Insurance Choice with Non-Monetary Plan Attributes: Limited Consideration in Medicare Part D

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Abstract

I propose an empirical model of demand for prescription drug plans where non-monetary plan attributes stochastically determine the composition of the set of plans that an individual considers, and monetary plan attributes determine the individual's expected utility over contracts in her consideration set. This model reconciles the classic view of insurance contracts as lotteries with purely monetary outcomes with the empirical finding that choice among insurance plans is driven by their non-monetary attributes and financial attributes beyond their impacts on costs. I estimate the model using data from Medicare Part D allowing for unobserved heterogeneity in risk aversion and in consideration sets. I find that the latter plays a crucial role in plan choices: although 46 plans are available in the market, more than 90% of individuals consider no more than 5 plans. While the majority of available plans include a deductible, nearly 75% of all plans considered have no deductible. Just three firms account for over 60% of plans considered, while three other firms account for fewer than 0.5%. In contrast to previous literature that assumes full consideration of all plans, I uncover an important role for risk aversion in determining individual choices. My results inform the debate on how to refine market design for prescription drug plans in Medicare to improve the match between beneficiaries and plans.

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1 Introduction

Health insurance markets in the United States are moving towards increased consumer choice. Many employers today offer their employees a choice of sponsored health insurance plans. The Balanced Budget Act of 1997 provided Medicare beneficiaries the opportunity to receive their health benefits through private insurance plans, and the Medicare Modernization Act of 2003 expanded those plans into what is today known as Medicare Advantage, or Part C. Since 2006 Medicare beneficiaries have the choice of prescription drug plans offered by private companies through Medicare Part D. Recently, following the Affordable Care Act of 2010, more individuals are choosing among private insurance plans through the expanded Medicaid program and online health exchanges. Few markets compare in economic magnitude to health care: in the United States, health care spending accounts for approximately 18% of GDP and continues to grow. The insurance products available and the corresponding choices individuals make in such markets have a large impact on their access to quality health care and overall well-being.[1] Public policy considerations surrounding health care and insurance are top of mind for many and are widely debated in contemporary politics. Efforts to improve the outcomes for individuals in health insurance markets must confront market inefficiencies, such as market power and asymmetric information. Depending on their nature, these inefficiencies may or may not require policy interventions in order to improve health and market outcomes. To this end, an understanding of the foundations of individual choice in health insurance markets is crucial to assessing the impact of any new policies, interventions, or modifications to market design.

Rationalizing health insurance choices is, however, notoriously difficult. Many choice patterns defy notions of optimality under economic models. It is not uncommon for individuals to select insurance plans that are strictly dominated by available alternatives.[2] In some settings, choices indicate preferences for attributes that do not conform to most economic models. The classic approach to insurance views contracts as lotteries with purely financial outcomes. Insurance appeals to risk averse individuals as a means to transfer wealth from good states of the world, in which they are not sick, to bad states of the world, where health needs are costly. In practice, this view of insurance is challenged by empirical patterns. Numerous studies of prescription drug coverage choice in Medicare have encountered such patterns: beneficiaries appear to overweight premiums relative to out-of-pocket costs and

[1] Prescription drug insurance alone has been shown to improve health outcomes. Diebold (2016) and Semilla, Chen, and Dall (2015), document substantial improvements in drug adherence and mortality rates among beneficiaries enrolled in Medicare Part D.

[2] In a relatively straightforward comparison of employer-provided health insurance plans where plans differed in deductible and premiums, and thus only require a dollar comparison across plans, Bhargava, Loewenstein, and Sydnor (2017) finds a substantial portion of individuals select plans that are strictly dominated regardless of preferences or health realizations. Handel (2013a) documents substantial inertia in employer-provided health insurances leading to dominated choices, albeit with reduced adverse selection.

ascribe value to both non-monetary attributes and monetary attributes above and beyond their financial impact.[3] During early years of the program, the average beneficiary faced a choice from approximately 50 insurance plans.[4] In a market setting with such a large choice set of complex products, beneficiaries and policymakers alike have expressed concern that the choice environment is difficult to successfully navigate.[5]

In this paper, I propose an empirical model of demand for prescription drug plans where non-monetary plan attributes stochastically determine the composition of the set of plans that an individual considers, and monetary plan attributes determine the individual's expected utility over contracts in her consideration set.[6] This model reconciles the classic view of insurance contracts as lotteries with purely monetary outcomes with the empirical finding that choice among insurance plans is driven by their non-monetary attributes and financial attributes beyond their impacts on costs. This model of limited consideration, in which individuals are assumed to select their preferred plan from an unobserved subset of the feasible set, preserves the structural interpretation of insurance demand as arising from risk aversion, while providing a natural role for various plan attributes to shift choice frequencies in ways beyond the impact of those attributes on the utility derived from a plan. In what follows, "choice set" denotes the full available menu of plans, and "consideration set" refers to the subset of plans considered. I estimate the model using data from Medicare Part D allowing for unobserved heterogeneity in risk aversion and in consideration sets. Incorporating limited consideration into an expected utility model of insurance demand provides an avenue for the data to identify the elements of the choice environment that underpin limited consideration. The model determines the causes of limited consideration, such as the plan attributes, but does not presume a specific underlying behavioral model of consideration set formation.

Interest in the role of human cognition and assumptions regarding which feasible alternatives an agent considers when making a choice has a long history, including Tversky (1972) and Manski (1977). Models of limited choice sets have been a part of the literature on marketing for decades, as in Roberts and Lattin (1991) and Ben-Akiva and Boccara (1995). More recent developments in economic models, and specifically those in the framework of decision-making under risk, are described in Section 3 below. This paper leverages this history and recent results regarding consideration and risk preferences in Barseghyan, Molinari, and Thirkettle (2019b) to obtain point identification of a structural model of insurance choice

[3]See, for example, Abaluck and Gruber (2011), Ketcham, Lucarelli, Miravete, and Roebuck (2012), and Heiss, Leive, McFadden, and Winter (2013).

[4]After adjustments to the market regulations, at present, on average beneficiaries face approximately 30 plans.

[5]See survey results in The Kaiser Family Foundation and the Harvard School of Public Health (2006), for example.

[6]I use the term "non-monetary" attributes throughout the paper in reference to both attributes that do not have an immediate monetary interpretation, as well as to the role of financial attributes above and beyond their impacts on costs.

alongside limited consideration. Moreover, the model is tractable to implement, even when the choice set is large. There are many potential underlying sources of limited consideration in the Medicare Part D market. Individuals may face constraints unobserved to researchers that result in the exclusion from consideration of certain plans deemed unfeasible. Many individuals face liquidity constraints and are unable to cover large unplanned expenses.[7] It is certainly imaginable that such a constrained individual might only consider plans with reduced or eliminated deductibles. Similarly, some beneficiaries live on a fixed income and a budget-constrained individual may only consider plans with monthly premiums below a reservation price. Market forces such as firm advertising or agent steering effects may lead beneficiaries to consider only plans offered by certain firms. Others may simply face cognitive or time limitations that manifest in a reduced number of plans considered at the time of enrollment. I remain agnostic about the behavioral mechanism behind limited consideration, and employ a consideration set formation model that allows for any of these mechanisms to play a role.

A model of expected utility with limited consideration is well suited to explain plan choice patterns among Medicare Part D beneficiaries. Using a sample of beneficiaries living in the largest of the standalone prescription drug plan (PDP) regions, I recover estimates of risk preferences while allowing the probability a plan is considered to depend on the attributes highlighted in previous literature. Heterogeneity in consideration sets plays a crucial role in rationalizing plan choices. Beneficiaries in my sample face the choice of 46 plans, but over 90% of individuals consider no more than 5 plans. The probability a given plan is considered is driven by the identity of the insuring firm, the premium, the deductible, and the presence of supplemental coverage in the infamous "donut hole" (a phase of coverage in which beneficiaries pay 100% of drug costs). I estimate the highest premium plan is considered 10% as much as the lowest premium plan, all else equal. Similarly the highest deductible plan is considered 18% as often as a comparable zero deductible plan. In contrast, attributes that are not as easily observed by beneficiaries, such as the number of popular drugs covered, do not play a role in consideration. The consideration impacts of the firm and deductible alone are appreciable. Just three firms account for over 60% of considered plans, while the three smallest account for fewer than 0.5%. Although the majority of plans offered in the market include a deductible, nearly 75% of considered plans have no deductible. These patterns of consideration result in beneficiaries clustering on lower premium and zero deductible plans offered by a few popular firms that are not necessarily as well matched to their drug needs as other available but unconsidered plans.

In contrast to the previous Medicare Part D literature, I recover substantial estimates of risk aversion in line with the literature that estimates risk aversion in field data.[8] My

[7] See discussion in Durante and Chen (2019) within the section *Dealing with Unexpected Expenses*.

[8] For example, Cohen and Einav (2007) finds among Israeli auto insurance customers a relatively low average

estimates more than double the mean risk aversion implied by a classic model of full consideration. My model highlights the sensitivity of risk preference estimation to the treatment of consideration. The material role of limited consideration, taken together with the distribution of risk aversion, translates into an important cost of limited consideration because beneficiaries frequently do not consider their best plans. Beneficiaries lose, on average, $226 in certainty equivalent terms, from considering a subset of plans that often does not include the plan best suited to their drug needs and risk preferences.

My estimates of risk preferences suggest a distribution of optimal choices that differs substantially from the empirical distribution. Estimates of plan consideration probabilities bridge the gap between these two distributions. The plans that are optimal for a large share of beneficiaries but are infrequently chosen are found to have relatively low consideration probabilities. Correspondingly, the most highly considered plans are those that are optimal for a relatively small share of beneficiaries and yet are often chosen. These estimates contribute to the primary source of the cost of limited consideration - by considering so few plans, individuals often do not evaluate plans that are best according to utility. Using my estimated structural model, I show that a counterfactual where certain consideration effects are removed leads to, holding all else equal, increases the size of consideration sets in the population and improves choice quality. The elimination of the firm effects, for example, more than triples the average consideration set size and increases the likelihood individuals consider their optimal plan.

This setting, in which economic theory suggests monetary attributes are the only utility-relevant plan features, but empirical patterns contradict that modeling assumption, previously created a dilemma for researchers. The model of limited consideration resolves some of the inconsistencies that have become commonplace in modeling insurance choices. Estimates and model implications are sensitive to the treatment of non-monetary attributes, and the usefulness of estimates of risk aversion without accounting for plan attributes is limited. This paper provides a tractable alternative to modeling insurance decisions that both preserves the role of risk preferences and guides policymakers towards how beneficiaries are navigating this complex choice environment. My results indicate that documented sub-optimal choice patterns are not a sign that the trend of increasing the role of consumer choice in health insurance is a lost cause. Accounting for limited consideration clarifies that consumer choices are not inexplicable, but rather reflect the navigation of a large, complex choice environment and the importance of certain easily ascertained features of the plans offered. Accordingly, the impact of adjustments to market regulations, plan design, or the manner in which plan information is presented to beneficiaries, will depend both on true risk preferences and the

risk aversion but a substantial fraction of customers exhibit very high risk aversion. Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2013) finds overall high levels of risk aversion among North American auto and home insurance customers.

effect of such adjustments on consideration.

2 Institutional Background

Prior to the Medicare Modernization Act of 2003, Medicare provided hospital (Part A) and physician services (Part B) insurance coverage for elderly Americans and those with disabilities and certain serious illnesses. In 2006 prescription drug coverage was added to the program. Beneficiaries seeking prescription drug coverage have the option of enrolling in a standalone prescription drug plan (PDP) through Medicare Part D or to bundle prescription coverage with the other health insurance through Medicare Part C (also known as Medicare Advantage). Any individual enrolled in either Parts A or B is eligible for coverage through Part D. Both Medicare Parts C and D are regulated by the Centers for Medicare and Medicaid Services (CMS) but provide beneficiaries a choice among plans offered by private insurance companies. To mitigate adverse selection, for every month an eligible beneficiary does not enroll in Part D, a penalty is accrued and applied as a perpetual surcharge upon eventual enrollment.[9] The penalty is the same regardless of which plan is ultimately chosen and is typically deducted directly out of social security benefits.

Participants in Part D select a plan for the following year between October 15^{th} and December 7^{th} during annual open enrollment. Those who do not qualify for low-income subsidies cannot change plans throughout the year.[10] The menu of available plans is determined based on which of the 34 CMS regions a beneficiary resides in.[11] Within each region, beneficiaries face a large set of plans to choose from, where the premiums are subsidized by the federal government and are fixed across individuals. As shown in 2.1, in 2010, regional choice sets varied from a minimum of 39 plans to a maximum of 54 plans.[12] Firms participating in a market can offer multiple plans and have some discretion over ways to differentiate their plans. All plans offered through the program must meet CMS requirements on minimum plan generosity, including covering at least 2 drugs within 148 therapeutic categories, and virtually all drugs within certain crucial therapeutic classes.

Every year CMS releases cost-sharing standards for a base plan design. All plans in the program are required to be at least as generous actuarially as the standard plan. The standard plan divides beneficiary spending into four phases: the deductible, the initial coverage phase, the coverage gap (known colloquially as the "donut hole"), and the catastrophic coverage

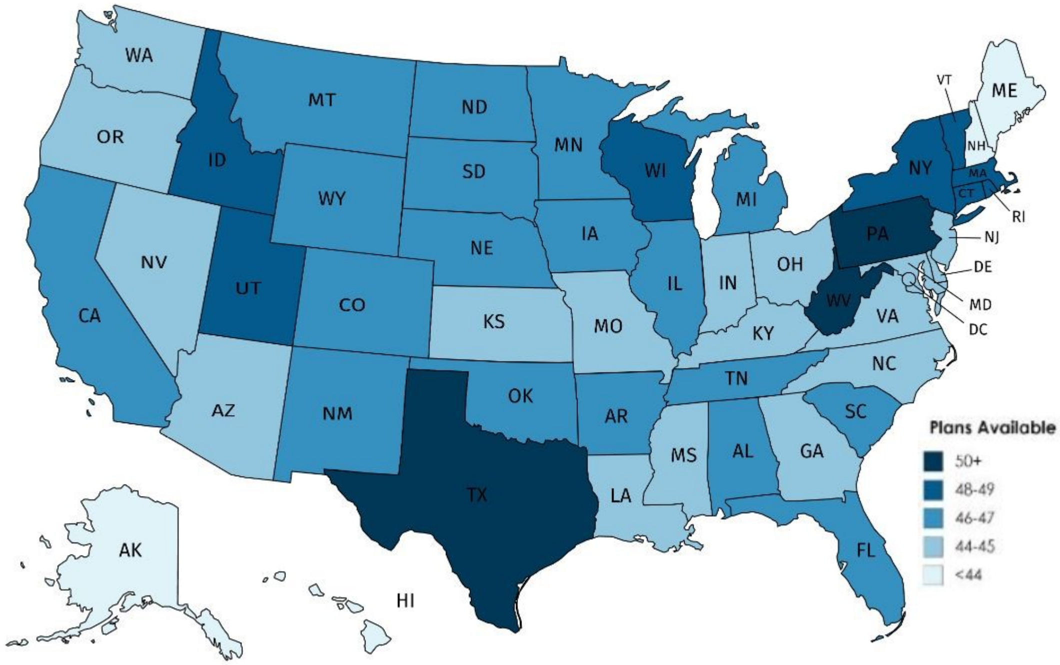
[9] If an eligible beneficiary receives prescription drug coverage that meets CMS standards through another channel, such as an employer program, this penalty is not amassed.

[10] Recently CMS has relaxed this rule slightly. Individuals are permitted to change plans throughout the year if they are moving into a plan CMS rates as 5-star in terms of quality.

[11] There are additional regions covering beneficiaries living in United States territories.

[12] In the data description below in Section 4, the plans listed here include only standalone PDPs, without an employer waiver, and exclude plans that were discontinued midyear due to CMS intervention.

