Estimating the Heterogeneous Welfare Effects of Choice Architecture: An Application to the Medicare Prescription Drug Insurance Market

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We develop a structural model for estimating the welfare effects of policies that alter the design of differentiated product markets when some consumers are misinformed about product characteristics. We use the model to analyze three proposals to simplify Medicare markets for prescription drug insurance: (1) reducing the number of plans, (2) providing personalized information, and (3) changing defaults so consumers are reassigned to cheaper plans. First we combine national administrative and survey data to determine which consumers appear to make informed enrollment decisions. Then we analyze the welfare effects of each proposal, using the revealed preferences of informed consumers to proxy for the concealed preferences of misinformed consumers. Results suggest that the menu reduction would harm most consumers whereas personalized information and reassignment would benefit most consumers. Each policy produces large gains and losses for small groups of consumers, but no policy changes average consumer welfare by more than 14% of average expenditures.

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One of the research frontiers in empirical microeconomics is to assess the equity and efficiency of policies that modify *choice architecture*—the design of a market environment in which people make decisions (Thaler and Sunstein 2008). Examples of policies designed to simplify choice architecture include restricting the number of options consumers can choose from, providing people with personalized information via decision support tools, and altering the default options. Such policies are often hypothesized to benefit consumers who are misinformed about their options and to harm those who are informed (Camerer et al. 2003). Yet, there are several empirical challenges with using revealed preference analysis to estimate the distribution of welfare effects. First, the researcher must identify the decision makers and determine which of their decisions are based on misinformation. Second, a method is needed to infer the preferences of misinformed consumers. Third, researchers must predict how a counterfactual policy would affect consumer behavior and market prices. Finally, all of this information must be aggregated into theoretically consistent welfare measures.

We develop a framework for addressing these challenges in large differentiated product markets and use it to evaluate the welfare effects of several recent proposals to simplify Medicare markets for prescription drug insurance. Our research builds on recent empirical studies that have refined standard revealed preference methods to address heterogeneity in information (e.g. Allcott and Taubinsky 2015, Bernheim et al. 2015, Handel 2013, Handel and Kolstad 2015). These studies aim to recover preferences and welfare by leveraging field experiments, laboratory experiments, natural experiments, and surveys to distinguish between active and passive choices made by consumers who differ in their knowledge of market institutions. Their applications utilize data from online sample frames or workers at a few firms who chose among a small number of options. We add to this literature and address the central research challenges by providing the first national analysis of a high-stakes differentiated product market that is both subsidized and regulated by the government.

Medicare Part D created a nationwide government-designed, taxpayer-subsidized series of markets for standalone prescription drug insurance plans (PDP). In 2013, the PDP market enrolled 23 million people with federal outlays of $65 billion (US Department of Health and Human Services 2014). Due to concerns about consumer confusion, the Centers for Medicare and Medicaid Services (CMS) and others have proposed several reforms designed to simplify choice architecture (e.g. McFadden 2006, Thaler and Sunstein 2008, Federal Register 2014). These include restricting the number of available plans, providing consumers with customized information about their available options, and altering default rules and reassigning people to plans. Similar policies have been proposed for the health insurance exchanges implemented under the Patient Protection and Affordable Care Act (ACA) and to markets for other goods and services.

We assess the benefits and costs of these prospective policies by drawing on a novel combination of administrative records and survey data on consumers' knowledge of the market, their enrollment decisions, and the financial consequences of those decisions for a national sample of the non-poor Medicare PDP enrollee population from 2006-2010. We worked with CMS to link the annual responses given by people who participated in their longitudinal Medicare Current Beneficiary Survey (MCBS) to administrative records on the insurance enrollment decisions made by those individuals in Part D, as well as the universe of their drug claims, their demographic characteristics, and their evolving chronic medical conditions. Although the survey and administrative data sets have been analyzed separately by prior studies, we believe this is the first time they have been consistently linked by researchers.

Linking the two data sets is important for our purposes because the MCBS tests respondents' knowledge of key market institutions and asks about the effort they exerted to learn about the market. Equally important, the MCBS allows us to determine whether each enrollee made health insurance decisions on their own or had help from somebody else. This information substantially improves our ability to apply revealed preference logic to investigate how knowledge and decision making relate to consumer demographics. Given the large amounts of money at stake and the age range of the eligible population, it is unsurprising to find that 37% of enrollees do not make health insurance decision on their own. Enrollees are more likely to get help if they are older, sicker, lower income, less educated, less internet savvy, or diagnosed with Alzheimer's disease or dementia or depression.

We use the linked data to isolate a subset of enrollment decisions that we suspect will not reveal the decision maker's preferences in an econometric model of drug plan choice because the person appears to be misinformed about key features of the market and her beliefs cannot be fully observed. In contrast, we rely on the conventional assumption of full information in the absence of evidence to the contrary. Specifically if an enrollee correctly answers an MCBS question testing her knowledge of the market and chooses a plan that can be justified as maximizing a utility function satisfying standard axioms of consumer preference theory under full information, then we treat her decision as providing information about her preferences. We use the nonparametric GARP-like test from Ketcham, Kuminoff, and Powers (2015) to identify choices that cannot be explained as maximizing utility under full information in the context of our model. As in Chetty et al. (2015) and Handel and Kolstad (2015) we distinguish between active and passive choice processes and we explicitly recognize that people incur hassle costs from searching for information and switching insurance plans. We find that the probability of making an informed decision increases with education and with the effort that people exert to learn about the market. The probability decreases as people age, as they are diagnosed with cognitive illnesses, and as their drug expenditures increase.

We then estimate multinomial logit models of the enrollment process separately for the apparently informed and misinformed choices. If taken literally, the model for misinformed choices would imply that those consumers are risk-loving and have an average willingness to pay to avoid switching out of their status quo brand of nearly $4300. The parameters for informed choices, on the other hand, imply risk premia that are broadly consistent with prior studies (e.g. Cohen and Einav 2007, Handel 2013, Handel and Kolstad 2015) and WTP for status quo brands of $1300. Following the approach suggested by Bernheim and Rangel (2009), we infer the preferences for consumers in the misinformed group from the choices made by observationally similar consumers from the informed group. The key assumption is that information is uncorrelated with preferences after controlling for observable demographics. Then we build on Small and Rosen (1981) and Leggett (2002) to adapt the standard multinomial logit welfare framework to allow for the possibility that an uninformed consumer could be made better off by a policy that provides information or even reduces the number of choices.[1] We also adapt the computational approach from Bayer and Timmins (2005) to allow equilibrium plan premiums to adjust following a policy in response to consumer sorting and adverse selection. This framework allows us to consider how the welfare effects of implementable prospective policies targeting choice architecture vary across people with different drug needs, demographics, and choice processes. The measure of average consumer welfare that we use to summarize these effects is consistent with Camerer et al.'s (2003) proposal to evaluate the relative merits of prospective policies based on the criterion of asymmetric paternalism; that is, producing large benefits for uninformed consumers while imposing little or no harm, and perhaps even benefiting, informed consumers.

In the first policy experiment, we calibrate our model to match the federal government's recent proposals to limit each insurer to sell no more than two plans per market (Federal Register 2014). In the second policy experiment, we calibrate our model to replicate a field experiment conducted by Kling et al. (2012) in which Part D enrollees were sent personalized letters with information on the amount of money they could expect to save by switching to their lowest-cost plans. In the third policy experiment, we calibrate our model to match the federal government's recent proposal to alter the default and automatically reassign people to lower-cost plans (Health and Human Services 2014). We find that all three policies have winners and losers. Our results suggest that the CMS proposal to limit the number of plans would reduce welfare for the mean and median consumer and effectively operate as an income transfer from consumers and taxpayers to insurers. Further, there appears to be great scope for insurers to increase the size of these transfers if they are free to choose which plans they retain as would exist within the scope of the policy proposed by CMS. In contrast, providing personalized information would

[1] This approach is consistent with behavioral as well as neoclassical frameworks, e.g. in Stigler and Becker (1977) the presence of costly information creates the potential that people who are less than fully informed may experience welfare gains from modifying choice architecture.

benefit the average enrollee. Assigning people to low-cost default plans benefits the median consumer as well under most assumptions about the effects of the policy, about the information that consumers have about their future drug consumption, and about the interpretation the logit parameters on peoples' status quo brands and plans. Under some assumptions the reassignment policy yield expected gains for 92% of enrollees, while menu restrictions benefit as few as 2% of enrollees. Under every policy and every set of assumptions that we consider, however, the average gain in consumer welfare never exceeds 14% of consumers' current drug plan expenditures. These effects are often overshadowed by transfers from insurers to taxpayers, suggesting that the primary benefit of such policies may be to reduce government spending in the Part D market. Finally, we analyze demographic differences between those who would win and those who would lose from each policy.

I. Medicare Part D

People typically become eligible for Medicare benefits in the US when they turn 65. In 2006 Medicare Part D extended these benefits to include prescription drug insurance sold through standalone PDPs. Prior to the ACA, Part D was the largest expansion of public insurance programs since the start of Medicare. A novel and controversial feature of Part D is that it created a quasi-private marketplace for delivering insurance, serving as a precursor to the markets created by the ACA. Part D created 34 spatially delineated markets within which the average enrollee chose among 50 drug plans sold by 20 private insurers. Subject to CMS approval, private insurers can sell multiple PDPs in each market. The default for new or uninsured Medicare beneficiaries is to be uninsured.[2] After an enrollee chooses a plan she is automatically assigned to that same plan the following year unless she chooses to switch to a different one during the annual open enrollment window. Enrollees pay monthly premiums as well as out of pocket (OOP) costs for the drugs they purchase. Taxpayers subsidize non-poor enrollees' premiums by an average of 75.5%.

PDPs differ in terms of premiums, OOP costs of specific drugs, and measures of quali-

[2] Enrollees who qualify for low-income subsidies are autoenrolled to certain plans, but we exclude them from our empirical analysis.

ty such as customer service, access to pharmacy networks, the ability to obtain drugs by mail order, and the prevalence and stringency of prior authorization requirements. The novelty of the market together with the complexity of the product led many analysts to speculate that consumers would not make informed choices. Liebman and Zeckhauser (2008) summarize this concern when they write that: “Health insurance is too complicated a product for most consumers to purchase intelligently and it is unlikely that most individuals will make sensible decisions when confronted with these choices.” Some analysts have gone on to suggest that Medicare Part D is a prime candidate for libertarian paternalism (e.g. McFadden 2006, Thaler and Sunstein 2008). Likewise the government has expressed a desire to simplify health insurance markets and nudge enrollees toward cheaper plans. In 2014, for example, CMS proposed limiting insurers to selling no more than two plans per region, which would reduce the average consumer’s number of choices by about 20% (Federal Register 2014). The US Department of Health and Human Services also announced that it is considering revising the design of insurance markets to automatically reassign people to low-cost plans unless they choose to opt out (Health and Human Services. 2014). The welfare effects of these types of policies depends on several factors including consumers’ preferences for PDP attributes, the cost of switching plans, and how the policies affect consumers’ decision processes and outcomes.

Several prior studies have investigated the role of information and consumer behavior in Medicare Part D. One of the primary findings is that most people could have saved money by switching plans (e.g. Abaluck and Gruber 2011, Heiss, McFadden and Winter 2013, Ketcham, Lucarelli and Powers 2015). Over the first five years of the program, the average enrollee could have reduced their annual expenditures (premium + out of pocket) by $340, which is equivalent to 25% of average expenditures. It is less clear what this reflects about consumer decision making. When enrollees are surveyed about their experiences in Part D most report being satisfied with the plans they chose (Heiss, McFadden and Winter 2010, Kling et al. 2012). Furthermore, Ketcham, Kuminoff and Powers (2015) demonstrate that most of the people who could have saved money by switching chose plans that were either superior in some measure of quality or provided greater protection from negative health shocks. Hence, one explanation for why people leave money on the table is that they are making informed decisions to pay for quality and risk protection. On the other hand, when Kling et al. (2012) asked 406 Wisconsin enrollees how much they thought they could save by switching plans, most respondents underestimated the true figure. Kling et al. also found that sending enrollees a letter with personalized information about their potential savings increased the rate at which enrollees switched plans by 11.5 percentage points. Overall, the existing evidence suggests that at least some consumers are misinformed, but others may be choosing to pay more for plans with higher quality and/or greater risk protection.

II. Linking Administrative Records to Enrollee Surveys

We collaborated with CMS to link administrative records on PDP enrollees to their responses in the Medicare Current Beneficiary Survey (MCBS). This is the first time the two data sets have been linked. Our data collection process began by using CMS administrative records on beneficiaries' basic demographic characteristics, their prescription drug claims, the set of PDPs available to them, and their actual plan choices over the first five years of Part D. Then we used their drug claims to estimate what each enrollee would have spent had they purchased the same bundle of drugs under each alternative PDP in their choice set. This was done by combining their actual claims with the cost calculator developed in Ketcham, Lucarelli and Powers (2015).[3] Next we used administrative data from CMS's Chronic Condition Data Warehouse to determine if and when each individual had 16 different medical conditions. This includes dementia and Alzheimer's disease, which are associated with diminished cognitive performance (Agarwal et al. 2009).[4] Like prior studies of PDP choice we limit our analysis to enrollees who chose a standalone PDP, who did not receive a low-income subsidy, and who were enrolled in a PDP for the entire calendar year.[5]

[3] We have confirmed the calculator's accuracy by finding a correlation of .92-.98 each year between the OOP prescription drug costs calculated for the actual plan and the actual OOP cost observed in the administrative data.

[4] In addition to an indicator for Alzheimer's or dementia, we observe diagnoses of depression, acute myocardial infarction, atrial fibrillation, cancer, cataracts, heart failure, chronic kidney disease, chronic obstructive pulmonary disease, diabetes, glaucoma, hip/pelvic fractures, ischemic heart disease, osteoporosis, and strokes/transient ischemic attack.

[5] We exclude those receiving "low income subsidies" because they are autoenrolled into plans, they receive larger premium subsidies,

Finally, we worked with CMS to link the administrative data with supplementary information on PDP enrollees who also participated in the MCBS from 2005-2011. The MCBS is a nationally representative rotating panel questionnaire that began in 1991 and is administered to approximately 16,000 people annually. It collects information about Medicare beneficiaries and their use of health care services. Each participant is interviewed up to three times per year for four consecutive years, regardless of whether they stay at the same address or move into and out of long term care facilities. Importantly for our purposes, participants are asked a series of questions designed to test whether they understand key features of the PDP market. These knowledge questions are explained below. The MCBS also asks participants if and how they obtained information about Medicare services and it provides richer data on enrollee demographics than the CMS administrative files. This includes variables describing income, education, marital status, employment status, and enrollees' use of the internet. Also of particular value for our study, the MCBS indicates whether a proxy responded to the survey, including the knowledge questions, and whether the individual beneficiary herself makes health insurance enrollment decisions or whether someone makes them for her.

and their copayments are much more uniform across plans. Hence while interesting to study for policy, they are less relevant for our evaluation of prospective policies designed to alter choice architecture. Despite excluding them, our sample has similar income levels to the national average of people age 65 and above. In our sample 55% of households have annual income over $25,000 (weighted 2006-2010 dollars), compared with 63% (constant 2010 dollars) based on all householders 65 and older in the Census American Community Survey.

TABLE 1—SUMMARY STATISTICS FOR THE MCBS-ADMINISTRATIVE SAMPLE

	2006	2007	2008	2009	2010	2006-2010
number of enrollees	810	2,624	3,133	3,641	4,070	14,278
Medicare Beneficiary Survey variables						
High school graduate (%)	78	78	79	79	80	79
College graduate (%)	21	20	21	23	25	22
Income>$25k (%)	55	52	53	56	58	55
Currently working (%)	13	14	13	13	13	13
Married (%)	62	54	54	55	55	55
Has living children (%)	93	93	93	93	93	93
Uses the internet (%)	33	32	34	36	39	36
Has visited website for Medicare info (%)	24	22	25	26	28	26
Has called 1-800-Medicare for info (%)	32	24	19	15	12	18
Administrative variables						
mean age	77	77	78	78	78	78
female (%)	62	62	62	62	62	62
white (%)	94	93	93	94	94	93
Alzheimer's or dementia (%)	7	8	9	10	11	9
Depression (%)	9	8	10	11	11	10
mean number of drug claims	38	34	36	35	35	35
mean number of available plans	43	56	55	50	47	51
mean number of available brands	20	24	23	23	20	22
mean premium ($)	363	362	406	476	513	444
mean out-of-pocket costs ($)	1,010	842	873	920	903	896
mean potential savings, ex post ($)	546	347	295	332	337	340

Note: The table reports means for key variables for the sample of Medicare Part D enrollees found in both the MCBS and cost calculator samples in the given year. See the text for additional details.

Approximately half of all survey respondents purchased a standalone PDP during the first five years of the program.[6] Our linked sample includes 5,233 individuals who made 14,278 annual enrollment decisions between 2006 and 2010. Table 1 reports means of key variables. The MCBS reveals that the typical enrollee is a retired high school graduate with living children. Approximately 22% have a college degree, 55% are married, and 55% have annual pre-tax household incomes over $25,000.[7] Only 36% report that they ever personally use the internet to get information of any kind. However, 26% used a website to obtain information about Medicare programs and 18% obtained information

[6] Respondents who do not purchase a standalone PDP can instead obtain prescription drug insurance through an employer sponsored plan or a Medicare Advantage plan

[7] In comparison, the American Community Survey reports that 63% of all householders age 65 and older had annual incomes over $25,000 in 2010. The most likely reason why we observe a slightly lower fraction in our data (55%) is that our data exclude enrollees who received federal low-income subsidies in Part D.

by calling 1-800-Medicare.

