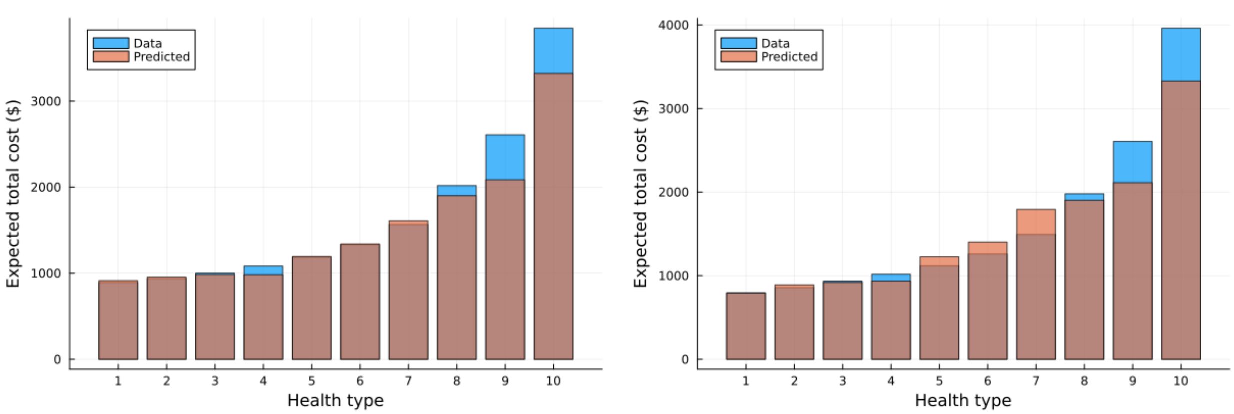
Type	$\beta_{constant}$	$\beta_{premium}$	$\beta_{E[OOP]}$	$\beta_{sd(OOP)}$	$\beta_{quality}$
θ_1	2.37	-9.49	-2.86	-2.08	6.12
θ_2	-1.30	-5.97	-1.60	-1.58	5.12
θ_3	1.70	-8.34	-2.22	-1.86	6.07
θ_4	-3.54	-8.92	-1.97	-1.03	6.18
θ_5	2.63	-7.73	-1.49	-1.70	5.59
θ_6	2.29	-6.56	-1.25	-1.86	6.03
θ_7	-3.99	-1.52	-0.13	-2.30	5.94
θ_8	-1.01	-2.90	-0.11	-0.99	3.86
θ_9	1.95 [1.47, 2.41]	-4.10 [-4.40, -3.74]	-5.84 [-6.01, -5.66]	4.95 [4.80, 5.11]	2.63 [2.47, 2.80]
θ_{10}	-14.53 [-16.23, -12.36]	-17.52 [-18.23, -16.68]	-1.84 [-1.86, -1.82]	0.42 [0.42, 0.43]	14.34 [13.72, 14.83]
N	XXX	XXX	XXX	XXX	XXX

Notes: Premium and out-of-pocket costs are in hundreds of dollars. Quality is measured using CMS 5-star rating system. Quasi-bayesian 95% confidence sets are reported in brackets.

I evaluate the fit of the model in several ways. Figure 9 plots expected total cost per beneficiary by type, both in the data and as predicted by the model. As plan characteristics vary across realizations of the state of the world, this computation relies on the predicted CCPs which are not part of the set of moments I target in estimation. On average across types the model predicts an expected total cost of \$1,528.25 in the first period of enrollement, while the actual initial expected total cost is \$1,646.93. In subsequent periods, the model predicts an expected total cost of \$1,529.65, while the actual expected cost is \$1,602.09. As can be seen from Figure 9, notwithstanding the simple parametrization the model does a good job at predicting the expected total cost for most types, with the exception of health types 9 and 10, which are the two types with the highest expected total cost.

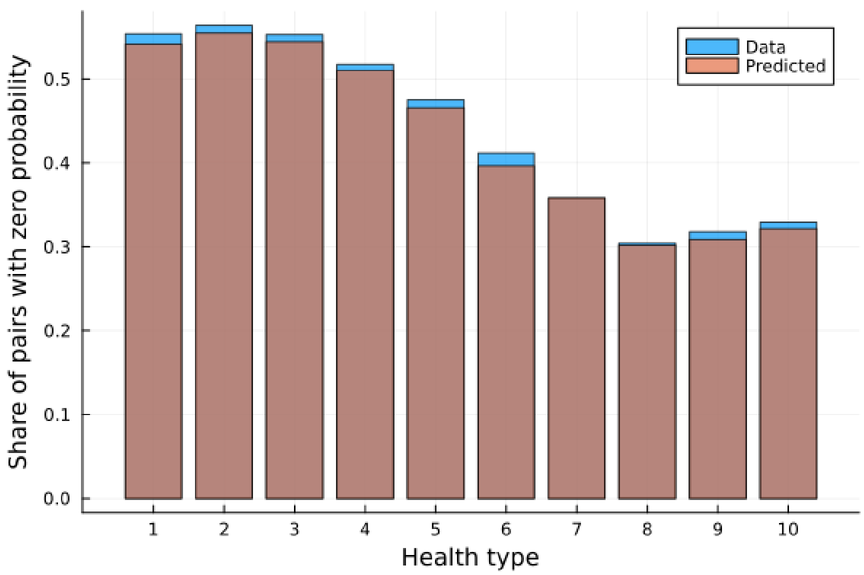
Figure 9: **Actual vs predicted expected total cost by type**