Figure 2.1: Counts of Plans Offered, 2010



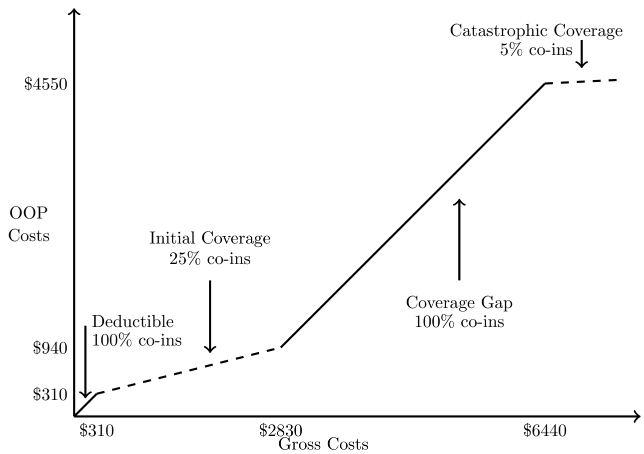
phase. Figure 2.2 provides a graphical representation of the 2010 standard plan. During the deductible phase, a beneficiary is responsible for 100% of drug costs. Once the deductible of \$310 is reached, the plan's initial coverage begins, during which the plan covers 75% of drug costs and the beneficiary pays the remaining 25% out of pocket. Once the initial coverage limit of \$2,830 is reached, a beneficiary enters the coverage gap where 100% of costs are borne by the beneficiary until an out-of-pocket threshold of \$4,550 is reached.[13] Any claims beyond the out-of-pocket threshold are treated as catastrophic and the beneficiary pays the maximum of a \$6.30 copay or a 5% coinsurance.[14]

While the market is highly regulated, firms have the ability to differentiate the plans they offer. Market regulations during most of the program's existence limit the number of plans a firm can offer in a given market and require a meaningful level of distinction between plans offered by the same firm to avoid confusion from seemingly redundant plans. There are multiple ways a firm can differentiate the plans they offer from one another and from those offered by other firms in a region. Insurers have wide discretion over the plan formulary, which lists all drugs covered under a plan and how generously they are covered by classifying each included drug into a tier (lower tiers correspond to lower cost drugs). Firms can also adjust the cost-sharing structure of a plan, with many choosing to offer plans with a reduced

[13] As part of the Affordable Care Act, the coverage gap was mandated to be phased out, absorbed into the initial coverage phase, over 2011-2020. It was fully eliminated a year ahead of schedule in 2019.

[14] For branded drugs the copay is \$6.30 and for generic drugs it is \$2.50.

Figure 2.2: 2010 Standard Plan Design



or fully eliminated deductible. Under such a design, claims are processed according to the initial coverage structure from the first dollar.

Although with some exposition here the government designed plan appears relatively comprehensible, this simple plan description belies some of the further complexities of the products beneficiaries face. Consider, for example the deductible of a given plan. In the standard plan, this is described simply as a dollar amount up through which costs are borne fully by the beneficiary. Each year CMS determines a maximum deductible allowed under the standard plan, but firms can offer reduced or zero deductible plans (and in the cases where a firm is offering multiple plans, they can use differing deductible amounts to differentiate those plans). Many of the plans with a deductible exempt low cost drugs (categorized as tier 1 or 2) from the deductible, and rather process them under the standard cost-sharing used during the initial coverage phase. To understand the impact of the deductible on out-of-pocket costs, a beneficiary must have an understanding of the timing of their claims, as well as which tier classification has been assigned to their needed drugs under different plans, since plans have discretion over this classification. This complexity requires that a beneficiary evaluating two plans that at first blush appear to differ only in the deductible phase, may still be facing a rather complex comparison. To ease this process, CMS encourages beneficiaries to use the online PlanFinder tool, where beneficiaries can enter their zip code, expected drug needs, and pharmacy preferences to receive personalized estimates of out-of-pocket costs under each available plan.

Despite these complexities, Part D has been, on the whole, lauded as a success. Studies, including Diebold (2016) and Semilla et al. (2015), have found substantial improvements in prescription drug adherence and mortality rates among beneficiaries enrolled in the program. The program is widely used and popular among beneficiaries, with 43 million beneficiaries enrolled in 2018. From the start, however, there has been concern that the plan choice environment is too complex, especially for a more senior population. Beneficiaries themselves expressed interest in a reduced choice set in order to alleviate the difficulty in choosing a plan.[15] The number of plans offered has decreased from the initial years of the program with the average beneficiary now facing a set of approximately 30 plans. The program remains popular with the majority of Medicare beneficiaries receiving prescription drug coverage through it.

3 Literature Review

This paper shares a core motivation with previous studies on Medicare Part D plan choice: to understand and evaluate plan choices according to economic models of decision making. Well known studies include Heiss et al. (2013) and Abaluck and Gruber (2011), as well as the exchange resulting from the latter in Ketcham, Kuminoff, and Powers (2016) and Abaluck and Gruber (2016a).[16] This paper differs methodologically from such prior studies. Abaluck and Gruber (2011) evaluates initial plan choices in 2006 using data from a switch agent. Abaluck and Gruber (2011) estimates a conditional logit as a linear approximation of a CARA expected utility model with plan attributes included additively. Although incorporating plan attributes into the utility framework improves the explanatory power of the model, the resulting estimates are challenging to interpret in the classic insurance model, for reasons I now discuss. The resulting coefficients of those attributes are compared to those of premiums or out-of-pocket costs to monetize the attribute and assess an approximate willingness to pay. There are reasons to assume a beneficiary may ascribe a "cost" to certain attributes - for example, paying a deductible may cause disutility due to liquidity constraints that make a large single payment particularly challenging. The modeling technique of adding the deductible as a term in the utility specification, however, suggests a constant utility "cost" of the attribute across all possible health realizations, similar to the premium.[17] If the utility relevance of the deductible is meant to capture a burden or hassle cost of the attribute, in some contexts it is undesirable to model that cost as equal in the state of the world in which the beneficiary is not sick and does not incur the deductible and the state of the world in which she is sick and pays the deductible. Inclusion of attributes such as the deductible can offer insight into which plan features relate to choice probabilities, but with the existing modeling approach this is at the expense of the economic interpretation. As I explain in

[15] For example, The Kaiser Family Foundation and the Harvard School of Public Health (2006) notes that in the first year of the program 73% of seniors found the program too complicated, as did 91% of pharmacists and 92% of doctors surveyed. 60% of seniors agreed that Medicare should select a small number of good plans to help seniors have an easier time choosing.

[16] Additionally important early studies include Heiss, McFadden, and Winter (2010), Lucarelli, Prince, and Simon (2012), Kling, Mullainathan, Shafir, Vermeulen, and Wrobel (2012), and Ketcham et al. (2012).

[17] See Handel (2013b) and Handel and Kolstad (2015) for a discussion of this topic.

Section 7.4, my proposed modeling approach resolves this tension.

Using a conditional logit model as described above, results indicate that beneficiaries are selecting plans in a manner considered inconsistent with the rational behavior of an expected utility maximizer who evaluates plans based on their monetary features. Specifically, beneficiaries overweight premiums relative to out-of-pocket costs, place little to no value on a plan's risk reduction features, and value financial aspects of plans, such as deductible and gap coverage, beyond the impact of such attributes on expected costs. Drawing similar overarching conclusions, Heiss et al. (2013) estimates a multinomial logit model to approximate a CARA expected utility model including the theoretically relevant cost variables. Such a model without plan attributes poorly describes the choice patterns of beneficiaries in Medicare administrative data. Moreover, the implied risk preferences are surprisingly unstable over time, with one year of modest risk aversion and one year of substantial risk preference.[18] In both of these studies, a logit is used as a linear approximation to the CARA expected utility function.[19]

Given the complexity of prescription drug plans, the large number of plans available, and the advanced age of beneficiaries, it is hardly surprising that individuals would fail to behave in a manner fully consistent with standard economic models. The literature on menu complexity and heuristic shortcuts in insurance also shares motivational elements with this paper. In the Part D market, Ketcham, Lucarelli, and Powers (2015) finds evidence that it is not the size of the choice set alone that drives choices inconsistencies. The quality of choices is estimated to improve with larger choice sets due to increased switching, with the exception of the cases where additional plans are relatively more expensive. In other health insurance markets, there is evidence that consumers use heuristic shortcuts to limit the choice set before choosing plans (Ericson and Starc (2012)), as well as that choices improve when products are standardized and the choice set becomes less complex (Ericson and Starc (2016)).

Inconsistencies with model implications can also be suggestive of model misspecification. Ketcham et al. (2016) implement a very general test of rationality, using General Axiom of Revealed Preference (GARP) arguments to determine if plan choices are consistent with any utility specification. Although focused predominantly on highlighting that the majority of plan choices are consistent with some utility function, and thus evidence of widespread suboptimality of plan choices is potentially indicative of model misspecification, the fact remains that even under such a general framework a sizable fraction of initial plan choices remain inconsistent with utility maximization.[20] Many of the studies on Part D plan choice have

[18]Similarly to Abaluck and Gruber (2011), the coefficient of risk aversion is estimated based on a ratio of the estimated coefficients on variance of costs and mean costs. In 2008, Heiss et al. (2013) estimate a positive coefficient on variance, implying riskier plans correspond to higher choice probabilities.

[19]For a derivation of such an estimating model from the CARA expected utility framework, see Abaluck and Gruber (2011).

[20]In the main version of this test, 21% of choices over 2006-2010 were inconsistent with utility maximization.

differed in model, data, and measures of choice quality, but there is an empirical consensus that seniors are leaving money on the table.[21] Such deviations from rationality are not unique to prescription drug insurance choices. Bhargava et al. (2017) describes a case of employer offered health insurance plans in which a substantial portion of individuals select insurance plans that are strictly dominated by available alternatives, and in such an unambiguous manner that basic arithmetic would highlight that dominance.[22] In the market for auto collision insurance Barseghyan et al. (2019b) and Barseghyan, Coughlin, Molinari, and Teitelbaum (2019a) document a substantial fraction of individuals selecting a policy that is dominated by other available plans, regardless of risk preferences.

A commonly suggested and intuitive explanation for the prevalence of what economists deem suboptimal choices is limited consideration.[23] In a model of limited consideration, individuals are assumed to select a plan (or product, more generally), from a considered subset of the feasible set. Choices, therefore, do not reveal preference over the entire choice set, but rather only over the considered set. Previous studies, including Abaluck and Gruber (2011) and Abaluck and Gruber (2016b), have mentioned limited consideration as a possible explanation for the role of plan attributes in choices.[24] A well-studied and generally accepted form of limited consideration in the Medicare Part D market is inertia.[25] Fundamentally, inertia is an type of limited consideration in which the agent considers only their existing plan or no plans at all. Ho, Hogan, and Scott Morton (2017), studying Medicare Part D choices over time, documents the role of inertia and the way in which certain shocks - most notably in premium, a highly visible plan attribute - can break beneficiaries from their inertia. Abaluck and Gruber (2016b) also study Medicare Part D choices over time, and documents a role for inertia and finds little evidence of learning or improved performance of beneficiaries as they gain more experience in the market over time. Polyakova (2016) explores the interaction of inertia, adverse selection, and market regulations and finds inertia and switching costs contribute to the sustainment of an adversely-selected equilibrium in Medicare Part D.

Additional explanations for observed choice patterns in the market have recently been explored in the literature. Keane, Ketcham, Kuminoff, and Neal (2019) and Ketcham, Kuminoff, and Powers (2019), for example, propose an alternative approach in which Part D

The further relaxed consistency test found 14% of those choices are not rationalizable.

[21] See in addition Ketcham et al. (2015), Kesternich, Heiss, McFadden, and Winter (2013), Kling et al. (2012), among others.

[22] The setting included pairs of plans differing only in the deductible, but the additional premium charged for the lower deductible plans exceeded the amount by which the deductible was reduced, guaranteeing larger costs under all realized health scenarios.

[23] Models of limited consideration and limited attention have a long history in economics, including Simon (1959).

[24] Both studies posit that the importance of firm fixed effects in matching choice patterns may suggest individuals are rationally using trusted firms as a heuristic shortcut when unable or unwilling to make the time-consuming or difficult financial comparison across all plans.

[25] Inertia is the well-documented pattern of behavior in insurance markets whereby individuals passively remain in existing plans at the time of a renewal rather than actively select from the set of available plans.

choices are assumed to be made with varying degrees of consumer informativeness. In the former a a mixture-of-experts model is used to model plan choices as probabilistically revealing of preferences. The latter uses survey data as a signal of whether consumers are informed and assess the welfare implications of various market interventions assuming the observed choices of informed individuals proxy for the preferences of uninformed individuals. In contrast, Brown and Jeon (2019) build on the work of Matějka and McKay (2015) and Fosgerau, Melo, Palma, and Shum (2017) and propose a model of rational inattention whereby beneficiaries for whom the choice stakes are high, those with high variance of out-of-pocket costs across available plans, acquire more information about the plans before enrollment.

Beyond the framework of health insurance, this paper builds on the methodology of limited consideration in discrete choice models. The alternative specific consideration model used below has been developed and shown to be nonparametrically identified under certain conditions in Barseghyan et al. (2019b).[26,27] This paper highlights a major appeal of such models to empirical applications. The introduction of consideration sets provides a natural role for non-monetary plan attributes in a model of insurance choice - the probability a given plan is considered can be modeled as a function of its attributes. This is the key distinction of this paper compared to previous studies. In such an insurance model, there is a distinction between what enters expected utility and reflects the uncertainty of the environment and the plan attributes that enter consideration and hence do not depend on the state of the world. In cases where plan attributes impact choice beyond their financial impact on utility-relevant monetary costs, consideration sets provide a theoretically sound avenue to relate attributes to choice. A limited consideration model can marry the theoretical underpinnings of expected utility with the empirical reality present in this market. These techniques offer a tractable modeling alternative to standard methods, even in the presence of such a large feasible choice set.

4 Data

The primary data source in this study is administrative data from CMS. These data include information for a 5% random sample of 2010 Medicare beneficiaries. The relevant enrollee data include information on basic demographics, plan choice, and the full set of drug claims filled under the beneficiaries' plans. These beneficiary and claims data are paired with plan information, linking premiums and plan coverage structures for all plans available to each beneficiary. Additional information on the formularies and drug prices negotiated for each plan is included in public use files released for purchase by CMS, as well as the restricted

[26]The model in Barseghyan et al. (2019b) expands on the work of Manski (1977) and Manzini and Mariotti (2014).

[27]A conceptually similar, but econometrically different and parametrically specified, model was used in Goeree (2008) to estimate demand for computers when advertising plays a role in consideration set formation.

access version of the formulary file for 2010.[28] Official firm names listed in the restricted files are matched to the common company names beneficiaries would see at the time of plan choice using a crosswalk published by Ketcham et al. (2016).

4.1 Analysis Sample

The aim of this study requires restricting the sample to beneficiaries selecting standalone prescription drug plans (PDPs), excluding those who forgo prescription drug coverage, those with coverage outside of Medicare and those who opt instead for Medicare Advantage (Part C) plans.[29] Additionally, I exclude from the sample all individuals receiving a low-income subsidy. The enrollment, pricing, and choice environments for those individuals differ substantially from the standard Medicare population, and I lack relevant data on payments. I also exclude individuals who have more than one Medicare drug plan over the course of the year, are dual eligible for Medicaid, or drop their coverage mid-year for any reason other than death. As a final general sample restriction, I exclude individuals who either currently have or initially enrolled in Medicare due to end-stage renal disease, as their health needs differ quite dramatically from the overall Medicare population.

Every year during open enrollment, beneficiaries select a plan for the entirety of the following year.[30] If a beneficiary's existing plan remains available, they default into the same plan without an active choice. A concern in any choice environment of this sort is the distinction between the role of preferences and the role of inertia in observed choices. The role of inertia is left for future research, and for this paper, I abstract from this complication by restricting attention to "active choices." Active choices include the enrollment decisions of those joining Medicare Part D upon eligibility, as no default option is available. Additionally, I include individuals that are first choosing a Part D plan but for a few common reasons, are not making that choice at the time of eligibility. This includes those that either retained employer drug coverage (through the form of a Retiree Drug Subsidy plan) for a period of time after entering Medicare, initially retained other creditable prescription coverage while Medicare enrolled, or went for a period of time without any drug coverage. If these individuals joined Part D during 2010, their choices are included in my sample.[31] The final group included as active choosers are those who are actively switching plans from the previous year.[32]

[28] Although the restricted version of the formulary file is available, surprisingly, information on negotiated base prices for drugs is only included in the public use versions of the data.

[29] My data include information on whether individuals receive outside coverage but lack any specific information on offerings, pricing, and claims for such cases.

[30] Beneficiaries receiving low-income subsidies are permitted to change plans monthly. The beneficiaries within the present sample, however, cannot change plans until open enrollment, where they can select a different plan for the subsequent year.