The administrative variables reveal that total expenditures on PDP premiums and OOP drug costs ranged from $1,204 to $1,416 per year for the average enrollee. This is a significant share of income given that 45% of the enrollees in our sample report annual gross household incomes below $25,000. The data also reveal that the percentage of enrollees diagnosed with some form of dementia increased by 4 percentage points over our study period.

A potential limitation of working with the MCBS sample is that it is not designed to be nationally representative without weighting, and selecting the appropriate weights is complicated by panel rotation and by our exclusive focus on respondents who participated in the PDP market.[8] To assess whether using unweighted MCBS data might compromise the external validity of our results, we compared the unweighted demographics of the average enrollee in our linked sample with a random 20% sample of all Part D enrollees from CMS's administrative files. Table A1 shows that the average enrollee in our linked sample is 1 to 2 years older. Otherwise, the two samples are virtually identical in terms of race, gender, rates of dementia and depression, number of PDP brands and plans available, expenditures on plan premiums and OOP costs, and the maximum amount of money that the average enrollee could have been saved by enrolling in a different plan. Given the strong similarity in demographics and PDP expenditures between the two samples, we expect that our findings from the linked MCBS-administrative sample can be generalized to the broader population of non-poor Part D enrollees.

III. Modeling and Identifying Enrollment Decisions Based on Incomplete Information

Only 8% of all enrollment decisions made between 2006 and 2010 resulted in the enrollee minimizing drug expenditures. The last row of Table 1 shows that the average enrollee could have saved between $295 and $546 per year in terms of lower premiums and OOP costs by choosing a different plan. This is equivalent to reducing total PDP expendi-

[8] For example, by design the MCBS does not attempt to sample individuals from 3 out of the 34 PDP regions: 1(Maine and New Hampshire), 20 (Mississippi), and 31 (Idaho and Utah).

tures by 23% to 40%. Why are so many people leaving so much money on the table? We hypothesize that the answer differs from person to person. Some may be making informed decisions to purchase more expensive plans because those plans provide more risk protection and customer service. Others may not fully understand how the market works or may be underestimating their potential savings as found by Kling et al. (2012).

Evaluating the welfare effects of prospective policies requires us to distinguish between these two groups so that we can discern whose choices likely reveal their preferences to us and whose do not. It also requires us to select a parametric approximation to the utility function. The main novelty of our approach to is to allow for heterogeneity in beliefs about plan attributes. We focus on identifying parameters that describe how plan attributes affect PDP choice and then use they survey and administrative data to identify which choices appear to be informed.

A. Initial Enrollment Decision

When a beneficiary first enters the market in year 0 she must actively choose a plan to obtain insurance. She will choose the plan that maximizes her utility, given her beliefs about plan attributes. As with prior literature on insurance choice (e.g., Handel and Kolstad 2015), we estimate a static model that approximates this process with a simple linear model,

(3) $U_{ij0} = \alpha \acute{c}_{ij0} + \beta \acute{\sigma}^2_{ij0} + \gamma \acute{q}_{ij0} + \epsilon_{ij0}$.

$\acute{c}_{ij0}$ denotes the amount that person *i* expects to spend under plan *j* in terms of the premium plus out of pocket costs for prescription drugs, $\acute{\sigma}^2_{ij0}$ is the variance of out of pocket costs, $\acute{q}_{ij0}$ is a vector of quality attributes, and ϵ_{ij0} is an idiosyncratic person-plan specific taste shock. The accents indicate that the variables reflect person *i*'s subjective beliefs about plan attributes at the time of her enrollment decision. Heterogeneity in beliefs is discussed below. Finally, we assume that there is a constant utility cost of the time and effort required to learn about a plan and enroll in it. Because this cost is assumed to be constant across plans it will cancel out of between-plan comparisons and we therefore suppress it in (3) for brevity.

B. Reenrollment Decisions

After an enrollee makes her initial choice in year 0 she is automatically assigned to that same plan in year 1 unless she actively chooses to switch to a different plan during open enrollment.[9] As before, we assume that it is costly to make an active decision. In contrast, because no effort is required for the consumer to select her default plan the passive decision to do so now has a relatively higher payoff:

$$(4)\ U_{ij1} = \alpha \acute{c}_{ij1} + \beta \acute{\sigma}_{ij1}^2 + \gamma \acute{q}_{ij1} + \eta \Delta \acute{B}_{ij1} + \delta \Delta \acute{P}_{ij1} + \epsilon_{ij1}.$$

We use two terms to capture the utility cost of actively switching plans: $\Delta \acute{P}_{ijt}$ is an indicator for whether plan *j* is a non-default plan sold by the same insurer as the default plan, and $\Delta \acute{B}_{ijt}$ is an indicator for whether plan *j* is a non-default plan sold by a different insurer. The disutility of switching plans is captured by η and δ. The decision process follows the same structure as (4) in enrollment years *2,…,*T.

All else constant, between-brand switches are likely to require more time and effort than within-brand switches: $\eta < \delta < 0$. For instance, many insurers require enrollees to have prior authorization from their doctors to purchase certain drugs. Existing prior authorization paperwork is more likely to be transferrable between plans within the same brand than across different brands. To obtain the same drugs after switching to a new insurer the consumer may have to go through additional doctor visits and paperwork. Likewise, a consumer who switches between brands may need to spend time learning how to navigate the new pharmacy network and customer service centers. Table A2 provides the number of initial and subsequent enrollment decisions and the switching rate among those making reenrollment decisions for each year.

C. Heterogeneity in Information

We model heterogeneity in information by allowing people's choices to be driven by

[9] Plans are occasionally discontinued, which can force people to make an active choice. In such case, we can revert to equation (3) to model the initial enrollment decision.

different beliefs about PDPs. If consumer beliefs are unknown to the analyst, as with suspect choices then the standard revealed preference logic of discrete choice estimation breaks down. To overcome this challenge, we adapt two features Bernheim and Rangel's (2009) proposed approach to revealed preference analysis in the presence of partially latent heterogeneity in beliefs.[10] First, we use theory and data to identify enrollment decisions that we suspect may not reveal consumers' preferences for PDP attributes due to incomplete information. We label these choices as *suspect*, using Bernheim and Rangel's terminology. *Nonsuspect* choices, in contrast, are assumed to be fully informed in the sense that decision makers' beliefs about plan attributes coincide with the objective measures we have collected. Put differently, we follow Bernheim and Rangel's proposal to respect consumer sovereignty and invoke the standard assumption of full information in the absence of evidence to the contrary. For these people, we can apply the logic of revealed preferences and estimate a model of PDP choice to infer their tastes for cost reduction, risk protection, and plan quality. Importantly, the standard discrete choice models (i.e. logit and probit) require the analyst to accurately characterize consumers' beliefs about their options to establish econometric consistency (Train 2009). This requirement is usually addressed by collecting objective measures of product attributes and then assuming they coincide with consumer beliefs; i.e. by assuming people are fully informed (e.g. Ackerberg et al. 2007, Train 2009, Kuminoff, Smith and Timmins 2013).

For the subset of consumers making suspect choices, we calibrate their preference relations using proxy measures derived from the behavior of observationally similar consumers who we observe making nonsuspect choices as proposed by Bernheim and Rangel (2009). [11] While the nonsuspect (n) and suspect (s) groups have different beliefs about plan attributes, we assume that they maximize utility functions characterized by the same underlying preference parameters.[12]

[10] Partially latent heterogeneity in beliefs is an example of what Bernheim and Rangel refer to as "ancillary conditions" on decision making.

[11] While we follow Bernheim and Rangel (2009) in these two notable ways, we adopt a different approach to assessing the expected change in consumer welfare from policies that alter choice architecture. Likewise in our implementation, we rely on revealed preferences from others, whereas Bernheim and Rangel's proposal may also rely on within-person proxies from ancillary conditions in which choices are believed to be more likely preference revealing. We explore these between versus within-person aspects further in the robustness section.

[12] This approach has precedence in Geweke and Keane () and Keane and Wasi (2013).

(5) $U_{ijt}^{n} = \alpha c_{ijt} + \beta \sigma_{ijt}^{2} + \gamma q_{jt} + \eta \Delta B_{ijt} + \delta \Delta P_{ijt} + \epsilon_{ijt}$.

(6) $U_{ijt}^{s} = \alpha \acute{c}_{ijt} + \beta \acute{\sigma}_{ijt}^{2} + \gamma \acute{q}_{ijt} + \eta \Delta \acute{B}_{ijt} + \delta \Delta \acute{P}_{ijt} + \epsilon_{ijt}$.

We dropped the accents in (5) to indicate that we are using objective measures of plan attributes for the nonsuspect group. Their expected PDP costs are defined as $c_{ijt} = p_{jt} + E[oop_{ijt}]$, their type-specific variance is defined as $\sigma_{ijt}^{2} = var(oop_{ijt})$, and q_{jt} is a vector containing the CMS quality index and brand dummy variables. All variables are calculated using the techniques developed in prior studies of PDP choice as described in III.A.

Because we do not observe the beliefs of people making suspect choices, we cannot identify their preferences from their observed behavior: if we replace the subjective beliefs in (6) with objective measures of plan attributes then, in general, we must also allow the values of the preference parameters and the error term to change in order to maintain the same utility ranking of plans,

(7) $U_{ijt}^{s} = \acute{\alpha} c_{ijt} + \acute{\beta} \sigma_{ijt}^{2} + \acute{\gamma} q_{ijt} + \acute{\eta} \Delta B_{ijt} + \acute{\delta} \Delta P_{ijt} + \acute{\epsilon}_{ijt}$.

Intuitively, if people make suspect choices because they have downward biased expectations about their OOP costs at the time they choose a plan (i.e. $c_{ijt} > \acute{c}_{ijt}$) then we would expect $\alpha < \acute{\alpha}$. If they answer the MCBS knowledge question incorrectly because they mistakenly believe that their PDP choice will have no effect on their out of pocket costs, then we would expect $\beta < \acute{\beta}$. Likewise, if they have downward biased beliefs about their potential savings from switching plans, then we would expect $\eta < \acute{\eta}$ and $\delta < \acute{\delta}$. Quantifying these differences is essential to evaluate the potential welfare gains of information-based policies and other potential modifications to choice architecture.

To facilitate estimation we make the standard assumption that the idiosyncratic person-plan specific taste shocks in (5) and (7) are *iid* draws from type I extreme value distributions. However, notice the variance may differ between the suspect and nonsuspect groups. This is because the idiosyncratic shocks in (7) will absorb any residual utility differences needed to maintain the preference ordering over plans when we move from (6) to (7). Therefore, when we follow the standard approach to normalizing the error variance to equal $\pi^2/6$, the coefficients estimated for the suspect group will be scaled by the ratio of the group-specific variances (Train 2009). After making this normalization, we can rewrite the estimating equation for the suspect groups as

(8) $U_{ijt}^{s} = \alpha^{s} c_{ijt} + \beta^{s} \sigma_{ijt}^{2} + \gamma^{s} q_{ijt} + \eta^{s} \Delta B_{ijt} + \delta^{s} \Delta P_{ijt} + \epsilon_{ijt}$,

where $\alpha^{s} = \acute{\alpha}\sqrt{var(\epsilon_{ijt})/var(\acute{\epsilon}_{ijt})}$ and similarly for β^{s}, γ^{s}, η^{s}, and δ^{s}. Our econometric model is designed to identify the parameters of (5) and (8).

D. Identification

Equations (3)-(4) illustrate how the model parameters can be identified from data on suspect and nonsuspect enrollment decisions. In practice, we pool the data from initial and subsequent enrollment decisions and estimate the parameters simultaneously using the specification in (5) for nonsuspect choices and separately using the specification in (8) for suspect choices. Conditional on the assumed parametric form for utility and the distributional assumption on ϵ_{ijt}, a multinomial logit model of all nonsuspect enrollment decisions identifies the parameters defining marginal rates of substitution between cost, variance, and quality, α, β, γ . The switching parameters, η and δ, can be identified by the rates at which individuals making nonsuspect choices actively switched out of the plans they initially chose in a model of their subsequent enrollment decisions (4). The same arguments can be made to identify the parameters of (8) for the suspect group. Our ability to differentiate the decision making processes behind suspect and nonsuspect choices is critical to assessing who would win and who would lose from prospective policies designed to simplify choice architecture.

E. Three Potential Indicators of Suspect Choices

We follow the prior literature on Part D by assuming that consumer i's utility from drug plan *j* depends on the mean and variance of her potential expenditures under that plan during year *t*. Expenditures are defined by the plan premium, p_{jt}, plus the OOP costs, $oop_{jt}(x_i t)$, of an exogenously given vector of drug quantities, x_{it}. In the primary results we follow prior literature and assume that the relevant vector of drug quantities is determined *ex post*, that is, the set of drugs actually consumed after the plan was chosen. In the robustness section we adopt the other extreme and assume that consumers only know their drug consumption in the year preceding their PDP enrollment decision. Utility may also depend on measures of plan quality, q_{ijt}, that reflect the time and effort required for an individual to obtain her eligible benefits under the plan. Examples include customer service, access to preferred pharmacy networks, and the ease of obtaining drugs by mail order.

Our first indicator of suspect choices is derived by applying Ketcham, Kuminoff, and Powers' (2015) nonparametric test for whether consumers making active enrollment decisions are choosing plans that cannot be rationalized as maximizing a well behaved utility function under full information. To simplify notation we denote total costs as $c_{ijt} = p_{jt} + oop_{ijt}$. We assume that consumers are risk averse and have preference orderings that are complete, transitive, and strongly monotonic over expected cost savings, risk reduction, and quality.[13] Under this assumption, a fully informed utility maximizing consumer will never choose a plan, *j*, that is dominated by another, *k*, in the sense that the following four conditions hold simultaneously.

$(1.a)\ E(c_{ikt}) \leq E(c_{ijt})$.

$(1.b)\ var(c_{ikt}) \leq var(c_{ijt})$.

$(1.c)\ q_{ijt} \leq q_{ikt}$.

$(1.d)\ At\ least\ one\ of\ the\ inequalities\ is\ strict.$

In words, a fully informed utility maximizing consumer will never choose a plan that has higher costs, higher variance, and lower quality than some feasible alternative. We refer

[13] Completeness says that consumers can compare any two plans. Transitivity says that if plan A is preferred to plan B, and plan B is preferred to plan C, then plan A must be preferred to plan C. Strong monotonicity says that, all else constant, consumers prefer plans with more of any positive attribute.

to active plan choices that satisfy (1.a)-(1.d) as being *dominated*. In theory, a consumer may choose a dominated plan if she is risk loving, if she dislikes quality, if she has a negative marginal utility of income, or if she is not fully informed about her options. We believe that incomplete information is the most plausible of these four explanations. Hence, if we observe a consumer choosing a dominated plan we label that choice as suspect, in the sense that we as researchers suspect that the consumers' choice may not reveal her preferences. In particular, such choices suggest that the consumer was not fully informed, so that a standard econometric model of PDP choice that uses the same objective measures of plan attributes as our nonparametric test will not reveal to us her preferences for product attributes.

On the other hand, consumers who violate at least one of the four conditions are necessarily choosing plans on what Lancaster (1966) dubbed the "efficiency frontier" in attribute space. Every plan on an individual's efficiency frontier can be rationalized as maximizing some utility function that satisfies completeness, transitivity, strong monotonicity, and risk aversion under the assumption of full information. For example, a fully informed risk averse consumer may maximize utility by choosing a more expensive and lower quality plan that better insures against negative health shocks. We define such choices as being nonsuspect because they provide no evidence to suggest the consumer is uninformed.

To test whether enrollees chose dominated plans we define PDP cost, variance, and quality using techniques developed in the prior literature on modeling PDP choice (Abaluck and Gruber 2011, Ketcham, Kuminoff, and Powers 2015). First we assume that fully informed utility-maximizing consumers will have unbiased expectations of their own drug needs for the upcoming year: $E(c_{ijt}) = c_{ijt}$.[14] Then we use the cost calculator to define c_{ijt} for every available plan based on consumer *i*'s actual drug claims in year *t*.

Measuring $var(c_{ijt})$ is complicated by the fact that we only observe consumer *i* under one realization from her distribution of possible health states in year *t*. We address this

[14] Our results are robust to assuming consumers are myopic: $E(c_{ijt}) = c_{ijt-1}$. This is unsurprising since individual prescription drug use is highly correlated over time.

challenge by approximating $var(c_{ijt})$ with the distribution of expenditures that would have been made under plan *j* in year *t* by the set of individuals who looked similar to consumer *i* in year *t-1* in terms of prescription drug claims. More precisely, we use CMS's random 20% sample of all PDP enrollees to assign each individual in the MCBS sample to 1 of 1000 cells defined by the deciles to which they belonged in the national distributions of the prior year's total drug spending, the prior year's total days' supply of branded drugs, and their prior year's days' supply of generic drugs. Then we calculate $var(c_{ijt})$ for the distribution of drugs consumed by everyone in consumer *i*'s cell and PDP region.