(a) Initial period (b) Subsequent periods



Perhaps more importantly, Figure **??** plots predicted and actual limited consideration by type, that is, for periods following the first one the fraction of feasible choice pairs that are not observed in the data across all markets (for a given type) and that the model predicts to happen with zero probability. The actual fraction of choice pairs that are not considered in the data is 43.86%. The model predicts that, on average across types, 43.03% of feasible choice pairs are not considered. While these moments belong to the set I target in estimation, the close prediction highlights the capability of the model to predict a pervasive feature of the data that gets lost in most random utility modeling.

Figure 10: **Actual vs predicted limited consideration by type**



5 Counterfactual Policy Analysis

In this section I use the model to examine the main policy of interest to be implemented under the Inflation Reduction Act, namely the imposition of a cap on out-of-pocket costs. I then simulate the impact of this policy on the switching behavior of beneficiaries and on the total expected expenditure for beneficiaries.

Currently, the standard benefit design does not impose any cap on out-of-pocket expenditure. Whenever costs exceed the catastrophic threshold, cost sharing requires beneficiaries to cover 5% of the total drug costs, or a copay that is determined each year for brand and generic drugs.[5]

The policy sets the cap at $2,000 from 2025, directly affecting those that in my sample belong to the highest two health types. In order to study the effect of a cap more generally, I compute the percentile in the out-of-pocket cost distribution for the two highest types that corresponds to the $2,000 cap, and I simulate a cap corresponding to that percentile for each health type separately. The results for the implied distribution of virtual switching costs are shown in Figure 11. Note that these implied costs are endogenous, hence they are only helpful to understand the relative differences for a given environment. The average implied switching cost drops from $350.67 to $336.24, while the distribution of implied switching costs becomes more dispersed and its standard deviation increases from $147.71 to $265.99. These changes translate into an average increase in switching rates in the counterfactual of 2.29 percentage points, equivalent to a 20% increase in switching.

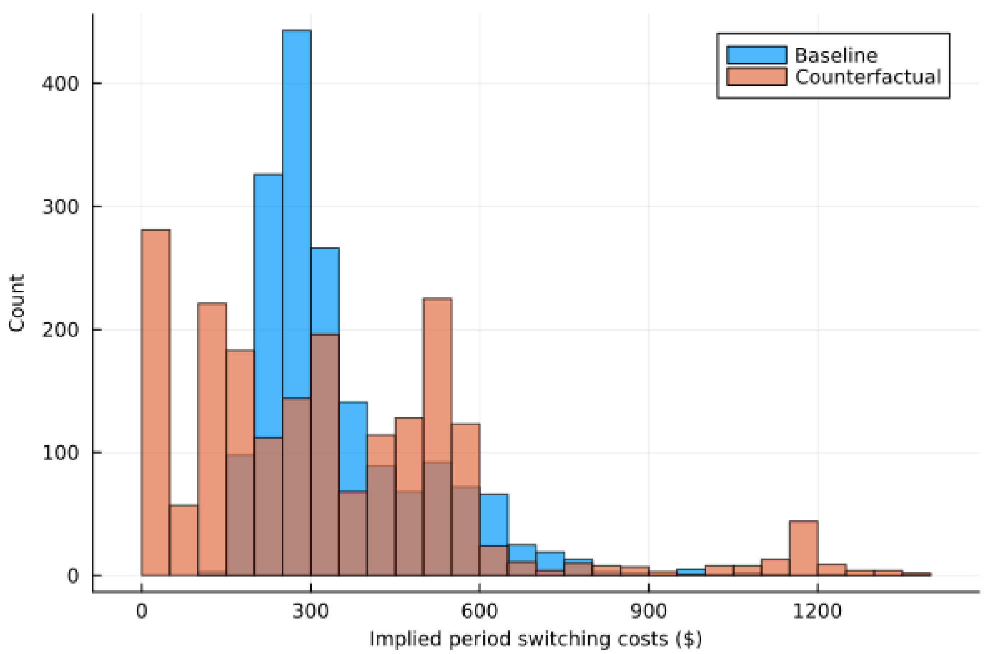


Figure 11: Counterfactual switching cost distribution

I interpret the fact that switching does not increase uniformly (i.e., the distribution of implied switching costs does not shift uniformly towards the left tail in terms of Fist Order Stochastic Dominance) as an output of the ambivalent effect of a policy that caps out-of-pocket costs: on the one hand, limiting the range of out-of-pocket costs makes it easier for consumers to compare plans, and hence it reduces the cost of learning