[31] This latter group does face the above described penalty upon enrollment, but the resulting surcharge is constant across all plans and is typically charged directly out of Social Security payments. As such, I abstract away from the role of the penalty on the choice of plan.

[32] Without the Part D Plan Election Type Beneficiary Summary File, it is difficult to determine if a plan

The set of plans available to beneficiaries is determined by the region of residence. This study focuses on active choices among residents of California (Region 32), the largest of the PDP regions. Table 4.1 presents summary statistics of the full 2010 active choosers sample and the 2010 California subsample. Californians in 2010 could choose from 46 plans, offered by 19 different firms. On the whole, the California beneficiaries are similar along characteristics to their national counterparts, but differ along choice patterns in specific dimensions. On average, California beneficiaries are less white, slightly younger, and, correspondingly, file fewer claims. In a similar fashion to the national average, these beneficiaries are largely choosing plans offered by the most popular firms. These individuals, however, enrolled in zero deductible plans in much larger numbers than the average active chooser in the US. The majority of the 46 plans available to the California beneficiaries include a deductible, yet 69% of the sample enrolled in a plan without a deductible.

The plans offered in the California market exhibit substantial variation in attributes previously documented as choice-relevant in the literature. The 46 available plans were provided by 19 different insurance firms; 16 plans included the maximum deductible, 11 included a reduced deductible, and 19 did not included a deductible; 20% of the plans offered some form of coverage in the donut hole. Of the 100 most popular drugs by sale among beneficiaries, the plans in California covered between 71 and all of them, with an average of approximately 91 drugs covered. The plans offered varied in average cost-share in the initial coverage phase from 33% to 58%. Among this large and varied choice sets, beneficiary choices were fairly concentrated. Only 16 of the 46 plans garnered enrollment in excess of 1% of the sample.

4.2 Distribution of Expected Out-of-Pocket Costs

Although the CMS data is rich, it only contains claims and spending information for beneficiaries under their chosen plans. To estimate a model of plan choice, I require the counterfactual costs beneficiaries would face under the set of alternatives available to them, as well as a measure of the variance of out-of-pocket (OOP) costs. To estimate these counterfactual costs, I construct a plan calculator that takes in any specified set of claims for an individual and computes the out-of-pocket expenses that the specified sequence of claim events generates under every plan available. Consider an individual who fills a number of prescriptions each month. Under each available plan's formulary, each of those drugs claimed is classified by tier that determines the cost-sharing structure used, whereby cheaper drugs are assigned a lower tier than more costly drugs. Additionally, within each plan a different base price of the

change is an active choice or a passive transition upon termination of the existing plan. Conservatively, I include as active choosers those switching plan types, for example from an HMO to a PDP, from 2009 to 2010, as well as those who select a 2010 plan offered by a different firm than their 2009 plan.

Table 4.1: Summary Statistics: Active Choosers

	U.S.	CA
Sample Size	69,278	4,412
2010 Months Covered	9.9	9.3
Age	71.0	69.8
Female	.584	.566
White	.936	.889
Black	.041	.018
Hispanic	.004	.013
Asian	.007	.035
Monthly Claims	2.5	2.3
Days Supply	43.2	42.3
Average Total OOP	$625	$635
Average Total Gross Costs	$1,727	$1,639
Number Plans Offered	46.6	46
Avg Deductible	$97.18	$64.00
Zero Deductible	.539	.690
Avg Monthly Premium	$35.56	$38.12
Top 1 Most Popular Firm	.317	.372
Top 2 Most Popular Firms	.507	.505
Top 3 Most Popular Firms	.613	.632
Min Premium within Firm	.449	.306
Min Deductible within Firm	.578	.722
Min Premium or Deductible within Firm	.927	.985

Note: Statistics computed over "active choosers" in the 2010 sample based on description above. All statistics reflect unweighted averages.

drug has been negotiated to which the plan's cost sharing structure is applied. The calculator procedure involves determining the tier each plan assigns a drug and calculating the out of pocket costs for each claim accounting for the cumulative claim and corresponding coverage phase.[33]

The purpose of the calculator is to quantify counterfactual spending distributions under the set of available plans with the understanding that a rational beneficiary would compare

[33] There are multiple numeric codes used to identify drug by molecule, formulation, and strength. These numeric systems do not, however, identify drugs uniquely. The claims data identifies drugs by National Drug Codes (NDCs), as well as a CMS created number referred to as the Formulary RX ID. The public use formulary data identify drugs by NDCs and RXCUIs. However, multiple NDCs can be used for the same drug. As such, NDCs are considered the same if they are linked through Formulary RX IDs. For example, consider a drug denoted as NDC_1 and $FRXID_1$. If NDC_1 is also listed as corresponding to $FRXID_2$, and $FRXID_2$ is elsewhere linked to NDC_2, I consider NDC_1 and NDC_2 the same drug. For each claim passed through the calculator, I apply the lowest tier and base price of any linked NDC, allowing for some potential, albeit minor, substitution.

plans in terms of the out-of-pocket costs in each plan. It is not obvious what sequence of claims an individual anticipates at the time of plan choice. Some have assumed that beneficiaries have "perfect foresight", and assume that at the time of plan choice, beneficiaries compare the expected out-of-pocket costs of the drugs they would come to claim during the year of coverage.[34] Alternatively, some studies have assumed a myopic approach, assuming that beneficiaries base their expectations on their previous year drug claims when data is available or current drug needs.[35] It is also possible to take a "rational expectations" approach and assume individuals predict their drug needs will be realized from a distribution of costs under each plan based upon the realized costs of a set of "similar" individuals. For expected mean expenditures, the results in Section 7 adopt a perfect foresight assumption. The robustness analysis in Appendix C presents results under a myopic approach, projecting the first month of claims experience in 2010 for the remainder of a beneficiary's time in the plan (note the popular and CMS-promoted online tool to help with plan choice, PlanFinder, uses this approach).

Any measure of higher order moments of the distribution of expected costs requires the latter approach of binning similar individuals. To estimate a distribution of out-of-pocket costs an individual in the analysis sample expects, beneficiaries are grouped into bins of "similar" individuals based on average monthly number of claims and average monthly gross cost of claims.[36] Details of this procedure are outlined in Appendix A. A random sample is drawn from each bin and their claims are passed through the plan cost calculator to estimate a distribution of costs under each plan. The higher order moments of the cost distribution that enter an individual's utility function are computed from this sample distribution of similar individuals.

5 Reduced Form Evidence of Limited Consideration

In previous studies of Part D enrollment, even though data and models may differ, there is evidence that seniors are selecting drug plans that are more expensive for their drug needs than available alternatives. It is challenging in empirical settings to distinguish between preferences and consumer "mistakes." To motivate the model described in Section 6, I conduct a reduced form analysis to show that the patterns of choice inconsistencies documented in previous studies manifest in my sample. Table 5.1 presents statistics on plan choices among the California sample. The top panel performs a GARP-style test of rationalizability following Ketcham et al. (2016). I compute the share of individuals selecting plans on the

[34] For example, ex post claims are used as the anticipated mean out-of-pocket costs under plans in Abaluck and Gruber (2011) and as one of two alternative models in Abaluck and Gruber (2016b).

[35] See, for example, Kesternich et al. (2013), Heiss et al. (2013), and Abaluck and Gruber (2016b).

[36] In cases where claims correspond to multiple months' supply of drugs, we treat it as multiple claims. For example, a claim for a 90 day supply of a drug is treated as 3 claims in this exercise.

mean of OOP expenditure frontier, the mean and variance of OOP expenditure frontier, and the mean-variance-firm frontier.[37] By focusing on dominance, these measures test whether choices are consistent with *some* utility function rather than a certain specification. In the classic insurance framework, the monetary cost variables (and potentially higher order moments of the cost distribution) are considered utility relevant. These statistics display that the individuals in this sample are not selecting optimally according to the monetary plan attributes economic theory suggests are relevant.[38] Fewer than 17% of beneficiaries select the lowest cost plan for their realized drug needs. Using a relaxed measure, I find approximately 24% of beneficiaries select a plan within 5% of their minimum cost plan, and around 30% within 10% of the minimum cost plan.

Table 5.1: Choice Rationalizability and
Clustering on Certain Attributes

	% of Sample
Rationalizability Test	
Mean Cost Frontier	16.6
Mean-Variance Frontier	43.0
Mean-Variance-Firm Frontier	89.0
Attribute Choice Patterns	
Zero Deductible	69.0
Market's Lowest Premium	9.8
Min Premium within Firm	30.6
Min Deductible within Firm	72.2
Min Deductible or Premium within Firm	98.5
Gap Coverage	5.6
Top 1 Most Popular Firm	37.2
Top 2 Most Popular Firms	50.5
Top 3 Most Popular Firms	63.2

Notes: Mean cost computed based on assumption of perfect foresight of drug claims and monthly premiums prorated for total months of 2010 enrollment. Variance estimated from a distribution of 100 randomly sampled "similar" individuals as described in Appendix A. Most popular firms reflect the firms with the largest enrollment shares among the analysis sample.

[37] For the sake of comparison to previous studies, I use a perfect foresight model of expected costs whereby the realized 2010 claims for each individual is priced through each available plan. If instead the mean of a random sample of "similar" individuals is used or the first month of drug needs is projected forward, the patterns remain.

[38] Overall the rationalizability of plan choices is higher in this sample than previous studies. This may be due to improved choice performance in 2010 relative to earlier years, or sampling criteria. In contrast to earlier studies, my sample includes fairly young beneficiaries, partial-year enrollees, and active switchers. It is possible those groups choose slightly better than the average beneficiary in the first year of the program.

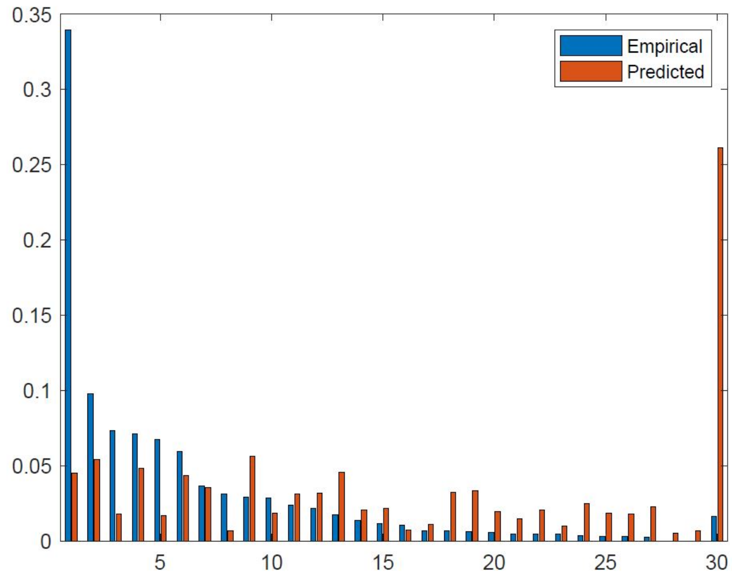
It is consistent with standard insurance theory for a risk averse individual to pay more for less variance in expenditures. Evaluating plan choices on the mean-variance frontier implies choices are dominated only if there is another plan available that is at least as good in terms of mean and variance of expenditures and strictly better in at least one of those measures. Rationalizability of observed choices improves by this measure but the majority of plan choices remain dominated. This means that, on the whole, the foregone savings are not offset by a reduction in risk. A major boost to explanatory power comes from incorporating preferences for a specific firm. In this formulation 89% of plan choices are consistent with utility maximization of some utility function. This test of rationality designates a choice as a mistake if a beneficiary selects a plan that is dominated in the mean-variance space by another plan offered by the *same* firm. In this market, each firm offers typically 1-3 plans within a region, leaving little room for a dominating plan. And yet, 11% of this sample selects such a dominated plan.

Another pattern that emerges in the lower panel of Table 5.1 is the prevalence of certain attributes among chosen plans. The majority of California beneficiaries select a plan without a deductible, even though, as described in Section 4.1, the majority of plans offered in California include a deductible. Beneficiaries are on the whole selecting plans with low deductibles, low premiums, and offered by one of the three most popular firms.[39] As a statistical test of explanatory relevance, Table 5.2 presents results of a simple logit regression. Column (1) includes in the regression the monetary variables describing the distribution of costs included in a standard model of insurance demand. Column (2) includes plan attributes and firm fixed effects. The Pseudo R^2 of the regression in Column (2) is approximately three times that of Column (1). Figure 5.1 graphically contrasts the explanatory power of these logit regressions by plotting the implied choice probabilities under each set of estimates. The right-most bar is a composite plan aggregating all 17 plans in which between 1 and 10 individuals in the sample enrolled. The improvement in fit with the additional attributes is visually obvious.

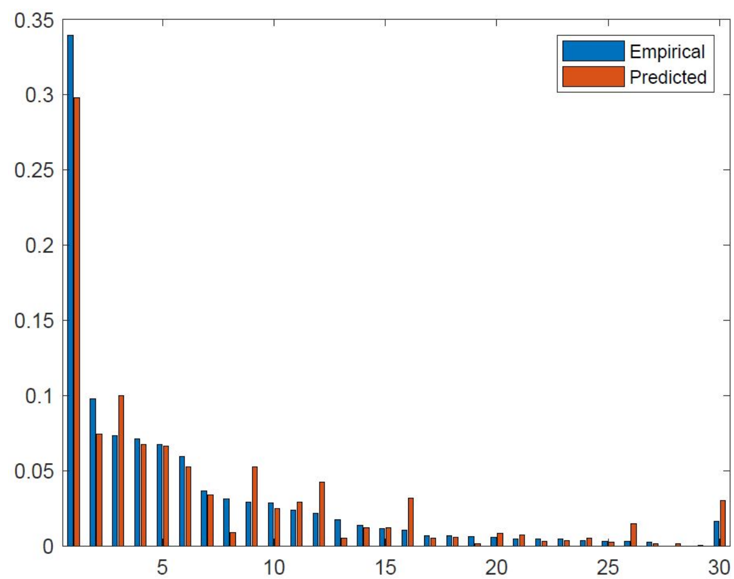
With the exception of the measure of average cost-share, the additional plan attributes in Column (2) are highly significant regressors. Some of these attributes - firm dummies, the count of top 100 drugs covered, and the average cost-share - are non-monetary attributes. There is no immediate way to compare these variables to those related to the costs of each plan. The deductible, while financial in nature, is also not directly related to costs. Insofar as the deductible of a plan impacts the costs of prescription drugs under each plan, it is already accounted for in the expected out-of-pocket cost term. The coefficients on the plan attributes above reflect a relationship between the attributes and plan choice above and beyond their impacts on costs. In specifications where the coefficient on premium and expected out-of-

[39]Generally, reduced deductibles come at the expense of a higher premium.

Figure 5.1: Logit Implied Choice Distribution



(a) Excluding Non-Cost Attributes



(b) Including Non-Cost Attributes

Notes: Panel (a) plots the model implied choice probabilities from Column (1) of Table 5.2 in red. Panel (b) plots the model implied choice probabilities from Column (2) in red. In both figures, the blue bars correspond to the empirical choice shares. Plans are ordered from the plan with the largest enrollment share on the left to the plans with zero enrollment. The rightmost plan corresponds to a composite plan of the 17 plans in which between 1 and 10 individuals enrolled.

Table 5.2: Conditional Logit Estimates:
Impact of Non-Monetary Attributes

	(1)	(2)
Premium + $\mathbb{E}$OOP	-0.507***	-0.381***
(hundreds)	(.009)	(.011)
Variance	-0.022***	-0.007***
	(.002)	(.002)
Deductible	–	-0.634***
(hundreds)		(.026)
Gap	–	-0.767***
		(.076)
Top100 Drugs	–	-0.071***
		(.006)
Avg CS	–	-0.231
		(.611)
Firm Dummies	No	Yes
Pseudo R^2	0.130	0.353

Notes: Standard errors are in parentheses. Variance denotes the variance of $\mathbb{E}$OOP measured in hundreds of dollars. *** Significant at 1% level.

pocket costs are permitted to differ, the estimates suggest an over-weighting of premiums relative to out-of-pocket costs. These estimates only reflect correlation but are informative for a structural model. The reduced form regressions in Table 5.2 indicate a model that includes only monetary attributes cannot rationalize observed choices as well as a model that accounts for additional non-monetary plan attributes.