Put differently, the values in Table 2 row 1 imply that 78% to 85% of consumers' PDP choices can be rationalized as maximizing some utility function satisfying risk aversion, completeness, transitivity, and strong monotonicity under our assumptions about how to measure mean and variance of cost. In the absence of any further information about these choices, the default assumption of consumer sovereignty would lead us to label all of them as *nonsuspect.* This approach has the potential for type II error, as enrollees with incomplete information could have chosen undominated plans. We account for this possibility by developing two additional suspect choice indicators.

Consumers may also have heterogeneous preferences over PDP quality. For example, plans differ in their pharmacy networks, customer service, ease of obtaining drugs by mail order, and various aspects of formulary coverage not captured by mean and variance of ex post costs, such as the prevalence of prior authorization (PA) requirements. PA requirements for certain drugs may be unattractive to consumers who believe they have a high likelihood of purchasing those drugs and irrelevant to consumers who do not. Likewise, consumers differ in their proximity to in-network pharmacies. These factors vary across insurance brands and consumers but not across plans within a brand. Therefore we use brand dummy variables as a proxy measure of horizontally differentiated quality, in addition to a vertical index of average plan quality developed by CMS.[15] For a chosen plan to be dominated the enrollee must have been able to choose another plan offered by

[15] A 2006 MedPac survey asked beneficiaries about the factors affecting their initial choice of PDP. 90% of respondents stated that company reputation was "important" or "very important" to their choice and 84% gave the having a preferred pharmacy in the plan's network (84%)

the same insurer that would have lowered both the mean and variance of their drug expenditures. The first row of Table 2 shows that between 15% and 22% of consumers chose dominated plans each year.

TABLE 2—SUSPECT CHOICE INDICATORS, BY YEAR

		Percent of enrollees					
		2006	2007	2008	2009	2010	2006-2010
(1)	choosing a dominated plan	18	22	18	15	16	17
(2)	fail to answer knowledge question correctly	41	29	31	28	28	30
(3)	(potential savings / total spending) ≥ 0.5	23	12	11	11	9	11
(4)	union of rows (1)-(2)	51	45	43	38	39	42
(5)	union of rows (1)-(3)	59	51	50	45	45	48

Note: The table reports the share of choices triggering each suspect choice indicator, by year. The MCBS knowledge question asks whether the enrollee's out of pocket costs are the same under every available drug plan. The correct answer is coded as yes for enrollees who filed drug claims in both the prior and current years if their out of pocket costs did in fact vary across plans in both years. Row 4 reports the share of enrollees satisfying the criteria in either of the first two rows. Row 5 reports the share of enrollees satisfying the criteria in any of the first three rows. See the text for additional details.

Our second suspect choice indicator comes from a question on the MCBS that is designed to test enrollees' knowledge of the Part D program. Participants are asked to state whether the following sentence is true or false. *Your OOP costs are the same in all Medicare prescription drug plans*. For people with no drug claims, the statement is true. For virtually all people with drug claims the statement is false due to variation in formularies, deductibles, negotiated drug prices and other plan design attributes. This variation is economically important. The average beneficiary's OOP costs for her chosen bundle of drugs vary by over $1,100 across the plans available to her. Misunderstanding this crucial feature of the market could cause enrollees to spend far more than they would have if they were fully informed.[16]

[16] The MCBS asks five other questions that test knowledge of Part D, but we suspect that they are less critical to understanding the market. They are (correct answer in parentheses): "All Medicare prescription drug plans cover the same list of prescription drugs" (false); "Everyone in Medicare has at least two Medicare prescription drug plans to choose from" (true); "Everyone with Medicare can choose to enroll in the voluntary Medicare prescription drug coverage regardless of their income or health "(true); "Medicare prescription drug plans can change the price of prescription drugs only once per year"(false); "Generally, once you join a Medicare prescription drug plan, you can only change to another plan during the 'Open Enrollment period' each year" (true); "If you have limited income and resources, you may get extra help to cover prescription drugs for little or no cost to you"(true). Howell, Wolff and Herring (2012) provide further analysis of the MCBS knowledge questions.

We use each person's actual drug claims to determine the correct answer to the MCBS question. Because respondents may be unsure about which enrollment year the question is referring to, we code a person's answer for year *t* as correct if the answer they gave in that year is correct for either year *t* or year *t-1*. Row 2 of Table 2 shows that a substantial share of respondents gave the wrong answer—41% in the first year of the program and between 28% and 31% in each subsequent year. The reduction over time is consistent with prior evidence on learning in the early years of the program (Ketcham, Lucarelli, and Powers 2015, Ketcham, Lucarelli, Miravete and Roebuck 2012).

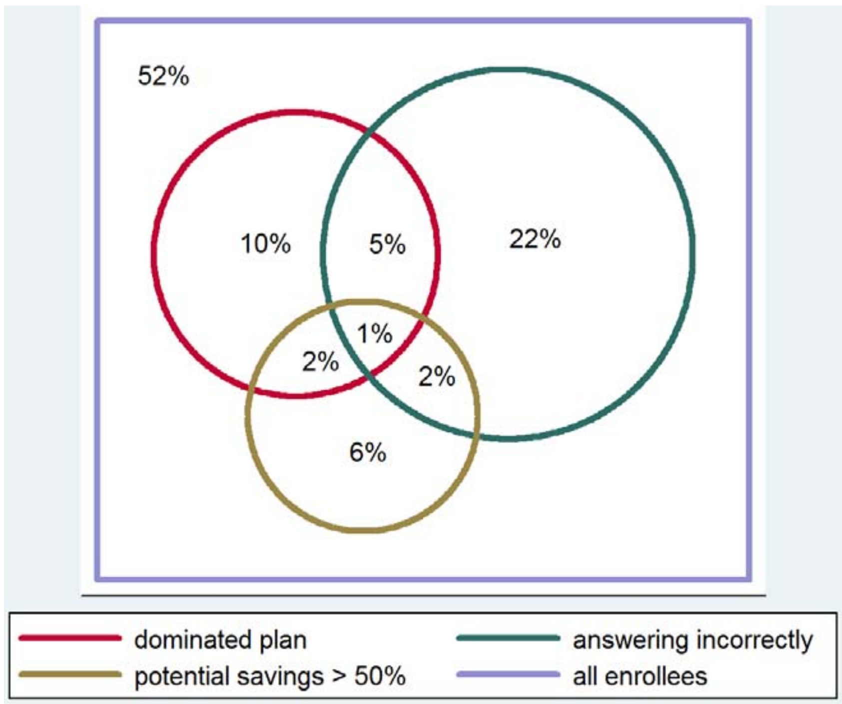
Our final candidate indicator of incomplete information is based on having relatively large potential savings. All else constant, people who could have reduced their expenditures by more than 50%, for example, may be less likely to have fully understood their options before they made their enrollment decisions. Row 3 shows that 23% of all enrollees were in this category in the first year of the program. The share declined to 12% the following year and to 9% by 2010. In contrast with the other two theory-based indicators, this indicator is based on an ad hoc judgment about what constitutes reasonable tradeoffs between cost, variance, and quality.

The Venn diagram in Figure 1 illustrates how the three indicators relate to each other. Their union comprises 48% of all enrollment decisions, but only 1% of decisions are in the intersection. Hence, each of the three measures provides distinct information about the choice process and its financial implications. The MCBS knowledge question appears to be particularly informative. Twenty-two percent of people in our sample gave the wrong answer but did not choose a dominated plan or have extreme potential savings. The average person in this group could have saved 12% more by switching to a different plan than the average person who answered the knowledge question correctly. Our main policy analysis focuses on the union of the first two indicators—dominated plan choices and incorrect answers to the MCBS knowledge question—due to their basis in data and theory. This group includes 42% of all enrollment decisions.[17] Given the potential limita-

[17] We analyze the robustness of our main results to defining suspect choices by the union of the first two measures and potential savings thresholds of 50% and 25%. This has little effect on our main results because the share of consumers who are reclassified from nonsuspect to suspect is small, as can be seen from Figure 1.

tions of survey data (e.g. as noted by Handel and Kolstad (2015) for similar types of questions), our ability to complement them with theoretically-grounded measures based on choice outcomes is a strength of our work. Below we consider how the key results differ across these different approaches to identifying suspect choices.

FIGURE 1: RELATIONSHIPS BETWEEN SUSPECT CHOICE INDICATORS



Note: The Venn diagram is drawn to scale. It shows the share of enrollees who have every possible combination of suspect choice indicators. “Answering incorrectly” refers to giving the wrong answer to the MCBS knowledge question for Part D. See the text for additional details.

F. Refining Our Suspect Choice Indicator for Dynamics

Similar to Chetty et al. (2015) and Handel and Kolstad (2015) we refine our suspect choice indicators to distinguish between active and passive choice processes and to explicitly recognize that people incur hassle costs from searching for information and switching insurance plans. The reason is that the disutility of switching plans creates some ambiguity in our coding of choices as suspect or nonsuspect. To see this, consider person A in Table 3. We observe her enrollment decision in 2006 but she first enters the MCBS in 2007. Because she was not surveyed in 2006 we lack the full information needed to code her choice as suspect or nonsuspect in that year. After entering the MCBS she answers the knowledge question correctly in 2007 and 2008 but stays in the same plan she chose in 2006 even though it is dominated by a lower-cost plan that her insurer introduced in 2007. One explanation is that she is unaware of the new plan. An observationally equivalent explanation is that she is fully informed but her utility cost of switching, $\delta\Delta P_{ijt}$, exceeds the benefits. Because we cannot distinguish between these hypotheses without making further assumptions we drop the two observations.

TABLE 3—EXAMPLES OF DYNAMICS IN CODING CHOICES AS SUSPECT OR NONSUSPECT

	Enrollment year, consumer A					Enrollment year, consumer B				
	2006	2007	2008	2009	2010	2006	2007	2008	2009	2010
Active (a) or passive (p)	a	p	p	a	p	a	p	p	a	p
Fail to give right answer on MCBS = 1	.	0	0	0	0	0	0	1	1	.
Chose a dominated plan = 1	0	1	1	0	0	0	1	1	1	0
Suspect (s) or non-suspect (ns)	.	.	.	ns	ns	ns	ns	s	s	.

Note: The table uses two consumers to show how we classify active and passive enrollment decisions as being suspect or nonsuspect. See the text for additional details.

The potential utility cost of switching plans also led us to code some dominated plan choices as being nonsuspect. Person B provides an example. We code her passive choice of a newly dominated plan in 2007 as nonsuspect, deferring to the evidence from her active decision in 2006. In contrast to person A, we see that person B answered the MCBS knowledge question correctly in 2006. Hence in the presence of switching costs her passive choice in 2007 is consistent with maximizing some utility function satisfying risk aversion, completeness, transitivity, and monotonicity under the assumption of full information. One potential worry is that this approach will cause us to confuse switching costs with inertia resulting from incomplete information. We address this concern by reporting results from an alternative set of welfare calculations that interpret $\hat{\eta}$ and $\hat{\delta}$ even for those making nonsuspect choices as reflecting inertia due to incomplete information rather that the disutility of switching plans. These results are included in our robustness checks below.

G. Who is More Likely to Make Suspect Choices?

To develop intuition for the potential mechanisms driving the probability of making a suspect choice, we estimate linear probability models in which the dependent variable, S_{it}, is an indicator for whether person *i* in CMS region *r* chose a dominated plan and/or answered the MCBS knowledge question incorrectly in the year *t* enrollment cycle,

(2) $S_{irt} = \kappa + \lambda d_{irt} + \phi_r + \rho_t + e_{it}$.

On the right of the equality d_{irt} is a vector of demographics defined from the variables in Table 1, some of which change over time, and ρ_t and ϕ_r are vectors of fixed effects for years and CMS regions. The fixed effects capture variation in the complexity of choice architecture across space and time. For example, in the first year of the program the number of plans per region ranged from 27 to 52. The number of available plans also changed over time, increasing noticeably between 2006 and 2007. This variation allows us to test the choice overload hypothesis that consumers are less likely to make informed decisions as the number of options grows.

The first column of Table 4 reports results for our full sample of 14,278 enrollment decisions. The omitted demographic indicators define the reference enrollee as a 65 to 69 year old unmarried and retired white male with no high school diploma. The estimated coefficients imply that obtaining a high school degree is associated with a 3.5 percentage point reduction in the probability of making a suspect choice and this differential increases to 8.1 percentage points for enrollees with a college degree. We also see lower probabilities for enrollees who have experience using the internet (-2.4 percentage points), who report using websites to learn about Medicare programs (-6.1percentage points), and who reporting called 1-800-Medicare for information (-6.0 percentage points). The last result is consistent with Kling et al.'s (2012) secret shopper audit of the Medicare help line in which actors calling the number for information found that customer service representatives consistently identified low-cost plans based on the actors' fictional drug needs.

Looking at the administrative variables, we see the probability of making a suspect choice increasing in age, consistent with prior evidence on the decline in cognitive performance for individuals over 65 (Agarwal et al. 2009, Tymula et al. 2013). The predicted probability is approximately 5 percentage points higher for enrollees in their late 70's and approximately 11 percentage points higher for enrollees in their late 80's. This is after controlling separately the positive effects of diagnosed cognitive illnesses normally associated with aging, namely dementia (+4.9 percentage points) and depression (+3.3 percentage points) and on the increased complexity of decision making associated with greater drug needs through the total number of drug claims and total drug spending.[18]

In comparison we find that income, gender, race, marital status, and the existence of children have small and statistically insignificant effects. We also obtain a precisely estimated zero on the number of available plans. Because the OLS model includes fixed effects for years and regions, the coefficient on the number of plans is identified by the within-region changes over time in the number of available plans. The estimated coefficient provides evidence against the hypothesis that choice overload causes suspect choices.

[18] One standard deviation increases in drug claims and total spending increase the predicted probability of making suspect choices by 5.2% and 4.3% respectively.

TABLE 4—ASSOCIATION BETWEEN SUSPECT CHOICES AND DEMOGRAPHICS

	Dominated plan choice or fail to give right answer to knowledge question					
	all choices		active choices		passive choices	
Constant	0.460	[0.126]***	0.592	[0.198]***	0.343	[0.224]
Medicare Beneficiary Survey variables						
High school graduate	-0.035	[0.015]**	-0.009	[0.019]	-0.051	[0.019]***
College graduate	-0.046	[0.014]***	-0.054	[0.019]***	-0.041	[0.017]**
Income>$25k	-0.016	[0.013]	-0.010	[0.017]	-0.021	[0.015]
Currently working	0.027	[0.017]	-0.002	[0.022]	0.041	[0.020]**
Married	-0.009	[0.013]	-0.009	[0.017]	-0.007	[0.016]
Has living children	-0.011	[0.022]	-0.008	[0.028]	-0.016	[0.026]
Uses the internet	-0.024	[0.014]*	-0.020	[0.018]	-0.027	[0.017]
Has visited website for Medicare info	-0.061	[0.014]***	-0.062	[0.018]***	-0.057	[0.017]***
Has called 1-800-Medicare for info	-0.060	[0.012]***	-0.039	[0.018]**	-0.075	[0.015]***
Administrative variables						
Number of available plans	-0.001	[0.003]	-0.005	[0.005]	0.002	[0.004]
Female	0.011	[0.012]	0.009	[0.016]	0.014	[0.015]
Nonwhite	0.031	[0.024]	0.045	[0.030]	0.022	[0.030]
Age: 70-74	0.013	[0.015]	0.011	[0.020]	-0.001	[0.020]
Age: 75-79	0.049	[0.017]***	0.031	[0.022]	0.044	[0.022]**
Age: 80-84	0.053	[0.018]***	0.059	[0.024]**	0.035	[0.023]
Age: over 84	0.112	[0.019]***	0.111	[0.025]***	0.098	[0.025]***
Alzheimer's or dementia	0.047	[0.019]**	0.046	[0.027]*	0.048	[0.023]**
Depression	0.033	[0.017]**	0.015	[0.024]	0.046	[0.021]**
Total spending / $1000	0.005	[0.002]***	0.005	[0.002]***	0.006	[0.002]***
Number of drug claims	0.002	[0.000]***	0.002	[0.000]***	0.002	[0.000]***
Number of plan choices	14,278		5,129		9,149	
Number of enrollees	5,233		3,938		4,259	
Mean of the dependent variable	0.42		0.41		0.42	
R-squared	0.07		0.09		0.07	

Note: The three columns report coefficients and standard errors estimated from linear probability models of suspect choices. The omitted dummy variable categories define the baseline enrollee as a 65 to 69 year old white male. The dependent variable is an indicator that equals one if his plan choice violates basic axioms of consumer preference theory or if he incorrectly stated that his out of pocket costs would be the same in every available plan. Active choices are defined as those in which there is no assigned default plan or the enrollee chooses to switch out of his default plan. Passive choices are defined as those in which the enrollee chooses to remain in his default plan. All regressions include fixed effects for enrollment year (2006-2010) and enrollment region, and use robust standard errors clustered by enrollee. *,**, and *** indicate that the p-value is less than 0.1, 0.05, and 0.01 respectively.

The last two columns of Table 4 show results from repeating the estimation after dividing enrollment decisions into active and passive choices. Similar to Chetty et al.

