The Impact of Consumer Inattention on Insurer Pricing in the Medicare Part D Program*

Kate Ho† Joseph Hogan ‡ Fiona Scott Morton §

May 1, 2014

PRELIMINARY AND INCOMPLETE

Abstract

Medicare Part D presents a novel privatized structure for a government benefit. Incentives for firms to provide low prices and high quality are generated by consumers who choose among multiple products in each market. In this paper we use detailed data on enrollees in New Jersey to demonstrate that consumers switch plans very infrequently and in response to shocks to their own plan's characteristics or their own health status rather than changes in other options available to them. Based on these insights, we estimate a model of consumer plan choice with inattentive consumers. We then turn to the supply side and examine insurer responses to this behavior. We show that premium increases are consistent with insurers raising prices to profit from consumer inertia. We use the demand model and a model of firm pricing to show that Part D program costs would be substantially lower if consumer inattention was removed.

*We thank Mark Duggan, Gautam Gowrisankaran, Bentley MacLeod and Eric Johnson for helpful comments. All errors are our own.

†Columbia University and NBER, kh2214@columbia.edu.

‡Columbia University, jph2154@columbia.edu.

§Yale University and NBER, fiona.scottmorton@yale.edu.

1 Introduction and Motivation

The addition of pharmaceutical benefits to Medicare in 2006 was the largest expansion to the Medicare program since its inception. Not only is the program large, it is also innovative in design. Traditional Medicare parts A and B are organized as a single-payer system; enrollees see the physician or hospital of their choice and Medicare pays a pre-set fee to that provider, leaving no role for an insurer. In contrast, Part D benefits are provided by private insurance companies that receive a subsidy from the government as well as payments from their enrollees. The legislation creates competition among plans for the business of enrollees, which is intended to drive drug prices and premiums to competitive levels. Each Medicare recipient can choose among the plans offered in her area based on monthly premiums, deductibles, plan formularies, out of pocket costs for drugs, and other factors such as the brand of the insurer and customer service.

The premise of the Part D program was that the choices of consumers would discipline plans into providing low prices and high quality, and that this would result in better outcomes than consumers would obtain from a government-run plan. Critically, these better outcomes require that market forces work, in the sense that demand moves to the plans that consumers prefer because they are lower cost or have higher quality. This in turn requires that consumers choose effectively among firms according to features they value. This paper analyzes both demand and pricing in the Medicare Part D market. We demonstrate that, in reality, consumer choices are made with substantial frictions. Consumers rarely switch between plans and do not actively shop for quality, reducing the effective demand elasticity faced by insurers. We provide evidence that, in the absence of strong incentives to price low to prevent loss of market share, insurers choose to price above the efficient level. The reduced competition from consumer inattention allows plans to extract high rents from consumers, and we find that reductions in consumer inattention would result in substantial cost savings.

One concern when Part D began was that the prices the plans paid for drugs would rise because plans would lack the bargaining power of the government. Duggan and Scott Morton (2011)[16] demonstrate that this did not happen. Rather, prices for treatments bought by the uninsured elderly fell by 20% when they joined Part D. Since the inception of the program, increases in pharmaceutical prices have been restrained, partially due to aggressive use of generics by many insurers. From 2006-2011, growth in pharmaceutical prices in the United States averaged 2.78% annually. Adjusting for rebates, expenditures on drugs comprised 77% to 80% of payments to insurers from 2006 to 2011, with the percentage falling over that period. The remainder of plan costs primarily consists of administrative, marketing, customer service, and like activities. The PCE deflator for services during this same time period increased at an average annual rate of 2.40%. Yet, despite these modest increases in the costs of providing a Part D plan, premiums were on average 62.75% higher in 2009 than they were in 2006, the first year of the program, which corresponds to a 17.62% compound annual growth rate, a rate significantly above the growth rate of costs.