There are many possible mechanisms through which these non-monetary attributes can affect plan choice. Some may find the large menu of plans burdensome and employ heuristics to reduce the choice set to a more manageable size. Other beneficiaries may act on their uncertainty over future needs by only considering plans with more generous coverage. Others, still, may have liquidity constraints and only consider plans with a reduced or eliminated deductible. Premiums may receive additional weight over expected out-of-pocket costs due to budget constraints. The model and procedure below do not require the researcher to take a stance on how exactly beneficiaries are paying attention to plan attributes. This agnostic approach is focused on flexibly approximating this process in order to learn what beneficiaries appear to be paying attention to when they make initial Part D plan choices and leaves to future work more precise exploration of the details underlying the consideration set formation process in this market.

6 Model of Plan Choice

6.1 Utility Specification

My model of plan choice maintains the expected utility framework standard in the literature of decision-making under uncertainty. Individuals are assumed to have utility over wealth and face a distribution of financial losses. In this empirical setting, each beneficiary has uncertain drug needs during the year and the coverage and cost structure of each available plan translates those drug needs into out-of-pocket costs. Denoting costs by C and initial wealth by W, the realized wealth of an individual is given by $W - C$. I assume individuals are risk averse, and their utility is governed by a coefficient of risk aversion, ν, assumed to be constant across values of wealth. This emits a utility model of constant absolute risk aversion (CARA) of the form:

$$U(C) = -\frac{1}{\nu}\exp(-\nu(W - C)),$$

Plans differ in whether and how generously drugs are covered and how cost-sharing is determined. These uncertain drug needs therefore correspond to different distributions of out-of-pocket costs under each plan. I denote the random variable of out-of-pocket costs individual i incurs under any plan j as $C_{ij} \sim F_{C_{ij}}$. Additionally, risk aversion is assumed to be heterogeneous across agents with $\nu_i \sim F_\nu$. The utility of individual i from choosing plan j is given by

$$U_{ij} = -\frac{1}{\nu_i}\exp(-\nu_i W_i)\exp(\nu_i C_{ij})$$

Under the assumption of expected utility, agents are assumed to take into account the distribution of financial losses they face and take an expectation of utility under each available plan. Conditional on a beneficiary's coefficient of absolute risk aversion, expected utility takes the form

$$EU_{ij} = -\frac{1}{\nu_i}\exp(-\nu_i W_i)\mathbb{E}\left(\exp(\nu_i C_{ij})\right)$$

Note that for a fixed value of ν_i, $\mathbb{E}\left(\exp(\nu_i C_{ij})\right)$ is the moment generating function of the random variable C_{ij}. Similarly to elsewhere in the literature, out-of-pocket costs are assumed to be Normally distributed, $C_{ij} \sim N\left(\hat{\mu}_{ij}, \sigma^2_{ij}\right)$, where $\hat{\mu}_{ij} = p_j + \mu_{ij}$ is the mean out-of-pocket expenditures of individual i under plan j, shifted by the person-invariant premium for plan

j.[40] The cost parameters μ_{ij} and σ^2_{ij} are computed outside of the model as described in Section 4.2 and Appendix A. Substituting for the moment generating function, expected utility can be written as a function of the mean and variance of out-of-pocket costs.

$$EU_{ij} = -\frac{1}{\nu_i}\exp(-\nu_i W_i)\exp(\nu_i \hat{\mu}_{ij} + \frac{1}{2}\nu_i^2 \sigma_{ij}^2)$$

Although utility values depends on unobserved individual wealth, relative utility and the ordinality of plan utility are not impacted by the positive multiplicative term $\frac{1}{\nu_i}\exp(-\nu_i W_i)$. This value can be divided away from all utility levels and utility rankings remain unchanged. Therefore, for estimation purposes, a simpler form of expected utility suffices.

$$EU_{ij} = -\exp(\nu_i \hat{\mu}_{ij} + \frac{1}{2}\nu_i^2 \sigma_{ij}^2) \tag{6.1}$$

6.2 Choice Sets and Limited Consideration

Motivated by empirical findings that numerous plan attributes affect individuals' choices beyond the financial impact of those attributes on drug costs, the point of departure from a standard expected utility models is in consideration sets and the role plan of attributes in consideration. Rather than incorporating a random error into utility, stochastic choice, conditional on preferences, arises through the formation of the consideration set. Moreover, it is through the consideration set that plan attributes impact choice. As described in Section 3, previous studies have found evidence of plan attributes determining plan choice in ways beyond the experienced financial impacts of those attributes, but have struggled with a rational utility explanation of such a role. This model posits that these important, but not directly utility-relevant, variables impact choice by determining the composition of the consideration set a beneficiary evaluates when selecting a plan.

A model of limited consideration relaxes the assumption in standard discrete choice models that a chosen plan is revealed preferred to all available plans. Beneficiaries are assumed, rather, to select an unobserved subset of the feasible choice set to actively consider and compare and select a plan from that subset. I model an alternative specific consideration probability model, similar to that found in Barseghyan et al. (2019b). Under the assumption of limited consideration, an observed choice of plan j^* by individual i implies 2 things: 1) plan j^* was in individual i's consideration set, and 2) among all of the plans considered, j^* was preferred.

I denote beneficiary i's choice of plan j^* by $y_{ij^*} = 1$, and an individual's consideration

[40] See Abaluck and Gruber (2011).

set by M_i, which is a subset of the entire feasible set of plans $\mathcal{M}$. The probability individual i chooses plan j^*, suppressing conditioning notation, is:

$$Pr(y_{ij^*} = 1) = \sum_{M \subseteq \mathcal{M}: j^* \in M} Pr(M_i = M) Pr\left(EU_{ij^*} > EU_{ik}\ \forall\ k \in M\right) \tag{6.2}$$

Each plan appears in an individual's consideration set with probability φ_j. Plan consideration probabilities are homogeneous across agents facing the same feasible choice set.[41] Conditional on observables, each plan's appearance in a consideration is assumed independent.[42] By independence, the probability of any consideration set $M_i = M \subseteq \mathcal{M}$ can be written in terms of the individual plan consideration probabilities:

$$Pr(M_i = M) = \prod_{k \in M} \varphi_k \prod_{k' \notin M} \left(1 - \varphi_{k'}\right).$$

In such a model, it is possible for an individual to draw an empty consideration set, $M_i = \emptyset$. In such cases, a simple completion rule is needed, such as those discussed in Barseghyan et al. (2019b). For simplicity this additional component of probability is left implicit, but in the event an individual draws $M_i = \emptyset$, I assume one of the 46 available plans is chosen with equal probability. The probability any beneficiary i selects plan j^* can be written as:

$$Pr(y_{ij^*} = 1) = \sum_{M \subseteq \mathcal{M}: j^* \in M} \prod_{k \in M} \varphi_k \prod_{k' \notin M} \left(1 - \varphi_{k'}\right) Pr\left(EU_{ij^*} > EU_{ik}\ \forall\ k \in M\right) \tag{6.3}$$

As written, equation 6.3 requires enumeration of all possible consideration sets M. In a setting such as Medicare Part D where beneficiaries in California have 46 plans available, such an enumeration is computationally unfeasible. Rather than approximate such a sum with simulation of consideration sets, as done in Goeree (2008), this choice probability can be simplified to fully avoid the need to account for every potential consideration set. The utility model in equation 6.1 does not include an error term, and at any given value of risk aversion ν_i, all plans can be ranked by expected utility. That is, fix $\hat{\nu}$, and order plans from worst to best in terms of expected utility $EU_{i1} < EU_{i2} < ... < EU_{ij^*} < EU_{ij+1} ... < EU_{iJ}$. Therefore, for plan j^* to have been selected at $\nu = \hat{\nu}$, the consideration set must not have included (at the minimum) plans $j+1, ..., J$, since if those plans were present, j^* would not

[41] This assumption can be relaxed by allowing φ_j to depend on beneficiary attributes.

[42] As noted below in Section 6.3 consideration probabilities are modeled as functions of plan attributes. Therefore specific forms of correlation between the consideration of similar plans is permitted.

be selected. Let $k \succ_{\hat{\nu}} j^*$ denote the set of plans that dominate j^* at a given value $\hat{\nu}$. Thus, conditional on $\nu_i = \hat{\nu}$, $Pr\left(EU_{ij^*} > EU_{ik} \; \forall \; k \in M\right) = 0$ if M contains any plans in the set $k \succ_{\hat{\nu}} j^*$ and $Pr\left(EU_{ij^*} > EU_{ik} \; \forall \; k \in M\right) = 1$ if M does not contain any plans $k \succ_{\hat{\nu}} j^*$.

Such a ranking and collection of dominating plans can be computed at any values of $\nu \in [0, .\bar{\nu}]$, where $\bar{\nu}$ is the upper bound on the coefficient of absolute risk aversion. Using this simplification, equation 6.3 for a given value of ν_i can be written without regard for specific consideration set as:

$$Pr(y_{ij^*} = 1 | \nu_i = \hat{\nu}) = \varphi_{j^*} \prod_{k \succ_{\hat{\nu}} j^*} (1 - \varphi_k) \tag{6.4}$$

These sets of dominating plans can be computed for each individual at any value of risk aversion. Using the Riemann approximation procedure described below, averaging equation 6.4 across individuals allows for approximation of the choice probabilities of the form:

$$Pr(y_{j^*} = 1) \int Pr(y_{j^*} | \nu) dF_{\nu}. \tag{6.5}$$

6.3 Estimation

6.3.1 Consideration Probabilities

Beyond the utility-relevant variables governing the distribution of costs a beneficiary faces under each plan, I allow choices to depend additionally on non-monetary and monetary attributes through consideration. Consideration is modeled to depend on the insuring firm, the deductible, whether a plan offers any gap coverage, the count of 100 most popular drugs covered, and the average cost-share in the initial coverage phase.[43] To account for the higher weight placed on premiums relative to out-of-pocket costs in reduced form regressions, the plan's premium is also included as a determinant of consideration. Each plan's consideration probability, φ_j, is modeled as a function of these characteristics:

$$\varphi_j = f(\text{firm}_j, \text{premium}_j, \text{deductible}_j, \text{gap}_j, \text{Top100}_j, \text{AvgCS}_j) \tag{6.6}$$

For intuition on how attributes relate to consideration, it is helpful to consider only two

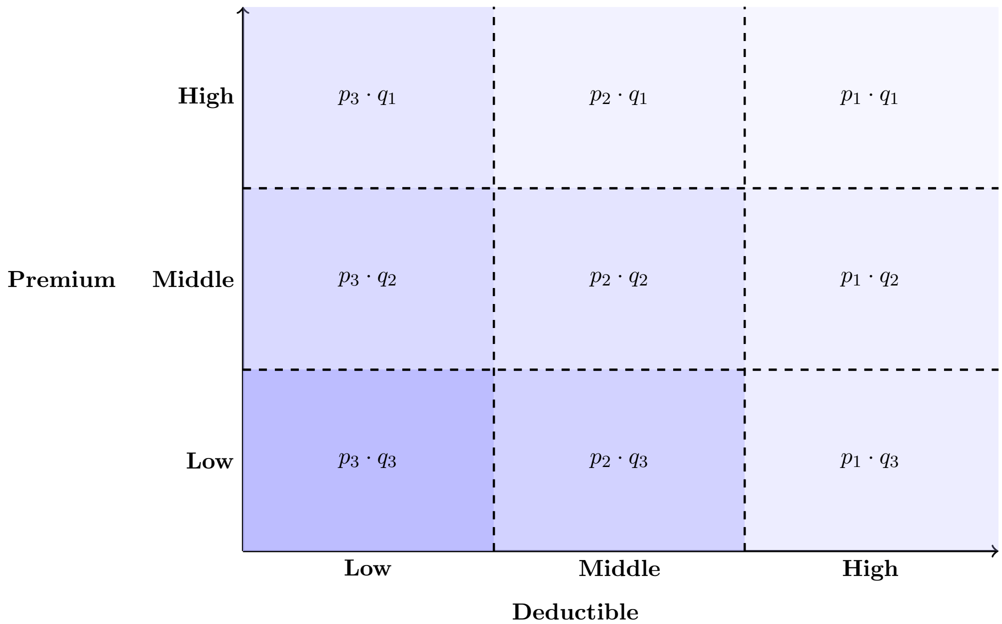
[43] The standard CMS plan includes a 25% cost-share in the initial coverage phase, but the realized cost-share can differ substantially due to modified plan structure, formulary, and differing drug needs across individuals. After estimating expenditures in every plan under perfect foresight, I compute the average ratio of out-of-pocket costs to gross expenditure within the initial coverage phase across all individual's whose out-of-pocket spending was between the deductible and initial coverage limit. Accordingly, this variable takes the same value for all beneficiaries.

attributes: deductible and premium. An individual may limit their consideration of plans based on these attributes for a number of plausible reasons. The online tool CMS provides to aid in plan choice, PlanFinder, allows for plans to be sorted based on premiums or deductibles. This may lead an individual to only see the plans with the lowest premiums or deductible. In the presence of liquidity constraints, an individual may be unable to afford large lump expenses and only consider plans with reduced or eliminated deductibles. If an individual faces budget constraints, they will not consider plans with monthly premiums in excess of a reservation price. In a more general model of limited consideration, individuals are modeled as simply less likely to consider a plan with less desirable observable attributes than one with better attributes. There is an unambiguous ordering of both deductible and premium from most to least preferred. A lower deductible (premium) is clearly better than a higher deductible (premium), all else equal.

Figure 6.1 visually demonstrates the connection between the desirability of a plan attribute and consideration probabilities. In this example, deductible and premium each take one of three values: low, medium, or high. The probability of considering a low deductible plan (p_3) is higher than the probability of considering a medium deductible plan (p_2), which is higher than the probability of considering a high deductible plan (p_1). A similar ordering of consideration follows for premium. The bottom left region corresponds to the best plans along these two attributes - those with the most preferred low deductible and the most preferred low premium. The darker shade of blue reflects the largest consideration probability of these plans. As you move away from the bottom left of the figure, plans become increasingly less desirable along these attribute dimensions. Consideration is modeled to diminish as plans move further and further away from best along each attribute dimension. The lightest shaded box in the upper right corner corresponds to plans with both the highest premium and highest deductible and are, thus, least likely to appear in an individual's consideration set.

With the exception of the insuring firm, all of the included attributes have such an objective ranking. All else equal, lower deductibles, premiums, and cost-sharing is preferred. Similarly covering more drugs is preferred to fewer, and gap coverage is better than no gap coverage. The intuition of Figure 6.1 is applied across these multiple dimensions. Although the illustrative example was a simplification, the idea of such diminishing consideration is appealing and converges to a specification of consideration that reflects a geometric decay of consideration probabilities as plans progressively become less and less desirable in their attributes. In the absence of an objective ranking over firms, and to reflect the numerous underlying mechanisms causing individuals considering firms differentially, I model a base consideration probability for each of the 19 firms in the market. It is to this base probability that the reductions in consideration according to attributes is applied. The details of the

Figure 6.1: Consideration Intuition with 2 Attributes



Note: $p_1 < p_2 < p_3$ represents the consideration probabilities for each deductible and $q_1 < q_2 < q_3$ the consideration probabilities for premiums.

parameterization is discussed in Appendix B.

6.3.2 Maximum Likelihood

In practice, the integral in equation 6.5 is estimated through a Riemann integral approximation. The support of the coefficient of risk aversion, $[0, \bar{\nu}]$, is divided into a fine grid. At each value of ν on the grid, for each individual, the set of plans $k \succ_\nu j^*$ is computed, as described in equation 6.4. To approximate the integral over the distribution of ν, I weight the choice probabilities above at each value of ν in the grid based on the probability density function of risk aversion at those grid values. Weighted individual choice probabilities are then logged and summed. I maximize the resulting loglikelihood to recover the values of the model parameters - including those governing the distribution of risk aversion - that best match the observed choices.

In all specifications, I assume the coefficient of absolute risk aversion is distributed according to a Beta distribution, $\nu \sim Beta(\beta_1, \beta_2)$. The Beta distribution is an appealing assumption due to its flexibility. Risk aversion is assumed to be bounded above by .01, a liberal assumption in light of Rabin (2000). Estimates are not sensitive to this assumption. See Appendix B for more details on the procedure.