(2015) we define a choice as *active* if one of the following statements is true: (1) it is the person's initial enrollment decision, (2) the plan the person selected the prior year was eliminated, or (3) the person switched to a new plan during open enrollment. If none of these statements is true, the enrollee took no action during open enrollment and was therefore assigned to the same plan she chose last year—her default plan—in which case we code her choice as being *passive*. Taking no action during open enrollment does not imply that a "passive" enrollee is inattentive. She may have carefully considered her options and decided that her default plan was still her best available option. On the other hand, an inattentive consumer would be more likely to passively stay in her default plan when it becomes dominated due to changes in her drug needs or changes in the set of available plans. Likewise, an inattentive consumer would be less likely to learn that her out of pocket costs vary across plans.[19]

The results show that active and passive choices essentially mirror those of the pooled sample. The baseline probability of making a suspect choice is only one percentage point higher for passive decisions (42% versus 41%). The most striking difference in the demographic coefficients is that enrollees who are currently employed are 4% more likely to make passive suspect choices but no more likely to make active suspect choices.

Overall, the linear probability models suggest that the probability of making a suspect choice declines as education increases and as people exert effort to learn about the market using the internet or 1-800-Medicare. The probability increases as people age, as they are diagnosed with cognitive illnesses, and as their drug spending increases. These results are consistent with the hypothesis that information is costly to acquire (Stigler and Becker 1977) and that decision making costs vary systematically with age and human capital (Agarwal et al. 2009, Tymula et al. 2013). Conditional variation in race, gender, the number of choices, and active versus passive choices appears to be less important.

As a final consideration we evaluate the relationship between use of proxy decision makers and our suspect choice measures. Specifically we capitalize on the MCBS infor-

[19] Under the joint hypothesis that some consumers are inattentive and that inattentive consumers are more likely to make passive choices, we would expect the baseline probability of making a suspect choice to be higher for passive enrollment decisions. We would also expect proxy measures for human capital, cognitive functioning, and effort to obtain information to play a more important role in determining whether active enrollment decisions yield suspect choices.

mation about who answered the knowledge questions, the beneficiary or a proxy, and who makes health insurance choices. The first two columns of Table A3 show the percent and attributes of people who answered the MCBS themselves versus had a proxy respondent. The results show that those who had proxies answer the MCBS were less educated, less internet use, were older, more likely to be married and male and substantially more likely to have Alzheimer's or dementia. Similar patterns appear with respect to who makes health insurance choices, as evident in the last three columns. Interestingly, those who receive help are more likely to make suspect choices—they are less likely to provide the correct answer to the knowledge question, more likely to choose a dominated plan, and have higher potential savings. Overall, the sample includes 8,659 choices from people who answered the MCBS themselves, hence stating their own knowledge about the PDP market, and stated that they make health insurance choices on their own. Below repeat our analysis on this subsample to determine how our ability to identify the decision makers and their knowledge affects our key results.

IV. Welfare Effects of Modifying Choice Architecture

When some decision makers are not fully informed, reforms that modify choice architecture by reducing information costs and/or simplifying the choice process can, in principle, increase some consumers' welfare. Consider a policy implemented between periods 0 and 1 that changes the set of available plans from J to K. Consumer welfare may be directly affected through three channels. First, the policy may change the menu of options by adding choices, removing choices, and adjusting their costs or quality. Second, the policy may change how consumers or firms make decisions, e.g. by lowering the cost of information in a way that reduces the disutility of switching plans. Finally, if the policy induces consumers and firms to adjust their behavior then those adjustments may feed back into the levels of endogenous attributes (e.g. premiums) through the equilibrium sorting process.

The expected change in welfare for people in the nonsuspect group can be derived by integrating over ϵ_{ijt} in the standard expression for compensating variation to generate the log sum ratio from Small and Rosen (1981).

$$(9)\ \Delta E[CV_i^n] = \frac{1}{\alpha}\left\{ln\frac{\sum_{k\in K}[exp(V_{ik}^{n1})]}{\sum_{j\in J}\left[exp\left(V_{ij}^{n0}\right)\right]}\right\},$$

where V_{ij}^{n0} and V_{ik}^{n1} denote the observed part of the utility function in (5) evaluated for PDPs j and k before and after the policy. The temporal subscript is suppressed for brevity such that $V_{ij}^{n0} = V_{ijt}^{n0}(\theta) = U_{ijt}^{n0} - \epsilon_{ijt}$, where $\theta = [\alpha, \beta, \gamma, \eta, \delta]$.

Welfare calculation is more involved for those making suspect choices. The observed part of (8) determines how PDP attributes affect their enrollment decisions, but their ex post realized utility from those decisions is determined by (5). This follows from our assumption that the suspect and nonsuspect groups share the same underlying preference parameters. Therefore, a single plan's contribution to expected utility is defined by integrating over the product of (5) and the probability of choosing that plan based on (8). Aggregating over the PDP menu prior to the policy yields the following general expression

$$(10)\ E[U_i^{s0}] = \sum_{j\in J}\int_{-\infty}^{\infty}\left(V_{ij}^{n0} + \epsilon_{ij}\right)F_j\left(V_{ij}^{s0} - V_{i1}^{s0} + \epsilon_{ij}, \dots, V_{ij}^{s0} - V_{iK}^{s0} + \epsilon_{ij}\right)d\epsilon_{ij},$$

where $F_j(\cdot)$ is the derivative of the joint CDF of the idiosyncratic taste shocks with respect to ϵ_{ij}. Subtracting this expression from the post-policy measure of expected utility, dividing by the marginal utility of income, and integrating over the idiosyncratic taste shocks yields the expression for welfare derived by Leggett (2002).

$$(11)\ \Delta E[CV_i^s] = \frac{1}{\alpha}\left\{ln\frac{\sum_{k\in K}[exp(V_{ik}^{s1})]}{\sum_{j\in J}\left[exp\left(V_{ij}^{s0}\right)\right]} + \sum_{k\in K}\left[\psi_{ik}^{s1}\left(V_{ik}^{n1} - V_{ik}^{s1}\right)\right] - \sum_{j\in J}\left[\psi_{ij}^{s0}\left(V_{ij}^{n0} - V_{ij}^{s0}\right)\right]\right\},$$

where $V_{ij}^{s0} = V_{ijt}^{s0}(\theta^s) = U_{ijt}^{s0} - \epsilon_{ijt}$, $\theta^s = [\alpha^s, \beta^s, \gamma^s, \eta^s, \delta^s]$, and ψ_{ij} is the logit probability of choosing plan j so that $\psi_{ij}^{s0} = exp\left(V_{ij}^{s0}\right)/\sum_{m\in J}[exp(V_{im}^{s0})]$.

The first term inside braces in (11) is the standard log sum ratio evaluated at θ^s. It provides a biased measure of welfare when $\theta^s \neq \theta$ because suspect choices are based on incomplete information. The second and third terms adjust the log sum ratio to account for the welfare implications of the difference between θ^s and θ for each choice, weighted by the predicted probability of making that choice before and after the policy. In the special case where $\theta^s = \theta$, equation (11) reduces to the standard welfare measure in (9).

The conceptual logic underlying (11) is not new. In the presence of costly information, in principle some people are less than fully informed in ways that create potential welfare gains from modifying choice architecture (Stigler and Becker 1977). More recently, Leggett (2002), Bernheim and Rangel (2009), Fleurbaey and Schokkaert (2013) and others have considered theoretical approaches to assessing welfare when consumer choices cannot be uniformly interpreted as revealing preferences. In fact, equation (11) implements Bernheim and Rangel's proposal to use preference relations estimated from nonsuspect choices as proxies for people making suspect choices.[20]

To the best of our knowledge, our study is the first to use (11) to evaluate the welfare effects of prospective policies in a way that draws on national evidence from surveys and observed behavior to identify which consumers appear to be uninformed.[21] Moreover, our broader welfare framework defined by (9) and (11) recognizes that modification to choice architecture may simultaneously create winners and losers. For example, consider the partial equilibrium welfare effects of a policy that eliminates a single high-cost plan. That is, apart from the equilibrium sorting effects, nobody can be made better off from such a policy under the conventional assumption that everyone is fully informed. At the opposite extreme, nobody can be made worse off when the policy is imposed by a government that

[20] Alternatively, to use the language popularized by Kahnemann, Wakker, and Sarin (1997), one can think of $V_{ij}^{n}(\theta)$ as an approximation to the "hedonic utility" derived by consuming a good and $V_{ij}^{s}(\theta^s)$ as an approximation to the "decision utility" function that is maximized by people who are less than fully informed about their choices.

[21] Perhaps the closest comparison is to Allcott and Taubinsky's (2015) recent field experiment in which shoppers in a single hardware store were randomized to different information treatments regarding the energy efficiency of certain types of light bulbs. They used the results to implement a version of Bernheim and Rangel's (2009) logic to evaluate welfare effects of EPA's restrictions on energy inefficient bulbs.

is assumed to be benevolent and fully informed about consumer preferences. Our approach allows for a middle ground between these extremes. The calculation in (9) maintains that fully informed consumers cannot be made better off from restrictions on their ability to choose for themselves. Equation (11) recognizes that consumers who are not fully informed may benefit from elimination of a high cost plan if they are more likely to choose that plan than consumers with similar same drug needs who appear to be informed. Furthermore, aggregating the gains and losses over informed and uninformed consumers yields a criterion for policy evaluation consistent with the concept of asymmetric paternalism proposed by Camerer et al. (2003).

Equations (9) and (11) also highlight the information needed to calibrate the model and evaluate a prospective policy. First we must estimate the parameters describing how suspect and nonsuspect choice probabilities vary with plan attributes, θ and θ^s, in order to calibrate ψ_{ij}^{s0}, V_{ij}^{n0}, and V_{ij}^{s0}. Then we must map each prospective policy into the parameters and endogenous plan attributes in order to calibrate ψ_{ij}^{s1}, V_{ij}^{n1}, and V_{ij}^{s1}.

VI. Calibrating the Model

This section summarizes our general approach to calibration. Part A summarizes our results from multinomial logit models of suspect and nonsuspect choices; Part B explains how we allow plan premiums to adjust to sorting behavior; and Part C discusses how we calculate insurer revenue and government expenditures. Additional calibration details specific to each policy are discussed in the next section.

A. Multinomial Logit Estimation

Our main estimates for θ and θ^s are based on multinomial logit models of enrollment decisions made between 2007 and 2010. We drop 2006 because that was the first year of Part D, making it less representative and less relevant for evaluating prospective policies. Tables 1 and 2 show that in 2006 consumers had higher OOP costs, higher potential savings, and were more likely to answer the MCBS knowledge question incorrectly. All three observations are consistent with consumers learning and adapting to the new market during the inaugural enrollment cycle. Dropping the 810 enrollment decisions in 2006 reduces our sample size from 14,278 to 13,468, while dropping decisions that we could not confidently categorize as suspect or nonsuspect reduces our final estimation sample to 11,608 enrollment decisions made by 3,937 people.

TABLE 5—LOGIT DECISION UTILITY MODELS OF PRESCRIPTION DRUG PLAN CHOICE

	All choices	Non-suspect choices	Suspect choices
Plan characteristics			
expected cost	-0.254***	-0.403***	-0.127***
	(0.009)	(0.016)	(0.009)
variance	-0.039	-1.760***	1.746***
	(0.125)	(0.203)	(0.227)
CMS quality index	0.911***	0.755***	1.025***
	(0.049)	(0.066)	(0.075)
Switching indicators			
different plan, same brand	-3.498***	-3.461***	-3.603***
	(0.063)	(0.085)	(0.099)
different brand	-5.274***	-5.325***	-5.424***
	(0.052)	(0.070)	(0.082)
pseudo R^2	0.62	0.63	0.63
number of plan choices	11,608	6,804	4,804
number of enrollees	3,937	2,532	1,758

Note: The table reports parameter estimates from decision utility functions estimated from data on all choices; from nonsuspect choices only; and from suspect choices only. See the text for the definition of suspect choices. All models include brand fixed effects and are estimated using choices made between 2007 and 2010. Standard errors are clustered by enrollee. *,**, and *** indicate that the p-value is less than 0.1, 0.05, and 0.01 respectively.

The first column of Table 5 reports our estimates from a logit model that pools all choices. The statistically insignificant coefficient on variance reinforces the findings of Abaluck and Gruber (2011) and Ketcham, Kuminoff and Powers (2015) that simple linear models of PDP choice imply the typical enrollee does not consider risk protection. The next two columns repeat the estimation on subsamples of nonsuspect and suspect choices. Comparing the results across the three columns reveals that the counterintuitive result from the standard pooled model is driven by the suspect choices. Enrollees making nonsuspect choices clearly display risk aversion, and the implied risk premiums are in line with research from other contexts, as shown in Table A4. They also display far greater price sensitivity. The large difference in the implied marginal utility of income between the two groups is also notable. This implies that the switching cost—defined by dividing the switching indicators by the expected cost coefficient—is more than three times as large for suspect choosers as for nonsuspect choosers.

Researchers hold divergent views on the interpretation of such switching cost estimates. Our primary results below rely on the convention of interpreting $\hat{\eta}$ and $\hat{\delta}$ as the disutility of switching plans. Dividing our estimates for those parameters by the marginal utility of income in Table 5 implies that, all else constant, people making nonsuspect choices are willing to pay \$859 to avoid being randomly assigned to a different plan offered by the same insurer and \$1,321 to avoid being randomly assigned to a plan offered by a different insurer. These figures reflect the combined effect of several factors. First, they are a function of individual-specific time-constant deviations from the brand and plan dummy coefficients in our linear approximation for utility and will therefore capture unobserved person-brand and person-brand specific tastes that cause an individual to consistently prefer the same brand and plan. Second, they reflect disutility of the time and effort needed to collect information, initiate a switch, and learn how to navigate a new plan. It seems plausible that the net effect of these factors would be around the levels estimated for nonsuspect choices but unlikely as large as the levels estimated for suspect choices (\$2837 and \$4271 respectively). Our welfare calculation in (11) can be interpreted as treating the differences between $\hat{\eta}$,$\hat{\delta}$ and η^s, δ^s as inertia due to incomplete information on the part of people making suspect choices. This raises the question of whether $\hat{\eta}$ and $\hat{\delta}$ may also reflect some inertia. While we have no direct evidence to suggest this is the case, in our robustness section we explore this possibility because prior studies have interpreted low rates of switching as evidence of limited attention, procrastination, confirmation bias, and status quo bias (e.g. Kling et al. 2012).

B. Validating the model and assumptions

Our solution to the central task of inferring consumer preferences when choices do not reveal them is to assume that they are revealed by other choices in our data. Because our data are a panel, this assumption is imposed between people as well as within-person over time among those who sometimes made suspect choices and sometimes made non-suspect choices. Unobserved heterogeneity between people may explain some of the differences in parameter estimates between suspect and nonsuspect choices, e.g. some differences in the cost parameters are potentially due to differences in the marginal utility of income rather than due to differences in subjective beliefs about plans' costs. Yet we think it less likely for such factors to explain within-person differences in the parameters estimated from years in which they made suspect versus nonsuspect choices. To evaluate this central assumption we reestimate our model separately four times for three groups of people: those who always made suspect choices, those who never made suspect choices, and those who sometimes but not always made suspect choices, estimated separately for the two choice types.[22] The central assumption would be bolstered by results showing that the estimated parameters suspect choices of the "sometimes suspect" consumers are similar to the "always suspect" and likewise for the nonsuspect choices of the "sometimes suspect" and never suspect consumers. The results in Table A6 show this pattern of results.

As a second test we introduce heterogeneity to the models to allow for differences across observed demographics in preferences for mean and variance of cost, for the CMS quality index, and for the status quo brand. The results in Table A7 show few statistically or economically significant differences. This suggests that the differences in the estimates for suspect and nonsuspect choices are unlikely to be due to differences in preferences that correlate with observed attributes. In the robustness section we assess whether our key policy findings change if we use these results instead of the simpler models in Table 5.

As a third test of the validity of the structural choice models in Table 5 we test the in-sample and out-of-sample fit against alternative models as in Keane and Wolpin (2007),

[22] Table A5 shows the demographics of people in the three groups.

Galiani, Murphy, and Pantano (2015) and Ketcham, Kuminoff and Powers (2015). In particular we test whether the models in Table 5 stratified by choice type outperform the pooled model and the model of the other type (suspect or nonsuspect) in making in- and out-of-sample predictions for a given type. As shown in Table A8, the suspect model virtually always outperforms both the pooled model and the nonsuspect model in terms of predicting suspect choices in and out-of-sample, and likewise for the nonsuspect model. This confirms that suspect and non-suspect choices are outcomes of meaningfully different choice processes.

C. Solving for Endogenous Premiums

Firms may choose to adjust plan premiums in response to changes in choice architecture. We allow for this possibility by assuming that firms will correctly anticipate how consumers will adjust their behavior and then reset their premiums to maintain the net revenue per enrollee that they earned prior to the policy. This is equivalent to assuming that CMS would accompany any change in choice architecture with a plan approval and oversight processes that yielded the net revenues observed under the status quo approval and oversight process.

For the baseline equilibrium we define the expected net revenue per enrollee in plan *k* as

$$(12)\ \pi_k^0 = \frac{p_k^0}{.255} - z_k - \frac{1}{N}\sum_i \psi_{ik}^0 (g_{ik} - oop_{ik}).$$

Premiums are divided by 0.255 to reflect the fact that beneficiaries pay on average 24.5% of actual plan premiums, with the remainder subsidized by taxpayers. The second term, z_k, represents the average cost of plan management and operations per enrollee (e.g. customer service) which we assume to be constant over any changes in enrollment induced by policy. The last term is the insurer's expected cost of drugs for the average enrollee; g_{ik} is the total cost of the drugs used by consumer *i* so that $g_{ik} - oop_{ik}$ represents expenditures paid by the insurer.