[5]The copay has changed throughtout the years. For the period covered by my sample, it was initially set to $XXX ($YYY) in 2011 and it increased up to $XXX ($YYY) in 2017 for each generic (bran) precription drug.

about the unobserved characteristics of the alternatives and improves switching to better options; on the other hand, it also reduces the incentive to switch to a better plan, since the monetary benefit of switching to a better plan decreases.

One element that is not evident from the switching cost distribution is how capping out-of-pocket costs influences limited consideration too: in the first period of enrollment the number of plans considered decreases by 16.42%, while in subsequent period it increases by 15.83%. The fewer plans that are considered in the first period are also better plans: compared to the baseline expected total cost of $1,528.25, with the counterfactual policy in place initial expected total cost drops to $1,166.72, equivalent to a 23.65% reduction. The more plans that are considered (and switched to) in the following periods, meanwhile, are also better: expected total cost in subsequent periods drops from $1,529.65 to $1,179.67, equivalent to a 22.88% reduction.

The drop in expected total expenditure is due to two separate effects. The first, mechanical, effect is a reduction in cost for every beneficiary who has out-of-pocket costs above the threshold. As out-of-pocket costs are weakly lower for all plans following the implementation of the policy, beneficiaries would save money even if they did not switch plans. The second effect is the reduction in the number of beneficiaries who have out-of-pocket costs above the threshold. This indirect effect is due to the fact that the policy makes it easier to select an initial a plan with lower out-of-pocket costs, or switch to it afterwards, and hence more beneficiaries choose better plans. To get an initial sense of the magnitude of the gains from endogenously selecting a better plan with respect to the mechanical gain, I compute the average percent improvement in the counterfactual when beneficiaries are allowed to re-optimize their choices compared to forcing them to stay in their previously chosen plan, which is now weakly cheaper. I compute the following gain for each type:

$$\text{Gain} = \frac{\text{Expected cost (counterfactual with fixed choices)} - \text{Expected cost (counterfactual)}}{\text{Expected cost (baseline)} - \text{Expected cost (counterfactual)}} \tag{30}$$

On average, this gain amounts to 31%, or an additional average saving of $112.37, implying a substantial additional benefit for enrollees.

6 Conclusions

In this paper I offer a theory of endogenous inertia in complex choices based on the rational inattention framework, where consumers' inertia is driven by the persistency of the environment and the cost of learning about the unobserved characteristics of the alternatives. I apply this theory to explain apparently suboptimal behavior in the context of prescription drug insurance. The model rationalizes why beneficiaries make suboptimal choices early on in the program; why enrollees are more responsive to some features of the plans; why there is limited switching and limited learning about the optimal choices over time; and why only a subset of alternatives is effectively considered when making a choice.

I develop an empirical framework that models dynamic demand with discrete choices and discrete state-space in the presence of information frictions, and I apply it to Medicare Part D data—a well-known market with several puzzling features that I explain in a unifying framework. I establish identification of the key parameters and develop a tractable estimation routine. Results suggest that consumers are more responsive to characteristics that are easier to observe or that vary less across realizations of the state of the world and that attention is focused on less than half of the available options in the choice set. The model suggests beneficiaries switch plan very seldom, even if their initial choice is suboptimal; for the period of time and the choices sets included in my sample, I estimate endogenous "virtual" switching costs averaging \$350.67. Importantly, the model is able to rationalize the observed behavior without relying on exogenous hard-to-intrepret switching costs, consumers' naivete or the presence of a large set of relevant unobserved characteristics. In fact, the framework is portable to any setting where consumers face a dynamic choice problem with options that are difficult to evaluate; from the econometrician perspective, identification requires the ability to observe the choice of the same product with different underlying characteristics. Several problems share these features, including insurance choice when the same insurerer varies the characteristics of the products sold across markets, financial products such as bank and credit card accounts, and mortgage refinancing problems.

