Paying Attention or Paying Too Much in Medicare Part D?*

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Abstract

We study individuals' decisions to switch prescription drug insurance plans (PDPs) in Medicare Part D from 2006-2010. Using panel data for a random 20% sample of all non-poor enrollees, we find that only 50% of individuals were in their original PDP by January, 2010. Individuals switch PDPs in response to increases in their status quo plans' costs. Contrary to choice overload, switching increases when more plans are available, particularly more relatively cheap plans. Over time, people become more responsive to large increases in their status quo plans' costs. These results are robust to different assumptions regarding consumers' expected costs under alternative plans.

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1 Introduction

Across a range of contexts, researchers are evaluating the veracity of the long-held view that consumers benefit from being offered more options. A leading challenge to this view is the hypothesis that facing more options impairs decision making through a set of phenomena known as "choice overload" (Iyengar and Lepper (2000)), "status quo bias" (Samuelson and Zeckhauser (1988)), "the paradox of choice" (Schwartz (2004)) and "inertia" (Dube, Hitsch and Rossi (2010)). Each of these terms carries somewhat different connotations and is ascribed to various underlying economic and psychological causes. Their common predictions, however, are that facing more options makes consumers less satisfied with their choices and more likely to remain in their status quo, even if the status quo is making no purchase at all. Yet a recent experiment on the elderly population specifically (Besedeš et al. (2012)) and a meta-analysis by Scheibehenne, Greifeneder and Todd (2010) yield conclusions antipodal to these other frequently-cited studies. Scheibehenne, Greifeneder and Todd (2010) determined that the existing experimental research does not support the choice overload hypothesis but instead demonstrates the benefits of adding choices. Similarly divergent opinions also exist regarding effects of experience on the dynamics of consumer decision making. For example, List (2003) and Miravete (2003) provide evidence that learning through experience creates financial benefits to consumers and ameliorates certain types of consumer biases. DellaVigna and Malmendier (2006), DellaVigna (2009) and Speigler (2011) provide empirical and theoretical evidence, respectively, to the contrary.

Medicare Part D represents a prominent setting where research may help resolve these broader tensions in the academic literature. In contrast with Medicare's traditional design, Part D relies on enrollees to choose their prescription drug coverage from private insurers competing within a government-created, taxpayer-subsidized market. Part D's relevance to choice overload stems from the high potential for the existence of such effects given the large number of complex products and the health and demographics of the consumers. Likewise, an attractive feature of Part D for evaluating the effects of experience is that it offers the rare ability for researchers to observe each consumers' entire experience across all firms in the market. Despite researchers' broad interest in the effects of choice overload and experience

on consumer decision making and the policy relevance of the Part D context, research has not yet examined how such factors influence consumers' dynamic decisions to switch between Medicare prescription drug plans (PDPs). We do this here. Specifically, this article has two primary objectives. First we evaluate how the number of options affects the likelihood of switching and how these effects differ when the additional options are relatively cheap versus relatively expensive to the individual. Second, we examine whether facing more options or having been in the PDP market longer cause people to be less likely to switch in response to their status quo plans becoming more expensive relative to the alternatives.

To achieve these objectives we analyze a random 20% sample of the entire population enrolled in a PDP, with a few additional criteria for inclusion in our study sample described below. For this sample we rely on rich data and institutional knowledge within CMS to develop an accurate method of calculating what each person would have spent in each available plan under a few alternative modeling approaches. We also use these resources to establish accurate measures of switching, experience, and the number of plans available in the region overall and the number available by level of cost to the individual.

To summarize these descriptive results, above-minimum spending fell dramatically across the first three years of the program. They climbed in the fourth year and, even at the nadir in 2008, persist at levels above $200. PDPs' retention of those who enrolled from 2006-2009 was only 50% in January, 2010. Rates of switching between PDPs in each open enrollment period, however, are persistently around 11%. In the year immediately after individuals switch PDPs, they experienced notably lower OOP spending than they would have if they had remained in their status quo plan. These savings also accrue into future years, and nearly 28% of those enrolled in a PDP in 2010 had previously switched between PDPs. As a result, between 2007 and 2010 the cumulative savings to individuals from switching PDPs surpassed $1.3 billion.

The results from empirical models that account for individual-specific unobserved heterogeneity, within-person changes in health over time and other factors yield additional insights. First, they demonstrate that the individuals' cost from the status quo plan, relative to the alternatives, is an important determinant of individuals' decisions to switch. Second, adding plans to the choice set systematically increases the likelihood of switching. This result holds

unless the additional plans are very dominated on cost to the individual, in which case adding more dominated plans has no influence on switching. These results are contrary to the predictions of choice overload and consumer confusion. Finally, we observe that over time people become more responsive to higher levels of cost under their status quo but less responsive to lower levels. This is consistent with people growing in their ability to respond to relative changes in their status quo plan while simultaneously growing in their state-dependent preferences for or value from their status quo plans.

In the next section we summarize the related literature on choice overload and experience and its expected implications for consumers' decisions to switch PDPs. Section 3 provides a description of the CMS data and the methods used to measure the key variables and the trends in those variables from 2006-2010. Results regarding individuals' switching decisions and choice overload are presented in Section 4. The role of experience in switching decisions is evaluated in Section 5. Section 6 provides the results from five alternative modeling approaches and Section 7 concludes.

2 Relevance of existing research for Medicare Part D

A number of articles have found evidence for choice overload, whether from increasing the number of options from 2 to 4 in a laboratory experiment (Samuelson and Zeckhauser (1988)), or by several hundred as for mutual funds (Kempf and Ruenzi (2006)).[1] Related, Madrian and Shea (2001) found that in the context of 401(k) plans offered by an actual employer, automatic enrollment greatly amplified participant inertia. Specifically, they concluded that status quo bias resulted in the default option being chosen far more frequently simply as a result of being the default. That article did not evaluate how such effects varied with the number or types of options provided. Building on these results and on the work of Klemperer (1995), Speigler (2011) developed a theoretical model to demonstrate that increasing the number of options increases consumers' status quo bias, resulting in greater price variation and suppliers' profits.

Applications of this research to Medicare Part D have been widespread, with particular

[1] Tversky and Shafir (1992) and Iyengar and Lepper (2000) represent two other salient experimental examples.

emphasis on the results of the experiments in Iyengar and Lepper (2000).[2] In Part D, the default option for non-participants is to continue not to participate. Likewise, the default for current enrollees during open enrollment is to remain in their status quo plans for the upcoming year. Additionally, the average number of available plans faced by individuals in 2006-2010 was 51, based on data described below. In contrast with the conclusions from Iyengar and Lepper (2000), however, satisfaction and participation in Part D both remain high, with 85 percent of participants reporting satisfaction and 90 percent of the Medicare population enrolled in some form of creditable prescription drug coverage (Centers for Medicare and Medicaid Services (2011*a*).[3]

The primary existing research supporting restrictions on consumer choice in Part D specifically is Abaluck and Gruber (2011) who conclude that, "consumers would be better off if there were less scope for choosing the wrong plan" (page 1109). Their proposed method of achieving this outcome is by constraining the number of insurance plans available to each person (Abaluck and Gruber (2009)).[4] Yet that research did not examine the effects of the number and scope of options directly. Further, it evaluated only the first year of Part D when consumers had no experience in the newly-created market and when the complementary information market was still being developed.

In the context of Part D, the first-order prediction from the choice overload hypothesis to be tested is that adding plans to an individual's choice set would suppress the likelihood that she switches out of her status quo plan. Extending beyond this hypothesized main effect, we also consider whether increasing the number of options obfuscates consumers' evaluation of the alternatives. If this occurs, facing more options would cause consumers to become less responsive to the relative costs of their status quo plans and less able to reduce their costs when they do switch.[5] Due to such concerns, in 2008 and 2009 CMS became more active

[2]For example, the Rhode Island Health Care Reform Commission in charge of designing the state's health insurance exchange stated that, "studies indicate that people are more likely to make a choice–and be satisfied with their choice—when they face a more limited set of choices," citing Iyengar and Lepper (2000) and Iyengar, Huberman and Jiang (2004) (The Rhode Island Healthcare Reform Commission (2011)).

[3]Additional evidence for high participation levels in 2006 is provided in Heiss, McFadden and Winter (2006) and for 2009 in Neuman and Cubanski (2009). Additional evidence regarding consumers' satisfaction with Part D is available from AARP (November 2007) and Medicare Today (2012).

[4]For a sampling of health policy articles supporting restricted choice in Part D and in the state health insurance exchanges see Day and Nadash (2012), Mikels, Reed and Simon (2009), Cummings, Rice and Hanoch (2009), Tanius et al. (2009), Hoadley (2008), and Huskamp et al. (2000).

[5]As an example from the health policy literature, Tanius et al. (2009) used a laboratory experiment to

in denying insurers' applications to sell plans that were viewed as too similar to other plans already sold by the same firm.[6]

In contrast with the subset of studies that have been commonly applied to Part D, the analysis by Scheibehenne, Greifeneder and Todd (2010) demonstrates that the studies of Iyengar and Lepper (2000) represent (unreplicable) outliers, with 50 experiments providing no overall evidence that more options affects satisfaction and purchasing decisions. Instead, they conclude that the existing research demonstrates, "'more choice is better' if decision makers had well-defined preferences prior to choice" (Scheibehenne, Greifeneder and Todd (2010), page 421). Given this condition, it is notable that Iyengar and Lepper (2000) state that they intentionally chose participants who would "not already have strong specific preferences." Part D consumers, likely having decades of experiences with various types of insurance, may enter the Part D market with existing preferences, e.g., for lower costs, and have well-established conceptions that lower costs can be achieved from plan attributes such as lower premiums, lower deductibles, and more generous formulary coverage. Also relevant for considering choice overload in Part D are Scheibehenne et al.'s (2010) conclusions that these null effects are independent of the size of the choice set, i.e., they find no evidence of nonlnear effects of adding options to the choice set. As a result, we expect that any effects of choice overload observed under the range of choice set sizes that has existed in Part D so far should also apply to much smaller or larger choice sets. We return to this issue in the conclusions.