6.4 Identification

To separately identify consideration from risk preferences, I require a large support of certain variables and a form of an exclusion restriction. There must be sufficient variation in the utility-relevant variables to shift utility rankings of plans without correspondingly shifting consideration probabilities. In this model, the only utility-relevant variables are those governing the distribution of costs under each plan. Other plan attributes are presumed to impact consideration but not directly enter utility. The one variable that directly enters both utility and consideration is the premium of the plan. Barseghyan et al. (2019b) establishes that some overlap between variables in utility and consideration does not threaten identification provided there are other variables that shift either utility or consideration, but not both directly (i.e., an exclusion restriction). The consideration-relevant variables that relate to drug costs - the deductible, gap coverage, count of drugs covered, and realized average cost-share - impact the distribution of costs in a complex, highly nonlinear way. As a result, there is sufficient independent variation between the plan attributes and the utility-relevant variables to satisfy exclusion.

Identification can be viewed in two stages. First, to identify the consideration probabilities, φ_j, I require a large support for the utility-relevant variables, $\hat{\mu}_{ij}$ and σ^2_{ij}. Intuitively, there are regions of the support of these variables where certain plans are unambiguously best, regardless of risk preferences. Under full consideration, I would expect to see all individuals in that region of the support choosing the best plan. The empirical share of individuals selecting the plan in that region of the support identifies the consideration probability for that specific plan. Such an exercise can be repeated throughout the large support to identify all of the φ_j probabilities. Variation of plan attributes within and across firms identifies the consideration effects of individual plan attributes. The second step is to identify the distribution of risk preferences. With consideration identified, this proceeds in the same manner as a full consideration model, as described in Matzkin (2007). Large variation in the mean and variance of costs traces out the distribution of ν among the population.

7 Results

7.1 Limited Consideration

The model of expected utility with limited consideration fits the data patterns of the California beneficiaries well. Heterogeneity in consideration sets plays a crucial role in prescription drug insurance choice. Table 7.1 presents the estimates of the impact of plan attributes on consideration. All parameters included are between 0 and 1 to bound corresponding consideration probabilities. The δ estimates reflect the total decay in consideration that occurs as the attribute progresses from the very best to the very worst. All else equal, the estimate for δ_{prem} indicates a plan with the highest premium is considered only 10% as much as the lowest premium plan. Similarly, a plan with the maximum deductible of $310 is considered 18% as much as an equivalent zero deductible plan. And plans lacking gap coverage are considered 86% as frequently as one with gap coverage.

Table 7.1: Model Results: Consideration Impact of Plan Attributes

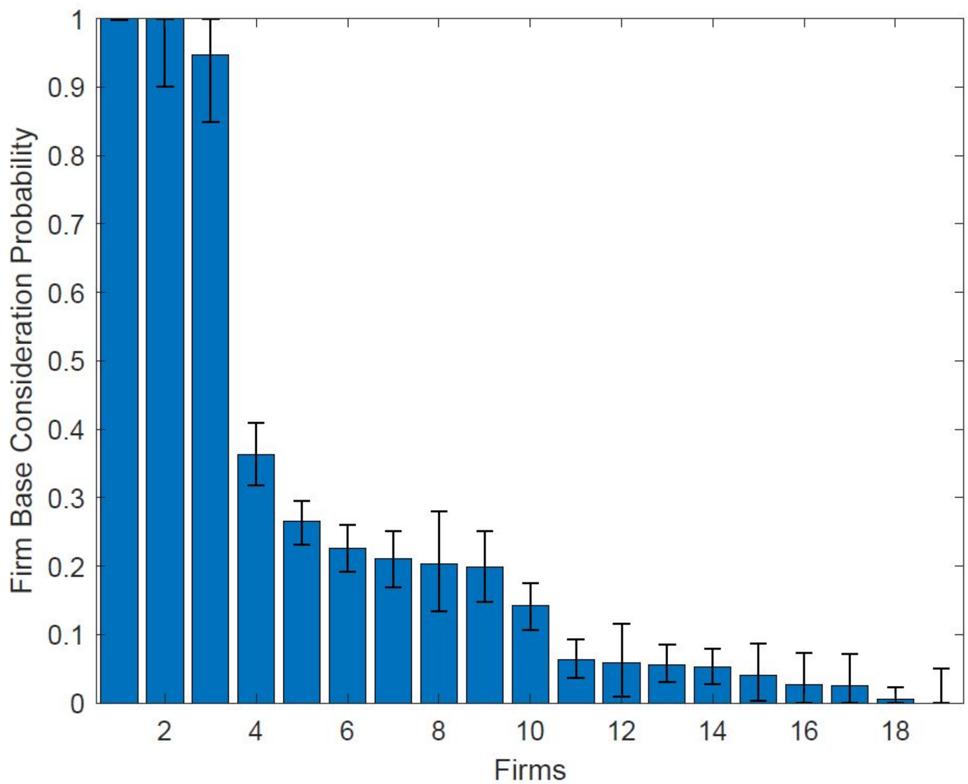
	Estimate	95% CI
δ_{prem}	0.100	[0.074, 0.140]
δ_{ded}	0.182	[0.163, 0.206]
δ_{gap}	0.859	[0.782, 0.953]
δ_{top100}	1.000	[0.999, 1.000]
δ_{avgcs}	1.000	[1.000, 1.000]

Notes: All δ terms are defined between 0 and 1 and reflect how much consideration a plan with the worst value of an attribute is considered relative to an equivalent plan with the best value of the attribute. Confidence intervals based on 1,000 bootstraps with sub-sampling to correct for estimates on the boundary.

The results in Table 7.1 are intuitive in a number of ways. As modeled, a plan's count of top 100 drugs covered and the average cost-share in the initial coverage phase do not impact its probability of consideration. These plan attributes are generally not immediately knowable to a beneficiary. An individual can find whether certain drugs are covered in a plan's formulary through tools such as Medicare's PlanFinder online tool, but a full count of such coverage of the 100 most popular drugs among beneficiaries is not published. Additionally, an astute beneficiary that seeks out extensive information on their plans can learn the copay and coinsurance rates for different tiers of drugs in the initial coverage phase - and in fact, that information is what the average cost-share variable is meant to proxy for - but such a precise aggregate measure is not feasible to compute for most individuals. Moreover it is computed based on all of the beneficiaries' drug needs, which is also not information any individual beneficiary has at the time of plan comparison. To the extent this captures behavioral trimming of choice sets based on desirable attributes, it is not particularly surprising that these more difficult to ascertain attributes are not strong drivers of consideration. The first three attributes, in contrast, are unambiguous and more easily known to beneficiaries. In fact, many online tools, including the PlanFinder, summarize this information for beneficiaries. As mentioned, individuals can even sort and filter available plans on the PlanFinder by premiums and deductibles.[44]

In addition to the impact of these attributes, the probability any plan is considered is largely determined by which firm offers the plan. Figure 7.1 presents the insuring firm base consideration probabilities. Three large firms, UnitedHealth, Blue Cross of California, and Anthem, garner near full base consideration. Each of these firms offers a plan included in the 5 most chosen plans within the sample. Nearly half of the 19 firms in the market are considered with probability below 10%, even before accounting for the impact of plan attributes. Such heterogeneous consideration across firms may reflect, among other explanations, the impact of differential advertising, agent steering effects, or enrollees' insurance experiences prior to Medicare. I leave to future research the detailed analysis of such explanations.

Figure 7.1: Model Results: Firm Base Consideration Probabilities



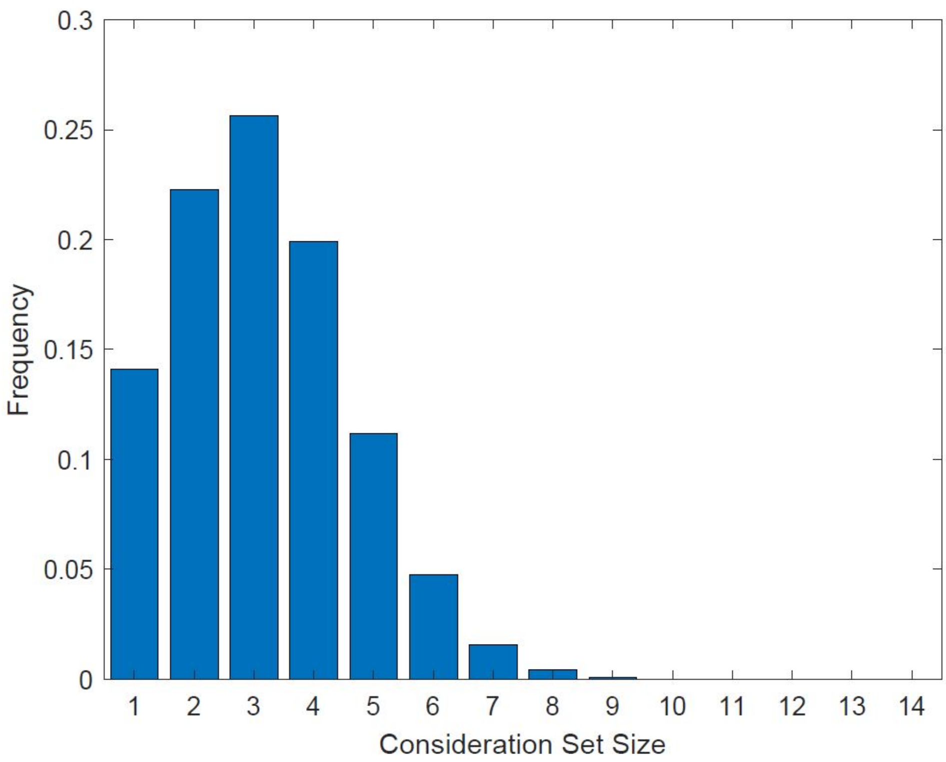
Notes: Firms are ordered based on estimated base consideration probabilities. Error bars present 95% confidence intervals based on 1,000 bootstrap repetitions with sub-sampling to adjust for estimates on the boundary.

My estimates capture substantial heterogeneity in consideration sets across beneficiaries. Figure 7.2 presents the implied distribution of consideration set sizes across individuals in the sample. Although the market includes 46 plans, consideration sets do not come even close to

[44]Following the Affordable Car Act, Medicare plans no longer include the coverage gap. As such, today's PlanFinder does not present this information.

including that many plans. The vast majority of beneficiaries consider no more than 5 plans, and no one is estimated to consider a set containing more than 14 plans. Approximately 14% of individuals evaluate a single plan. The composition of these consideration sets is highly concentrated among the plans that share the most popular attributes. As shown in Figure 7.3, the largest firms account for an overwhelming share of the plans considered. The three large firms described above constitute over 60% of all plans considered. The three firms with the smallest firm effects account for fewer than 0.5% of plans considered. In fact, 7 of the 19 firms each represent fewer than 1% of considered plans and cumulatively represent just over 2% of all plans considered. These plans, although infrequently considered and chosen, are nonetheless good plans for a nontrivial portion of the sample. As shown in the contrast of the blue shares of considered plans and the red shares of the feasible menu, this pattern is not an artifact of the number of plans offered, but rather, reflects the strong positioning of a few large firms.

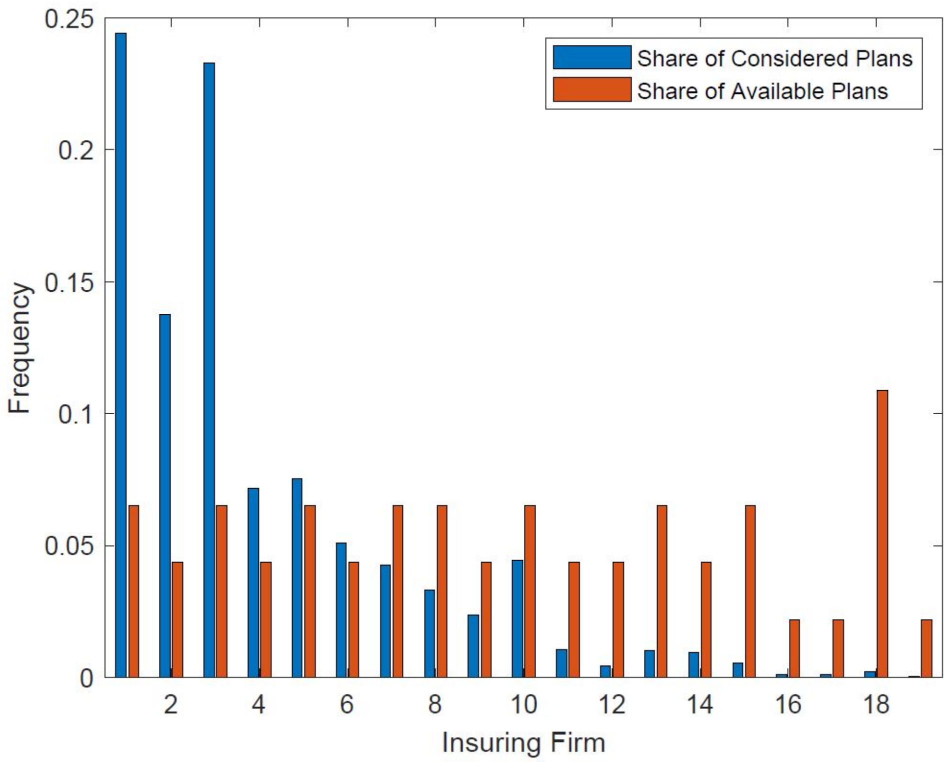
Figure 7.2: Implied Distribution of Consideration Set Size



Notes: Consideration set sizes estimated as the average over 1,000 simulations of individual risk aversion and consideration sets for the analysis sample.

Consideration sets are similarly skewed towards zero deductible plans. Plans without a deductible account for 19 of the 46 plans in California in 2010 but nearly 75% of consid-

Figure 7.3: Implied Shares of Consideration Sets and Choice Set by Firm



Notes: Firms are ordered as in Figure 7.1 based on estimated firm base consideration probabilities. Shares of consideration sets are based on 1,000 simulations of individual consideration sets for the analysis sample.

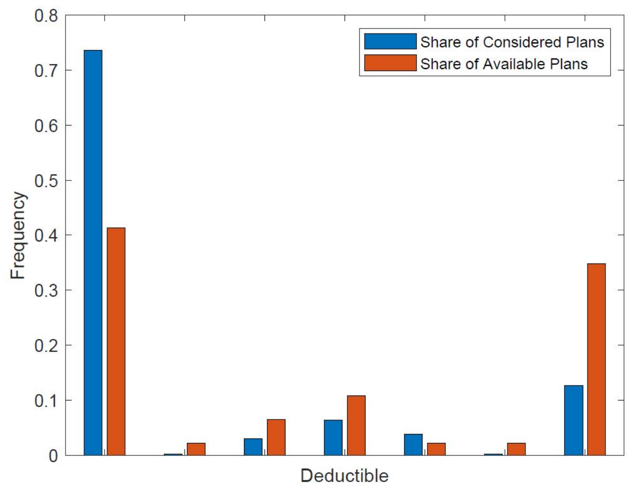
ered plans.[45] Figure 7.4 gives a simple illustration of this pattern in the first panel. The pattern of the premiums of considered plans is more nuanced. The second panel of Figure 7.4 plots the share of considered plans based on bins of premiums. The first bar represents the 10 lowest premiums, the second bar the next 10 lowest premiums, and so on. While the estimate of δ_{prem} conforms with the intuition that higher premium plans are considered less than more appealing lower premium plans, the plans with the lowest premiums are generally those with higher deductibles. Thus, this preference towards lower premium plans alongside low deductibles manifests in the plans in the second bin of premiums accounting for a disproportionate share of plans considered.

The resulting consideration probabilities of the 46 plans vary substantially. Figure 7.5 presents consideration probabilities, φ_j as described in Equation 6.6, for the 20 most popular plans. Plans are ordered based on empirical choice shares. Even among these relatively popular plans, consideration probabilities are frequently modest. Figure 7.8 below shows how these consideration probabilities bridge the gap between observed plan choices and those implied by risk preferences under full consideration. The results on consideration are consistent with a number of underlying sources of limited consideration. The strong impact of the deductible on consideration coheres to stories of liquidity constraints, a reality for many Americans, as noted in Durante and Chen (2019). It is both plausible and rational for such a constrained beneficiary to consider exclusively, or nearly exclusively, plans with an eliminated deductible, as my estimates indicate. The result that the count of top 100 drugs covered does not impact consideration presents a lack of evidence of filtering on drug plans based on formulary generosity, or at least using such a general measure of formulary generosity. The substantial role of firm effects in consideration lends support to a number of behavioral forces resulting in limited consideration. Familiarity of firms based on prior insurance experience or social influence, arising the insurer of friends or spouses, can lead beneficiaries to filter according to preferred firms. There is substantial firm advertising in this market and these results may reflect the consideration impact of advertising campaigns.