I use the model to analyze the impact of a policy included in the Inflation Reduction Act that caps out-of-pocket costs with the stated goal to reduce the costs associated with choosing a Medicare Part D health plan. I find that the policy indirectly simplifies the choice environment by limiting the amount of attention beneficiaries need to pay to out-of-pocket costs. Enrollees respond to the policy by directing their attention to a set of better plans and switching rates increase; meanwhile, implied switching costs become cheaper and with a more spread out distribution. On net, total expenditure drops. Accounting for the endogenous information acquisition process is crucial to explain why switching increases after the implementation of the policy and to quantify total savings.

There are many avenues for improvement left for future work. From an econometric perspective, initial beliefs could be estimated exploiting variation in first-period choices across markets instead of assumed off a distributional assumption. Computationally, the solution algorithm could be scaled up exploiting GPU parallel processing on a distributed architecture. Perhaps more importantly, a conceptual limitation of this analysis is that it only focuses on the demand-side of the market. The model does not account for the fact that insurers may strategically design their plans to take advantage of consumers' inattention. The literature examined extensively competition concerns under the assumption of exogenous switching costs; future work should explore the implications of endogenous switching costs on the equilibrium of the market, and more generally incorporate into the analysis the complexity of the choice environment, from the number of options available to the difficulty of evaluating those options.