Equation (13) shows the fixed point problem that we solve to obtain the new vector of premiums,

$$(13)\ \pi_k^1[\psi_{ik}^1(p_k^1), p_k^1] - \pi_k^0 = 0.$$

Because z_k is assumed to be constant it cancels out of the difference in (12). We observe p_k^0, g_{ik}, and oop_{ik} for all person-plan combinations from our data and we use our parameter estimates for suspect and nonsuspect choices to calculate ψ_{ik}^0. All that remains is to solve for p_k^1. The main challenge in doing so is to recognize that choice probabilities change with adjustments to the premium. All else constant, increasing the premium of plan *k* will reduce the probability that people select it. Therefore, we iterate between solving for a vector of premiums to satisfy (13), conditional on ψ_{ik}^1, and updating ψ_{ik}^1 to reflect changes in the vector of premiums. We find that it converges relatively quickly.

D. Changes in Firm Revenue and Government Expenditures

After solving for new vectors of plan premiums and choice probabilities we use the results to calculate changes in insurer revenue and government expenditures. Equation (14) defines the predicted change in insurer revenue per enrollee.

$$(14)\ \Delta\pi = \frac{1}{N}\sum_i \sum_{k\in K} \psi_{ik}^1\, \pi_k^1 - \frac{1}{N}\sum_i \sum_{j\in J} \psi_{ij}^0\, \pi_j^0.$$

While the revenue per enrollee for each plan is held fixed by (13), the overall market revenue per enrollee may change due to changes in the way enrollees sort themselves across the available plans.[23] This allows for the possibility that changes to choice architecture may mitigate or exacerbate adverse selection consistent with Handel (2013). Equation (15) defines the corresponding change in average government spending per enrollee.

$$(15)\ \Delta\tau = \frac{1}{N}\sum_i \sum_{k\in K} \psi_{ik}^1 \left[\frac{p_k^1(1-.255)}{.255}\right] - \frac{1}{N}\sum_i \sum_{j\in J} \psi_{ij}^0 \left[\frac{p_j^0(1-.255)}{.255}\right].$$

[23] This also means that average revenue per enrollee may change for any insurer offering multiple plans.

The term in brackets represents the component of the total plan premium paid by taxpayers.

VII. Evaluating Prospective Policies Designed to Simplify Choice Architecture

A. Menu Restriction

In early 2014, CMS proposed a series of changes to Medicare Part D that included a provision to limit each parent organization to offering only one basic and one enhanced plan in each region (Department of Health and Human Services 2014).[24,25] This would have forced some current enrollees to switch plans. While the proposal was controversial and has yet to be implemented, it provides an opportunity to investigate the heterogeneous welfare effects of a realistic menu restriction.

Our first policy experiment uses the set of enrollees and available plans in 2010—the last year of our enrollment sample—to simulate the welfare effects of the proposed menu restriction. Our data for that year describe 2,922 individuals, both new enrollees and those with experience. We assume that the regulation would have affected which single basic and single enhanced plan each sponsor continued to offer in one of four ways: the plans with the highest net revenue per enrollee, as defined in (12); the plans with the highest enrollment; the plans with the minimum cost to the enrollee; and the plans that are on the cost-variance-brand frontier for the greatest number of people. [26] Here we focus on most profitable and highest enrollment, because these are the two that yield the outcomes at the top and bottom of the range of results.[27] Retaining only the most profitable or highest enrollment plans in this way drops the average enrollee's menu from 47 plans to 31 plans. We use our baseline estimates for the observable part of utility to predict how this menu simplification would have affected the choice probabilities, assuming

[24] "Parent organizations" or "sponsors" are entities that contract with CMS to sell PDPs. They may include multiple brand names. Basic plans may differ in design but must be deemed actuarially equivalent to the standard benefits package for some representative enrollee(s). Enhanced plans offer supplemental benefits.

[25] The proposal included supply-side and demand-side stated rationales, such as to "…ensure that beneficiaries can choose from a less confusing number of plans that represent the best value each sponsor can offer" (Federal Register 2014).

[26] For profitability, we assume that there is sufficiently little variation in z_k within the set of plans offered by each insurer that it does not affect the ranking of plans by revenue per enrollee. Under this assumption the ranking of plans within each brand is defined by $\frac{p_k^0}{.255} - \frac{1}{N}\sum_i \psi_{ik}^0 (g_{ik} - oop_{ik})$.

[27] Results from all four scenarios are presented in Table A9.

no change in the behavior of suspect choosers. While part of the rationale for the menu restriction was to improve decision making, our linear probability models in Table 4 provide no evidence to support the hypothesis that this magnitude of reduction in the number of plans would reduce the probability of making a suspect choice. The proposed reduction is well within the range of within-region changes in the number of plans in our sample from 2006-2010.

There are four ways in which the menu restriction can affect consumer welfare. First, nonsuspect choosers experience an unambiguous welfare loss due their reduced freedom of choice. Second, forcing the individuals in the eliminated plans to switch reduces welfare. Third, welfare is potentially gained by people currently making suspect choices if the plans they chose were less likely to be selected by people with similar drug needs who made nonsuspect choices. The magnitude of the gain (or loss) depends on which plans are eliminated and the relative benefits of switching. Finally, when a large fraction of enrollees are forced to actively switch the increased sorting behavior will affect equilibrium premiums. As Handel (2013) points out, the direction of this effect is ambiguous. Increased sorting may or may not exacerbate adverse selection depending in part on whether the sorting is driven by suspect or nonsuspect choosers.

Table 6 column (1) summarizes the effects of the policy. The actual rate of switching in our sample for 2010 was 12% so the counterfactual switch rate of 33% represents a twenty-one percentage point increase. Most of this is due to forced switching out of plans that were eliminated. The more profitable plans that insurers choose to retain tend to be the higher-premium ones that provide more risk reduction and have higher quality ratings. As a result, the average enrollee's premium increases by $81 while their OOP expenditures decline by $31 for a net increase in expenditures of $47 (3.4%). Meanwhile, the average enrollee experiences a reduction in the variance of expenditures and an increase in quality, but both changes are relatively small, ranging from .3-2.2% of baseline averages.

The most important effect of the policy on consumer welfare is via the reduction in choice and forced switching. As a result, this policy would cause the average consumer to experience a welfare *loss* of $221, with only 2% of enrollees experiencing welfare gains. They are mostly people who made suspect choices in 2010 and would have been likely to reduce their expenditures and/or exposure to risk had their chosen plans been eliminated. As evident from the first two columns of Table A10, the small share who would gain from menu restrictions in which insurers retain their highest profit plans had higher drug spending, less education, higher prevalence of Alzheimer's disease or dementia or depression, were less likely to be working and had higher potential savings in 2010 under the status quo choice architecture. They otherwise look highly similar to those who would lose. The policy's main effect is to transfer income from consumers and taxpayers to insurers. As noted earlier, every dollar of premiums paid by enrollees is matched by nearly three dollars from taxpayers. The $81 increase in average premiums leads to a substantial increase in program costs ($236/enrollee) and insurer revenue ($310/enrollee).

The second column in Table 6 shows the results from the policy in the case where each insurer retains its plans with the largest current enrollment, as CMS could mandate. The results follow similar patterns, albeit with lower switching rates, smaller changes in plan attributes and smaller reductions in welfare and increases in insurer revenues. The characteristics of winners and losers likewise are closer together than under menu restrictions when insurers retain their most profitable plans. (Table A10 columns 3 and 4).

TABLE 6—EFFECTS OF A MENU RESTRICTION AND PERSONALIZED DECISION SUPPORT

	Menu Restriction		Personalized Decision Support	
	(1)	(2)	(3)	(4)
Criterion for inclusion on menu	profit	enrollment		
Effect on behavior of suspect choosers	none	none	$\theta^s \rightarrow \theta$	none
Utility cost of switching plans	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$(1-\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$	$(1-\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$
% enrollees switching plans	33	20	25	25
<u>Δ in average enrollee's expected</u>				
premium ($)	81	4	-16	-7
out of pocket costs ($)	-34	-6	12	24
variance (actual mean = 584)	-13	-4	-14	0.5
CMS quality index (actual mean = 3.32)	0.04	0.01	0.02	0.01
Δ insurer revenue / enrollee	310	29	-46	-15
Δ govt. spending / enrollee	236	13	-45	-21
Δ E[CV]	-221	-94	19	28
% enrollees with E[CV]>0	2	3	70	64

Note: The table reports the predicted effects of two counterfactual policies for 2010. In column (1) each insurer is restricted to have no more than two plans of their choosing. We assume insurers choose the two plans with the highest revenue per enrollee. In all columns, premiums adjust to hold plan revenue per enrollee fixed. In columns (2)-(3), we simulate a personalized decision support tool based on the field experiments in Kling et al. (2012). In column (2), the government's provision of personalized information is assumed to cause suspect choosers to behave like nonsuspect choosers. In column (3) the policy is assumed to have no effect on the behavior of suspect choosers. In both cases we calibrate the model to reproduce the 11.5% increase in switching observed by Kling et al. (2012). See the text for additional details.

B. Personalized Decision Support

Our second policy experiment evaluates the welfare effects of a hypothetical information campaign modeled on a randomized field experiment conducted by Kling, Mullainathan, Shafir, Vermeulen, and Wrobel (2012) [henceforth KMSVW]. Their analysis is motivated by the observation that while Medicare enrollees can learn about their personal PDP options and potential savings by calling 1-800-Medicare or using various cost calculators available online, a minority of enrollees report doing so (as seen in Table 1). KMSVW attribute this to "comparison friction" which they define as the wedge between available information and consumers' use of it. KMSVW tested an intervention in which several hundred treatment group enrollees (who agreed to participate in the experiment) were sent a decision support letter containing personalized information about their potential personal cost savings from switching to their lowest cost available plan. The letter also identified the name of the low cost insurer and contact information to initiate a switch. KMSVW observed an 11.5 percentage point increase in the switch rate for the treatment group relative to a control group that received a general letter with no personalized decision support.

In this experiment we estimate the heterogeneous welfare implications of a national rollout of the decision support tool in which the government mails letters to all enrollees that would be similarly worded to the one sent to the treatment group in KMSVW's study. Such a policy may affect welfare via several pathways. First, as the authors suggest, providing enrollees with personalized information may mitigate psychological biases and/or reduce information costs, making them better off. In the context of our model, this would be realized as increases in the switch rate and cost savings, as well as potential reductions in risk and increases in quality. Second, an important feature of the information campaign—if it were implemented by the government—is that it would necessarily be based on incomplete information about enrollees' drug needs. While CMS has full information about an individual's claims over their prior years in the PDP market, the individual may have private information about their own drug needs over the upcoming year. If enrollees with private information about changes in their drug needs choose to switch plans based on outdated information provided by CMS then these misinformed individuals could experience welfare losses. Finally, increased switching initiated by a national rollout could induce feedback effects on premiums that would further affect welfare.

We use KMSVW's estimated 11.5% increase in the switch rate to calibrate V_{ij}^{n1} and V_{ij}^{s1}. Specifically, we multiply the estimated switching parameters by the constant fraction, ω, that would be needed to generate an 11.5% increase in switch rate relative to the 12% baseline rate that we actually observe in 2010.

$$(16.a)\ V_{ijt}^{n1} = \hat{\alpha} c_{ijt} + \hat{\beta}\sigma_{ijt}^{2} + \hat{\gamma} q_{jt} + \omega\left(\hat{\eta}\Delta B_{ijt} + \hat{\delta}\Delta P_{ijt}\right).$$

$$(16.b)\ V_{ijt}^{s1} = \hat{\alpha}^{s} c_{ijt} + \hat{\beta}^{s}\sigma_{ijt}^{2} + \hat{\gamma}^{s} q_{ijt} + \omega\left(\hat{\eta}^{s}\Delta B_{ijt} + \hat{\delta}^{s}\Delta P_{ijt}\right).$$

where $0 \leq \omega \leq 1$. This approach raises an important question. Would the people currently making suspect choices adjust their behavior in response to the policy? Unfortunately the treatment effects reported by KMSVW do not allow us to answer this question. We address this shortcoming by reporting bounds on consumer welfare based on the two logically extreme scenarios. Let $\hat{\theta}$ denote the vector of estimated utility parameters. In the first scenario we assume that the policy causes suspect choosers to change their behavior to mirror nonsuspect choosers: $\hat{\theta}^s \to \hat{\theta}$. In this case all enrollees experience the same proportional reduction in $\hat{\eta}$ and $\hat{\delta}$. In the second scenario we assume there is no change in the behavior of suspect choosers so that all the direct benefits and costs of the policy are borne by nonsuspect choosers.

Table 6 column (3) reports results from the scenario where $\hat{\theta}^s \to \hat{\theta}$. The average enrollee's expected premium declines by $16 whereas expected OOP costs increase by $12. The latter reflects the potential welfare costs of misinformation when people with better private information than the government make decisions based on noisy nudges. More broadly, this suggests a tradeoff between the potential benefits of simplifying the presentation of information and the potential costs of suppressing important details about the assumptions underlying that information. Notably, the net effect on expenditures is slightly negative and this improvement is accompanied by a small reduction in variance and a small improvement in quality. Although we estimate that 70% of consumers would benefit from this policy, the overall effect on average consumer surplus is $19. Those who gain are similar in demographics to those who would lose, although they tend to have lower prescription drug spending and lower prevalence of Alzheimer's or dementia and depression (Table A10 columns 5 and 6).

Column (4) reports results from the scenario where those making suspect choices do not change their behavior. In this case, the model implies a net $17 increase in the average enrollee's total drug expenditures and the average consumer's welfare is still positive. Overall, the policy appears to be welfare improving for most consumers. Depending on our assumption about the change in behavior for suspect choosers, our findings suggest that between 64% and 70% of enrollees would be made better off. The $7-$16 reductions in average premiums also generate \$21-\$45 reductions in taxpayers' premium subsidies per enrollee, collectively reducing insurers' net revenues.

C. Automatic Assignment to a Low-Cost Default Option

Our final policy experiment evaluates the welfare effects of replacing CMS's current revealed preference approach to defining each enrollee's default plan with an alternative policy that would set the default to be the plan that would maximize each enrollee's potential savings. We envision the policy being implemented as a stronger version of the decision support nudge in the prior section. Not only would enrollees be informed of their minimum cost options, they would be automatically assigned to those options unless they chose to opt out by actively switching to a different plan. As before, we assume CMS would predict each enrollee's minimum cost plan using their drug claims from the prior year. Consistent with CMS's current approach, first-time enrollees would still be required to make active decisions.

This prospective policy incorporates greater ambiguity than the prior two policies considered here regarding how a change in the default option would affect decision making. The best case scenario for consumers would be one in which $\hat{\eta}$ and $\hat{\delta}$ represent the cost of collecting information and initiating a switch. In this case, the policy simply erases these costs for the new low-cost default. Despite the lower costs, some consumers may still prefer their original plans if those plans provide greater quality or variance reduction. Assuming it is costless for enrollees to opt out and continue in their old plans, the policy could reduce consumer welfare for only two reasons: (1) endogenous increases in plan premiums, or (2) (mis)assignment to plans requiring higher expenditures due to changes in drug needs. The first column of Table 7 shows that the aggregate effect of these two mechanisms is dominated by the aggregate effect of lower expenditures and search costs.

Under the maintained assumptions, our model predicts that 31% of consumers would switch to the low-cost default whereas 63% would opt out and continue in their current plans. Even with less than one third of consumers switching, the predicted average cost savings are \$92. Combining this with the reduction in search costs and endogenous premiums yields an average welfare gain of \$154, with 90% of consumers benefiting from the policy. It effectively acts to transfer revenue from insurers to consumers and taxpayers.

TABLE 7—EFFECTS OF ESTABLISHING A PERSONALIZED LOW COST DEFAULT PLAN

	(1)	(2)	(3)
Utility cost of switching to			
actual default plan	0	0	$\delta\Delta P_{ijt}$
assigned default plan	0	$(\eta-\delta) \times \Delta B_{ijt}$	0
% enrollees choosing			
actual default plan	63	78	26
assigned default plan	31	12	58
other plan	6	10	16
Δ in average enrollee's expected			
premium (\$)	-42	-17	-67
out of pocket costs (\$)	-50	-23	-76
variance (actual mean = 584)	14	5	36
CMS quality index (actual mean = 3.32)	0.02	0.01	0.01
Δ insurer revenue / enrollee	-208	-86	-340
Δ govt. spending / enrollee	-123	-50	-194
Δ E[CV]	154	48	-112
% enrollees with E[CV]>0	90	85	38

Note: The table reports the predicted effects of a counterfactual policy that would set the default plan for each enrollee as the plan that would minimize his total drug spending (premium + out of pocket). Each column reports results for a different assumption about the effect of the policy on the utility cost of switching to the assigned default plan and the utility cost of switching back to the enrollee's actual default plan. The actual default plan is the one the enrollee chose the prior year. The minimum cost plan is determined by the enrollee's drug claims in the prior year. In all columns, premiums adjust to hold plan revenue per enrollee fixed. See the text for additional details.