These figures accord fairly well with government estimates of cost increases. The CBO finds[11] that plan profits and administrative expenses were higher per beneficiary in 2010 than 2007, and that profits grew at an 8.6% annual rate over that time period. This finding raises the question of why slow growth in the costs of drugs and plan administration were not passed back to consumers in the form of lower premiums: unlike in a competitive market, margins increased rather than coverging towards zero. One possibility is that Part D may be well designed to create competition among treatments that keeps the prices of drugs low, yet may not do so well at creating competition among plans in order to restrain the prices consumers face. If so, the program would be providing excess profit to the insurance industry. Since the program is 75% subsidized by the federal government, any lack of effective competition would also increase government expenditures. Because the amount of money at stake is significant, the issue of competition among plans in Part D merits further investigation, both to determine the reasons for the price increases, and also to evaluate whether there are policy design changes that might stimulate more effective competition among plans.

Our analysis uses detailed data on individual enrollees to investigate the extent to which consumers switch among plans, and why they switch, to determine whether market pressures on plans create a competitive environment. We analyze the pricing decisions of plans in response to the observed consumer behavior and present evidence that plans are indeed taking advantage of sub-optimal consumer search. Armed with these results, we evaluate several possible policy interventions designed to increase competition in the Part D market.

The first section of the paper describes the Medicare Part D program and discusses reasons why the market may not function efficiently. In particular, the structure of Part D plans is sufficiently complex that many enrollees may not fully understand the costs and benefits of various plans. Next we review the literature related to both Medicare Part D specifically and markets with choice frictions generally. Most relevant to this paper is a body of previous literature providing evidence on the existence of consumer choice frictions in these markets (e.g. Abaluck and Gruber (2011)[2], Handel (2012)[23]). Our analysis of consumer choices (using a dataset of non- subsidized enrollees in New Jersey) will obtain conclusions consistent with those of Abaluck and Gruber (2011)[2], who use a sample of national data, and Ketcham et al. (2012)[31], who study consumers in plans run by CVS Caremark. However we will use our enrollee-level data to estimate a more detailed demand model that captures some of the reasons why consumers make mistakes when choosing plans. This will enable us to evalute the impact of policies that "switch off" some but not all elements of consumer choice frictions.

The next section of the paper describes our data and briefly analyzes how well enrollees choose among plans. We then analyze overspending and switching between plans by Part D enrollees in more detail. Similar to previous studies, we find that consumers consistently make choices that lead to overspending relative to the lowest-cost plan for them, and that this pattern does not appear to diminish with either experience in the program or time. We also find that consumers who switch plans perform significantly better in the subsequent year as measured by dollars spent above estimated ex-ante optimal costs, that these errors are increasing in the number of years since the consumer last switched plans, and that the fraction of consumers for whom it is optimal to remain in the current plan from year to year is negligible. Nevertheless, only a small percentage of consumers switch in any given year, and we document several key facts related to this finding. First, lack of switching does not appear to be justified by differences in risk tolerance or heterogenous preferences for plan design, as, on average, switching consumers choose plans that dominate on both costs and coverage. Second, although consumers respond rationally to changes in the cost and benefit design of their own plan, they are much less sensitive to changes in other plans. Third, consumers switch much more often when prompted by discrete "shocks" to their health or current plan characteristics, and the types of plans they choose are affected by the types of shocks they experience. Fourth, we find that the value of switching, as measured by potential cost savings, is similar in magnitude for both those consumers who do and do not switch. Taken together, these findings suggest that consumer inattention rather than explicit switching costs are the most convincing explanation for the observed inertia in plan choices. Finally, we find no evidence of learning by consumers with regard to searching for plans. The only consumers who switch plans every year are those who repeatedly receive shocks to the characteristics of their current plan, and those who do continually roll-over their plan selection each year fare worse and worse. We conclude that consumers are best described not as rational shoppers capable of enforcing market discipline, but as inattentive buyers. Motivated by these findings, we estimate a two-stage decision model of consumer switching behavior which accounts for inattention as a source of inertia and for the possibility that consumer preferences are affected by their shocks. The findings indicate that inattention is an important part of the story, that switchers' preferences are affected by the shocks they experience, and also that switchers over-weight premiums and gap coverage when they make their choices (consistent with the findings of previous papers e.g. Abaluck and Gruber (2011)[2]).