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A Appendix: Evidence

Figure 12: **Within-type distribution of overspending**

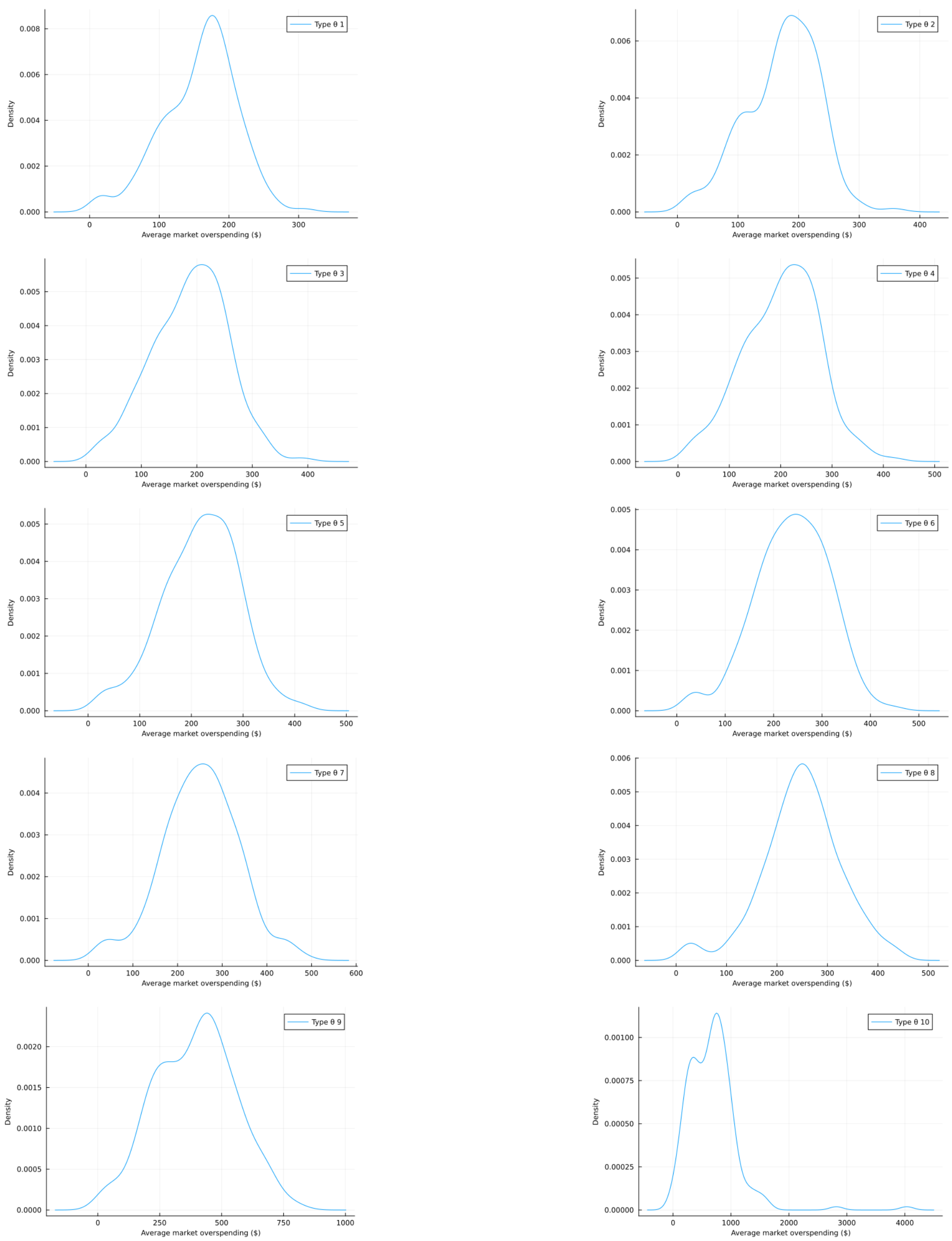


Figure 13: **Within-type distribution of zero shares**

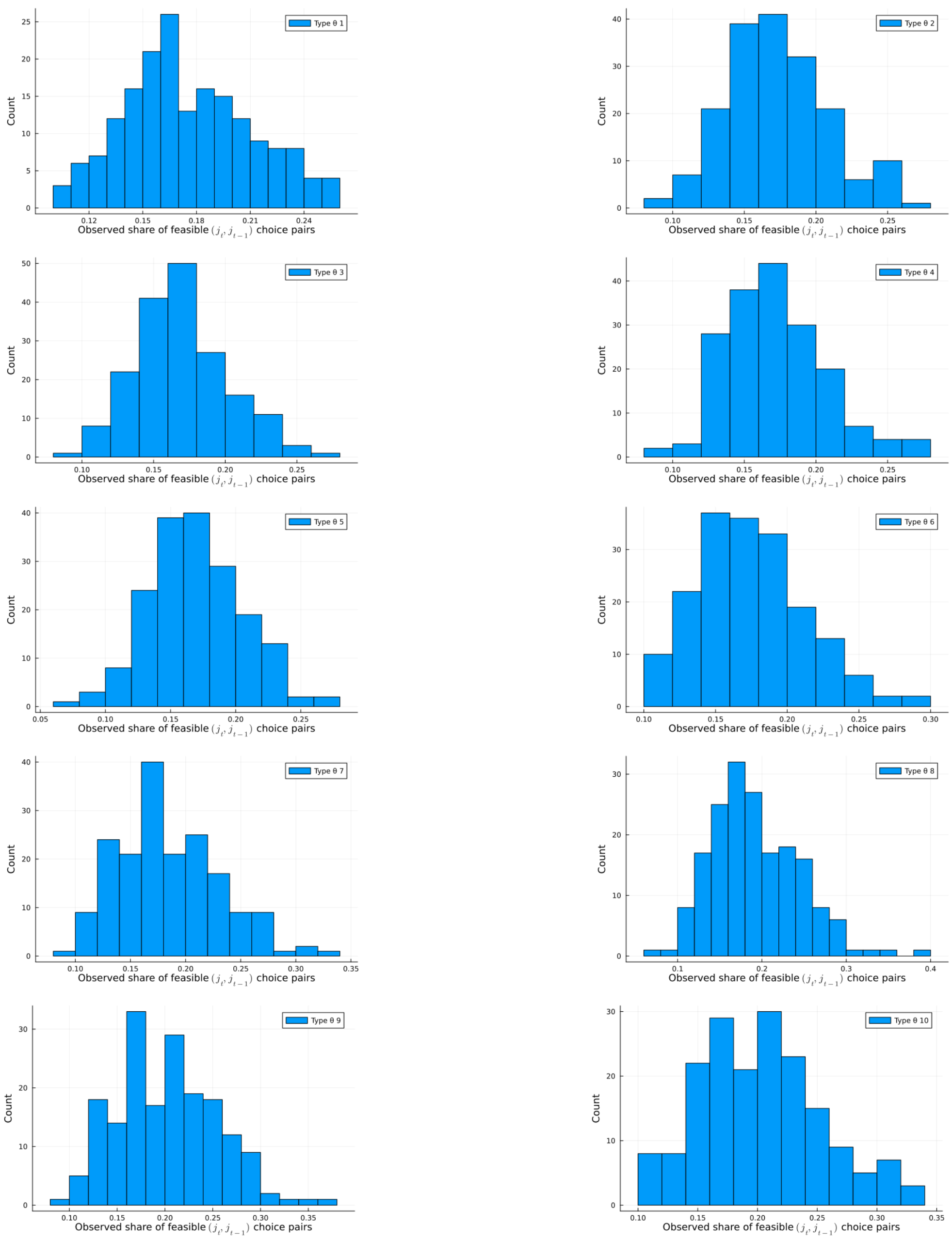
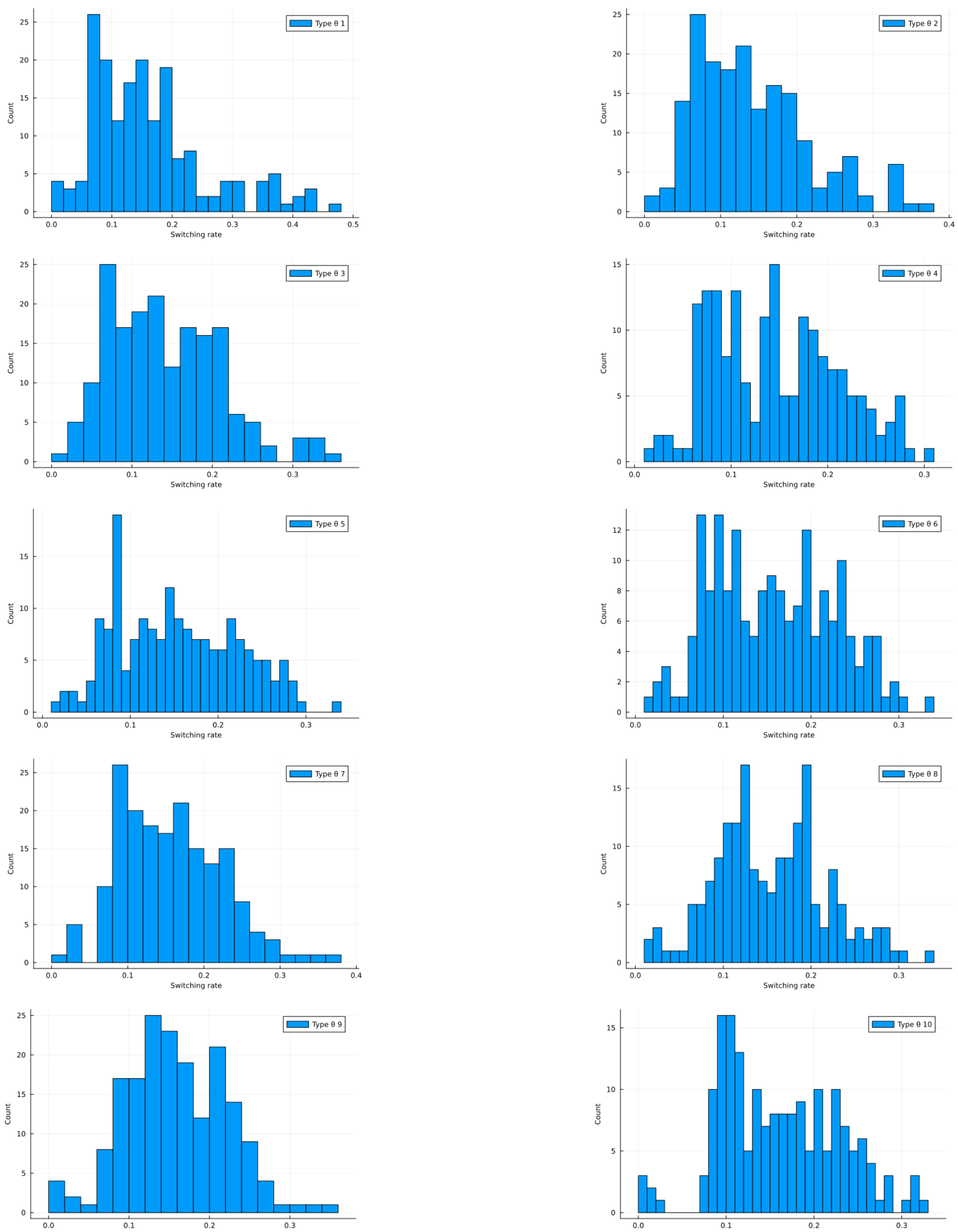