These assumptions, however, may yield an overly optimistic view of this policy. First, another potential interpretations of $\hat{\eta}$ noted earlier is the cost of learning to navigate a plan offered by a different insurer (e.g. prior authorization paperwork, new pharmacy networks, new customer service protocols). This cost would not be eliminated by the policy. To consider the implications for welfare, we recalibrate the model so that the policy reduces the cost of switching to the low-cost default from $\hat{\eta}\Delta B_{ijt} + \hat{\delta}\Delta P_{ijt}$ to $(\hat{\eta} -$

$\hat{\delta})\Delta B_{ijt}$. Under this interpretation, these welfare-relevant “navigation costs” are the difference in the cost of switching between brands relative to switching within brands. Results are reported in column (2). The continued presence of navigation costs reduces the share of enrollees choosing the new default to 12% which, in turn, reduces the magnitudes of average consumer surplus, government spending, and insurer revenue albeit with no qualitative changes in the pattern of results.[28]

Finally, the last column of Table 7 illustrates the importance of what may seem like a small detail—the design of the opt-out feature. We repeat the simulation summarized in column (1) except that now we make it costly for enrollees to switch back to their previously-chosen plans. The cost is set to equal to the estimated cost of switching between plans offered by the same insurer. Intuitively, people may incur a cost from paying attention to the new policy, learning how the opt-out feature works, determining whether they expect to prefer their newly assigned default to their old plan and, if not, exercising their opt out option. Comparing columns (1) and (3) shows that when people pay a significant utility cost of opting out, many of them choose the newly assigned default even though it is welfare reducing. The share choosing the default increases by 27 percentage points, from 31% to 58%. By reducing the disparity in switching costs between the consumer’s previously chosen plan and all plans other than their assigned default, the opt out cost also induces an 10 percentage point increase in switching to other plans, from 6% to 16%. While the average consumers’ PDP expenditures decline by even more than in column (1) the mean and median consumer are now made worse off by the policy. Overall, these results illustrate that in the presence of significant opt out costs, consumer welfare gains may not be resilient to the effects of imperfect information on the design of the policy.

The demographics of winners and losers under each of the three assumption are provided in Table A9 columns 9-14. Under all three, those who would gain tend to be less educated and would have had higher OOP drug spending and higher potential savings under the status quo policy, but they otherwise appear highly similar to those who would

[28] This approach may still overstate benefits to the extent that $\hat{\eta}$ and $\hat{\delta}$ represent latent preferences. As we increase the post-policy cost of switching to the new default option to $\hat{\eta}\Delta B_{ijt} + \hat{\delta}\Delta P_{ijt}$ the benefits to consumers approach zero. The extreme case in which $\hat{\eta}$ and $\hat{\delta}$ are entirely latent preferences is equivalent to reverting to the pre-policy equilibrium in which case the policy has no effect on consumer welfare.

lose.

VIII. Robustness Checks

Table 8 reports the sensitivity of our main estimates for consumer welfare, taxpayer spending, and insurer revenue to alternative specifications of our model. The columns match the policy scenarios summarized in Tables 6 and 7, and the first three rows of Panel A provides the results from those scenarios for convenience. The fourth row of panel A reports an alternative set of measures for consumer welfare in which we reinterpret the switching cost parameters for nonsuspect choices, $\hat{\eta}$ and $\hat{\delta}$, as reflecting inertia caused by incomplete information. We investigate the welfare implications of the inertia hypothesis by calculating welfare in an extreme scenario in which there is assumed to be no latent preference heterogeneity and it is assumed to be costless to switch plans. In this case, $\hat{\eta}$ and $\hat{\delta}$ affect decision making, but not welfare. The change in compensating variation can be expressed as

$$(17)\ \Delta E[CV_i^n] = \frac{1}{\alpha}\left\{ln\frac{\sum_{k\in K}\left[exp\left(V_{ik}^{n1}\right)\right]}{\sum_{j\in J}\left[exp\left(V_{ij}^{n0}\right)\right]} + \sum_{k\in K}\left[\psi_{ik}^{n1}\left(V_{ik}^{n^*1} - V_{ik}^{n1}\right)\right] - \sum_{j\in J}\left[\psi_{ij}^{n0}\left(V_{ij}^{n^*0} - V_{ij}^{n0}\right)\right]\right\},$$

where V_{ik}^{n1} and V_{ij}^{n0} depend on $\hat{\eta}$ and $\hat{\delta}$ but the "true" values of these parameters are set to zero when we calculate $V_{ik}^{n^*1}$ and $V_{ij}^{n^*0}$.

In the case of the menu restriction the welfare effect on the average consumer changes from a loss of -\$221 to a loss of -\$2. If it is costless to switch plans then there is no direct welfare loss from forcing people to switch. If $\hat{\eta}$ and $\hat{\delta}$ actually reflect a combination of switching costs and incomplete information then the welfare effect would be bounded by -\$221 and -\$2. Hence, the average consumer would be worse off from the menu restriction even if we assume they incur no disutility from switching. Under the inertia hypothesis, welfare gains are also larger from the decision support tool because the people who are induced to switch plans no longer experience a disutility of switching. For the same reason, the inertia hypothesis reduces the sensitivity of the welfare effects of default assignment to assumptions about how the policy affects the disutility of switching. Now under all three assumptions the results yield positive gains ranging from $46-64.

TABLE 8—ROBUSTNESS CHECKS ON OUR MAIN RESULTS

	Menu Restriction		Decision Support		Default Assignment		
	(1)	(2)	(3)	(4)	(1)	(2)	(3)
Criteria for inclusion on menu	profit	enrollment					
Effect on behavior of suspect choosers	none	none	$\theta^s \rightarrow \theta$	none	none	none	none
Utility cost of switching to actual default					0	0	$\delta\Delta P_{ijt}$
Utility cost of switching to assigned default					0	$(\eta\text{-}\delta) \times \Delta B_{ijt}$	0
	A. Baseline results with suspect → dominated plan | MCBS						
Δ insurer revenue / enrollee	310	29	-46	-15	-208	-86	-340
Δ govt. spending / enrollee	236	13	-45	-21	-123	-50	-194
Δ E[CV] | η,δ → disutility of switching	-221	-94	19	28	154	48	-112
Δ E[CV] | η,δ → incomplete information	-2	-23	107	93	64	49	46
	B. Ex ante approach using prior year's drug claims, baseline definition of suspect						
Δ insurer revenue / enrollee	324	24	-62	-10	-211	-80	-343
Δ govt. spending / enrollee	244	10	-41	-6	-128	-48	-200
Δ E[CV] | η,δ → disutility of switching	-233	-102	70	67	198	57	-52
Δ E[CV] | η,δ → incomplete information	-1	-25	175	133	91	63	89
	C. Suspect → dominated plan						
Δ insurer revenue / enrollee	302	34	-30	-13	-208	-86	-334
Δ govt. spending / enrollee	231	15	-33	-23	-124	-50	-193
Δ E[CV] | η,δ → disutility of switching	-229	-100	28	18	149	45	-143
Δ E[CV] | η,δ → incomplete information	6	-24	118	97	53	47	36
	D. Suspect → dominated plan | MCBS | potential savings > 50%						
Δ insurer revenue / enrollee	306	27	-80	-13	-201	-81	-339
Δ govt. spending / enrollee	233	11	-70	-20	-119	-47	-195
Δ E[CV] | η,δ → disutility of switching	-194	-80	11	21	142	44	-70
Δ E[CV] | η,δ → incomplete information	-11	-19	91	69	66	45	70
	E. Suspect → dominated plan | MCBS | potential savings > 25%						
Δ insurer revenue / enrollee	310	22	-153	-17	-195	-79	-336
Δ govt. spending / enrollee	236	8	-123	-20	-115	-45	-193
Δ E[CV] | η,δ → disutility of switching	-156	-56	12	22	137	44	16
Δ E[CV] | η,δ → incomplete information	-27	-12	87	38	82	44	122

Note: The table summarizes the sensitivity of our main results to alternative definitions for suspect choices in panels C, D and E, and to an alternative interpretation of the switching indicators to reflect inertia due to incomplete information in the fourth row of each panel. The first three rows of panel B repeat our main results from tables 6 and 7 for convenience. See the text for additional details.

Panel B provides results from an alternative approach in which we replace the assumption that consumers have perfect foreknowledge about their future drug costs and distribution with an assumption that their expectations are fully myopic, e.g. based on their prior year's drug consumption (the "ex ante" approach reported in Ketcham, Lucarelli, Miravete and Roebuck 2012 and Ketcham, Lucarelli and Powers 2015). The results are qualitatively identical to those from the ex post assumption reported in the article. The main quantitative difference is that the welfare gains from personalized decision support are larger because the ex ante approach assumes there is no information asymmetry between people and CMS. The full set of results from the ex ante approach are reported in Tables A13-A17.

Panels C, D and E of Table 8 report the sensitivity of our main results to three alternative approaches to defining suspect choices under the baseline approach using ex post drug claims to determine plan costs and choice of dominated plan. Panel C ignores the MCBS knowledge question and defines choices as suspect based solely on dominated plans.[29] Panel D considers the union of dominated plan choices, the knowledge question, and potential savings greater than 50% as shown by Figure 1 and the last row of Table 2. Panel E expands the set of suspect choices from panel C to include those with potential savings between 25% and 50%. Hence, moving from C through E incrementally increases the set of choices labeled as suspect from a minimum of 17% to a maximum of 66%, with the base results in Panel A fitting logically between Panels C and D. Altering how suspect choices are defined has little effect on our main results. The reason is that of our three suspect choice indicators, the choice of a dominated plan has the largest effects on our estimates for θ^s. This means that when we classify a greater share of choices as suspect, the difference between θ^s and θ declines. More people benefit from simplifications to choice architecture, but the average gain among those who benefit is smaller. These effects offset each other in a way that leads to small welfare increases in some scenarios and small welfare declines in others.

As a next set of robustness checks, we restrict the analysis to the 55% of the sample who answered the MCBS knowledge questions and chose health insurance on their own, without use of proxies. The results are provided in Tables A18-A21. While the smaller sample reduces the statistical significance in the relationships between observed de-

[29] Table A11 provides the linear probability models for likelihood of making a suspect choice using this definition, while Table A12 provides the PDP choice model estimates.

mographics and the probability of making an uninformed decision, as evident in Table A10, the remaining results virtually identical to the full sample. This suggests that while having access to this knowledge as researchers is novel, it does not seem to alter the predicted effects of policy reforms at least in Part D. As another set of checks we restrict the sample to those in states that did not offer “state pharmaceutical assistance programs” (SPAPs). These programs provide additional premium and copay subsidies to lower-income individuals who are in our sample because they were not poor enough to qualify for the federal low income subsidies. The CMS data do not permit us to see who was receiving an SPAP, so one concern is that this source of measurement error may cause us to misidentify suspect choices and misspecify the logit models. As Tables A22-A25 show, this sample has rates of dominated choices, estimated logit parameters, and policy implications highly similar to the full sample. The final set of robustness checks rely on the results from the logit models with heterogeneity reported in Table A5. These results, shown in Tables A26 and 27, are qualitatively and quantitatively similar to those from the simpler models.

IX. Summary

We have developed a structural model capable of evaluating who would win and who would lose from a wide range of paternalistic reforms in a differentiated product market. We used the model to evaluate three prospective policies that have been proposed to simplify markets for prescription drug insurance created under Medicare Part D. Our analysis was enabled by a novel combination of administrative records and survey data on consumers’ knowledge of the market, their enrollment decisions, and the financial consequences of those decisions for a nationwide sample of the Medicare population. We used the data to first identify which consumers appear to make informed decisions that reveal their preferences to us then to estimate separate models of decision making for the informed and uninformed groups.

The results from our policy experiments suggest that CMS’s recent proposal to simplify the choice process by reducing the number of drug plans would reduce welfare for the mean and median consumer and increase transfers from taxpayers to insurers. In contrast, our results suggest that providing personalized information about the potential savings from switching plans and assigning people to low-cost default plans would benefit the average enrollee. However, these gains are always less than 14% of consumer expenditures, typically under 10%, and are often overshadowed by transfers from insurers to taxpayers. We note four limitations with our study. First, our analysis largely excludes supply side responses to the prospective policies apart from the adjustments in premiums and the insurers' decisions about which plans to provide under menu restrictions. Second, our analysis does not embed any responses by consumers in their decisions about whether to participate in the PDP market or not. Given the large taxpayer subsidies to all PDP enrollees, enrollment decisions likely have large effects on expected consumer surplus and taxpayer costs to the extent that such decisions change under the prospective policies. Third, our study holds constant the drugs consumed across plans and under alternative policies, again excluding some potentially welfare-relevant changes from the policies. Finally, we follow prior studies in this area and estimate static models, whereas drug insurance choices may embed dynamics. We consider each of these limitations as important avenues for further research.

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Supplemental Appendix to

Estimating the Heterogeneous Welfare Effects of Choice Architecture: An Application to the Medicare Prescription Drug Insurance Market

By Jonathan D. Ketcham, Nicolai V. Kuminoff and Christopher A. Powers

TABLE A1—COMPARING MCBS SAMPLE MEANS WITH ADMINISTRATIVE DATA

	2006	2007	2008	2009	2010
	Medicare beneficiary survey sample				
age	77	77	78	78	78
% female	62	62	62	62	62
white (%)	94	93	93	94	94
Alzheimer's or dementia (%)	7	8	9	10	11
Depression (%)	9	8	10	11	11
number of available brands	20	24	23	23	20
number of available plans	43	56	55	50	47
premium ($)	363	362	406	476	513
out-of-pocket costs ($)	1,010	842	873	920	903
mean potential savings, ex post ($)	546	347	295	332	337
	Random 20% Sample of all Part D Enrollees				
age	76	76	76	76	76
% female	63	64	63	63	62
white (%)	93	92	92	92	93
Alzheimer's or dementia (%)	7	9	9	10	10
Depression (%)	9	9	10	10	11
number of available brands	19	24	22	23	20
number of available plans	43	56	55	50	47
premium ($)	362	369	415	487	516
out-of-pocket costs ($)	994	890	857	892	886
mean potential savings, ex post ($)	521	355	298	337	333

Note: The top half of the table reports means based on enrollees in the merged administrative-MCBS sample that we use for estimation. The bottom half of the table reports means based on a random 20% sample of all enrollees in Medicare Part D.

TABLE A2—NUMBER OF ENROLLMENT AND REENROLLMENT DECISIONS AND SWITCHING RATES, BY YEAR

	2006	2007	2008	2009	2010
number of enrollment decisions	2,265	5,861	6,019	6,009	5,754
number of reenrollment decisions with a pre-selected default	0	1,878	5,163	5,016	4,817
share of consumers making reenrollment decisions who switch to:					
a different plan offered by the default insurer		6.8	4.1	1.6	2.6
a plan offered by a different insurer		6.2	7.5	9.7	7.0

TABLE A3—SURVEY DATA ON WHO MAKES HEALTH INSURANCE DECISIONS

	MCBS respondent		Who makes health insurance decisions?		
	Beneficiary	Someone else	Beneficiary-respondent	Beneficiary-respondent gets help	Someone else
number of enrollment decisions	13,235	1,041	8,659	3,663	1,524
Potential indicators for suspect choices					
fail to give right answer on knowledge question (%)	32	33	30	34	38
chose a dominated plan (%)	17	19	16	20	19
mean potential savings ($)	337	378	329	352	376
Medicare Beneficiary Survey variables					
High school graduate (%)	81	60	83	77	63
College graduate (%)	23	13	25	19	15
Income>$25k (%)	56	49	57	53	48
Currently working (%)	13	15	15	10	13
Married (%)	54	62	51	62	59
Has living children (%)	93	94	92	96	93
Uses the internet (%)	37	19	40	33	20
Has visited website for Medicare info (%)	25	26	26	26	24
Has called 1-800-Medicare for info (%)	18	16	19	17	15
Administrative variables					
mean age	78	81	77	78	80
female (%)	64	43	61	70	52
white (%)	94	89	94	93	90
Alzheimer's or dementia (%)	8	33	5	10	30
Depression (%)	10	14	8	11	15
mean number of drug claims	34	43	33	38	41
mean number of available plans	51	51	51	51	51
mean number of available brands	22	22	22	22	22
mean premium ($)	443	451	442	444	453
mean out-of-pocket costs ($)	867	1,264	808	957	1,202

TABLE A4—RISK PREMIUMS FOR 50-50 BETS IMPLIED BY CHOICE MODEL ESTIMATES FOR NONSUSPECT CHOICES IN TABLE 4

Risk Premium as a fraction of the bet	Size of Bet
0.04	100
0.39	1,000
0.62	2,000
0.74	3,000
0.80	4,000
0.84	5,000
0.87	6,000
0.89	7,000
0.90	8,000
0.91	9,000
0.92	10,000

To assess the estimates from the logit model for non-suspect choices, we compare its implied risk premiums in a manner comparable with prior literature. Specifically, deriving the risk premium from logit model as a 1st order approximation to a CARA model yields the following expression for the risk aversion coefficient:

$$\rho = \frac{-2\beta/1{,}000{,}000}{\alpha/100}, \text{ where } U_{ij1} = \alpha \acute{c}_{ij1} + \beta \acute{\sigma}^2_{ij1} + \gamma \acute{q}_{ij1} + \eta \Delta \acute{B}_{ij1} + \delta \Delta \acute{P}_{ij1} + \epsilon_{ij1}.$$

The estimates in Table 4 for the non-suspect group yields $\rho = .000873$. Table A5 translates this into a risk premium for various 50-50 bets.