In the next section we analyze the supply side of the Part D marketplace. Our finding that no measure of consumers can really be deemed "frictionless" suggests that as in Klemperer (1987)[33] prices will not converge to marginal costs and plans will extract rents from their initial consumers. Using a dataset of nationwide plan characteristics and enrollment, we provide evidence in support of this prediction. We show that premiums rise steadily over time and that plans with larger market shares set price in a manner consistent with high choice frictions.

These findings suggests that consumer inattention and other choice frictions increase Part D program costs - and reduce consumer surplus - for two reasons. First most consumers do not choose the plan with the lowest expected cost to them, and second firms respond by changing their pricing strategies. We investigate these issues by simulating the evolution of the Part D marketplace under several different policy-relevant counterfactuals. First we consider a situation where consumer inattention is removed, for example under the scenario where there is no default option so that consumers are required to re-optimize their plan choice every year. Our results suggest that this policy would reduce the cost of the program substantially. Errors made by consumers (defined as the difference between the cost to the consumer of the predicted choice and the lowest-cost option for them) would fall by approximately 40%. However this policy, while removing the costs of consumer inattention, does not address the issue that even attentive consumers do not choose their lowest-cost plan. In addition the policy could potentially lead to exit from the Part D program which would have negative effects on consumers. We address these points by considering a second counterfactual policy exercise where the enrollee's pharmacist is given incentives to move enrollees from their chosen plan to the lowest-cost option available to them in the previous year, if the saving from this switch would have been over \$200. Our simulations assume that pharmacists receive a \$50 payment per enrollee from this practice and that enrollees stay in the plan to which the pharmacist assigns them. The results indicate that 85% of total over-spending would be removed by this policy. Although we note that not all the frictions removed here are necessarily due to consumer errors - some may represent heterogeneous preferences that the social planner would not wish to ignore - the magnitudes of the cost savings from this counterfactual are considerable.

These counterfactuals do not yet tell the whole story because the current simulations hold premiums fixed. In the next iteration of the paper we will use accounting data on plan costs to simulate the path of premiums under the different counterfactual scenarios. (Both counterfactuals effectively remove inattention and this removes the dynamics from the premium-setting game, making the simulation straightforward.) We can then add the incremental savings from plan premium changes to our estimated savings from the changes in consumer choices, generating a prediction of total equilibrium savings from this change to the Part D program and to consumers.

Studies such as ours are crucial both to future policies concerning Part D plan design, information provision, and quality regulation, but also to those same issues in health insurance. The Patient Protection and Affordable Care Act (2010) created health plan exchanges through which consumers who are not eligible for employer-sponsored insurance can access health insurance coverage. In this setting consumers again face an array of plans, regulated in quality, and provided by private insurers. The success of that marketplace, and the use of competition as a means to control costs and deliver quality, requires policy-makers to make choices regarding the design and regulation of exchanges. We hope this paper will contribute to making those policy choices.

2 Medicare Part D

Pharmaceutical benefits were not part of Medicare when it was first launched in 1965. However, the rising share of pharmaceuticals in the cost of healthcare created significant out of pocket expenditures for seniors and led to the creation of the Part D program under President Bush in 2006. The novelty of this government benefit is the fact that it is essentially privatized: insurance companies and other sponsors compete to offer subsidized plans to enrollees. The sponsor is responsible for procuring the pharmaceutical treatments and administering the plan.