Figure 14: **Within-type distribution of switching rates**



B Appendix: Proofs

B.1 Proof of Proposition 4.1

I start by showing how several quantities can be directly identified from the data exploiting empirical distributions. To see how CCPs are identified from the data, consider how one can recover choice probabilities conditional on the state realization for each type i and each time period t:

$$\hat{s}(j_t|\omega, \theta, j_{t-1}) = \sum_{i=1}^{N} \frac{\mathbf{1}(j_{it} = j_t, \omega_t = \omega, \theta_i = \theta, j_{i,t-1} = j_{t-1})}{\sum_{\tilde{i}=1}^{N} \mathbf{1}(\omega_t = \omega, \theta_{\tilde{i}t} = \theta, j_{\tilde{i},t-1} = j_{t-1})} \tag{31}$$

Similarly, I assume that the prior belief distribution matches the empirical distribution of the state variable, so that for initial time period $t = 0$ is estimated as:

$$\hat{\mu}_0(\omega) = \sum_m \frac{\mathbf{1}(\omega_{m0} = \omega)}{\sum_m \mathbf{1}(\omega_{m0})} \tag{32}$$

The transition probabilities of observed state variables are estimated by the empirical distribution as Ill:

$$\hat{\Gamma}(\omega, \omega') = \sum_{t=1}^{T-1} \sum_{r=1}^{R} \frac{\mathbf{1}(\omega = \omega_{rt}, \omega' = \omega_{r,t+1})}{\mathbf{1}(\omega = \omega_{rt})} \tag{33}$$