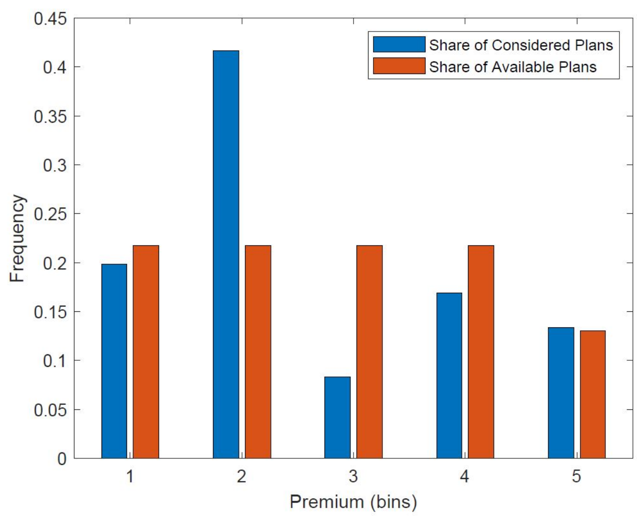
The cumulative impact of these attributes on consideration results in consideration sets that are much smaller in size than the feasible choice set. The modal consideration set contains 3 plans and over 90% of beneficiaries consider a set with 5 or fewer plans. To parse the effects of each attribute on the resulting consideration set composition, I simulate consideration sets when certain impacts of consideration are eliminated. Figure 7.6 plots the distribution of consideration set sizes across these counterfactual schemes. Holding all other estimates fixed, Panel (a) presents the impact on consideration set size when the firm effect is eliminated. In practice, this exercise translates to assigning all firms a base consideration

[45] Moreover, 95% of beneficiaries consider at least one plan with a fully eliminated deductible.

Figure 7.4: Implied Shares of Consideration Sets and Choice Set
by Deductible and Premium



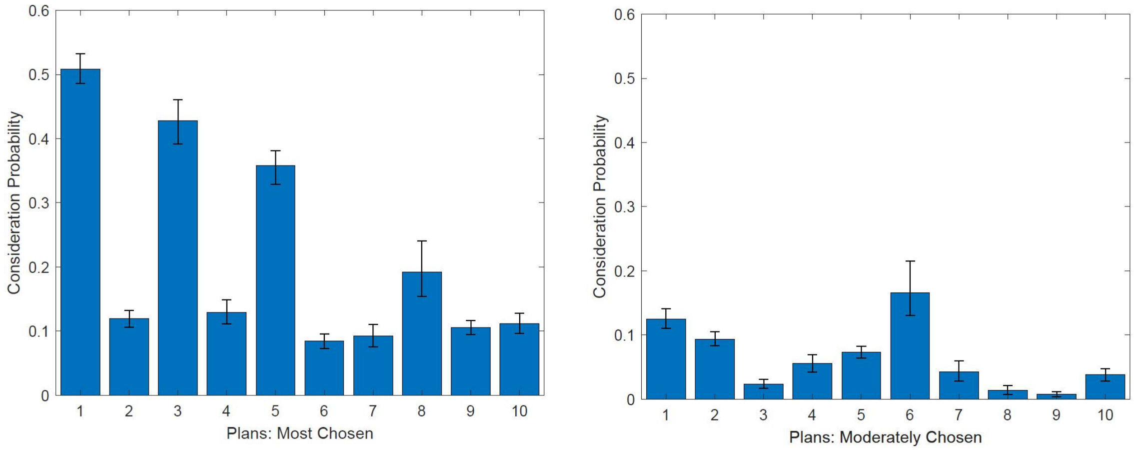
(a) Share of Consideration Sets by Deductible



(b) Share of Consideration Sets by Premium (bin)

Notes: Panel (a) is ordered left to right from \$0 to \$310 deductibles. Premiums in Panel (b) are ordered lowest to highest by bins of 10. Shares of consideration sets are based on 1,000 simulations of individual consideration sets for the analysis sample.

Figure 7.5: Plan Consideration Probabilities of 20 Most Chosen Plans



(a) 1-10 Most Popular Plans

(b) 11-20 Most Popular Plans

Notes: Panel (a) presents the model implied consideration probability for the 10 plans with the largest shares of enrollment, with the most chosen plan first and the 10^{th} most chosen plan last. Panel (b) presents the same information for the 11^{th} through 20^{th} most chosen plans. Error bars present 95% confidence intervals based on 1,000 bootstrap repetitions with sub-sampling to adjust for estimates on the boundary.

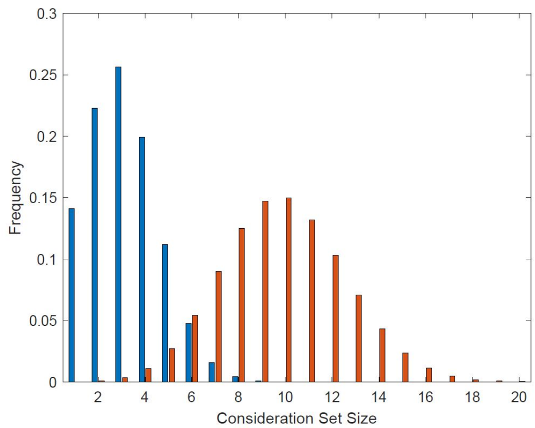
probability of 1. This alteration results in a rightward shift of the distribution of consideration set size, as fewer plans are immediately eliminated as a result of firm filtering. Panel (b) presents the opposite exercise where the firm effect is the sole determinant of consideration. Because the three largest firms have base consideration probabilities of 1, or nearly 1, by construction consideration sets have a larger minimum number of plans. The bottom two panels reflect the elimination of the deductible and the premium from consideration, generating a more modest increase in the size of consideration sets.

7.2 Risk Preferences

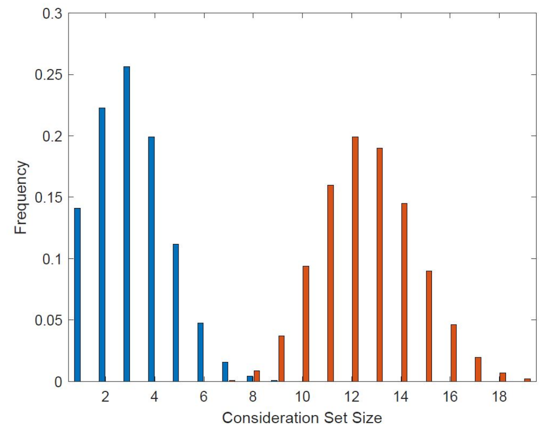
In contrast to the previous literature on plan choice in Medicare Part D, I find estimates of risk aversion among California's beneficiaries comparable to other insurance settings. Table 7.2 describes estimates of risk preferences in the sample. The top panel provides the mean and variance of risk aversion in the model with limited consideration. The estimate of mean risk aversion is on par with previous studies that use field data to measure risk preferences, and comes along with moderate variance.[46] These estimates can be difficult to interpret and compare without additional context. Table 7.2 includes a measure of risk premium for an individual with CARA utility facing a lottery that results in a loss of $1,000 with 25%

[46] For example, see Barseghyan et al. (2019a),Handel and Kolstad (2015), Handel (2013b), Barseghyan et al. (2013), and Cohen and Einav (2007). In particular, Barseghyan et al. (2019a) finds that the incorporation of limited choice sets can rationalize auto collision choices with lower and more homogeneous of risk aversion than standard full consideration models. My estimates of the mean and variance risk aversion are on the lower end of the fairly narrow confidence intervals of that model.

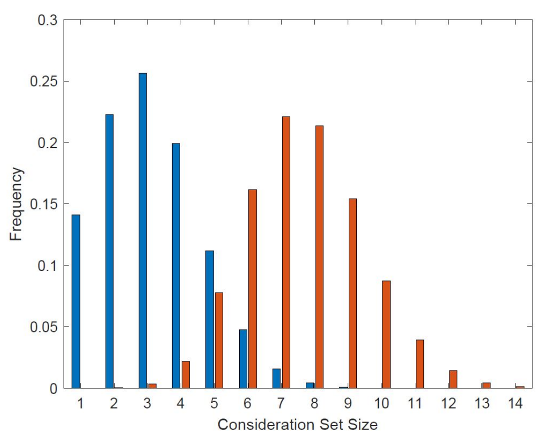
Figure 7.6: Baseline and Counterfactual Distributions of Consideration Set Size



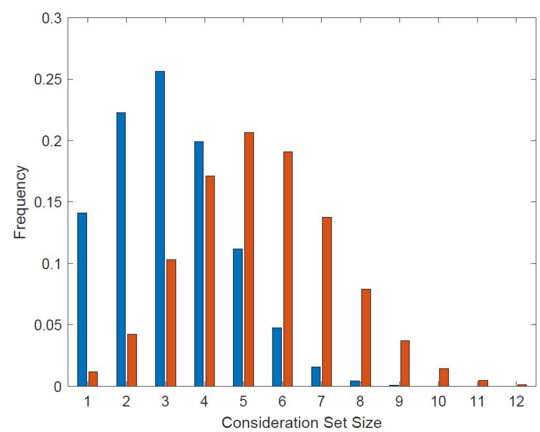
(a) Removing Firm Effect



(b) Only Firm Effect



(c) Removing Deductible Effect



(d) Removing Premium Effect

Notes: All subfigures present implied consideration sets sizes of the baseline estimates in blue and when the following adjustments to estimates are simulated in red: Panel (a) all firm base probabilities are set to 1; Panel (b) δ_{prem}, δ_{ded}, and δ_{gap} in Table 7.1 are all set to 1; Panel (c) δ_{prem} is set to 1; Panel (d) δ_{ded} is set to 1. Shares of consideration sets are based on 1,000 simulations of individual consideration sets for the analysis sample.

probability. Such a lottery has an expected value of a \$250 loss. An individual with a coefficient of risk aversion equal to my baseline mean estimate would be willing to pay a risk premium of \$102 to avoid such a lottery. In contrast, a standard CARA random expected utility model with full consideration substantially underestimates risk aversion, as shown in the lower panel of Table 7.2. A full consideration model with a constant coefficient of risk aversion across agents finds risk neutrality and matches choice patterns poorly. Incorporating heterogeneity in risk aversion increases the suggested levels of risk aversion, but even the upper bound of the confidence interval in such a model falls below the lower bound of the confidence interval on mean risk aversion under limited consideration.

Table 7.2: Model Estimates: Risk Preferences

	Estimate	Risk Premium	95% CI
Limited Consideration			
$\mathbb{E}$(Risk Aversion)	$9.52 \cdot 10^{-4}$	\$102	$[5.59 \cdot 10^{-4}, 1.40 \cdot 10^{-3}]$
Var(Risk Aversion)	$3.14 \cdot 10^{-6}$		$[9.75 \cdot 10^{-7}, 6.31 \cdot 10^{-6}]$
Comparison - CARA RUM Full Consideration			
Homogeneous Risk Aversion	$1.33 \cdot 10^{-7}$	\$0	$[7.28 \cdot 10^{-8}, 1.33 \cdot 10^{-7}]$
Heterogeneous $\mathbb{E}$(Risk Aversion)	$4.28 \cdot 10^{-4}$	\$43	$[3.78 \cdot 10^{-5}, 4.60 \cdot 10^{-4}]$
Var(Risk Aversion)	$1.71 \cdot 10^{-6}$		$[1.14 \cdot 10^{-8}, 2.17 \cdot 10^{-6}]$

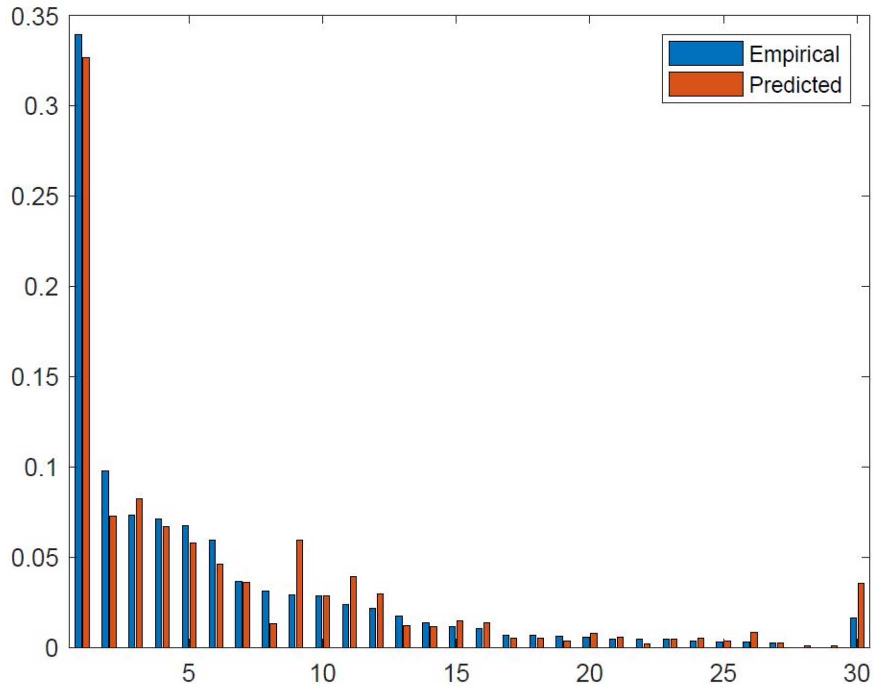
Notes: CI based on 1,000 bootstraps. In limited consideration model, sub-sampling used to correct for estimates on the boundary. Risk premium is calculated for a beneficiary facing a lottery that results in a loss of \$1,000 with 25% probability.

The inclusion of a role for these non-monetary and non-cost attributes is important for estimating risk aversion in this setting. The assumption of full consideration results in an underestimation of risk aversion. The financial stakes in the market for prescription drug insurance are relatively modest for most beneficiaries, although certainly not trivial. In other insurance settings, however, the financial implications are enormous. Failing to account for consideration and the resulting estimates of a misspecified choice model limits the usefulness of the model for understanding consumer behavior or policy implications. While the way in which biased estimates of risk aversion would naturally imply misspecified demand for insurance is well understood, the material importance of limited consideration is not.

7.3 Plan Choice under Limited Consideration

Choices in this market are driven both by risk aversion and limited consideration. Taken together, the model of expected utility with limited consideration matches the observed choice patterns of beneficiaries well. Figure 7.7 plots the implied choice distribution of the baseline model alongside the empirical distribution of plan choices. The right-most bar of the figure is a composite plan comprised of all the plans for which between 1 and 10 beneficiaries in the analysis sample enrolled.[47]

Figure 7.7: Empirical and Model Choice Distributions



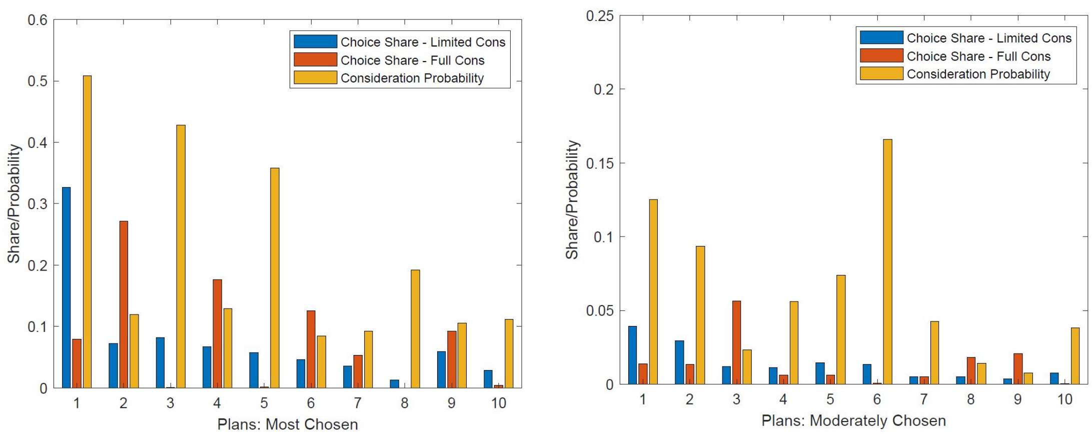
Notes: The blue bars correspond to the empirical choice shares, and the red bars are the implied choice distribution based on 1,000 simulations. Plans are ordered from the plan with the largest enrollment share on the left to the plans with zero enrollment. The rightmost plan corresponds to a composite plan of the 17 plans in which between 1 and 10 individuals enrolled.