Regarding the effects of experience, prior research has shown that as they gain experience with a good or service over time, they become less likely to switch to an alternative. This effect has been found in markets for frequently purchased and utilized goods such as laundry detergent (Osborne (2011)) and diapers and baby towels (Heilman, Bowman and Wright (2000)), for far less-frequently purchased goods such as personal computers (Prince (2011))

conclude that, "individuals have a more difficult time choosing the best option when faced with large number of prescription drug plans than when faced with few."

[6] As evidence of the stated motivation for this change, the 2008 Call Letter stated, "CMS will negotiate with [prescription drug plan (PDP)] sponsors to ensure that each bid they submit represents a meaningful variation based on plan characteristics that will provide beneficiaries with substantially different options. ... We expect that organizations will take steps to ensure that the array of PDP benefit packages submitted can be *reasonably understood and compared* by beneficiaries in terms of key plan characteristics" (our emphasis added) (Centers for Medicare and Medicaid Services (2007)).

and for services purchased annually but less-frequently utilized such as automobile insurance (Israel (2005*a*)). The precise mechanisms underlying this positive relationship between inertia and experience differ across theoretical models and empirical contexts, but they rely on some combination of increasing switching costs and asymmetric learning. Switching costs arise as consumers make investments in the specific product that they have been purchasing, where those investments do not carry over to alternatives. Such switching costs may arise from either economic or psychological factors. Asymmetric learning occurs as consumers' gain knowledge of their status quo via their experiences but do not gain knowledge regarding the alternatives (Klemperer (1995), Osborne (2011), Prince (2011)).[7,8] Other related evidence, however, suggests that consumers' abilities to navigate through such new and growing information markets may themselves grow with experience (Miravete (2003), List (2003), List (2004), List (2006), and List and Millimet (2008)). In Part D, if experience promotes consumers' ability to find better-matching plans, then we would expect people over time to become more likely to switch away from their status quo plans. In contrast, if a person's switching costs or asymmetric learning grow over time, then we expect she would become more likely to remain in her status quo plan. As a second order effect, experience may also enhance or dampen changes over time in how responsive people are to changes in the relative costs of their status quo plans.[9]

Like automobile insurance studied by Israel (2005*a*) and Israel (2005*b*), PDPs are purchased annually and may have economic (non-psychological) switching costs and asymmetric learning that increase with experience. Whereas in automobile insurance these switching costs enter through loyalty discounts, in Part D they are likely incorporated via prior autho-

[7]An example of this is evident even in the seminal paper on status quo bias by Samuelson and Zeckhauser (1988) which states, "Assuming that he or she understands his or her current plan, a reasonable strategy would be to undertake a comparative analysis including only some subset of competing plans (ignoring the others altogether). Thus, the status quo alternative gains a decision advantage by virtue of the asymmetric position it holds in the decision reckoning."

[8]Some of this existing research evaluates and finds that inertia increases with tenure in the status quo plan rather than with experience in the market per se. This focus is partly due to data limitations that allowed the researchers observe only individuals' tenure at a single firm and not the total extent of their market participation.

[9]Consistent with the prediction that switching costs would dominate, Heiss, McFadden and Winter (2010) conclude that, "there is a lock-in effect, and so it may have been a good strategy for plan providers in this repeated-interaction market to offer cheap plans in the first period and then to increase premiums and/or reduce plan quality over time."

rization requirements for certain drugs as well as from costs of establishing new mail order prescriptions. Regarding asymmetric learning, Part D enrollees frequently file claims, unlike auto insurance, potentially facilitating rapid learning about dimensions such as the plan-specific formulary and the quality of customer support. On the other hand, some measures of this information are readily available from sources including the CMS online "plan finder" that facilitates consumers' ability to compare plans. Because of the presence of these sources of information about the alternatives, the role of asymmetric learning in Part D may be minimal. The link between asymmetric knowledge about the status quo and experience may also be weak in Part D: CMS requires plans to notify their existing enrollees, but only their existing enrollees, of any upcoming changes in their premiums, deductibles, or formulary coverage, including providing a list of specific drugs that will be dropped from the formulary. Presumably this type of statutorially-established informational asymmetry may be whittled down by firms' marketing efforts and by the provision of information by intermediaries. On balance, these institutional details suggest that the effects of experience in Part D might diverge from the previously studied contexts where experience has been shown to inhibit switching.

3 Data and Descriptive Results

3.1 Part D Plan Turnover Rates

Our study combines several rich data sources for 2006-2010 available only from CMS. We begin with the 20% sample of Medicare beneficiaries, which is defined as everyone enrolled in Medicare with a randomly-assigned Medicare Beneficiary Identity Code that ends with 0 or 5 (Centers for Medicare and Medicaid Services (2012*a*). To assess the overall level of PDPs' enrollee turnover rates, we create a variable from the Master Beneficiary Summary-Base (A/B/D) files (Centers for Medicare and Medicaid Services (2012*c*), née the CMS Enhanced Denominator File) that indicates whether each person who started in a PDP without a low-income subsidy was still in the same PDP at the beginning of the following

year.[10] This variable shows the extent to which enrollees are inert from the plans' perspective. Low turnover rates would indicate that plans may have substantial opportunity to "harvest" gains from incumbent enrollees but also substantial incentive to compete for initial enrollment decisions (Dube, Hitsch and Rossi (2009)).

Table 1: Share of enrollees not enrolled in their original plan at the beginning of each subsequent year

	2007	2008	2009	2010
Among non-poor PDP enrollees who started in				
2006	18.8	32.8	44.0	53.0
2007	--	26.2	42.6	53.8
2008	--	--	24.8	42.1
2009	--	--	--	33.0

Table 1 reports the overall turnover rates separately by year in which the individual enrolled in any PDP without a low-income subsidy for the first time. Among those who first enrolled in a PDP in 2006, 19 percent were no longer enrolled in their initial plans by January, 2007. This climbed to 33 percent by January, 2008, 44 by 2009, and 53 percent were no longer enrolled in their initial PDP at the beginning of 2010.[11] Similar trends but with higher turnover levels are found among those who started in 2007, 2008 and 2009. Within at most 12 months of their initial PDP choice, 26 percent of those who started in 2007, 25 percent of those starting in 2008 and 33 percent of those starting in 2009 had already transitioned out of their original PDPs.[12] Over time, the retention rates continued to fall,

[10]Due to plan terminations and consolidations, determining whether a person remained in their initial plan is more complex than simply comparing whether the individual had the same contract and plan ID in the subsequent year. We relied on the CMS Plan Information Files (Centers for Medicare and Medicaid Services (2011*b*)) and the CMS Plan Crosswalk Files that tracks evolution in given plans' contract and plan IDs across years to provide an accurate measure of whether the individual was in the same plan over time. Prior to our analysis, the crosswalk files were incomplete and were not developed for conducting longitudinal research. For example, the crosswalks sometimes indicated that a plan was renewed by CMS at the request of the insurer, but the insurer subsequently chose not to offer that plan. In such cases, the plans do not appear in the latter year's Plan Information File, indicating that it was a terminated plan despite the existing crosswalk file's indication that the plan was renewed. We implement logic that capitalizes on all information available in these two files to develop accurate measures of true switching as distinct from non-switching that occurred from mergers or "forced switching" that occurred from terminations. Our efforts created the Part D Plan Crosswalk Extract file used internally within CMS and now available to external researchers.

[11]The 47 percent who remained in their original plan includes those who were still in the same PDP but acquired low-income subsidy status in the interim. We exclude those who had a low-income subsidy at the outset because many of them were assigned to a PDP by CMS and did not choose a plan for themselves.

[12]These non-retention rates include those who left PDPs for various reasons, including death. This is distinct from the measure of switching between PDPs that we use in our empirical analysis, as described below.

so that by the beginning of 2010, across all four of these cohorts almost exactly half (50.1%) were no longer enrolled in their original PDP.

3.2 The Cost Calculator

The remainder of this article focuses on individuals' decisions to switch between PDPs. Hence we restrict our analysis to those who were enrolled for the entire year in a single PDP, did not receive a low-income subsidy at any point in the year, were age 65 or higher and alive at the end of the year, did not live in a US territory outside of the 50 states or District of Columbia and did not have a duplicate entry in any year of the enrollment files. For these individuals we observe whether they switched between PDPs during each open enrollment period or whether they remained in their status quo PDP.

One of our central measures of interest is the cost of the individual's status quo plan relative to the available alternatives. To define this we develop and implement a cost calculator that estimates what each person would have spent in each PDP available in her region in each year. This cost calculator is based on institutional knowledge and data sets existing within CMS. It incorporates every aspect of every plan that determines individuals' total out-of-pocket (OOP) costs. These include the plans' formularies and cost sharing structure by pharmacy type; the deductible; coverage of drugs in each phase—below the deductible, below the initial coverage limit, within the gap, and above the catastrophic coverage limit; free first-fill; whether the plan covers statutorially-excluded drugs not reimbursed by CMS; and the underlying *plan-specific* drug prices, which we calculate using the universe (100%) of claims from the Prescription Drug Event (PDE) data for each year.[13] Details about the development of plan-specific total drug prices are in Appendix C.[14]

We apply this cost calculator to the Prescription Drug Event (PDE) file that lists every drug claim submitted on behalf of Medicare beneficiaries, including drug identifiers, date filled, gross price, amount paid by the insurer, patient OOP cost and formulary tier (available

[13]This highly-detailed information on each plan's design is found in the CMS Part D Plan Characteristics Files, which are based on administrative data used to review and approve plans (Centers for Medicare and Medicaid Services (2012*a*)). For example, these files provide the OOP price for every formulary tier, phase, and drug which are key inputs to our cost calculator, as discussed further in Appendix B.