The Basic Part D plan is tightly regulated in its benefit levels so that there is little option for carriers to reduce quality and thereby lower costs and attract enrollees. Plans must offer coverage at the standard benefit level, and each bid must be approved by CMS. The coverage rules include restrictions on plans' formularies including which therapeutic categories or treatments must be covered. Importantly, plans are mandated to cover "all or substantially all" drugs within six large drug treatment classes, as well as two or more drugs within roughly 150 smaller key formulary drug types. Therefore plans cannot lower their costs by simply deciding not to pay for any psychiatric drugs, for example. These restrictions also limit the potential for cream-skimming on the part of plans. Furthermore, plans must evaluate their out of pocket costs using particular actuarial models. This limits a plan's ability to attract consumers by shifting costs to a part of the benefit that the enrollee will pay later, or has a hard time evaluating.

Enrolling in Part D is voluntary, and one might be concerned that adverse selection would mean only sick seniors enroll. However, the subsidy for the program is set by legislation to be an average of 74.5% of costs, so for the vast majority of seniors, enrolling is financially favorable (see McFadden et al. 2006) and most eligible seniors did enroll. In addition, the newly eligible who delay enrolling (perhaps until they become sick) are required to pay a higher price for coverage when they do join. Moreover, the subsidy payment to a plan for an individual enrollee is risk-adjusted according to the person's demographics and health status. Thus sponsors receive a higher payment for a sicker enrollee, reducing the incentive of plans to seek out healthy participants.

Many observers have noted that the Part D choice problem is remarkably difficult and the empirical literature has confirmed that consumers do not choose well. In 2006 when the program began there were at least 27 plans offered in each county in the United States. An enrollee had to consider how premiums varied across these plans. Additionally, she had to identify which drugs she planned on taking in the year ahead and compare the out of pocket costs for that set of drugs across those plans. Finally, the enrollee might receive an adverse health shock during the coming year that would change the set of medications demanded; she would want to compare an expectation of possible expenditures across plans. Furthermore, no major program like this existed in the United States at the time Part D began, so seniors likely had no experience attempting to make these calculations. Lastly, many of these consumers in Part D are older Americans; outside the dual-eligible and disabled, Medicare eligibility begins at age 65. The Part D program therefore requires the elderly to carry out a fairly difficult cognitive task.

Part D benefits are provided through two types of private insurance plans. The first is a simple prescription drug plan (PDP) which provides coverage only for prescription drug costs. In 2006, 10.4 million people enrolled in PDPs. Medicare Advantage plans (MA-PD) function similarly to an HMO; such plans insure all Medicare-covered services, including hospital care and physician services as well as prescription drugs. In 2006, 5.5 million people enrolled in MA-PDs. By 2013, of the 32 million Part D enrollees, almost 20 million were enrolled in PDPs. In this paper, we focus our attention solely on PDPs and prescription drug coverage.

A Medicare enrollee can choose among all the PDPs and MA-PDs offered in her region of the country. A plan sponsor contracts with CMS to offer a plan in one (or more) of the 34 defined regions of the US. The actuarial value of the benefits offered by a plan must be at least as generous as those specified in the MMA legislation. In the 2006 calendar year this included a deductible of \$250, a 25% co-pay for the next \$2000 in spending, no coverage for the next \$2850 (the "doughnut hole"), and a five percent co-pay in the "catastrophic region", when out-of-pocket expenditures exceed $3600. As these figures change annually, we report them through 2013 in Table 1. A sponsor may offer a basic plan with exactly this structure, or one that is actuarially equivalent but has no deductible, for example. Enhanced plans have additional coverage beyond these levels and therefore higher expected costs and higher premiums.

Table 1: Defined Standard Benefit Parameters, 2006-2013

	2006	2007	2008	2009	2010	2011	2012	2013
Deductible	$250	$265	$275	$295	$310	$310	$320	$325
Initial Coverage Limit	$2,250	$2,400	$2,510	$2,700	$2,830	$2,840	$2,930	$2,970
Catastrophic Theshold (Total)	$5,100.00	$5,451.25	$5,726.25	$6,153.75	$6,440.00	$6,447.50	$6,657.50	$6,733.75
Catastrophic Theshold (OOP)	$3,600	$3,850	$4,050	$4,350	$4,550	$4,550	$4,700	$4,750
Pre-ICL Coinsurance	25%	25%	25%	25%	25%	25%	25%	25%
Catastrophic Generic-Drug Copay*	$2.00	$2.15	$2.25	$2.40	$2.50	$2.50	$2.60	$2.65
Catastrophic Branded-Drug Copay*	$5.00	$5.35	$5.60	$6.00	$6.30	$6.30	$6.50	$6.60