Combining these two estimates, I obtain a data estimate of the type-specific predispositions:

$$\hat{q}_t(j_t|j_{t-1}, \theta) = \sum_{\omega_t} \hat{\mu}_t(\omega_t|j_{t-1}) \hat{s}_t(j_t|\omega_t, \theta, j_{t-1}) \tag{34}$$

while the joint distribution $\mu_{t+1}(\omega_{t+1, j_t}; \theta)$ is identified directly from the data thanks to its factorization:

$$\hat{\mu}_{t+1}(\omega_{t+1}, j_t; \theta) = \sum_{\omega_t, j_{t-1}} \hat{\Gamma}(\omega_t, \omega_{t+1}) \hat{s}_{it}(j_t|\omega_t, \theta, j_{t-1}) \hat{\mu}_t(\omega_t, j_{t-1}; \theta) \tag{35}$$

where I exploited the fact that:

$$\hat{\mu}_t(\omega_t|j_{t-1}) = \frac{\hat{\mu}_t(\omega_t, j_{t-1})}{\hat{\mu}_t(j_{t-1})} \ , \ \ \hat{\mu}_t(j_{t-1}) = \sum_{\omega_t} \hat{\mu}_t(\omega_t, j_{t-1}) > 0 \tag{36}$$

and the initial condition is provided by the prior belief distribution $\hat{\mu}_0(\omega)$.

Having established direct identification from the data of these elements (conditional on the assumption on prior beliefs), I proceed to show how I can jointly identify preferences and learning costs pinning down per-period utilities for each option $j = 1, 2, \ldots, J$ without any further parametric assumption.

Start by defining the choice-specific value function for a given type θ:

$$v(\omega_t, j_t; \theta) = u(\omega_t, j_t; \theta) + \beta \sum_{\omega_{t+1}} \Gamma(\omega_t, \omega_{t+1}) \widetilde{V}_{t+1}(\omega_{t+1}, j_t; \theta) \tag{37}$$

Proceeding similarly to Hotz and Miller (1993) and Magnac and Thesmar (2002), I can show that in this setting, there is a known one-to-one mapping, $m(\omega_t, j_{t-1}; \theta) : \mathbb{R}^J \to \mathbb{R}^J$, which maps the vector of choice probabilities $(s(1|\omega_t, j_{t-1}; \theta), \ldots, s(J_t|\omega_t, j_{t-1}; \theta))$ to the vector $(\Delta_1(\omega; \theta), \ldots, \Delta_J(\omega; \theta))$, where $\Delta_j(\omega; \theta)$ denotes the difference in choice-specific value functions.

$$\Delta_j(\omega;\theta) := v(\omega_t, j_t;\theta) - v(\omega_t, 0;\theta) \tag{38}$$

The mapping $m(\omega_t, j_{t-1};\theta)$ is constructed as follows. Given the general formulation of a conditional choice probability:

$$s(j_t|\omega_t, j_{t-1};\theta) = \frac{q(j_t|j_{t-1};\theta)\exp\left(v(\omega_t, j_t;\theta)/\kappa\right)}{\sum_{\tilde{j}_t} q(\tilde{j}_t|j_{t-1};\theta)\exp\left(v(\omega_t, \tilde{j}_t;\theta)/\kappa\right)} \tag{39}$$

consider the ratio of choice probabilities for two different actions in the same state:

$$\frac{s(j_t|\omega_t, j_{t-1};\theta)}{s(0|\omega_t, j_{t-1};\theta)} = \frac{q(j_t|j_{t-1};\theta)\exp\left(v(\omega_t, j_t;\theta)/\kappa\right)}{q(0|j_{t-1};\theta)\exp\left(v(\omega_t, 0;\theta)/\kappa\right)} \tag{40}$$

Taking logs and re-arranging the resulting expression, I find:

$$\log\left(\frac{s(j_t|\omega_t, j_{t-1};\theta)}{s(0|\omega_t, j_{t-1};\theta)}\right) - \log\left(\frac{q(j_t|j_{t-1};\theta)}{q(0|j_{t-1};\theta)}\right) = \frac{v(\omega_t, j_t;\theta)}{\kappa} - \frac{v(\omega_t, 0;\theta)}{\kappa} := \Delta_j(\omega_t;\theta) \tag{41}$$

I denote with $m_j(\omega_t, j_{t-1};\theta)$ the j-th element of $m(\omega_t, j_{t-1};\theta)$, and set it equal to $\Delta_j(\omega_t;\theta)$. Since the conditional choice probabilities and the predispositions can be identified from the data and the mapping has this known formulation, the vector $(\Delta_j(\omega_t;\theta))_{j=1,\ldots,J_t}$ is also identified.