[14]For the analysis we utilized the internal CMS data. However the majority of this information is available to academic researchers through the Research Identifiable Files.

only from the research-identifiable file, Centers for Medicare and Medicaid Services (2012*d*)), plus the pharmacy type (merged on from the Pharmacy Characteristics File). By using the claims for each person in the order they were filled, this cost calculator estimates an annual measure of the individual's gross drug spending and OOP drug spending in each available plan for each year. We measure the total OOP cost of each plan for each person in each year by adding the consumer's annual premiums for each plan from the premium file within the Part D Plan Characteristics Files to the calculated OOP drug spending.[15] We denote this measure of total OOP cost as C_{ijt} for individual i from choosing plan j that belongs to her choice set in year t. We utilize the distribution across plans for a given person and year to determine the difference between the status quo plan and minimum-cost plan, defined as $A_{it} = C_{it} - \min_j\{C_{ijt}\}$, where C_{it} is the actual chosen plan. We refer to A_{it} as "the individual's relative cost of the status quo plan," or as "above-minimum spending" to clarify that it is defined relative to the cost of the cheapest of all plans available to her.[16]

We validate the accuracy of this cost calculator by comparing each individual's actual out-of-pocket (OOP) costs, observed by CMS, with the OOP costs that we simulate for the actual plan, finding correlation coefficients for the two ranging from 0.98 in 2009 to 0.92 in 2006 and 2007.[17] This high level of accuracy of the cost calculator comes from our ability to incorporate information and institutional knowledge held within CMS that were only partially incorporated into previous cost calculators (Abaluck and Gruber (2011), Ketcham et al. (2012)). For example, this includes our ability to generate accurate underlying plan-specific prices, where the cost calculator of Ketcham et al. (2012) relied on a third-party data source (formerly Wolters Kluwer Health, now Symphony Health Solutions) to generate

[15] To ensure consistency across each person's choice set, we use the calculated OOP costs even for the actual plan.

[16] We do not intend the term above-minimum spending to carry any normative implications, but rather to highlight that this variable is concerned with only the total OOP amount that the consumer could have saved by choosing her minimum-cost plan.

[17] By comparison, the cost calculator used in Ketcham et al. (2012) yielded correlations of only 0.80 in 2006 and 0.77 in 2007. The current cost calculator yields a few cases where the calculated gross spending in the actual plan sharply diverges from the actual gross spending. We eliminate these individuals from all years of the data if in any single year the the dollar difference between their calculated and actual spending as well as the ratio of these two gross spending measures both fall below the 0.1 or above the 99.9 percentile for the year. Investigating the underlying causes of these outliers showed that they were typically due to implausible units dispensed on one claim, so that their calculated gross spending diverged greatly from their actual gross spending.

these plan-specific prices, and the cost calculator of Abaluck and Gruber (2011) held a given drug's price constant across all plans. We find that allowing drug prices to vary across plans matters substantially, with an average within-person range in total drug spending (the sum of OOP and other payers' spending), holding drug consumption constant and only allowing the plans' drug prices to vary, of $462 in 2006 up to $764 in 2008 and an average standard deviation in gross drug spending across plans for a given person-year ranging from $140 in 2006 up to $198 in 2009. This contrasts with the approach in Abaluck and Gruber (2011) which imposes $0 variance across plans in gross spending for a given person in a given year.

As another specific example of the types of improvements incorporated into this cost calculator, we built into it precise information about gap coverage. In the public use files, gap coverage is presented as a categorical variable. In reality, however, even plans with gap coverage tremendously differ in the extent of coverage in the gap, e.g., some formulary tiers are covered at certain rates in the gap while other tiers may have less or no coverage. We accessed the open text fields provided by the plans themselves to allow the cost calculator to accurately assign the each plan's specific cost-sharing rules in the gap for every drug.[18]

Several modeling decisions are required to implement this cost calculator. First, as analysts we do not know the quantities or mix of prescriptions each person would have filled in her available but unchosen plans, i.e. due to differences from the actual plan in demand-side (OOP prices) or supply side (e.g., prior authorization requirements) cost controls. We adopt two different approaches. First, for a given person and year, we hold the drugs constant across every plan in the choice set. We refer to this approach as the "perfectly inelastic" method. Second, we alter the gross and OOP spending to account for price elasticity of demand for drugs. In that approach we rely on the average elasticity for Medicare enrollees of -0.54 estimated by Shea et al. (2007).[19]

The second decision that analysts face regards how to measure the information that consumers use to form their expectations about the upcoming year. The context of Part D plan choice incorporates uncertainty about future prescription drug use. In our main

[18]This was required for 2006 only, as in later years this information was embedded within the Research Identifiable File Tier Characteristics Table available to researchers. These details are embedded within the cost calculator code accompanying this article and available through the journal's website.

[19]A more extended consideration of these issues is provided in the appendix of Ketcham et al. (2012).

approach we use the prescriptions filled in the next year, i.e., the year for which the individual is making an enrollment decision. The models of switching that we implement relying on this approach evaluate consumers' sensitivity to the actual, realized costs of their status quo plan relative to the cheapest plan in the upcoming year. We refer to this as the *ex post* approach. To assess the importance of these key assumptions for our primary results, we also allow for two different possibilities. These are the *ex ante* or "plan finder" approach and the "rational expectations" approach as described in Section 6 below.

3.3 Trends in Spending, Switching and Savings from Switching

As a first measure of how PDP enrollees fared over time, the first row of Table 2 reports the total OOP spending in each year. The results show a large reduction in individuals' average total OOP from 2006 to 2007, amounting to an average decrease of $208. These reductions continued and OOP spending fell another $71 in 2008 before climbing in both 2009 and 2010, albeit remaining under the 2006 levels. To provide a benchmark for comparison, the fourth row reports the Government Accountability Office Drug Price Index for the corresponding years (Government Accountability Office (2011)). In contrast with the 6.2% net decrease in total OOP spending among PDP enrollees, the GAO index shows a net increase of 29.1% from 2006-2010.[20]

The remainder of Table 2 reports the trends in the OOP cost of the individual's minimum-cost plan(s) and the trend in above-minimum spending. Because these measures may be sensitive to the assumed price elasticity of demand for drugs, we report them first using the assumption that prescription drug demand is perfectly inelastic, and second assuming an elasticity of -0.54. As with total OOP spending, the OOP spending under the minimum-cost plan fell each year from 2006-2008 before climbing in both 2009 and 2010.

The net effect of these two trends is captured in the above-minimum OOP spending measures. Above-minimum spending fell sharply from 2006-2007 as in Ketcham et al. (2012). Under the assumption of perfectly inelastic demand, above-minimum spending fell by $173 (33%). Above-minimum spending fell by another $54 in 2008, yielding a level equal to only

[20]Even setting aside the reductions from 2006 to 2007, the 7.9% increase in OOP spending from 2007-2010 is well below the contemporaneous increase in the GAO index of 23.7%.

56% of the 2006 level. Above-minimum spending climbed in 2009 but plateaued at $329 in 2010, still $191 (37%) below the 2006 level and also under the 2007 level. The trend under the assumption of elastic demand is highly similar, albeit with lower levels of above-minimum spending and thus also smaller changes over time. Under both approaches, above-minimum spending as a percent of total OOP spending was at its lowest levels in 2010, matching the lows achieved in 2008 near 20%.

Table 2: Trends in out-of-pocket spending and above-minimum spending among non-poor PDP enrollees, 2006-2010

	2006	2007	2008	2009	2010
Total OOP spending ($)	1590	1382	1312	1435	1492
Year to year percent change in OOP spending	--	-13.1	-5.1	9.4	3.9
Percent change in OOP spending relative to 2006	--	-13.1	-17.5	-9.7	-6.2
GAO Drug Price Index year to year change	--	5.4	8.1	7.0	5.9
GAO Drug Price Index change relative to 2006	--	5.4	13.9	21.9	29.1
Ex post approach with perfectly inelastic demand for drugs					
OOP Spending in minimum-cost plan ($)	1070	1036	1019	1104	1163
Above-minimum OOP spending ($)	520	347	292	331	329
Above-minimum OOP spending as percent of total OOP (%)	33	25	22	23	22
Ex post approach with price elasticity of demand for drugs of -0.54					
OOP Spending in minimum-cost plan ($)	1235	1145	1078	1153	1217
Above-minimum OOP spending ($)	355	237	234	282	275
Above-minimum OOP spending as percent of total OOP (%)	22	17	18	20	18

NOTE: OOP is out-of-pocket.

To analyze switching decisions, we further limit the sample to those who met the cost calculator criteria for two consecutive years. This ensures that we are comparing two similar sequential open enrollment decisions for full-year non-low-income subsidy coverage because people are likely to make different choices for part-year versus full-year and subsidized versus unsubsidized coverage in ways that would affect switching. Through this restriction and the fact that no switching could occur for 2006, our sample consists of 1,512,275 individuals making 3,960,499 switching decisions, with 433,154 for 2007, 1,141,521 for 2008, 1,183,741 for 2009 and 1,202,083 for 2010. The overall rate of switching between PDPs among those who stayed enrolled in a PDP and did not acquire a low-income subsidy is reported in the first row of Table 3. This rate was 11.7% for 2007, fell by nearly one percentage point in 2008 and then remained virtually flat at just under 11 percentage points through 2010.[21] By

[21]These switching rates are below the overall retention rates reported above because this is restricted to only PDPs' enrollees decisions to switch PDPs during open enrollment between two full years of enrollment

comparison, switching rates between non-poor individuals' initial, partial year of enrollment and their first full year of enrollment were notably higher in almost every year, at 8.5% for 2007, 22.1% for 2008, 17.6% for 2009 and 25.3% for 2010.

Table 3: Switching and savings from switching, 2007-2010

	2007	2008	2009	2010
Switched between PDPs from the prior year (%)	11.7	10.9	10.6	10.7
Ex post approach with perfectly inelastic demand for drugs				
Mean savings from switching ($)	178	256	254	206
Median savings from switching ($)	132	223	222	154
Percent that saved >$0 from switching (%)	66.1	81.7	86.2	77.4
Ex post approach with price elasticity of demand for drugs of -0.54				
Mean savings from switching ($)	102	194	195	144
Median savings from switching ($)	101	158	180	112
Percent that saved >$0 from switching	65.1	82.7	88.0	80.9

NOTE: OOP is out-of-pocket. All values are from the sample that was enrolled in a single PDP without a low-income subsidy for the entire prior year.