These results are broadly consistent with the range of prior results, e.g. as reported in Table 5 of Cohen and Einav (2007). Cohen and Einav find the mean consumer would be indifferent between a 50-50 bet of winning \$100 and losing \$76.5, whereas the median consumer is virtually risk neutral. In contrast, our results imply the mean non-suspect consumer is indifferent between a 50-50 bet of winning \$100 and losing \$95.8 although Cohen and Einav argue that preferences likely differ between their automobile insurance context other contexts like drug insurance. Likewise, Handel (2013) finds that the median individual is indifferent between a bet of winning \$100 and losing \$94.6. In the model preferred by Handel and Kolstad (2015), the mean consumer is indifferent between a bet of winning \$1,000 and losing \$913. This controls for friction and inertia. Not controlling for these factors makes them indifferent between winning \$1000 and losing \$367. In comparison, our results imply indifference between winning \$1,000 and losing \$610. In general we should expect our number to fall in between the two extremes in their paper, although the comparison is indirect because their estimates include choices that we label as suspect.

TABLE A5—CHARACTERISTICS OF THOSE WHO MAKE ALWAYS, NEVER AND SOMETIMES SUSPECT PDP CHOICES

	Always suspect	Sometimes suspect	Never suspect
number of enrollees	3,841	1,194	5,763
Medicare Beneficiary Survey variables			
High school graduate (%)	75	78	81
College graduate (%)	17	19	26
Income>$25k (%)	49	52	59
Currently working (%)	12	8	15
Married (%)	50	56	58
Has living children (%)	93	92	93
Uses the internet (%)	27	35	40
Has visited website for Medicare info (%)	21	31	30
Has called 1-800-Medicare for info (%)	12	17	17
Administrative variables			
mean age	79	79	77
female (%)	65	67	60
white (%)	92	95	93
Alzheimer's or dementia (%)	13	9	8
Depression (%)	11	13	9
mean number of drug claims	41	37	31
mean number of available plans	52	52	52
mean number of available brands	23	23	23
mean premium ($)	432	386	447
mean out-of-pocket costs ($)	1,071	990	764
mean potential savings, ex post ($)	377	323	285

TABLE A6—PDP CHOICE LOGIT MODEL RESULTS STRATIFIED BY THOSE WHO MAKE ALWAYS, NEVER AND SOMETIMES SUSPECT PDP CHOICES

	Always suspect	Sometimes suspect: suspect choice	Sometimes suspect: non-suspect choice	Never suspect
Plan characteristics				
expected cost	-0.136***	-0.092***	-0.503***	-0.395***
	(0.010)	(0.021)	(0.041)	(0.017)
variance	1.498***	3.182***	-1.171**	-1.788***
	(0.256)	(0.599)	(0.526)	(0.220)
CMS quality index	1.051***	1.112***	0.612***	0.755***
	(0.087)	(0.184)	(0.186)	(0.073)
Switching indicators				
different plan, same brand	-3.812***	-2.436***	-1.484***	-3.949***
	(0.115)	(0.192)	(0.140)	(0.108)
different brand	-5.861***	-3.799***	-3.662***	-5.691***
	(0.102)	(0.154)	(0.158)	(0.084)
pseudo R^2	0.67	0.44	0.45	0.67
number of plan choices	3,841	552	642	5,763
number of enrollees	1,363	353	353	2,144

TABLE A7— PDP CHOICE LOGIT MODELS WITH DEMOGRAPHIC INTERACTIONS

	All choices		Non-suspect choices		Suspect choices	
Plan characteristics						
expected cost	-0.254***	-0.714***	-0.403***	-0.837***	-0.127***	-0.308***
	(0.009)	(0.090)	(0.016)	(0.157)	(0.009)	(0.105)
variance	-0.039	-0.197	-1.760***	-2.242***	1.746***	1.706***
	(0.125)	(0.294)	(0.203)	(0.469)	(0.227)	(0.520)
CMS quality index	0.911***	1.127***	0.755***	0.986***	1.025***	1.275***
	(0.049)	(0.067)	(0.066)	(0.088)	(0.075)	(0.111)
Switching indicators						
different plan, same brand	-3.498***	-3.414***	-3.461***	-3.531***	-3.603***	-3.330***
	(0.063)	(0.100)	(0.085)	(0.148)	(0.099)	(0.136)
different brand	-5.274***	-5.273***	-5.325***	-5.378***	-5.424***	-5.374***
	(0.052)	(0.080)	(0.070)	(0.114)	(0.082)	(0.116)
Expected cost x						
college graduate		0.034		0.067*		0.052**
		(0.022)		(0.035)		(0.025)
income > $25k		0.022		0.026		0.031
		(0.017)		(0.029)		(0.020)
age		0.004***		0.003		0.001
		(0.001)		(0.002)		(0.001)
number of drug claims		0.003***		0.005***		0.002***
		(0.000)		(0.000)		(0.000)
Variance x						
college graduate		-0.292		-0.271		0.499
		(0.260)		(0.517)		(0.464)
currently working		0.223		0.631		0.733
		(0.357)		(0.521)		(0.658)
married		0.051		0.175		-0.232
		(0.252)		(0.400)		(0.477)
female		0.164		0.379		-0.003
		(0.254)		(0.428)		(0.499)

TABLE A7 (CONTINUED)— PDP CHOICE LOGIT MODELS WITH DEMOGRAPHIC INTERACTIONS

	All choices		Non-suspect choices		Suspect choices	
CMS quality index x						
number of drug claims		-0.007***		-0.008***		-0.006***
		(0.001)		(0.002)		(0.002)
Switching between brand x						
college graduate		0.231*		0.311**		0.194
		(0.122)		(0.159)		(0.205)
uses the internet		0.230**		0.152		0.262
		(0.108)		(0.149)		(0.181)
income > $25k		-0.250**		-0.174		-0.341**
		(0.105)		(0.146)		(0.163)
Switching within brand x						
college graduate		-0.022		-0.052		0.031
		(0.161)		(0.211)		(0.281)
uses the internet		0.086		0.199		-0.343
		(0.143)		(0.194)		(0.259)
income > $25k		-0.187		-0.014		-0.386*
		(0.134)		(0.185)		(0.200)
pseudo R^2	0.62	0.62	0.63	0.64	0.63	0.63
number of plan choices	11,608	11,608	6,804	6,804	4,804	4,804
number of enrollees	3,937	3,937	2,532	2,532	1,758	1,758

TABLE A8—VALIDATION OF LOGIT MODELS STRATIFIED BY SUSPECT VS NONSUSPECT AGAINST ANALOGUE POOLED MODEL

	In-sample fit (2008)						Out-of-sample fit (2009)								Weighted absolute errors			
	suspect			non-suspect			suspect				non-suspect				in-sample		out-of-sample	
	data	|model error|		data	|model error|		data	|model error|			data	|model error|			|model error|		|model error|	
		s=ns	s		s=ns	ns		s=ns	s	ns		s=ns	s	ns	s=ns	s≠ns	s=ns	s≠ns
Percent of consumers choosing:																		
gap coverage	12	2	3	12	3	2	11	0	0	1	11	0	0	1	3	3	0	1
dominated plan	32	8	5	7	8	6	27	7	5	9	8	6	8	4	8	6	7	5
min cost plan within brand	51	7	3	70	8	11	51	6	1	4	66	5	11	8	8	8	6	5
Mean consumer expenditures ($)																		
premium + OOP	1,513	26	0	1,221	20	0	1,732	22	0	44	1,368	19	43	1	24	0	22	1
overspending on dominated plans	70	29	21	14	6	7	55	24	18	29	14	3	2	4	16	13	12	11
Percent of consumer switching plans	14	1	0	15	1	0	13	2	1	4	19	5	5	4	1	0	4	3

Table A5 provides the results from a logit model validation exercise. The purpose is to determine whether the models estimated separately by suspect and non-suspect choices outperform the pooled model, and whether the suspect model better predicts suspect choices than the non-suspect model does and vice versa. For this exercise the estimation sample is 2008 while the prediction sample is 2009. We chose these two years because they incorporate the largest year-to-year change in the choice set in our data—a central aspect to the out-of-sample validation methods developed by Keane and Wolpin (2007). In particular, the number of plans available fell by 10%, although three new brands entered the market, precluding our use of brand indicators in the models. The results show that both in-sample and out-of-sample predictions are closer to the data along a number of policy-relevant outcomes when we base the predictions on separate models for the given type of choice.

TABLE A9—EFFECTS OF A MENU RESTRICTION UNDER FOUR ALTERNATIVE ASSUMPTIONS ABOUT WHICH BASIC AND WHICH ENHANCED PLAN EACH SPONSOR WOULD RETAIN

	Menu Restriction			
	(1)	(2)	(3)	(4)
Criterion for inclusion on menu	profit	enrollment	frontier	expenditures
Effect on behavior of suspect choosers	none	none	none	none
Utility cost of switching plans	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$
% enrollees switching plans	33	20	27	25
Δ in average enrollee's expected				
premium ($)	81	4	33	-3
out of pocket costs ($)	-34	-6	-24	-5
variance (actual mean = 584)	-13	-4	-12	-5
CMS quality index (actual mean = 3.32)	0.04	0.01	0.00	0.00
Δ insurer revenue / enrollee	310	29	136	5
Δ govt. spending / enrollee	236	13	97	-8
Δ E[CV]	-221	-94	-160	-124
% enrollees with E[CV]>0	2	3	2	3

TABLE A10—CHARACTERISTICS OF WINNERS AND LOSERS UNDER VARIOUS PROSPECTIVE POLICIES

	Menu Restriction				Decision Support				Default Assignment					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Criterion for inclusion on menu	profit		enrollment											
Effect on behavior of suspect choosers	none		none		$\theta^s \rightarrow \theta$		none		none		none		none	
Utility cost of switching to actual default									0		0		$\delta \Delta P_{ijt}$	
Utility cost of switching to assigned default									0		$(\eta-\delta) \times \Delta B_{ijt}$		0	
	E[CS] > 0	E[CS] < 0	E[CS] > 0	E[CS] < 0	E[CS] > 0	E[CS] < 0	E[CS] > 0	E[CS] < 0	E[CS] > 0	E[CS] < 0	E[CS] > 0	E[CS] < 0	E[CS] > 0	E[CS] < 0
number of enrollees	48	2,874	82	2,840	2,057	865	1,864	1,058	2,632	290	2,477	445	1,120	1,802
non-suspect (%)	0	64	0	65	57	78	73	45	62	69	62	70	62	63
suspect (%)	100	36	100	35	43	22	27	55	38	31	38	30	38	37
mean Δ in E[CS] ($)	58	-226	23	-97	58	-75	66	-38	172	-12	57	-4	267	-348
Demographics														
College graduate (%)	15	24	16	24	23	26	24	23	24	27	23	29	21	26
Income>$25k (%)	44	57	45	57	56	60	58	55	57	60	57	60	57	57
Currently working (%)	2	13	5	13	13	12	13	12	13	12	13	12	13	13
Married (%)	48	57	57	56	55	60	57	55	56	61	56	61	56	57
Age	80	79	81	78	79	78	79	78	79	77	79	77	79	78
female (%)	63	62	65	62	63	58	62	62	62	60	62	58	63	61
white (%)	96	94	89	94	93	94	94	93	94	95	93	96	94	94
Chronic Medical Conditions														
Alzheimer's or dementia (%)	17	12	13	12	11	15	10	15	12	10	12	11	10	13
Depression (%)	19	11	17	11	10	14	10	13	11	10	11	10	10	12
Cancer (%)	15	7	9	7	7	8	7	8	8	6	8	6	8	7
acute myocardial Infarction (%)	2	1	1	1	1	1	1	1	1	1	1	1	1	1
atrial fibrillation (%)	13	11	12	11	10	13	11	12	11	12	11	11	13	10
cataracts (%)	21	27	26	26	27	25	27	25	26	27	27	25	27	26
heart failure (%)	17	18	22	18	17	20	18	18	18	16	18	15	21	16
chronic kidney disease (%)	27	15	20	15	14	19	15	17	16	12	16	12	16	15
chronic obstructive pulmonary disease (%)	17	11	12	11	10	13	10	13	12	9	12	10	11	12
diabetes (%)	35	27	32	27	26	32	25	32	27	29	27	28	29	27
glaucoma (%)	8	14	11	14	14	13	13	15	14	12	14	13	14	13
hip/pelvic fracture (%)	6	1	1	1	1	1	1	1	1	1	1	2	1	1
ischemic heart disease (%)	58	37	50	37	36	43	35	43	38	39	37	39	40	36
osteoporosis (%)	15	17	15	17	17	17	16	17	17	14	17	13	18	16
stroke/transiet ischemic attack (%)	8	4	6	4	4	5	4	5	4	5	5	4	5	4
Annual Prescription Drug Use														
number of claims (mean)	48	35	39	35	34	36	34	37	35	35	35	33	38	33
mean premium ($)	545	497	509	497	501	489	509	477	503	449	507	442	543	469
mean out-of-pocket costs ($)	1,785	1,043	1,199	1,051	996	1,196	980	1,187	1,092	720	1,102	792	1,181	977
mean potential savings, ex post ($)	519	326	281	330	338	308	333	323	340	229	348	226	449	254

TABLE A11— ASSOCIATION BETWEEN SUSPECT CHOICES AND DEMOGRAPHICS USING ONLY DOMINATED CHOICE TO IDENTIFY SUSPECT CHOICES

	all choices		active choices		passive choices	
Constant	0.077	[0.079]	0.015	[0.123]	0.257	[0.153]*
Medicare Beneficiary Survey variables						
High school graduate	-0.013	[0.009]	0.001	[0.011]	-0.025	[0.012]**
College graduate	0.012	[0.009]	0.007	[0.011]	0.013	[0.010]
Income>$25k	0.018	[0.008]**	0.021	[0.010]**	0.015	[0.009]
Currently working	-0.004	[0.010]	-0.014	[0.012]	0.002	[0.013]
Married	-0.008	[0.008]	-0.012	[0.010]	-0.006	[0.010]
Has living children	0.000	[0.014]	-0.005	[0.017]	0.001	[0.017]
Uses the internet	-0.008	[0.008]	-0.019	[0.011]*	-0.001	[0.010]
Has visited website for Medicare info	0.002	[0.008]	0.013	[0.011]	-0.005	[0.010]
Has called 1-800-Medicare for info	-0.011	[0.009]	-0.009	[0.013]	-0.013	[0.012]
Administrative variables						
Number of available plans	0.001	[0.002]	0.002	[0.003]	-0.002	[0.003]
Female	0.003	[0.008]	0.010	[0.009]	-0.002	[0.009]
Nonwhite	-0.002	[0.014]	-0.010	[0.017]	0.005	[0.018]
Age: 70-74	0.007	[0.010]	0.008	[0.012]	0.000	[0.013]
Age: 75-79	0.008	[0.011]	-0.011	[0.013]	0.015	[0.014]
Age: 80-84	0.001	[0.011]	0.007	[0.014]	-0.008	[0.015]
Age: over 84	0.019	[0.012]	0.026	[0.016]	0.010	[0.016]
Alzheimer's or dementia	-0.007	[0.013]	-0.013	[0.017]	-0.007	[0.015]
Depression	0.025	[0.012]	0.015	[0.015]	0.032	[0.015]
Total spending / $1000	0.001	[0.001]	0.001	[0.001]	0.008	[0.003]
Number of drug claims	0.002	[0.000]	0.002	[0.000]	0.002	[0.000]
Number of plan choices	20,689		8,370		12,319	
Mean of the dependent variable	0.19		0.19		0.18	
R-squared	0.033		0.039		0.07	

TABLE A12— LOGIT DECISION UTILITY MODELS OF PRESCRIPTION DRUG PLAN CHOICE USING ONLY DOMINATED CHOICE TO IDENTIFY SUSPECT CHOICES

	All choices	Non-suspect choices	Suspect choices
Plan characteristics			
expected cost	-0.254***	-0.386***	-0.017
	(0.009)	(0.013)	(0.011)
variance	-0.039	-1.911***	4.631***
	(0.125)	(0.186)	(0.438)
CMS quality index	0.911***	0.795***	0.976***
	(0.049)	(0.057)	(0.111)
Switching indicators			
different plan, same brand	-3.498***	-3.451***	-3.789***
	(0.063)	(0.071)	(0.165)
different brand	-5.274***	-5.409***	-5.326***
	(0.052)	(0.061)	(0.135)
pseudo R^2	0.62	0.65	0.63