Notes: *Enrollee pays greater of copay or 5% coinsurance

The way in which sponsors bid to participate in the program is important to an analysis of competition. Sponsors must apply to CMS with a bid for the amount at which each plan they wish to offer can provide the benefits of a basic plan to enrollees. Any costs of enhanced benefits in enhanced plans must be excluded at this stage. Importantly, the costs that the plan is meant to include in its bid are those it will expend to administer the plan, including for example, the cost of drugs, overhead, and profit, and net of any costs paid by the enrollee such as the deductible or copayments and reinsurance paid by CMS. The bid is supposed to reflect the applicant's estimate of its "average monthly revenue requirements" (e.g. how much it wants to be paid) to provide basic Part D benefits for a well-defined statistical person. CMS takes these bids and computes a "national average monthly bid amount" (NAMBA). In 2006 the various plans were equal weighted, but in subsequent years the average was calculated with enrollment weights. The bid amounts must be paid by a combination of the government and enrollees if the plan is to be compensated enough to participate in Part D. The government subsidy percentage (74.5%) is written into the law. CMS uses this number plus an estimate of its reinsurance costs and other payments to determine how much of the bid the beneficiaries must pay on average. This is called the beneficiary premium percentage, and in the first year of the program it was 34%. The Base Beneficiary Premium (BBP) is then the average bid (NAMBA) times the percentage payable by consumers. The premium for any given plan is this BBP adjusted by the full difference between the plan's own bid and the NAMBA average. If a plan's monthly bid is $30 above NAMBA, then its premium will be $30 above the BBP, and similarly if the bid is below the NAMBA. Premiums for enhanced plans are also increased based on the cost of their enhanced benefits. An attractive feature of the regulation is that it creates incentives at the margin for enrollees to choose lower-cost plans, because a plan that is more costly than others must shift 100% of its incremental costs to consumers rather than sharing them with the government. This reduces the incentive of the plan to increase costs or quality above those levels consumers are willing to pay. In addition, conditioning payments to plans on the NAMBA rather than their own bid reduces the incentive for plans to overstate their costs in order to increase the payment they receive.

Enhanced plans provide coverage that is more generous than the defined standard benefit, and for which they charge correspondingly higher premiums. This added benefit typically takes the form of either additional coverage in the "doughnut hole", reduced copayments, or coverage of certain drug types specifically excluded from normal Part D coverage, such as vitamin supplements, cosmetic drugs and barbiturates. Plan sponsors wishing to offer plans with enhanced coverage must first offer a basic plan within the same region, and sponsors are prohibited from offering more than two enhanced plans in any given region. In addition, the enhanced plans must provide significantly enhanced benefits relative to the basic plan, and the two enhanced plans must be "meaningfully distinct" in terms of coverage. The part of a plan's bid attributable to enhanced benefits increases the premium charged. However, enhanced plans do not receive a higher subsidy; rather, the incremental costs are borne entirely by enrollees. The amount of this additional premium is negotiated between the CMS and the plan sponsor depending on the average risk of likely enrollees. While plans do not have complete control over their premiums due to the Part D bidding mechanism, enhanced plans in particular are able to fine-tune their premiums relatively well, and all plans can with fairly strong certainty increase or decrease their premium.