With this set of switching decisions, we rely on the cost calculator to measure how much each individual saved as a result of switching. For someone who chose to switch, this is the difference between her total OOP spending in her new plan and what her OOP spending would have been if she had stayed in her status quo plan, i.e., $B_{it} = C_{it} - C_{ij_{t-1}t}$ where $C_{ij_{t-1}t}$ denotes the OOP spending in year t if the person stayed in her plan from year $t-1$. Because this is a within-person, within-year comparison, it eliminates the effects on OOP spending of all time-varying and time-invariant individual-specific effects including health.

As reported in Table 3, the mean and median savings from switching exceed $100 in each year. These savings increased sharply from 2007-2008 and remained high in 2009. They declined in 2010 but still remained above the 2007 levels. These savings accrued to a large majority of those who switched plans, with reductions ranging from 77-88% of them for 2008-2010. These levels are also above 2007, during which 65-66% of switchers achieved lower OOP spending as a result of switching.[22]

in any PDP. This eliminates everyone who left the non-poor PDP market for various reasons, including acquiring a low-income subsidy, death, and switching to other types of plans.

[22]It is worth noting that these results are based on a demanding analytical standard, as it compares individuals' actual, *ex post* realized costs about which consumers may have some uncertainty or otherwise limited information.

To consider additional dynamic aspects of savings from switching, we also establish counterfactual spending measures whereby people stayed in their initially-chosen plan for the remainder of their time in a PDP. This approach allows for savings from switching to accrue to the individual in years even beyond the single year following the switch itself. Under the inelastic approach, by 2010 the average annual OOP savings by those who ever switched was $233, yielding actual OOP spending 13% below what it would have been without any switching. The estimated cumulative savings from switching between PDPs for 2007-2010 exceeds $1.3 billion, equivalent to 13% of the actual cumulative spending by PDP enrollees. Similar patterns with lower magnitudes are observed under the alternative approach of allowing the demand for drugs to be somewhat elastic.[23]

Table 4: Cumulative switching and savings from switching, 2007-2010

	2007	2008	2009	2010
Percent of current enrollees that have ever previously switched between PDPs (%)	11.7	16.9	23.1	27.6
Actual OOP spending by those who ever previously switched ($)	1882	1480	1500	1540
Ex post approach with perfectly inelastic demand for drugs				
OOP spending if stayed in original plan and never switched ($)	2062	1687	1725	1773
Annual savings by current enrollees who ever previously switched ($)	180	207	225	233
Savings as a percent of total OOP spending (%)	9.6	14.0	15.0	15.1
Total non-subsidy PDP full year enrollees	7,462,806	7,743,191	7,790,845	7,787,562
Annual savings from cumulative switching ($)	157,306,398	271,298,803	405,055,147	500,802,537
Total cumulative savings from switching ($)	157,306,398	428,605,201	833,660,347	1,334,462,885
Ex post approach with price elasticity of demand for drugs of -0.54				
OOP spending if stayed in original plan and never switched ($)	1987	1650	1686	1734
Annual savings by current enrollees who ever previously switched ($)	105	170	186	194
Savings as a percent of total OOP spending (%)	-100.0	-100.0	-100.0	-100.0
Total non-subsidy PDP full year enrollees	7,462,806	7,743,191	7,790,845	7,787,562
Annual savings from cumulative switching ($)	91,820,275	222,880,629	334,867,424	416,977,220
Total cumulative savings from switching ($)	91,820,275	314,700,905	649,568,329	1,066,545,549

NOTE: OOP is out-of-pocket.

3.4 Variables for Number of Plans and Experience

We rely on two distinct measures of the number of plans to evaluate the role of choice overload in people's switching decisions. First, we use the total number of plans available in the region. This is measured by counting the number of unique plan IDs listed for PDPs (and excluding employer plans) offered in each region and each year.[24] Second, we use the results from the

[23]These values are calculated for those who switched between two full years of enrollment. As such it represents an underestimate of the true total savings because savings also accrue to those enrolled for only a partial year.

[24]Employer plans are not available to people who were not employees of the particular firm.

cost calculator to count the number of plans by their relative costs. We define this as the number of plans that are within $100 of the person's minimum-cost plan, within $100-200 of the minimum, $200-300, $300-400, $400-500, and more than $500.[25] In contrast with the overall plan count, which is defined at the region level, this is an individual-specific variable with variation across individuals within a region.

Table 5: Average number of prescription drug plans available to the study sample, overall and by individual-specific relative cost categories

							Average within-person		
	Overall	2006	2007	2008	2009	2010	Minimum	Maximum	Range
Total standalone plans available	51.1	43.1	55.8	54.5	50.2	47.1	46.3	55.3	9.0
Number of plans available within									
$100 of minimum	4.8	3.0	6.2	5.8	4.0	4.0	2.2	8.2	6.0
$100-200 of minimum	8.8	4.4	11.3	10.6	7.6	7.3	4.6	13.6	9.4
$200-300 of minimum	10.4	6.5	12.6	10.8	10.4	9.3	6.3	14.5	8.2
$300-400 of minimum	8.6	7.2	10.0	8.9	8.4	7.6	5.2	12.1	6.9
$400-500 of minimum	5.5	6.2	5.8	5.2	5.6	5.4	2.9	8.6	5.8
>$500 of minimum	13.0	16.0	9.8	13.2	14.3	13.5	7.6	19.4	11.8

NOTE: The set of available prescription drug plans excludes employer-sponsored plans because those are not open to those not employed by the firm. The count by category of relative costs are from the *ex post* version assuming a price elasticity of demand for drugs of -0.54.

Table 5 reports the overall number of plans and the number of plans by relative cost category using the *ex post* approach. To streamline the presentation of results, here we report only the count by cost assuming a price elasticity of demand for drugs of -0.54. Consistent with the change in enforcement announced by CMS for 2008, the strong surge in the number of plans available in 2007 was followed by a decline in 2008. This decline continued through 2010, dropping from a high of 56 in 2007 to 50 in 2009 and to 46 in 2010. These declines from 2007-2010 appear concentrated among the lower-cost categories, with the largest percent reductions in the two cheapest categories (35 percent). In contrast, the highest cost category saw an increase in the number of plans over that period. The last two columns of this table show the averages of the minimums, maximums and within-person ranges of these variables. This is important because our identification for empirically testing the choice overload hypothesis relies on such within-person variation.

The final main variable of interest is experience. We define this as the cumulative number of months with coverage in a PDP without a low-income subsidy. We eliminate time in a

[25] We implemented a handful of alternative groupings and consistently found the same patterns of results as reported below.

PDP with a low-income subsidy for two reasons. First, such enrollees are auto-assigned to a benchmark plan and thus may not have any experience searching for plans. Second, the OOP cost-sharing structure for on-formulary drugs is substantially different when a person has a low-income subsidy, so that such experience likely has little informative value to consumers. We analyze the effects of total experience in the PDP market rather than the tenure in the status quo plan. Much of the prior research from other contexts used the cumulative time in the status quo because the available data did not permit the authors to observe total time in the market. Given that we can observe total experience here, we rely on it exclusively because tenure in the status quo plan is endogenous, as discussed extensively in Israel (2005*b*).[26] The average experience of our study sample climbed each year, beginning with exactly 12 months for everyone in the 2007 sample, to 21.1 months in 2008, 31 months in 2009 and 40.0 in 2010.

Two noteworthy observations come from juxtaposing these trends in the number of available plans and experience with the financial variables shown above. First, the trends in OOP spending and above-minimum spending show a consistent inverse relationship with the number of available plans. Spending and above minimum-spending were highest in 2006, when the number of plans available was smallest, and was second highest in 2010, when the number of plans available was at its second lowest level. The spending and above-minimum spending measures were lowest in 2007 and 2008, when the number of plans was at its highest levels. Spending and above minimum-spending began to climb in 2009, contemporaneous with the reduction in the number of plans available. Second, the decreases in OOP spending and above-minimum spending from 2006-2008 raise the potential that individual learning from experience may be important. Yet the uptick in the financial measures for 2009 and 2010, at least in terms of absolute dollars but not in percentage terms, suggest that the effects of such learning may be small relative to other market-wide changes over time.

3.5 Demographics, Health and Other Variables

We link on several CMS data sets to determine each individual's characteristics at each point in time. The individual's region, age (held constant as age at the end of 2010), sex, and race

[26]The number of months in the status quo plan and the total months of experience in the PDP market have a correlation coefficient of .88.

(defined using the Research Triangle Institute methodology developed by Eicheldinger and Bonito (2008)) are provided from the Beneficiary Summary File (Centers for Medicare and Medicaid Services (2012*b*)). Measures of each individual's health are provided through the Beneficiary Annual Summary File (BASF), from which we measure the total reimbursement (defined as the sum of what Medicare paid, what the individual paid, and what any secondary insurers paid) for the beneficiary for hospital inpatient stays, for physician services, and for all other non-Part D spending (Centers for Medicare and Medicaid Services (2012*a*)). Other health controls we incorporate from the BASF are the number of hospital inpatient admissions, outpatient visits, skilled nursing facility days and physician office visits. Additionally, the Chronic Condition Data Warehouse (CCW) provides indicator variables for 21 different clinical indications for 2005-2010, which we collapse into 16 different categories (Centers for Medicare and Medicaid Services (2012*a*)).[27] The list of illnesses and their prevalence by year are presented in Appendix Table A, as are the means of the other variables used but not reported elsewhere in this article.