Next, note that the choice-specific value function for a given type θ also satifies a type of Bellman equation and it can be re-written as:

$$\begin{aligned}
v(\omega_t, j_t;\theta) &= u(\omega_t, j_t;\theta) + \beta\sum_{\omega_{t+1}}\Gamma(\omega_t,\omega_{t+1})\widetilde{V}_{t+1}(\omega_{t+1}, j_t;\theta)\\
&= u(\omega_t, j_t;\theta) + \beta\sum_{\omega_{t+1}}\Gamma(\omega_t,\omega_{t+1})\kappa\ln\sum_{j_{t+1}} q_{t+1}(j_{t+1}|j_t)\exp\left(\frac{v_{t+1}(\omega_{t+1}, j_{t+1};\theta)}{\kappa}\right)\\
&= u(\omega_t, j_t;\theta) + \beta\sum_{\omega_{t+1}}\Gamma(\omega_t,\omega_{t+1})\kappa\ln\sum_{j_{t+1}} q_{t+1}(j_{t+1}|j_t)\exp(\Delta_j(\omega_{t+1};\theta))\exp\left(\frac{v_{t+1}(\omega_{t+1}, 0;\theta)}{\kappa}\right)\\
&= u(\omega_t, j_t;\theta) + \beta\sum_{\omega_{t+1}}\Gamma(\omega_t,\omega_{t+1})\kappa\left(\ln\sum_{j_{t+1}} q_{t+1}(j_{t+1}|j_t)\exp(\Delta_j(\omega_{t+1};\theta)) + \frac{v_{t+1}(\omega_{t+1}, 0;\theta)}{\kappa}\right)
\end{aligned}$$

Using the normalization on the per-period utility of the option $j = 0$, I can write for $v(\omega_t, 0;\theta)$:

$$\frac{v(\omega_t, 0;\theta)}{\kappa} = \beta\sum_{\omega_{t+1}}\Gamma(\omega_t,\omega_{t+1})\left(\ln\sum_{j_{t+1}} q_{t+1}(j_{t+1}|j_t)\exp(\Delta_j(\omega_{t+1};\theta)) + \frac{v_{t+1}(\omega_{t+1}, 0;\theta)}{\kappa}\right) \tag{42}$$

In the previous expression everything but $\frac{v(\cdot)}{\kappa}$ can be directly estimated from the data, hence by iterating over this equation I can solve for the stationary $\frac{v(\cdot)}{\kappa}$ function. Once this is is known, I can recover all other choice-specific value functions using:

$$\frac{v(\omega, j; \theta)}{\kappa} = \Delta_j(\omega; \theta) + \frac{v(\omega, 0; \theta)}{\kappa} \quad \forall \omega, \ j \tag{43}$$

Finally, I can use the recovered choice-specific value functions to obtain the per-period utilities:

$$\frac{u(\omega_t, j_t; \theta)}{\kappa} = \frac{v(\omega_t, j_t; \theta)}{\kappa} - \beta \sum_{\omega_{t+1}} \Gamma(\omega_t, \omega_{t+1}) \ln \sum_{j_{t+1}} q_{t+1}(j_{t+1}|j_t) \exp\left(\frac{v(\omega_{t+1}, j_{t+1}; \theta)}{\kappa}\right) \tag{44}$$

As it is clear from this last expression, preferences determining $u(\omega_t, j_t; \theta)$ and learning costs κ are only jointly identified. While it is not possible to separately identify them non-parametrically using observational data without imposing additional exclusion restrictions, counterfactual analyzing proportional changes in learning costs are still identified. This is also consistent with an interpretation where learning costs are not a primitive of the model, but a potential channel for policy intervention themselves.

B.2 Proof of Proposition 4.2

The proof follows by inspection of the formula for the CCPs:

$$s(j_t|\omega_t^m, j_{t-1}; \theta_i) = \frac{q(j_t|j_{t-1}; \theta_i) \exp\left(v(\omega_t^m, j_t, \theta_i; \boldsymbol{\beta})/\kappa\right)}{\sum_{\tilde{j}_t} q(\tilde{j}_t|j_{t-1}; \theta_i) \exp\left(v(\omega_t^m, \tilde{j}_t, \theta_i; \boldsymbol{\beta})/\kappa\right)}$$

As long as the left-hand side is positive for some j_t given j_{t-1}, from the optimality conditions one knows that it necessarily holds $q(j_t|j_{t-1}; \theta_i) > 0$. It follows that no inversion is needed to solve for the right-hand side: as long as there is enough variation in the choice probabilities, it can be projected onto variation in the choice specific value function. A similar logic underpins identification in a standard dynamic logit model.