TABLE A13—TABLE 3 RESULTS BASED ON EX ANTE RATHER THAN EX POST MEASURES OF DOMINATED CHOICE

	Dominated plan choice or fail to give right answer to knowledge question		
	all choices	active choices	passive choices
Constant	0.393 [0.125]***	0.705 [0.195]***	0.203 [0.227]
Medicare Beneficiary Survey variables			
High school graduate	-0.041 [0.015]***	-0.029 [0.019]	-0.049 [0.019]***
College graduate	-0.050 [0.014]***	-0.051 [0.018]***	-0.047 [0.017]***
Income>$25k	-0.017 [0.013]	-0.028 [0.017]*	-0.014 [0.016]
Currently working	0.022 [0.017]	-0.009 [0.021]	0.038 [0.020]*
Married	-0.004 [0.013]	0.008 [0.017]	-0.009 [0.016]
Has living children	-0.027 [0.022]	-0.023 [0.028]	-0.031 [0.027]
Uses the internet	-0.033 [0.014]**	-0.032 [0.018]*	-0.034 [0.017]**
Has visited website for Medicare info	-0.068 [0.014]***	-0.077 [0.017]***	-0.059 [0.017]***
Has called 1-800-Medicare for info	-0.046 [0.012]***	-0.026 [0.017]	-0.061 [0.016]***
Administrative variables			
Number of available plans	-0.000 [0.003]	-0.008 [0.005]*	0.005 [0.004]
Female	0.006 [0.012]	-0.001 [0.016]	0.011 [0.015]
Nonwhite	0.039 [0.024]	0.054 [0.030]*	0.029 [0.030]
Age: 70-74	0.011 [0.015]	0.011 [0.020]	-0.007 [0.020]
Age: 75-79	0.048 [0.017]***	0.038 [0.022]*	0.037 [0.022]
Age: 80-84	0.064 [0.018]***	0.070 [0.024]***	0.044 [0.024]*
Age: over 84	0.109 [0.020]***	0.100 [0.025]***	0.097 [0.025]***
Alzheimer's or dementia	0.039 [0.019]**	0.021 [0.027]	0.048 [0.023]**
Depression	0.027 [0.017]	0.002 [0.023]	0.045 [0.021]**
Total spending / $1000	0.005 [0.002]***	0.005 [0.002]**	0.005 [0.002]**
Number of drug claims	0.002 [0.000]***	0.002 [0.000]***	0.002 [0.000]***
Number of plan choices	14,278	5,129	9,149
Number of enrollees	5,233	3,938	4,259
Mean of the dependent variable	0.41	0.38	0.42
R-squared	0.066	0.084	0.068

TABLE A14—PDP CHOICE MODEL RESULTS BASED ON EX ANTE RATHER THAN EX POST MEASURES OF DOMINATED CHOICE AND EXPECTED COST

	All choices	Non-suspect choices	Suspect choices
Plan characteristics			
expected cost	-0.188***	-0.343***	-0.073
	(0.026)	(0.015)	(0.045)
variance	-0.231*	-1.809***	1.221***
	(0.125)	(0.207)	(0.189)
CMS quality index	0.924***	0.766***	1.088***
	(0.048)	(0.063)	(0.079)
Switching indicators			
different plan, same brand	-3.441***	-3.101***	-3.824***
	(0.061)	(0.080)	(0.100)
different brand	-5.254***	-5.065***	-5.647***
	(0.054)	(0.072)	(0.083)
pseudo R^2	0.61	0.56	0.68
number of plan choices	11,608	6,804	4,804
number of enrollees	3,937	2,532	1,758

TABLE A15—TABLE 6 RESULTS BASED ON EX ANTE RATHER THAN EX POST MEASURES OF DOMINATED CHOICE AND EXPECTED COST

	Menu Restriction		Personalized Decision Support	
	(1)	(2)	(2)	(3)
Criterion for inclusion on menu	profit	enrollment		
Effect on behavior of suspect choosers	none	none	$\theta^s \rightarrow \theta$	none
Utility cost of switching plans	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$(1\text{-}\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$	$(1\text{-}\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$
% enrollees switching plans	33	20	26	26
Δ in average enrollee's expected				
premium ($)	84	3	-14	-2
out of pocket costs ($)	-33	-8	-15	2
variance (actual mean = 584)	-15	-4	-13	0
CMS quality index (actual mean = 3.32)	0.04	0.01	0.02	0.02
Δ insurer revenue / enrollee	324	24	-62	-10
Δ govt. spending / enrollee	244	10	-41	-6
Δ E[CV]	-233	-102	70	67
% enrollees with E[CV]>0	2	3	88	68

TABLE A16—TABLE 7 RESULTS BASED ON EX ANTE RATHER THAN EX POST MEASURES OF DOMINATED CHOICE AND EXPECTED COST

	(1)	(2)	(3)
Utility cost of switching to			
actual default plan	0	0	$\delta\Delta P_{ijt}$
assigned default plan	0	$(\eta\text{-}\delta) \times \Delta B_{ijt}$	0
% enrollees choosing			
actual default plan	61	78	25
assigned default plan	33	12	60
other plan	6	10	15
Δ in average enrollee's expected			
premium ($)	-44	-16	-69
out of pocket costs ($)	-44	-18	-70
variance (actual mean = 584)	15	5	38
CMS quality index (actual mean = 3.32)	0.02	0.01	0.01
Δ insurer revenue / enrollee	-211	-80	-343
Δ govt. spending / enrollee	-128	-48	-200
Δ E[CV]	198	57	-52
% enrollees with E[CV]>0	92	87	44

TABLE A17—VALIDATION OF LOGIT MODELS STRATIFIED BY SUSPECT VS NONSUSPECT AGAINST ANALOGUE POOLED MODEL BASED ON EX ANTE RATHER THAN EX POST MEASURES OF DOMINATED CHOICE AND EXPECTED COST

	In-sample fit (2008)						Out-of-sample fit (2009)								Weighted absolute errors			
	suspect			non-suspect			suspect				non-suspect				in-sample		out-of-sample	
	data	|model error|		data	|model error|		data	|model error|			data	|model error|			|model error|		|model error|	
		s=ns	s		s=ns	ns		s=ns	s	ns		s=ns	s	ns	s=ns	s≠ns	s=ns	s≠ns
Percent of consumers choosing:																		
gap coverage	13	1	1	10	4	3	12	1	0	1	10	1	1	0	2	2	1	0
dominated plan	29	6	4	6	8	6	25	5	3	8	7	6	8	5	8	5	6	4
min cost plan within brand	52	5	2	66	8	9	52	5	0	2	63	6	11	8	7	6	6	4
Mean consumer expenditures ($)																		
premium + OOP	1,564	22	0	1,153	23	0	1,736	28	8	57	1,272	17	32	6	25	0	24	7
overspending on dominated plans	58	21	14	11	3	4	53	22	17	29	10	2	1	3	12	10	13	11
Percent of consumer switching plans	12	4	0	19	4	0	11	4	0	9	22	7	10	3	4	0	6	2

TABLE A18— ASSOCIATION BETWEEN SUSPECT CHOICES AND DEMOGRAPHICS FOR SUBSET OF PEOPLE WHO ANSWER MCBS AND MAKE CHOICES ON THEIR OWN

	Dominated plan choice or fail to give right answer to knowledge question					
	all choices		active choices		passive choices	
Constant	0.561	[0.161]***	0.603	[0.258]**	0.589	[0.287]**
Medicare Beneficiary Survey variables						
High school graduate	-0.031	[0.021]	-0.003	[0.026]	-0.048	[0.025]*
College graduate	-0.027	[0.017]	-0.037	[0.023]	-0.021	[0.020]
Income>$25k	-0.009	[0.016]	0.006	[0.021]	-0.018	[0.019]
Currently working	0.019	[0.020]	-0.016	[0.027]	0.037	[0.024]
Married	-0.022	[0.016]	0.002	[0.021]	-0.032	[0.019]*
Has living children	-0.005	[0.025]	0.016	[0.032]	-0.020	[0.031]
Uses the internet	-0.014	[0.018]	-0.018	[0.023]	-0.012	[0.021]
Has visited website for Medicare info	-0.067	[0.018]***	-0.061	[0.024]**	-0.066	[0.022]***
Has called 1-800-Medicare for info	-0.063	[0.014]***	-0.020	[0.022]	-0.090	[0.018]***
Administrative variables						
Number of available plans	-0.004	[0.004]	-0.007	[0.006]	-0.003	[0.005]
Female	0.008	[0.016]	0.024	[0.020]	0.002	[0.019]
Nonwhite	0.035	[0.032]	0.086	[0.040]**	0.007	[0.038]
Age: 70-74	0.009	[0.019]	-0.015	[0.026]	0.013	[0.025]
Age: 75-79	0.035	[0.021]*	0.002	[0.028]	0.044	[0.027]
Age: 80-84	0.049	[0.022]**	0.046	[0.030]	0.045	[0.028]
Age: over 84	0.114	[0.025]***	0.095	[0.034]***	0.118	[0.031]***
Alzheimer's or dementia	0.064	[0.030]**	0.093	[0.046]**	0.053	[0.035]
Depression	0.025	[0.023]	-0.019	[0.032]	0.051	[0.029]*
Total spending / $1000	0.009	[0.004]**	0.011	[0.006]*	0.008	[0.005]*
Number of drug claims	0.002	[0.000]***	0.002	[0.000]***	0.002	[0.000]***
Number of plan choices	8659		2961		5,698	
Number of enrollees	3,485		2,384		2,768	
Mean of the dependent variable	0.39		0.39		0.38	
R-squared	0.070		0.100		0.067	

TABLE A19— LOGIT DECISION UTILITY MODELS OF PRESCRIPTION DRUG PLAN CHOICE FOR SUBSET OF PEOPLE WHO ANSWER MCBS AND MAKE CHOICES ON THEIR OWN

	All choices	Non-suspect choices	Suspect choices
Plan characteristics			
expected cost	-0.275***	-0.446***	-0.131***
	(0.012)	(0.022)	(0.013)
variance	0.003	-1.678***	1.805***
	(0.183)	(0.275)	(0.357)
CMS quality index	0.962***	0.782***	1.078***
	(0.065)	(0.089)	(0.101)
Switching indicators			
different plan, same brand	-3.468***	-3.338***	-3.722***
	(0.086)	(0.109)	(0.144)
different brand	-5.274***	-5.383***	-5.358***
	(0.071)	(0.098)	(0.112)
pseudo R^2	0.62	0.64	0.62
number of plan choices	6,405	3,894	2,511
number of enrollees	2,385	1,555	1,011

TABLE A20— EFFECTS OF A MENU RESTRICTION AND PERSONALIZED DECISION SUPPORT FOR SUBSET OF PEOPLE WHO ANSWER MCBS AND MAKE CHOICES ON THEIR OWN

	Menu Restriction		Personalized Decision Support	
	(1)	(2)	(2)	(3)
Criterion for inclusion on menu	profit	enrollment		
Effect on behavior of suspect choosers	none	none	$\theta^s \rightarrow \theta$	none
Utility cost of switching plans	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$(1-\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$	$(1-\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$
% enrollees switching plans	32	19	25	25
Δ in average enrollee's expected				
premium ($)	77	9	-18	-8
out of pocket costs ($)	-32	-10	15	27
variance (actual mean = 584)	-14	-5	-12	2
CMS quality index (actual mean = 3.32)	0.03	0.01	0.02	0.02
Δ insurer revenue / enrollee	301	45	-52	-16
Δ govt. spending / enrollee	226	26	-52	-24
Δ E[CV]	-203	-81	18	23
% enrollees with E[CV]>0	2	4	68	64

TABLE A21— EFFECTS OF ESTABLISHING A PERSONALIZED LOW COST DEFAULT PLAN FOR SUBSET OF PEOPLE WHO ANSWER MCBS AND MAKE CHOICES ON THEIR OWN

	(1)	(2)	(3)
Utility cost of switching to			
actual default plan	0	0	$\delta\Delta P_{ijt}$
assigned default plan	0	$(\eta-\delta) \times \Delta B_{ijt}$	0
% enrollees choosing			
actual default plan	64	79	28
assigned default plan	31	12	56
other plan	6	9	16
Δ in average enrollee's expected			
premium ($)	-42	-16	-71
out of pocket costs ($)	-46	-22	-68
variance (actual mean = 584)	14	5	38
CMS quality index (actual mean = 3.32)	0.02	0.01	0.01
Δ insurer revenue / enrollee	-209	-83	-356
Δ govt. spending / enrollee	-123	-48	-207
Δ E[CV]	143	41	-103
% enrollees with E[CV]>0	89	82	38

TABLE A22— SUSPECT CHOICE INDICATORS, BY YEAR RESTRICTED TO THOSE WITHOUT STATE PHARMACY ASSISTANCE PROGRAMS AVAILABLE

		Percent of enrollees					
		2006	2007	2008	2009	2010	2006-2010
(1)	choosing a dominated plan	23	26	18	14	15	18
(2)	answering knowledge question incorrectly	40	28	30	28	28	29
(3)	(potential savings / total spending) ≥ 0.5	23	13	11	11	7	11
(4)	union of rows (1)-(2)	53	46	43	38	39	42
(5)	union of rows (1)-(3)	61	52	50	45	43	48

TABLE A23— LOGIT DECISION UTILITY MODELS OF PRESCRIPTION DRUG PLAN CHOICE RESTRICTED TO THOSE WITHOUT STATE PHARMACY ASSISTANCE PROGRAMS AVAILABLE

	All choices	Non-suspect choices	Suspect choices
Plan characteristics			
expected cost	-0.258***	-0.432***	-0.125***
	(0.012)	(0.022)	(0.013)
variance	-0.097	-2.337***	2.014***
	(0.199)	(0.382)	(0.302)
CMS quality index	0.959***	0.771***	1.080***
	(0.070)	(0.094)	(0.113)
Switching indicators			
different plan, same brand	-3.479***	-3.289***	-3.834***
	(0.089)	(0.117)	(0.149)
different brand	-5.276***	-5.301***	-5.504***
	(0.074)	(0.099)	(0.121)
pseudo R^2	0.62	0.63	0.63
number of plan choices	5,641	3,311	2,330
number of enrollees	1,911	1,228	851

TABLE A24— EFFECTS OF A MENU RESTRICTION AND PERSONALIZED DECISION SUPPORT RESTRICTED TO THOSE WITHOUT STATE PHARMACY ASSISTANCE PROGRAMS AVAILABLE

	Menu Restriction		Personalized Decision Support	
	(1)	(2)	(2)	(3)
Criterion for inclusion on menu	profit	enrollment		
Effect on behavior of suspect choosers	none	none	$\theta^s \rightarrow \theta$	none
Utility cost of switching plans	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$(1\text{-}\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$	$(1\text{-}\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$
% enrollees switching plans	30	19	25	25
Δ in average enrollee's expected				
premium ($)	69	1	-16	-6
out of pocket costs ($)	-30	-3	12	24
variance (actual mean = 584)	-15	-3	-12	1
CMS quality index (actual mean = 3.32)	0.05	0.01	0.03	0.02
Δ insurer revenue / enrollee	266	18	-48	-11
Δ govt. spending / enrollee	203	4	-47	-19
Δ E[CV]	-178	-80	11	21
% enrollees with E[CV]>0	3	4	70	67

TABLE A25— EFFECTS OF ESTABLISHING A PERSONALIZED LOW COST DEFAULT PLAN RESTRICTED TO THOSE WITHOUT STATE PHARMACY ASSISTANCE PROGRAMS AVAILABLE

	(1)	(2)	(3)
Utility cost of switching to			
actual default plan	0	0	$\delta\Delta P_{ijt}$
assigned default plan	0	$(\eta-\delta) \times \Delta B_{ijt}$	0
% enrollees choosing			
actual default plan	62	78	26
assigned default plan	32	12	58
other plan	6	10	16
Δ in average enrollee's expected			
premium ($)	-41	-16	-68
out of pocket costs ($)	-48	-21	-71
variance (actual mean = 584)	14	4	34
CMS quality index (actual mean = 3.32)	0.01	0.01	0.01
Δ insurer revenue / enrollee	-198	-79	-336
Δ govt. spending / enrollee	-120	-46	-200
Δ E[CV]	152	43	-71
% enrollees with E[CV]>0	88	82	43

TABLE A26—EFFECTS OF A MENU RESTRICTION AND PERSONALIZED DECISION SUPPORT BASED ON MODELS WITH HETEROGENEITY REPORTED IN TABLE A7

	Menu Restriction		Personalized Decision Support	
	(1)	(2)	(2)	(3)
Criterion for inclusion on menu	profit	enrollment		
Effect on behavior of suspect choosers	none	none	$\theta^s \rightarrow \theta$	none
Utility cost of switching plans	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$\eta\Delta B_{ijt} + \delta\Delta P_{ijt}$	$(1\text{-}\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$	$(1\text{-}\omega)$ x $(\eta\Delta B_{ijt} + \delta\Delta P_{ijt})$
% enrollees switching plans	33	20	25	25
Δ in average enrollee's expected				
premium ($)	78	4	-15	-8
out of pocket costs ($)	-33	-6	10	24
variance (actual mean = 584)	-13	-4	-14	0
CMS quality index (actual mean = 3.32)	0.04	0.01	0.02	0.01
Δ insurer revenue / enrollee	299	26	-47	-20
Δ govt. spending / enrollee	227	11	-43	-24
Δ E[CV]	-220	-113	33	30
% enrollees with E[CV]>0	2	4	71	66

TABLE A27— EFFECTS OF ESTABLISHING A PERSONALIZED LOW COST DEFAULT PLAN BASED ON MODELS WITH HETEROGENEITY REPORTED IN TABLE A7

	(1)	(2)	(3)
Utility cost of switching to			
actual default plan	0	0	$\delta\Delta P_{ijt}$
assigned default plan	0	$(\eta-\delta)$ x ΔB_{ijt}	0
% enrollees choosing			
actual default plan	63	78	26
assigned default plan	31	13	58
other plan	6	10	16
Δ in average enrollee's expected			
premium ($)	-43	-18	-67
out of pocket costs ($)	-47	-22	-75
variance (actual mean = 584)	14	5	36
CMS quality index (actual mean = 3.32)	0.02	0.01	0.01
Δ insurer revenue / enrollee	-210	-88	-343
Δ govt. spending / enrollee	-125	-52	-197
Δ E[CV]	151	47	-136
% enrollees with E[CV]>0	89	83	39