4 Switching and Choice Overload

In this section we evaluate the role of choice overload in explaining individuals' switching decisions. Our approach relies on the within-person variation over time in the number and mix of plans. Our specific objectives are to determine how individual decisions to switch plans depend on the individuals' relative costs from remaining in the status quo plan and the number of plans. To accomplish this we estimate linear probability models of the form

$$S_{it} = \theta_t + \theta_i + \alpha_1 A_{it} + \alpha_2 N_{it} + \alpha_3 H_{it} + u_{it}, \tag{1}$$

where S_{it} equals 100 if the individual switched for year t and 0 otherwise, θ_t correspond to year fixed effects, θ_i is an individual-specific time invariant unobservable, A_{it} is the person's above-minimum spending in units of \$100 if she remains in her status quo plan and H_{it}

[27]The CCW methodology utilizes peer-reviewed research to identify specific ICD-9, CPT4 and HCPCS codes indicating the presence of a diagnosis for each condition, as described online, `http://www.ccwdata.org/chronic-conditions/index.htm` The CCW creates these indicators by using information from the individual's Medicare Part A and Part B claims.

represents time-varying measures of the individual's health as described in Section 3. In the first specification, N_{it} is the number of plans available in the region and year. In the second specification, it is a vector of variables that count how many plans are within each category of OOP spending relative to the minimum-cost plan, as listed above. The coefficients on these main effects for N_{it} tests the prediction of choice overload that facing more plans will inhibit switching. To account for interdependence among observations, we estimate each model using a 100 iteration bootstrap with replacement that accounts for the clustering of switching decisions within individuals. We implement this linear specification as opposed to index models such as logit or probit due to the incidental parameters problem first reported by Neyman and Scott (1948).[28]

To this base model we add an interaction term to provide a test of the second order prediction about how choice overload affects individuals' decisions to switch plans. Specifically, we estimate linear probability models

$$S_{it} = \theta_t + \theta_i + \alpha_1 A_{it} + \alpha_2 N_{it} + \alpha_3 H_{it} + \alpha_4 A_{it} * N_{it} + u_{it}. \quad (2)$$

The interaction term(s) $A_{it} * N_{it}$ provides a test whether adding more options decreases individuals' responsiveness to changes in above-minimum spending they would incur if they remain in their status quo plans.

Table 6 shows the results from these models from the *ex post* elastic version. The results from alternative modeling approaches are reported in Section 6. The base model that controls for the number of plans available indicates that conditional switching rates were statistically significant and economically meaningfully higher in 2010 relative to 2007 but generally similar from 2007-2009. The results also show that each additional $100 of above-minimum spending by remaining in the status quo plan increases the probability of switching by 2.9 percentage

[28]This has been studied further by Nerlove (1967), Nerlove (1971), Heckman (1981), Abrevaya (1997), Katz (2001) and Greene (2004). This problem makes both the fixed effects and the parameters of the index inconsistent in those models when the individual heterogeneity is left completely unrestricted. Although it is possible to estimate fixed effects logit models with an unrestricted distribution of the unobserved characteristics, we see two drawbacks relative to the linear probability model. First, it can only be estimated on individuals with variation in the switching variable, i.e., those who switched in at least one year but not every year. This is a non-representative sample and would yield overestimates of the true marginal effects of the independent variables. Second, obtaining the marginal effects of interest requires further assumptions about the value of the unobserved effects, which defeats the purpose of leaving that distribution unresticted.

Table 6: Parameter estimates from models of switching Prescription Drug Plans, 2007-2010

	Number of plans overall						Number of plans by cost					
	No Interactions			Interactions			No Interactions			Interactions		
Above-minimum spending if stay in status quo plan ($100s)	2.88	[0.02]	***	4.99	[0.17]	***	4.03	[0.04]	***	6.80	[0.16]	***
Number of available plans	0.39	[0.01]	***	0.50	[0.02]	***						
*Above-minimum spending if stay ($100s)*Number of available plans*				-0.04	[0.00]	***						
Number of available plans within												
$100 of minimum							0.60	[0.01]	***	0.90	[0.02]	***
$100-200 of minimum							0.61	[0.02]	***	0.60	[0.02]	***
$200-300 of minimum							0.54	[0.01]	***	0.43	[0.02]	***
$300-400 of minimum							0.41	[0.02]	***	0.32	[0.02]	***
$400-500 of minimum							0.43	[0.02]	***	0.36	[0.02]	***
>$500 of minimum							0.00	[0.02]		0.58	[0.02]	***
*Above-minimum spending if stay ($100s)*Number of available plans within*												
$100 of minimum										-0.08	[0.01]	***
$100-200 of minimum										0.03	[0.00]	***
$200-300 of minimum										0.03	[0.00]	***
$300-400 of minimum										-0.01	[0.00]	*
$400-500 of minimum										-0.02	[0.00]	***
>$500 of minimum										-0.13	[0.00]	***
2008	0.10	[0.06]	*	0.11	[0.06]	*	1.74	[0.06]	***	-0.08	[0.06]	
2009	-0.20	[0.11]	*	-0.20	[0.11]	*	2.32	[0.11]	***	-0.02	[0.11]	
2010	1.16	[0.16]	***	1.09	[0.16]	***	3.64	[0.15]	***	1.55	[0.16]	***

NOTE: N = 3,645,570. Standard errors from 100 iteration bootstrap with replacement are in brackets. *** p<0.01, ** p<0.05, * p<0.1. All models also include individual fixed effects and controls for time-varying health. The number of plans by cost category and above-minimum spending in the status quo plan are defined using the *ex post* approach and assuming a price elasticity of demand for drugs of -0.54.

points. The results from the base model controlling for the number of plans by relative cost category show even greater responsiveness, with a 4.0 percentage point increase in switching in response to $100 higher above-minimum spending in the status quo plan. Thus individuals' relative OOP spending in their status quo plans is a significant factor in their decisions to switch plans.

Regarding the main prediction of choice overload's effects, the results for the number of plans do not support the hypothesis that facing more options inhibits switching. In contrast with the negative, significant effects predicted by the choice overload hypothesis, the results show highly significant positive effects of adding more plans. Specifically, the results indicate that adding 10 more plans increases switching rates by 3.9 percentage points, approximately a 40% increase from the sample mean switching rate.

As with the baseline model, the results from estimates of equation 2 show differences in conditional switching rates over time, with higher rates in 2010 than in 2007. The results from this model also shows large, positive main effects of both above-minimum spending and the number of plans on switching, with 10 additional plans increasing switching by 5.0 percentage

points. Due to the magnitudes of this main effect, the partial effect of increasing the status quo plan's relative costs remains positive at all relevant ranges of choice set size despite a statistically significant negative coefficient on the $\alpha_4 A_{it} * N_{it}$ term. Specifically, the partial effect indicates that increasing the status quo plan's relative costs increases the likelihood of switching until the choice set includes 125 plans. This is nearly 2.5 times the mean choice set size in the sample and nearly twice as large as the observed maximum number of plans faced by the sample, which was 66. Thus across all policy-relevant ranges, adding more plans increases switching rates. Likewise, the partial effect with respect to choice set size shows that adding plans also increases switching rates across a vast majority of the relevant range. Specifically, the partial effect indicates that switching increases when more plans are available at all levels below $1250 of above-minimum spending if the individual remains in the status quo plan. This is equivalent to the 99.8th percentile of the distribution of above-minimum spending in the status quo plan in the sample.

A numerical example can illustrate the magnitudes implied by the results from this model. With 30 plans, a $200 increase in above-minimum spending yields a 7.6 percentage point increase in the conditional switching rate. With 50 plans, an equivalent dollar increase yields an 6.0 percentage point increase in the conditional switching rate. Thus even relatively large increases in the choice set size yield modest reductions in how responsive people's switching decisions are to above-minimum spending should they remain in their status quo plan. And when the main effect of the difference in choice set size is included, the net effect of adding plans is clear: switching rates in response to $200 higher relative costs in their status quo plan are 8.4 percentage points higher when people are provided with 50 choices than with 30.

The third and fourth models use the number of plans by individual-specific relative cost category rather than the overall region-level count of available PDPs. These models also do not support the primary hypothesized effect of choice overload. To the contrary, results in the third model show that adding more of all but the relatively worst plans significantly increases switching. Specifically, each additional available plan within $100 of the minimum increases switching by 0.6 percentage points. These positive effects persist but diminish across each relative cost category except the most expensive category. Adding more of the relatively

worst plans to the choice set, those that would cost the individual more than $500 above her minimum-cost option, does not dampen switching. This is contrary to expectations under choice overload and consumer confusion. Instead, these results indicate that adding such cost-dominated options is simply irrelevant to individuals' decisions to switch plans.

Finally, the results in the fourth model provide a test of the second order choice overload effects of adding plans at each level of cost. Although these interactions achieve statistical significance, the magnitudes are miniscule and vastly outweighed by the main effect of adding plans. For example, adding 10 more of the cheapest plans reduces the responsiveness to $200 higher in above-minimum spending in the status quo plan by 1.6 percentage points, but the net effect on switching is to increase switching by 7.4 percentage points. Hence despite the fluctuations in the coefficients across categories, at $200 in overspending the effect of adding plans to the choice set declines monotonically with the cost of the additional plans made available. At larger increases in spending in the status quo plan, such as $400 or $600, however, the greatest increase in switching rates occurs from adding plans between $100-300 of the minimum. This results from the fact that the coefficients on the interactions are positive and significant for adding plans within $100-300 but negative for adding plans within $100 of the minimum. This reversal is unsurprising if the lowest-cost plans lack attributes besides cost that the higher cost plans have and are valued by individuals.

To evaluate whether the results in this section are sensitive to the chosen sample definition, we reestimated the models excluding switching decisions that did not meet a few additional criteria. These criteria eliminated decisions by anyone who moved between regions at any point from 2006-2010, the few instances where a "forced switch" occurred as a result of their status quo plans exiting the market, and decisions by those who later left the sample for various reasons, including death, acquiring a low-income subsidy, or switching to a Medicare Advantage plan. Such selection out of PDPs may bias the estimates of the effects of experience in unpredictable ways (Semykina and Wooldridge (2013)). The results are virtually identical to those for the full sample.