By estimating risk preferences without the distorting impact of other plan attributes, I am able to compute the model implied choice distribution under full consideration. For the 20 plans with the largest empirical enrollment shares, Figure 7.8 plots the implied distribution under limited consideration in blue, which as seen in Figure 7.7 is similar to the empirical distribution. The implied full consideration choice shares are shown next in red. On the whole, these two distributions differ quite substantially. The bridge between the two distributions is consideration. The third bar plotted in yellow is the model implied consideration probability for each plan. Plan consideration probabilities are large for those plans that are chosen relatively frequently but are optimal rather infrequently under full consideration. Similarly, plans that are chosen infrequently in practice compared to under full consideration correspond to relatively smaller consideration probabilities.

As a result of limited consideration, individuals cluster on plans with low deductibles offered by a few popular firms. Many of these plans, however, are not particularly well suited

[47] As a privacy measure, CMS has a cell suppression policy that prevents the release of statistics such as choice frequencies if fewer than 11 individuals underlie the statistic.

Figure 7.8: Choice and Consideration Probabilities:
Limited and Full Consideration, 20 Most Chosen Plans



(a) 1-10 Most Chosen Plans (b) 11-20 Most Chosen Plans

Notes: Plans are ordered left to right by empirical enrollment shares. Implied choice shares are estimated as the average over 1,000 simulations of individual risk aversion and consideration sets for the analysis sample.

to the drug needs and risk preferences of many. The discrepancy between the two choice distributions in Figure 7.8 is caused by many beneficiaries considering a set of plans that does not contain their best plan. As a measure of the cost of limited consideration in this population, I compute the difference in certainty equivalent of the chosen plan and the optimal plan. The average certainty equivalent loss across the sample in my model is \$226. Table 7.3 compares the average certainty equivalent difference under the same counterfactual exercise in Figure 7.6 in which consideration effects are eliminated in simulations, maintaining all other estimates. The reduction in the average difference in certainty equivalent between chosen and optimal plans arises from the corresponding increase in consideration set sizes displayed in Figure 7.6, and the increase in individual plan consideration probabilities. The changes in certainty equivalent difference highlight the sizable role of attributes in consideration and the cost of limited consideration.

The values in Table 7.3 admit the following two interpretations. Since the model of limited consideration nests many behavioral models of consideration set formation, the model is agnostic about why the attributes determine consideration sets. Take, for example, the firm effect. First, the impact of firm identity on choices can be purely a consideration impact; advertising by some firms in this market is substantial. In that case, the difference between the baseline certainty equivalent loss of \$226 and the \$88 loss under a counterfactual without the firm effect represents meaningful welfare improvement. By reducing consideration based on firm identity, beneficiaries are on average losing \$138. Second, if the impact of firm on plan consideration represents unobserved quality, then a counterfactual that removes an individual's ability to filter plans considered based on the firm would be welfare reducing. In that case the \$138 additional lost certainty equivalent can be interpreted as an average bound on the shadow price of unobserved quality.

A similar logic applies to the other counterfactual results. If the role of the deductible is through consideration, then removing this channel and the corresponding increase in consideration set sizes improves welfare.[48] Individuals save on average $85 in that counterfactual. However, if the role of the deductible in consideration represents liquidity constraints, then individuals will become worse off without the ability to limit plans based on deductible. For the deductible, premium, and gap effects, if the impact my model captures is consideration rather than constraints, the changes in average certainty equivalent can be interpreted as clear welfare improvements through reducing consideration obstacles. If, however, these effects are manifestations of binding constraints, these changes represent the shadow prices of said constraints.

Table 7.3: Baseline and Counterfactual Results:
Average Certainty Equivalent Loss Due to Limited Consideration

	Average CE Difference
Baseline Model	$226
Removing Firm Effect	$88
Only Firm Effect	$84
Removing Deductible Effect	$141
Removing Premium Effect	$147
Removing Gap Effect	$201

Notes: Average CE Difference computed as the average difference in certainty equivalent of the chosen plan and the optimal plan over 1,000 simulations of risk aversion and consideration sets. The counterfactual values are computed similarly when consideration sets are simulated with different components of plan consideration probabilities set to 1.

There has been discussion since Part D's inception that the large number of available plans is unwieldy even for the most sophisticated of enrollees. Changes to market regulations over time have reduced the number of available plans from approximately 50 in the early years of the program to closer to 30 plans presently. Without estimates of limited consideration, not to mention risk preferences, it is difficult to assess how a reduction in plans available will affect beneficiary choice quality. To illustrate this point, I conduct two counterfactual simulations that resemble CMS policies aimed at reducing the number of plans in the market. A priori, the welfare impact of such a policy is ambiguous. The removal of plans may harm individuals who are no longer able to select their preferred plans. However, the reduction in the size of

[48]For example, available plans in the CMS sponsored online PlanFinder tool can be sorted by deductible. It is plausible an individual presented with plans in that order does not look beyond the initially presented plans and only considers zero or low deductible plans.

the feasible choice set may remove distracting plans. In the first exercise, I simulate choices when the set of feasible plans excludes plans with few enrollees. This exercise is inspired by the policy position of CMS beginning in 2010 that recommends plans with few enrollees consolidate or exit the market. In my analysis sample, the elimination of all plans that do not meet an enrollment threshold of 0.5% of the sample corresponds to a reduction in the choice set from 46 to 20 plans.[49] The consideration sets continue to focus on a small set of plans and largely do not change. The 26 eliminated plans are both infrequently considered and infrequently optimal, and thus do not alter the certainty equivalent comparison substantially. Within the market of 20 plans, the average certainty equivalent difference of the chosen and optimal plans remains \$226. When comparing the simulated chosen plans to the optimal under the original menu of 46 plans, the average certainty equivalent differences increases slightly to \$230 due to the small number of beneficiaries whose optimal plans are no longer available.

The second counterfactual limits the number of plans an individual firm can offer. In 2010, CMS also introduced a meaningful differences requirement. In subsequent years, firms that offered multiple enhanced plans were required to establish a measurable difference in the expected costs of those plans.[50] As a result, most firms began to offer only two plans within a market.[51] I conduct a counterfactual where each of the 19 firms offers up to 2 plans.[52] This results in a feasible menu of 35 plans. Similarly to the previous exercise, this leaves the average certainty equivalent largely unchanged. Although there is effectively no impact on consumer outcomes without these additional plans, insofar as providing these plans is not costless to firms, removing them from the market makes economic sense. However, with the understanding that beneficiaries exhibit substantial limited consideration, many efforts to streamline the market do not improve consumer outcomes. These results suggest, rather, that policymakers seeking to push beneficiaries towards better plans may want to instead encourage firms to compete on or implement regulation to standardize plans along consideration relevant attributes. Without an understanding of true risk preferences and how certain plan attributes impact consideration, it is difficult for policymakers to determine the impacts of market regulations or design changes.

7.4 Comparison to Standard Models

The workhorse model of insurance demand is the expected utility model with full consideration. Individuals are assumed to derive utility based on their risk aversion and the distri-

[49] An enrollment threshold of 1% would lead to a choice set of 16 plans.

[50] Enhanced plans refer to plans that offer enhanced features relative to the standard base plan.

[51] CMS has recently relaxed this regulation.

[52] Similar to the policy, I allow the firm to offer one standard deductible plan without gap coverage and one enhanced plans. In the case a firm offers multiple plans of one type, I retain the plan with a higher empirical choice share.

bution of monetary outcomes under each available plan. Similar to the model under limited consideration presented in this paper, the only utility-relevant variables are those governing the distribution of losses. Non-monetary attributes are not provided a role in the decision framework. Beginning with the expected utility specification in Equation 6.1, I estimate a random utility model for comparison and to highlight the empirical advantages of accounting for limited consideration.[53] In both the homogeneous and heterogeneous risk aversion specifications, the utility error is assumed to be iid Type 1 Extreme Value distributed.

$$EU_{ij} = -\exp(\nu\hat{\mu}_{ij} + \frac{1}{2}\nu^2\sigma_{ij}^2) + \epsilon_{ij} \tag{7.1}$$

$$EU_{ij} = -\exp(\nu_i\hat{\mu}_{ij} + \frac{1}{2}\nu_i^2\sigma_{ij}^2) + \epsilon_{ij},\ \nu_i \sim Beta(\beta_1, \beta_2) \tag{7.2}$$

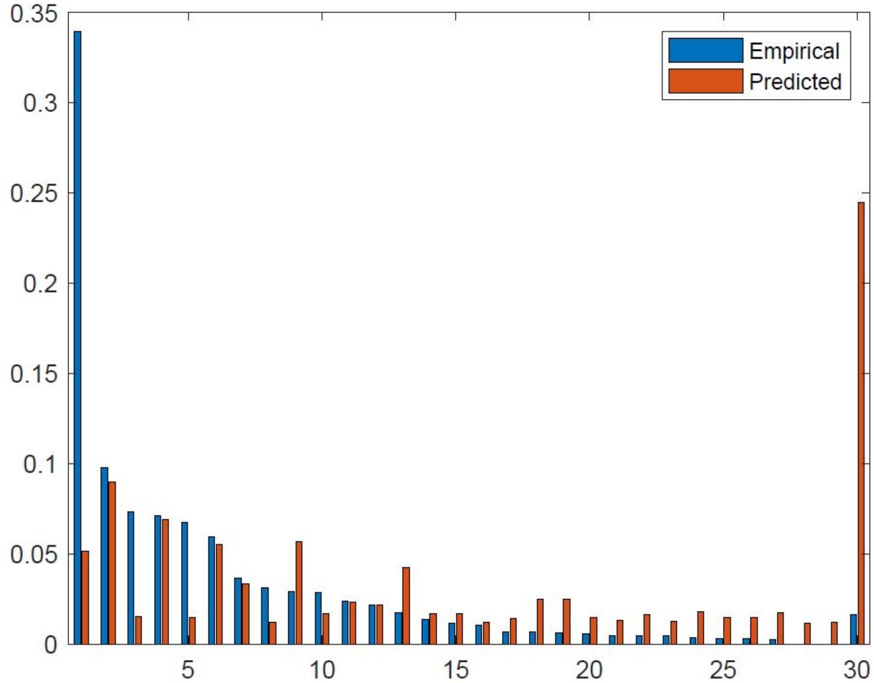
The resulting estimates of risk preferences are described in Table 7.2 above. The assumption of full consideration in the CARA expected utility model results in substantial underestimation of risk aversion. In a model of homogeneous preferences, beneficiaries are estimated to be effectively risk neutral, with an estimated risk premium for a 25% loss of $1,000 of a mere penny. This is a puzzling result in an insurance market, and the implied choice probabilities of this model come close to rolling a 46-sided die. The inclusion of random preferences also underestimates risk aversion relative to the model of limited consideration.[54] The omission of non-monetary, and non-cost more generally, attributes from a model of plan choice also diminishes the ability of the model to rationalize observed choice patterns. The empirical fit of the heterogeneous model is shown in Figure 7.9. The most popular plan is markedly under-predicted and the small plans within the composite bar on the far right are largely over-predicted.

Acknowledging the importance of non-monetary attributes in rationalizing the choice of prescription drug plans, previously used methods take the approach of adding the plan attributes directly into utility. This can be done by scaling up the attributes by a coefficient to estimate. This suggests an interpretation of the coefficient as translating the variable into a "cost", comparable to the monetary attributes such as premium and out-of-pocket costs. Denoting the included non-monetary attribute by X_j and the monetizing scaling coefficient

[53] It is worth noting that Apesteguia and Ballester (2018) describe a theoretical shortcoming of the random expected utility model in the insurance setting due to the implied non-monotonicity of choice probabilities in risk aversion.

[54] Although the estimate of mean risk aversion in the full consideration model here underestimate risk aversion, these estimates are still above those found in previous literature across all regions. It is possible that regional variation in consideration distorts further the estimation of risk preferences in the aggregate.

Figure 7.9: Implied Choice Distribution
CARA Random Utility Model (Heterogeneous)



Notes: Plans are ordered based on empirical choice shares. Predicted choice probabilities are computed based on averaging of 1,000 simulations across the analysis sample.

as γ, this translates in its simplest form here to the modified expected utility specification:

$$EU_{ij} = -\exp(\nu_i(\hat{\mu}_{ij} + \gamma X_j) + \frac{1}{2}\nu_i^2\sigma_{ij}^2) \tag{7.3}$$

In practice, expected utility is often estimated as a conditional logit by including the non-monetary attributes additively and a Type 1 Extreme Value error.[55] In some applications, this can be a reasonable modeling assumption, but in the choice over prescription drug plans, this approach has certain undesirable features. One issue is the manner in which the linear approximation of utility typically abstracts away from more precise distributional estimates of risk preferences. More challenging, however, is the interpretation of estimates in this modified model. The estimates of coefficients on non-monetary attributes are generally interpreted relative to the coefficient on either premium or out-of-pocket costs as a willingness to pay for the attribute. Such a comparative interpretation is common in discrete choice models. This comes from modeling the incursion of the attribute as a utility "cost", on par with monetary costs. As discussed in Handel and Kolstad (2015) and Handel (2013b), this approach treats the utility cost of the attribute as constant across the distribution of losses. Effectively, the utility cost of the attribute is a mean shift of the distribution of drug costs arising from

[55]See Abaluck and Gruber (2011) for a derivation of the conditional logit as a linear approximation of a CARA expected utility model.

uncertain drug needs. It can be difficult to attribute an economic meaning to these estimates. If the inclusion of a non-monetary attribute into utility is meant to capture a measure of non-financial plan quality or the impact of constraints such as liquidity constraints, it is not clear why that utility cost would be equivalent in the state of the world where an individual is healthy and does not file any drug claims and the state of the world where she is very ill and files many drug claims. Depending on the context this may or may not be of particular concern, but in this setting, it makes structural interpretation challenging.

This also raises questions regarding how to incorporate those estimates in a counterfactual analysis. The implications of such estimates in my analysis sample, specifically, do not conform with economic rationality. Table 7.4 presents estimates of the conditional logit with and without additional plan attributes. According to the estimates in Column (3), a dollar of deductible is equivalent to approximately \$1.25 in premium and \$1.92 in expected out-of-pocket costs. Taking these ratios, this would suggest that to reduce the deductible from the maximum allowed of \$310 to \$0, a beneficiary is willing to pay approximately \$390 in premiums or \$597 in expected out-of-pocket costs. Such estimates of WTP are wholly implausible and do not suggest an economic rationale for the estimated importance of the deductible in explaining plan choices. The monetary impact of the deductible is already accounted for in the expected out-of-pocket cost. As such, the result that the coefficient on deductible is statistically larger in magnitude than either premium or expected out-of-pocket costs in both Columns (3) and (4) is not consistent with the structural foundation of the model.

These counterintuitive results may be omitted from welfare analyses by assuming that the decision utility individuals use to select plans differs from their experienced utility. Under such an assumption, a researcher may be seen as estimating the foundational utility preferences driving behavior while accounting for the impact of such non-monetary attributes in choice. The inclusion of those variables in the estimation, however, can affect the primary estimates of interest. Columns (1) and (2) correspond to a standard insurance framework and include only utility relevant monetary variables. The inclusion of firm dummies and other attributes results in estimates of risk aversion approximately a third of the estimates without the attributes. The exercise to recover underlying preferences is sensitive to the inclusion of such additional variables.