5 Switching and Experience

We extend the model to evaluate how individuals' switching decisions evolve over time. Specifically, we allow the responsiveness to the status quo plans' relative costs to differ across years as well as with individual-specific experience. We also account for the fact that these within-person changes in experience and over time may be correlated with other factors such as changes in health. Hence we add three interaction terms to the switching model

$$S_{it} = \theta_t + \theta_i + \alpha_1 A_{it} + \alpha_2 A_{it} * \theta_t + \alpha_2 N_{it} + \alpha_3 H_{it} + \alpha_4 A_{it} * N_{it} + \alpha_5 A_{it} * E_{it} + \alpha_6 A_{it} * H_{it} + u_{it}. \quad (3)$$

The first interaction term, $A_{it} * \theta_t$, allows the effect of above-minimum spending to vary within person across years and the interaction term $A_{it} * E_{it}$ allows it to vary within person with experience (defined as the person's cumulative months in a PDP without a low-income subsidy). The former provides an estimate of how responsiveness changed over time for a variety of reasons such as improvement decision support tools, greater involvement of informed professionals or family members and greater familiarity with the Part D market.[29] In contrasts, the latter provides a between-person test of whether those with greater experience at any given point in time are less responsive to changes in their status quo than those with less experience.[30] In unreported results we also implemented models with the three-way interaction terms, $A_{it} * \theta_t * E_{it}$, and found that the differences across experience levels in terms of responsiveness to the status quo plans' was very similar across years. Because our models include $A_{it} * \theta_t$, α_5 is identified by between-person differences in responsiveness within a given year. These models, while including the individual-specific intercept, do not control for the individual-specific responsiveness (i.e., α_1) due to unobserved factors. Hence to mitigate this bias, we include a third interaction, $A_{it} * H_{it}$. Rather than interacting the full set of H_{it} variables, we restrict the interaction to total current drug consumption, measured as gross spending on prescription drugs as an additional measure of relevant health; age in

[29] At the same time, our model eliminates any changes over time due to changes in observed individual-specific health or due to changes in the composition of individuals in the PDP market, as the individual fixed effects account for these.

[30] Because our specifications include both individual-specific fixed effects and year fixed effects, we cannot also include a main effect for months of experience in Part D. Months of experience is a perfectly linear combination of the year indicators and individual fixed effects because it increases by exactly 12 months each year for each person in the sample.

2010 (as such does not vary within individual over time, to limit collinearity with experience); and having been diagnosed with Alzheimer's or related dementia because the prevalence of these illnesses is known to increase with age (Querfurth and LaFerla (2010)). As one specific example of the concerns this interaction accounts for is the possibility that those with greater experience were more responsive simply because their drug spending was higher, providing them with greater financial incentives to switch due to greater potential savings.[31]

Table 7 reports the results. For each year 2008-2010, individuals were more responsive to their status quo plan's relative costs than they were in 2007. Offsetting these year-specific gains, however, is the effect of individual-specific amount of time in the PDP market. At each point in time, those with more experience are less responsive to their status quo plan's costs than those with less experience. As an example of the magnitude of this effect, an additional 12 months of experience reduces the responsiveness to a $200 increase in the status quo plan's relative costs by 1.4 percentage points. Because this coefficient is identified via between-person differences, our confidence in it depends on the extent to which the model has controlled for other between-person differences that may affect responsiveness to the status quo plans' costs. The coefficients on the additional interaction terms show differences in these elasticities across the three observed characteristics we include. Specifically, the results show that those who are older are less responsive (consistent with the model in Stigler and Becker (1977)), those with Alzheimer's disease or other dementia are more responsive, and those with higher levels of drug spending are more responsive.

To estimate the total within-person change in responsiveness over time we utilize the year main effects and the coefficients on $A_{it} * \theta_t$ and $A_{it} * E_{it}$. Table 8 provides some numerical examples of the estimated conditional within-person change in responsiveness from 2007 to 2010. The results show that the within-person change over time causes people to become

[31] The identification and interpretation of the estimated effects of experience are influenced by our approach. Due to our sample inclusion criteria and incorporation of individual-specific effects, the effects of individual-specific experience are identified only in 2008-2010. This is a result of the fact that we only evaluate decisions to switch for 2007 by those who were enrolled for all of 2006. Hence no within-year variation in experience exists in our sample until 2008. One implication of this limitation is we cannot directly evaluate the role of learning in explaining the reductions from 2006 to 2007 while also accounting for individual-specific unobserved heterogeneity. A second concern may be that our estimates would miss the effects of experience if they occur primarily within the first partial year of enrollment. To evaluate this we implemented these models but included the switching decisions between a partial year of enrollment and a full year of enrollment. The coefficient on the experience interaction using this even larger sample is virtually identical to that reported here.

Table 7: Parameter estimates from models of switching that incorporate learning, 2007-2010

	Number of plans overall			Number of plans by cost		
Above-minimum spending if stay in status quo plan ($100s)	4.08	[0.36]	***	2.21	[0.31]	***
*Above-minimum spending if stay ($100s)*2008*	3.21	[0.07]	***	3.36	[0.06]	***
*Above-minimum spending if stay ($100s)*2009*	3.85	[0.12]	***	4.62	[0.11]	***
*Above-minimum spending if stay ($100s)*2010*	3.79	[0.17]	***	4.86	[0.15]	***
*Above-minimum spending if stay ($100s)*months of experience*	-0.06	[0.00]	***	-0.07	[0.00]	***
*Above-minimum spending if stay ($100s)*age in 2010*	-0.25	[0.02]	***	-0.22	[0.02]	***
*Above-minimum spending if stay ($100s)*has Alzheimer's disease*	-0.72	[0.04]	***	-0.79	[0.04]	***
*Above-minimum spending if stay ($100s)*current gross drug spending*	0.00	[0.00]	***	0.00	[0.00]	**
Current gross drug spending ($100)	0.02	[0.01]	***	0.03	[0.01]	***
Number of available plans	0.41	[0.02]	***			
*Above-minimum spending if stay ($100s)*Number of available plans*	-0.02	[0.01]	***			
Number of available plans within				0.63	[0.02]	***
$100 of minimum				0.63	[0.02]	***
$100-200 of minimum				0.36	[0.02]	***
$200-300 of minimum				0.13	[0.02]	***
$300-400 of minimum				0.06	[0.02]	***
$400-500 of minimum				0.11	[0.02]	***
>$500 of minimum				0.33	[0.02]	***
*Above-minimum spending if stay*Number of available plans within*						
$100 of minimum				0.01	[0.01]	*
$100-200 of minimum				0.11	[0.01]	***
$200-300 of minimum				0.12	[0.01]	***
$300-400 of minimum				0.07	[0.01]	***
$400-500 of minimum				0.05	[0.01]	***
>$500 of minimum				-0.05	[0.01]	***
2008	-6.53	[0.15]	***	-6.88	[0.16]	***
2009	-7.33	[0.24]	***	-8.68	[0.23]	***
2010	-3.78	[0.29]	***	-5.32	[0.25]	***

NOTE: N = 3,645,570. Standard errors from 100 iteration bootstrap with replacement are in brackets. *** p<0.01, ** p<0.05, * p<0.1. All models include year fixed effects, individual fixed effects and controls for time-varying health. The number of plans by cost category and above-minimum spending in the status quo plan are defined using the *ex post* approach and assuming a price elasticity of demand for drugs of -0.54.

less responsive to the lowest-level increases in their status quo plans' relative costs but more responsive to higher levels. For example, people were 2.2 percentage points less likely to switch in response to a $100 increase in 2010 than they were in 2007. In contrast, they were virtually no different between 2007 and 2010 in their responsiveness to a $200 increase, and they were 6.0 percentage points more likely to switch in 2010 than 2007 in response to a $600 increase.

These data do not permit us to observe individuals' decision process or switching costs. Yet this pattern of results is consistent with an environment in which individuals grow in their state dependent preferences for or value from their status quo plans and simultaneously grow in their abilities to navigate the PDP market. Increasing preferences or value from

Table 8: Estimated within-person conditional difference in switching between 2010 and 2007 in response to an increase in the status quo plan's costs

Increase in above-minimum spending if remain in the status quo plan:	$100	$200	$300	$400	$500	$600
Estimated difference between 2010 and 2007 switching probability	-2.15	-0.52	1.11	2.74	4.37	6.00

NOTE: Estimates are based on the results from the first model provided in the preceding table.

their status quo plans would explain why individuals become less responsive over time to the lowest-level increases in their status quo plans' relative costs (Dube, Hitsch and Rossi (2010)). This occurs because these preferences or value grow in ways not captured by the cost calculator, suppressing their willingness to switch to capture lower levels of savings. In contrast, increasing knowledge and awareness about PDPs over time would explain why people become more responsive to higher level increases in their status quo plans' relative costs.

6 Results under Alternative Modeling Approaches

In this section we evaluate the extent to which the results depend on the decisions that analysts must make about individuals' expectations regarding the relative costs of their status quo plan in the upcoming year. Here we implement and report results from five alternative modeling approaches. First, we rely on the same *ex post* approach used above but now we assume perfectly inelastic demand for prescription drugs. That is, we hold the drug consumption constant across all plans despite potentially large differences across plans in the OOP prices of drugs.

The results from these models are in Table 9. All of the insights from the elastic models above are replicated in these results. One difference is that all four of these models show that the conditional switching rates climbed each year from 2007-2010, whereas the three of the four models above suggested that only the 2010 rate was significantly above 2007. More importantly, the positive, significant effect of adding plans persists with magnitudes virtually identical to those before. Likewise the interaction terms retain their statistically significant but economically small coefficients. These results are observed in the version that relies on

Table 9: Parameter estimates from *ex post* models of switching assuming perfectly inelastic demand for drugs, 2007-2010

	Number of plans overall						Number of plans by cost					
	No Interactions			Interactions			No Interactions			Interactions		
Above-minimum spending if stay in status quo plan ($100s)	1.86	[0.02]	***	3.54	[0.12]	***	2.08	[0.02]	***	3.97	[0.13]	***
Number of available plans	0.41	[0.01]	***	0.52	[0.02]	***						
*Above-minimum spending if stay ($100s)*Number of available plans*				-0.03	[0.00]	***						
Number of available plans within												
$100 of minimum							0.55	[0.02]	***	0.88	[0.03]	***
$100-200 of minimum							0.56	[0.02]	***	0.61	[0.02]	***
$200-300 of minimum							0.46	[0.02]	***	0.40	[0.02]	***
$300-400 of minimum							0.42	[0.02]	***	0.33	[0.02]	***
$400-500 of minimum							0.49	[0.02]	***	0.45	[0.02]	***
>$500 of minimum							0.32	[0.02]	***	0.58	[0.02]	***
*Above-minimum spending if stay ($100s)*Number of available plans within*												
$100 of minimum										-0.08	[0.01]	***
$100-200 of minimum										0.01	[0.00]	***
$200-300 of minimum										0.04	[0.01]	***
$300-400 of minimum										0.02	[0.01]	***
$400-500 of minimum										-0.01	[0.00]	
>$500 of minimum										-0.06	[0.00]	***
2008	1.18	[0.06]	***	1.12	[0.06]	***	1.76	[0.06]	***	1.30	[0.06]	***
2009	1.66	[0.10]	***	1.63	[0.10]	***	2.30	[0.10]	***	1.67	[0.10]	***
2010	2.91	[0.15]	***	2.87	[0.15]	***	3.71	[0.15]	***	3.23	[0.15]	***

NOTE: N = 3,645,570. Standard errors from 100 iteration bootstrap with replacement are in brackets. *** p<0.01, ** p<0.05, * p<0.1. All models include year fixed effects, individual fixed effects and controls for time-varying health. The number of plans by cost category and above-minimum spending in the status quo plan are defined using the *ex post* approach and assuming perfectly inelastic demand for drugs.

the total plan count as well as the count by cost category. As before, adding cheaper plans increases switching more than adding relatively expensive plans.

Next, we implement an *ex ante* approach that assumes people choose based on the drug consumption in the current year (rather than the next year) but on plan design in the next year, as before. In this approach, the cost calculator combines the individual's claims from the current year with the plans' formulary coverage and premiums from the upcoming year for which the person is making an enrollment decision. This approach mimics the costs that an individual would be shown by the online CMS "plan finder" tool if they followed the tool's prompt and entered current drug consumption.[32] Thus the second version we report is this *ex ante* approach assuming elastic demand for drugs, while the third version assumes perfectly inelastic demand for drugs.

The results from the *ex ante* models of switching are reported in Table 10. To streamline the presentation, we report both the elastic and inelastic versions but using only the total

[32]We are thankful to a referee for pointing out the importance of considering this approach especially given the design of the plan finder tool.

Table 10: Parameter estimates from *ex ante* models of switching, 2007-2010

	Elasticity of demand for drugs = -0.54						Perfectly inelastic demand for drugs					
	No Interactions			Interactions			No Interactions			Interactions		
Above-minimum spending if stay in status quo plan ($100s)	1.78	[0.28]	***	6.26	[2.10]	***	1.12	[0.10]	***	2.83	[1.08]	***
Number of available plans	0.41	[0.02]	***	0.63	[0.12]	***	0.42	[0.02]	***	0.53	[0.08]	***
*Above-minimum spending if stay ($100s)*Number of available plans*				-0.08	[0.04]	*				-0.03	[0.02]	
2008	0.18	[0.08]	**	0.16	[0.07]	**	0.74	[0.06]	***	0.70	[0.08]	***
2009	0.58	[0.24]	**	0.45	[0.14]	***	1.66	[0.11]	***	1.62	[0.10]	***
2010	1.86	[0.26]	***	1.60	[0.16]	***	2.85	[0.15]	***	2.79	[0.15]	***

NOTE: N = 3,644,298. Standard errors from 100 iteration bootstrap with replacement are in brackets. *** p<0.01, ** p<0.05, * p<0.1. All models include year fixed effects, individual fixed effects and controls for time-varying health. The above-minimum spending in the status quo plan is defined using the *ex ante* approach.

count of plans. Increasing in the relative cost of remaining in the status quo plan promotes switching, as does adding plans to the choice set. The interaction term is marginally significant in the elastic version and insignificant in the inelastic version. Finally, as before, conditional switching rates increase over time and are highest in 2010.

For the final alternative approach, in place of the *ex post* approach's use of the person's actual prescription drug use in the upcoming year we instead employ a "rational expectations" assumption.[33] This approach, developed in the context of Part D in Abaluck and Gruber (2011), is based on the idea that individuals may be uncertain about their individual future drug consumption but instead may have expectations regarding the possible distribution of expenses that they may have next year based on their current health and drug consumption patterns. In the rational expectations modeling approach, the analyst attempts to approximate those expectations by assuming that the observed the *ex post* outcomes of "similar" people calculated for each available option represent the individual's perceived distribution of expenses. Here we adopt the the Abaluck and Gruber (2011) methodology wholesale and define "similar" based on the deciles of their prior year's gross drug spending, days' supply of branded drugs and days' supply of generic drugs. For our purposes, for each plan we then calculate the average of the *ex post* calculated OOP costs among all of the similar individuals in the region. Our one point of divergence from the preceding method is that we average across only non-subsidy PDP enrollees in the same region, i.e., all of those for whom we had calculated costs in the plan under the *ex post* approach.[34]

[33]We are thankful to a referee for suggesting we implement this alternative approach.

[34]This contrasts with the Abaluck and Gruber (2011) approach, as they used a random sample of 200 people from the population of all similar individuals in their data calculated through every plan to define the type-specific calculated averages for the plan. For example, they would have used a Medicare Advantage

Table 11: Parameter estimates from "rational expectations" models of switching, 2007-2010

	Elasticity of demand for drugs = -0.54						Perfectly inelastic demand for drugs					
	No Interactions			Interactions			No Interactions			Interactions		
Above-minimum spending if stay in status quo plan ($100s)	5.48	[0.03]	***	1.94	[0.14]	***	2.57	[0.02]	***	2.93	[0.13]	***
Number of available plans	0.32	[0.01]	***	0.18	[0.01]	***	0.44	[0.01]	***	0.46	[0.01]	***
*Above-minimum spending if stay ($100s)*Number of available plans*				0.07	[0.00]	***				-0.01	[0.00]	***
2008	-2.32	[0.06]	***	-2.44	[0.06]	***	-0.74	[0.06]	***	-0.73	[0.06]	***
2009	-3.86	[0.10]	***	-3.94	[0.10]	***	1.38	[0.10]	***	1.39	[0.10]	***
2010	-1.76	[0.13]	***	-1.74	[0.13]	***	2.90	[0.13]	***	2.91	[0.13]	***

NOTE: N = 3,483,504. Standard errors from 100 iteration bootstrap with replacement are in brackets. *** p<0.01, ** p<0.05, * p<0.1. All models include year fixed effects, individual fixed effects and controls for time-varying health. The number of plans by cost category and above-minimum spending in the status quo plan are defined using the "rational expectations" approach.

The results from the switching models that rely on the rational expectations approach to estimating the individuals' future costs of their status quo plan are reported in Table 11. Of all the modeling approaches, this one yields the largest main effects of the status quo plan's costs on switching. For example, the first version in this table implies that each $100 increase in the status quo plan's relative costs leads to a 5.5 percentage point increase in the probability of switching. As before, expanding the choice set also systematically increases switching rates. In contrast with above, the interaction term becomes positive and significant in the elastic version, albeit still small in magnitudes. This term is essentially zero in the inelastic version.

7 Conclusions

Our analysis yields two primary conclusions regarding the influence of choice overload and experience on consumers' dynamic decisions to switch between Medicare PDPs. First, within the range of choice set sizes that consumers have faced in Part D so far, increasing the size of the choice set increases individuals' likelihoods of switching plans. By switching, individuals reduce their spending. These results on choice overload contradict the subset of existing research on choice overload that is commonly appropriated for the Part D context. Our rejection of the choice overload hypothesis in Part D, however, is in agreement with the preponderance of prior evidence on the topic from other contexts. Although differences in the

enrollee in Alaska in their calculation of the rational expectations measure for the type-specific expected OOP costs in a standalone PDP in Florida, but they would not have used another similar Florida PDP enrollee if she was not among the 200 randomly chosen individuals.

existence of choice overload can be found across these prior studies, a widely-acknowledged precondition for such effects to occur is that consumers must not have strong existing preferences for certain products or product attributes (Iyengar and Lepper (2000)). Our results suggest that such preconditions are not met in Part D. These results represent consilience among several related domains of research (e.g., Lancaster (1966) and Huber, Payne and Puto (1982) and Simonson (1989)) in which adding options, even dominated ones, may promote rather than inhibit switching.

One common hypothesis regarding choice overload is that its effects are nonlinear. Applied to the Part D context, nonlinearity implies that marginal changes in size in an already large-sized choice set may have no effect on choice overload whereas marginal changes at small choice set sizes have either positive or negative effects. Because Part D has had relatively large choice set sizes throughout its history, researchers cannot directly test how switching decisions may be affected by changes in choice set size if the choice sets were extremely restricted relative to those under Part D currently. Any predictions about such effects are vastly out of sample.

Research from other contexts, however, provides some potential insights. Most relevant, experiments on retirement home residents' choices of insurance-like products evaluated the effects of expanding the choice set from 4 to 8 to 12 options (Besedeš et al. (2012)). The results showed that expanding the choice set improved people's choices, and these improvements were larger when the set expanded from 8 to 12 options than from 4 to 8 options. Importantly for our context, the study demonstrated that these gains resulted primarily from larger choice sets prompting people to rely more heavily on heuristics to find the options that were best for them. More generally, the experimental research has not found any evidence of non-linearities in the choice overload effect (e.g., Figure 2 of Scheibehenne, Greifeneder and Todd (2010)). Yet other empirical research found evidence of choice overload due to expansions in choice set size at sizes even larger than those we study here (Kempf and Ruenzi (2006)). On balance, then, large but previously unimplemented restrictions of Part D choice sets may have positive or negative consequences not evident from the marginal changes we study here. At the same time, if choice overload was predominant across the full range of choice set size in our sample from Part D to date, we would have expected to find uniformly null effects

from changes in choice set size.

Our second primary conclusion is that individuals become more sensitive over time to larger increases in their status quo plan's costs but less sensitive to small increases. These results contrast with several of the well-known articles on status quo bias. For example, one frequently-cited article demonstrating consumers' inattentiveness and status quo bias relied on choices of only entirely inexperienced "first-time" consumers (DellaVigna and Malmendier (2006)). Similarly, the result of status quo bias in Madrian and Shea (2001) is observed in the context of retirement planning, where consumers have little ability to discern whether their prior choices maximized their objective functions. In the contexts of those studies, and in contrast to Part D, consumers have little potential to learn and adjust their choices based on their experiences. Regarding our results, our identification of the within-person changes over time come from a relatively short time window that incorporates two to four switching decisions per person. Thus it remains to be determined how these effects have evolved in the meantime, e.g., whether the upward trend in conditional switching over time continued to dominate the smaller but negative effects of individual-specific experience. For example, the within-person time trends observed here may not be generalizable due to the recession that occurred during this time period.