8 Conclusion

This paper evaluates insurance choices in a setting where non-monetary plan attributes are suspected to influence plan choice using a theoretically appealing limited consideration framework that maintains the structure of expected utility. The motivation for this model comes

Table 7.4: Plan Choice Estimates: Conditional Logit

	(1)	(2)	(3)	(4)
Premium	-0.5580	–	-0.536	–
	(.013)		(.026)	
$\mathbb{E}$OOP	-0.451	–	-0.350	–
	(.011)		(.012)	
Prem + $\mathbb{E}$OOP	–	-0.507	–	-0.381
		(.009)		(.011)
Variance	-0.026	-0.022	-0.007	-0.007
	(.002)	(.002)	(.002)	(.002)
Deductible	–	–	-0.674	-0.634
			(.026)	(.026)
Gap	–	–	-0.391	-0.767
			(.094)	(.076)
Top100 Drugs	–	–	-0.060	-0.071
			(.007)	(.006)
Avg CS	–	–	-0.757	-0.231
			(0.611)	(.611)
Firm Dummies	No	No	Yes	Yes
Implied Risk Aversion	$1.13 \cdot 10^{-3}$	$8.74 \cdot 10^{-4}$	$4.10 \cdot 10^{-4}$	$3.49 \cdot 10^{-4}$

Notes: Standard errors are in parentheses. Dollar denominated variables are measured in hundreds of dollars. Each column provides coefficient estimates from separate conditional logit maximum likelihood estimations. Variance denotes the variance of $\mathbb{E}$OOP measured in hundreds of dollars. Columns (3) and (4) include firm fixed effects. Corresponding risk aversion is computed by adjusting the coefficients on Variance and $\mathbb{E}$OOP (or Premium + $\mathbb{E}$OOP) for nominal dollars and taking the ratio of twice the adjusted Variance coefficient divided by the adjusted $\mathbb{E}$OOP coefficient.

from the inconsistency between standard models of insurance choice which describe insurance contracts by their monetary outcomes and the empirical correlation between insurance plan choices and other plan attributes. Since prescription drug coverage was introduced to Medicare in 2006, researchers have encountered challenges in rationalizing a sizable fraction of observed plan choices, as is the case in many other health insurance markets. Expected utility alone, the classic workhorse model of insurance choices, does not match the choices of beneficiaries well. Alternative methods of adding non-cost plan attributes, which are important for matching empirical patterns, into a utility framework result in estimates that are difficult to structurally interpret in this environment.

The model incorporates both non-monetary attributes and the effect of monetary attributes above and beyond their direct impact on beneficiary costs into the decision framework through limited consideration. Relaxing the standard assumption of full consideration, I model beneficiaries as expected utility maximizers over an unobserved subset of available plans contained in their consideration set. There are numerous plausible explanations for limited consideration in this market. The analysis sample of beneficiaries in California in 2010 faced a choice set of 46 different prescription drug insurance plans. Due to the advanced age and health conditions of the typical beneficiary, it is likely some individuals are unable to evaluate the entire choice set. Even for individuals lacking cognitive limitations, the time required to consider and compare 46 plans may be too costly. These individuals may use certain plan attributes to trim the choice set down to a manageable size. The reduction of the choice set according to attributes may reflect unobserved constraints on an individual or the impact of firm advertising or the presentation of plans to the beneficiary. My model is agnostic about the underlying source of limited consideration but provides important insight into what features of plans drive consideration. Moreover, my model of consideration and the relationship of plan attributes to consideration, is computational tractable and is not subject to a curse of dimensionality as feasible choice sets increase. Since plan consideration probabilities are modeled as functions of plan attributes, it is the number of plan attributes, not the number of plans, that determines the number of parameters for estimation. This feature is especially appealing as the vector of estimated parameters may converge to a fixed number as the size of the choice set is increased. In a market with many choice sets, including the national PDP market, this is a very useful feature of the model.

My results show that heterogeneity in consideration sets plays an important role in plan choice. Despite the set of available plans, beneficiaries are largely considering no more than 5 plans. Which of the 46 plans beneficiaries consider depends largely on the identity of the insuring firm, the premium, the deductible, and whether the plan includes any form of supplemental coverage during the coverage gap. The impact of the firm and deductible alone are substantial. Shutting down the firm consideration effects more than triples the average consideration set size and improves plan choice by increasing the chance beneficiaries consider their optimal plan. The role of the firm in consideration is especially interesting and encourages future research. The strong effect of firms on consideration might reflect prior insurance experience of beneficiaries or firm familiarity through social and spousal influences. It is also plausible that extensive firm advertising is at play. Insofar as firm advertising may be steering beneficiaries towards sub-optimal choices through limited consideration, is is important for policymakers to have an understanding of those effects.

Results additionally highlight the importance of accounting for consideration when estimating risk preferences. I find estimates of mean risk aversion more than twice that of a full consideration model. My results on preferences and consideration are informative to policymakers as Americans increasingly encounter choices over health insurance plans. With influence over product standardization, presentation of information, and firm behavior, policymakers may be able to harness the information about *how* beneficiaries are choosing prescription drug plans to help remove the obstacles that prevent so many beneficiaries from considering and choosing their optimal plan. It may be desirable to incorporate into the enrollment process questions eliciting risk preferences in a manner similar to the Health and Retirement Study to present plans in a manner that reflects which plans are likely to be optimal for an individual. In light of strong firm effects and the substantial reduction in the cost of limited consideration in the absence of firm effects, it may be advisable for CMS to evaluate policies on firm marketing, especially with regards to the recent regulatory changes on marketing materials and meaningful difference requirements. In any such intervention, a clearer understanding of how individuals behave in this market is of utmost importance. My model and estimates provide new insight into that process.

Appendices

Appendix A Cost Calculator and Distribution Estimation

Using detailed data on the plan cost structure, I construct a program to compute the out-of-pocket costs for any series of ordered drug claims under every available plan in 2010 in the 34 major regions in the United States. The detailed claims data include information about gross and out-of-pocket realized drug costs under chosen plans, but a cost calculator is required to compute the counterfactual drug expenditures under the plans individuals did not select. The first step of the calculator is the collect the relevant set of plans to construct costs based on CMS region.

Prior to any calculation, I first assign every drug in the claims data, pricing data, and plan formulary a unique reference National Drug Code (NDC). Theoretically, each drug - defined by molecule, dosage, route of administration (tablet, injection, etc.), and brand name (if applicable) - is identified by a numeric code. The claims data identify drugs by NDC and a CMS created identifier called the Formulary RX ID. The plan formulary uses NDCs and another numeric system called RXCUIs. The base price data uses only NDCs to identify drugs. NDCs are not, however, unique identifiers.[56] The same drug may be listed under multiple NDCs within the data. Moreover, an individual's claim may record a drug under one NDC but the formulary for an available plan may use an alternative NDC. A naive mapping could erroneously determine the drug is excluded from the formulary. To address this I create a mapping of NDCs based on Formulary RX IDs. For each NDC in the claims data, I collect all Formulary RX IDs ever attributed to it. I then take the set of Formulary RX IDs and collect all of the NDCs to which those identifiers are ever linked. I repeat that process one additional time, and the resulting set of NDCs are deemed to represent the same drug. I then assign all linked NDCs the same unique numeric identifier in the claims, pricing, and formulary data.

A.1 Drug Cost Calculator

For any sequence of claims, I identify the coverage classification of each drug under each available plan. For every drug included in a plan's formulary, I determine the tier of coverage and whether that tier is covered in the donut hole. I also determine the base price of the claim by scaling the negotiated price of a 30 days supply of each drug under each plan to correspond to the days supply claimed. My calculator then processes the claims sequentially, determining the coverage phase and applying the relevant cost-sharing based on tier and phase. In the event a claim straddles multiple coverage phases, I prorate the claim across

[56] Formulary RX IDs and RXCUIs are similarly not unique.

spending zones in the manner CMS does in practice. The calculator keeps a running total of gross and out-of-pocket spending throughout the series of claims.

To assess the performance of the cost calculator, I compare the estimated out-of-pocket spending for each beneficiary's chosen plan to their realized out-of-pocket costs in the claims data. When I use as the base price of a drug the gross cost listed in the claims data, predicted and observed out-of-pocket spending have a correlation in excess of .95 for individuals across regions. In practice, I use the negotiated base prices listed in the pricing data to account for differences in base prices across plans. Occasionally there is a discrepancy between the information in the pricing file and what is reported in the claims data. Once I incorporate the negotiated base prices, the correlation between predicted and observed spending is .93 among the analysis sample. This simple test of accuracy is assuring, especially as I made a number of small simplifications in constructing the calculator that would prevent perfect prediction. I treated all claims as filed through in-network pharmacies and pro-rated one month cost-sharing for tractability.[57] In the catastrophic coverage phase, I treat all claims as though they are branded drugs. Out-of-pocket costs for those claims are therefore computed as the maximum between a 5% coinsurance and a \$6.30 copay. In practice, for generic drugs, the beneficiary pays the maximum of a 5% coinsurance and a \$2.50 copay. The data I use does not include information on whether a drug is branded or generic. However, few individuals enter the catastrophic coverage phase at all, and the differences in cost between these two pricing schemes is small.

A.2 Distribution of Out-of-Pocket Costs and Variance Estimation

Ad described in Section 4.2, higher order moments of the distribution of drug costs an individual expects under different plans requires an approximation of the distribution of out-of-pocket drug costs under each available plan. In practice, it is the variance of costs for which I need estimates. To this end, I assign each individual in my sample into a bin of "similar individuals" based on their average monthly gross drug costs and average monthly "effective" claim counts during their 2010 tenure. Effective claim counts adjusts counts for the number of months a claim covers. For example, if a beneficiary filled a claim for a 90 day supply, it is treated as effectively 3 claims. Average claim counts are are classified as one of the following: between 0 and 1, between 1 and 2, between 2 and 3, between 3 and 4, between 4 and 10, and more than 10. These claims bins are crossed with quintiles of average monthly gross spend. An additional bin of individuals with zero claims and zero spend is also defined. Bins with fewer than 100 individuals are dropped.

To estimate the cost distribution within each bin, I construct a sample of individuals

[57] In general, the three month copay was simply 3 times the one month copay, making this simplification quite innocuous.

without ESRD who are enrolled in a Part D plan for some portion of 2010 and the entirety of 2011. I use their 2010 claims experience to categorize them into one of the bins described above. I then randomly select 100 individuals from each bin and pass their entire 2011 claims experiences through the cost calculator for every plan. I compile monthly running totals of out-of-pocket spend for each randomly sampled individual. To adjust for the evolution of drug expenditure over time, I deflate all 2011 costs by the average ratio of 2010 spend compared to 2011. For every individual in my analysis sample, denoting their months of 2010 coverage by m, the variance of out-of-pocket costs in each plan is computed as the variance of the random sample's deflated out-of-pocket costs for m months of 2011.

Appendix B Estimation

B.1 Consideration Probabilities

In Section 6.3.1 I describe the intuition behind the consideration probabilities, φ_j. In practice, I model each plan's consideration probability, φ_j, as a function of plan j's characteristics listed above:

$$\varphi_j = f(\text{firm}_j, \text{premium}_j, \text{deductible}_j, \text{gap}_j, \text{Top100}_j, \text{AvgCS}_j)$$

To ensure consideration probabilities are in the unit interval, I impose the following functional form:

$$\varphi_j = \phi_{firm_j}\phi_{prem_j}\phi_{ded_j}\phi_{gap_j}\phi_{top100_j}\phi_{AvgCS_j},$$

where $\phi_{firm_j} \in [0,1]$ is the base consideration probability of the firm offering plan j, constant across all plans offered by that firm in the California market. The plan attributes enter consideration multiplicatively as well, with all δ terms $\in [0,1]$

$$\begin{aligned}
\phi_{prem_j} &= \delta_{prem}^{PremRatio}, \\
\phi_{ded} &= \delta_{ded}^{DedRatio} \\
\phi_{Gap} &= \begin{cases} \delta_{gap} \text{ if No Gap} \\ 1 \text{ if Gap,} \end{cases} \\
\phi_{Top100} &= \delta_{top100}^{(max(top100)-top100_j)}, \\
\phi_{AvgCS} &= \delta_{avgcs}^{(AvgCS_j - min(AvgCS))}.
\end{aligned}$$

Both ϕ_{prem_j} and ϕ_{ded_j}, which govern the roles of premium and deductible, respectively, depend on the ratio of a plan's premium and deductible relative to the maximum in the market. I define $PremRatio_j \equiv \frac{Prem_j - min(Prem)}{max(Prem)-min(Prem)}$ and $DedRatio_j \equiv \frac{Deduc_j}{max(Deduc)}$.

Appendix C Robustness Analysis

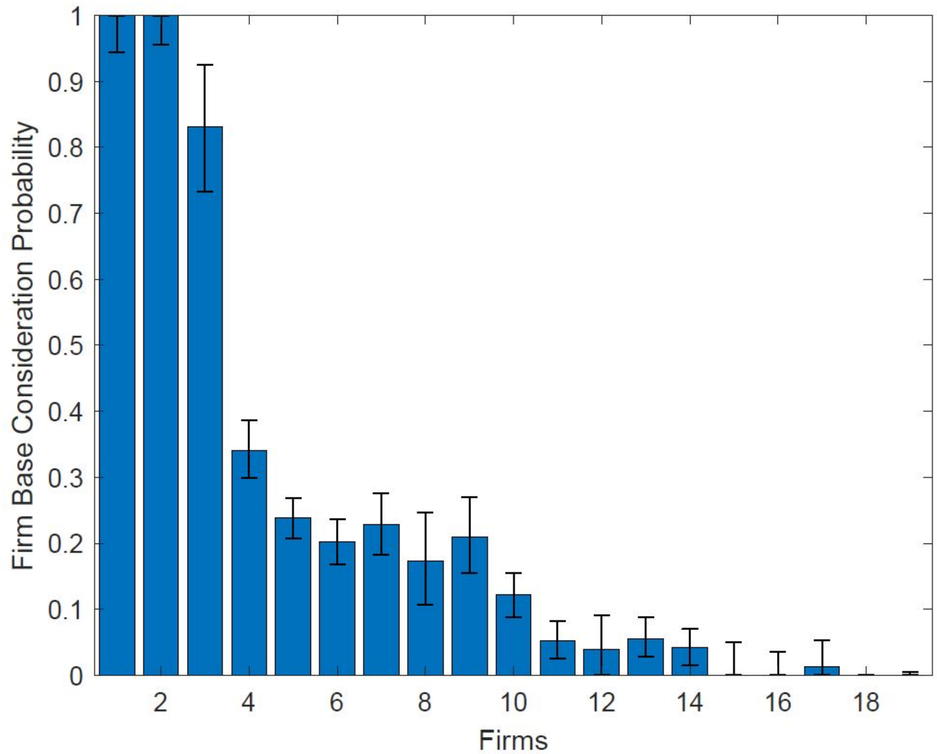
In my baseline analysis I assume perfect foresight of expected out-of-pocket drug costs. As a robustness check, I estimate my model using an alternative specification of expected out-of-pocket costs. Table C.1 presents estimates of the consideration impact of plan attributes. The reduction in consideration that occurs between the best and worst premiums and deductibles is larger in this specification. All else equal, these estimates suggest the highest premium plan is considered only 7% as much as the lowest premium plan. Plans with $310 deductibles receive 12% as much consideration as equivalent $0 plans. The impact of gap coverage is similar but slightly milder. Similar to the baseline analysis, the count of top 100 drugs covered and the average cost-share of a plan do not impact consideration. Figure C.1 plots firm base consideration probabilities in the same manner as Figure 7.1. The same patterns emerge as in the baseline results. Estimates of risk aversion are slightly higher than in the baseline analysis, but on the whole similar. Table C.2 presents estimates and confidence intervals for the mean and variance of risk aversion. There is substantial overlap in the confidence intervals for both statistics. These estimates show that the results in the baseline analysis are not driven by the assumption of perfect foresight of expected out-of-pocket expenses.

Table C.1: Robustness Results: Consideration Impact of Plan Attributes

	Estimate	95% CI
δ_{prem}	0.072	[0.051, 0.104]
δ_{ded}	0.120	[0.106, 0.136]
δ_{gap}	0.906	[0.822, 1.000]
δ_{top100}	1.000	[1.000, 1.000]
δ_{avgcs}	1.000	[1.000, 1.000]

Notes: All δ terms are defined between 0 and 1 and reflect how much consideration a plan with the worst value of an attribute is considered relative to an equivalent plan with the best value of the attribute. Confidence intervals based on 1,000 bootstraps with sub-sampling to correct for estimates on the boundary.

Figure C.1: Robustness Results: Firm Base Consideration Probabilities



Notes: Firms are ordered based on estimated base consideration probabilities in the baseline model, as in Figure 7.1. Error bars present 95% confidence intervals based on 1,000 bootstrap repetitions with sub-sampling to adjust for estimates on the boundary.

Table C.2: Robustness Estimates: Risk Preferences

	Estimate	Risk Premium	95% CI
Limited Consideration			
$\mathbb{E}$(Risk Aversion)	$1.08 \cdot 10^{-3}$	\$117	$[5.31 \cdot 10^{-4}, 1.70 \cdot 10^{-3}]$
Var(Risk Aversion)	$3.99 \cdot 10^{-6}$		$[9.53 \cdot 10^{-7}, 8.37 \cdot 10^{-6}]$

Notes: CI based on 1,000 bootstraps. In limited consideration model, sub-sampling used to correct for estimates on the boundary. Risk premium is calculated for a beneficiary facing a lottery that results in a loss of \$1,000 with 25% probability.

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