Throughout Part D's history, concerns have been raised that competition is suboptimal because of consumer inertia (e.g., Heiss, McFadden and Winter (2010)). This view is based on the presumptions that inertia in Part D is both widespread and anticompetitive (Farrell and Klemperer (2007)). Yet more recent work by Dube, Hitsch and Rossi (2009) has found that inertia can promote competition, as having more inert enrollees stiffens competition for initial enrollment choices. Further, our data show that by 2010, fully half of those who had ever previously enrolled in a PDP were no longer in their original plans. This level of turnover, in conjunction with CMS regulations that prohibit insurers from offering "teaser" rates to new enrollees, limits firms' ability to harvest gains from inert consumers without also losing potential new enrollees. Finally, in contrast with individuals' likelihood of remaining in their status quo plan growing over time, our results show that over time people become *more* likely to switch away from their status quo in response to it becoming relatively much more expensive. Collectively the evidence here, observed under various modeling assumptions,

provides little support for fears that consumer inertia and choice overload are widespread and inhibit consumers' abilities to compare alternatives.

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APPENDIX

A Means of variables not reported elsewhere, 2006-2010

	2007	2008	2009	2010
Above-minimum spending if stay in the status quo plan ($)	267.8	256.5	309.7	297.1
Female (percent)	63.0	63.3	63.0	62.3
Race, using Research Triangle Institute method				
White	93.01	92.98	92.95	92.92
Black	3.34	3.25	3.19	3.13
Hispanic	2.06	2.08	2.08	2.07
Asian	0.99	1.04	1.08	1.12
Other	0.55	0.59	0.65	0.68
Unknown	0.05	0.06	0.05	0.08
Age in 2010	79.7	78.9	77.9	76.80
Total reimbursements for				
Hospital inpatient stays	2952	2902	2945	2.97
Physician services	3172	3147	3293	3.43
All other non-drug spending	2860	2998	3215	3.40
Gross drug spending	2337	2003	2058	2049
Number of				
Inpatient admissions	0.3	0.3	0.3	0.28
Outpatient visits	4.4	4.2	4.3	4.37
Skilled Nursing Facility covered days	1.4	1.5	1.5	1.50
Physician office visits	8.5	8.1	8.2	8.81
Currently Diagnosed with (percent)				
Alzheimer's Disease, Related Disorders, or Senile Dementia	8.90	9.27	9.38	9.34
Acute Myocardial Infarction	0.78	0.77	0.72	0.73
Atrial Fibrillation	10.07	9.56	9.83	10.10
Cancer	8.05	7.79	7.83	7.81
Cataract	31.31	29.05	28.58	27.82
Chronic Kidney Disease	16.57	15.28	15.01	14.67
Chronic Obstructive Pulmonary Disease	10.65	10.79	11.87	12.91
Depression	9.98	9.43	9.49	9.45
Diabetes	9.38	9.58	10.07	10.46
Glaucoma	26.40	24.56	25.31	25.74
Heart Failure	13.67	12.90	13.05	13.03
Hip / Pelvic Fracture	0.82	0.84	0.80	0.77
Ischemic Heart Disease	36.28	33.90	33.97	33.67
Osteoporosis	16.27	16.29	16.53	16.33
Rheumatoid Arthritis / Osteoarthritis	23.99	23.40	23.81	24.05
Stroke / Transient Ischemic Attack	3.98	3.80	3.77	3.67
Moved regions (percent)	0.26	0.13	0.14	0.14
Forced switch due to plan closure (percent)	0.00	0.08	0.09	0.12
Prior months of experience on a PDP without low income subsidy	12.0	21.1	31.0	40.0

B Details regarding simulating each person's cost of each plan in each year

This appendix provides additional details about our approach to simulating what each person would have spent in each PDP available in his or her region in each year. The simulations differed somewhat for each year to incorporate changes in the standard benefit parameters (deductible, initial coverage limit, and catastrophic coverage limit) and due to changes in the types of additional benefits that were offered. For example, coverage of generic drugs during the deductible phase was not available at the launch of Part D but was in later years.

The CMS internal formulary files provide detailed information about which drugs (where a drug is defined by First DataBank's Clinical Formulation ID (GSN_SEQNO)) and brand names were covered by each plan. We linked this information with the tier cost-sharing files to provide the patient OOP cost. Both of these files are part of the CMS Part D Plan Characteristic Files. Different versions of those files are available throughout the year, so we use the version as of December 31 because a vast majority of the within-year changes reflect corrections to ensure the files capture the plan as it was administered for the year. For a given drug in a given plan and year, the OOP costs differ by the pharmacy type (mail order or retail), the pharmacy status (in-network preferred, in-network not preferred, and out-of-network) and what benefit phase the individual was in at the time of filling the prescription(under the deductible, under the initial coverage limit, in the coverage gap, and above the catastrophic coverage limit), and the days' supply dispensed (30 days or 90 days). One implication of this within-drug, within-plan variation in a drug's price is that it is quite challenging to try to identify an individual's plan based on the observed OOP price of the drugs they purchased. We combine the formulary files, the PDE data, and a pricing file created using a process described in Appendix C to build a file that lists every possible patient OOP price of every drug purchased by individuals in our sample for the given year. This linking between files is done by using First DataBank to crosswalk from the National Drug Code (NDC) on each claim to the Clinical Formulation ID (Generic Sequence Number) and brand name in the formulary files.

We use this file to determine what each person would have paid for each drug they purchased under each plan available in the region. To do this, we use each alternative plan's specific drug prices, as described in Appendix 2, in conjunction with the information on the actual claim from the actual plan to determine which OOP cost should be used in each alternative plan. That is, to the extent possible, we held constant all of the claim-specific attributes across all plans, e.g., we assumed that if an individual purchased a drug from a mail order pharmacy on her actual plan, she would have used a mail order pharmacy under each alternative plan as well. In some cases this was not feasible, e.g., if the plan had no mail order pharmacies, and we imposed decision rules under the assumption that the individual would choose the closest best alternative. To the extent this is inaccurate, this approach yields underestimates of the true costs the individual would have incurred in alternative plans, yielding overestimates of above-minimum spending since it did not affect the estimated costs in the actual plan.

The PDE data provide the prescription fill date (known as the date of service), which we

use to define the order of claims. This is essential to determine the benefit phase or phases, which we use in our cost calculator to estimate the OOP cost for the drug. We relied on CMS regulations that determined how beneficiaries would be moved through benefit phases, in conjunction with the plan-level characteristics file in cases where plans enhanced their coverage. Additional details are available from the authors and are evident in the statistical code used to develop and implement the cost calculator. In brief, for each person in each year, the cost calculator cycled through all of the individuals' claims in order of their fill date to create rolling totals for OOP costs and gross costs of covered drugs (where "covered" denotes drugs that advanced the "true OOP costs" for the purposes of determining the benefit phase), and OOP costs and gross costs of non-covered drugs (which by CMS rule cannot be used to advance the benefit phase). Particularly complex in this process was determining the OOP costs for claims that transitioned people across benefit phases. To confirm the accuracy of this simulation, we compared the calculated OOP and gross cost of the actual plan with the actual OOP and gross cost in the actual plan, as summarized from the PDE data. We find that our simulations were highly accurate, where after removal of a few outliers with implausible values we find correlation coefficients for calculated and actual gross spending of 1.0, and correlation coefficients for calculated and actual OOP spending of 0.92 in 2006 and 2007, 0.97 in 2008, 0.98 in 2009 and 0.97 in 2010.

C Calculating plan-specific drug prices

One important feature that can substantially influence an individual's OOP costs for a given plan is not captured in the formulary files or any other plan information files. The underlying drug prices for a given drug are determined by the plans, depending on their negotiations with pharmacies as well as drug manufacturers. These underlying prices influence individuals' OOP spending through two primary ways. First, in many instances, individuals' OOP costs are set as a percent of gross costs. This occurs under the deductible, where the individual typically pays 100%, as well as within the coverage gap and beyond the catastrophic coverage limit for most plans, and for some plans even within the initial coverage limit where they rely on coinsurance rather than copays. Second, gross spending is used to determine whether the claim causes the individual to exceed the initial coverage level, i.e., whether he has entered the coverage gap. Consequently, differences in gross costs alone can determine whether the individual enters the coverage gap, which even all else equal would have substantial effects on the individual's total OOP cost for a plan. One implication of this is that entering the gap is not a person-by-year level variable, but rather at the person-by-plan-by-year level, e.g., a person who entered the gap in her actual plan may not have entered the gap in some of the alternative plans due to differences in gross drug prices.

We rely on the 100% PDE data from all individuals (unconditional on meeting our sample criteria) to develop an accurate, underlying price of every drug filled in a year for every plan available in that year. For each prescription we calculate the unit price by dividing the total price by the units. To account for implausible values for the units or prices, if the unit price fell beyond the 5th or 95th percentile of nationwide prices for a given Clinical Formulation ID and brand name, we assigned the median nationwide price. We then average the unit prices for each combination of contract ID, pharmacy type (mail or retail), brand name to distinguish between brands and generics, and Clinical Formulation ID, each of which includes multiple NDCs. We group by contract ID because the prices are determined at the parent organization level and typically do not vary across plans within a contract ID.

For the most common drugs, this process yields an accurate measure of the average unit price in every plan. For less common drugs, and in plans with small enrollments, we rely on a series of imputations to determine the relevant price. First, if the retail pharmacy price was missing, we impute using the corresponding mail order price, and vice versa. If this does not assign a price, we impute by multiplying the market-wide average price for the pharmacy type (retail or mail) by a contract ID price index. For example, if this index shows that the contract ID prices average 20% above the nationwide average, then this drug's price for the given contract ID and pharmacy type is set to 20% above its average across all other contract IDs for the pharmacy type. Finally, if no price index is available for a plan, which could occur for plans with no enrollees, we simply assigned the average unit price for the drug.