Medicaid recipients who are also enrolled in Medicare receive their prescription drug benefits through Part D. Their premiums, deductibles, and copays are fully paid by the government. In 2006 approximately 36% of Part D enrollees were automatically enrolled because they were also on Medicaid (6.3 million). A second category of consumers who do not face the posted prices in Part D are Low Income Subsidy (LIS) recipients. These additional 2.2 million enrollees (in 2006) were eligible for low-income subsidies that reduce premiums and out of pocket costs associated with Part D. We omit both LIS and dual-eligible enrollees from our analysis because they do not pay the full (or any) cost of the plan they chose; additionally, many did not actively choose a plan but were auto assigned to one of several eligible plans. These enrollees may affect market structure, and plan characteristics such as price, however, because they are assigned to a plan with a premium lying below the benchmark. CMS determines the benchmark every year by averaging the premiums of the plans in the market. CMS used equal weights in the first year of the program and slowly transitioned to enrollment weights. If an LIS or dual-eligible enrollee chooses a plan with a premium above average, any additional costs must be borne by the enrollee. Since many dual-eligible and LIS enrollees do not actively choose a plan, they are assigned into a qualifying plan and in that way minimize their own payments.

There was a great deal of entry into Part D in 2006 on the part of sponsors, both private and public. There were 1429 PDP plans offered nationwide in 2006 (though this had fallen to 1031 by 2013); every state had at least 27 PDPs every year during our sample period. Enrollees select one of these plans during the open enrollment period each November to take effect in the subsequent calendar year. The program includes many sources of aid for enrollees in making these decisions. Most importantly, CMS has created a website called "Planfinder" that allows a person to enter her zip code and any medications and see the plans in her area ranked according to out of pocket costs. The website also enables prospective enrollees who are unsure of their treatments to estimate costs in each plan under three health statuses (Poor/Good/Excellent), to estimate costs in standard benefit plans based on total expenditures in the previous year, and to filter plans based on premiums, deductibles, quality ratings and brand names. A Medicare help line connects the enrollee to a person who can explain the program and use the Planfinder website on behalf of the caller in order to locate a good choice. Pharmacies, community service centers, and other advocates offer advice. Survey evidence (Kaiser Family Foundation (2006)[4], Greenwald and West (2007)[22]) indicates that enrollees rely on friends and family to help them choose a Part D plan as well, yet nonetheless find the choice process difficult and the number of choices confusing.

3 Literature Review

The introduction of Part D immediately created a literature evaluating outcomes from the novel program structure. An important early paper suggesting that the elderly make mistakes is that of Abaluck and Gruber (2011, hereafter AG)[2]. Their study uses data from WoltersKluwer, a firm that transfers data between plans, from 2005-6, and from a subset of pharmacies representing 31% of all prescription drug claims in the United States. The authors calculate premiums, out-of-pocket payments (OOP), and counterfactual payments that enrollees would have paid in alternate plans (holding drug purchases constant). These counterfactual estimates are a hallmark of Part D research and are critical to determining whether an enrollee is choosing the lowest cost plan. AG shows that only 12% of consumers choose the lowest cost plan; on average, consumers in their sample could save 30% on Part D expenditure (which is on average more than $1000) by switching to the best plan. Using an estimated demand system the authors demonstrate that consumers value premium reductions far more than reductions in expected OOP costs, that consumers don't value risk reduction, and that they value certain plan characteristics in a hedonic manner above and beyond the way those characteristics influence expected costs. These findings on poor plan choices have been replicated in other studies such as Zhou and Zhang (2012)[40], who find that in 2009 only five percent of beneficiaries choose the lowest-cost plan.

Several other studies have examined consumer choice in the Part D market. Heiss et al. (2012)[26] use administrative data from 2006 to 2008 to study the effects of various decision rules such as purely backward looking, random choice, largest plan, and minimum premium, and compare these choices to a rational expectations rule that minimizes the certainty equivalent expected out of pocket costs. They find that the rational expectations measure does not help explain a consumer's choice. In a field experiment, Kling et al. (2012)[34] demonstrate that giving Part D consumers individualized information about which plans will generate the most cost savings for them can raise plan switching by 11% and move more people into low cost plans. Nonetheless, they are unable to induce the high levels of plan switching consistent with rational choice. Ketcham et al. (2012)[31] document substantial overspending by enrollees relative to the optimal plan and show that enrollees with the biggest errors are the most likely to switch. However, their data are selected sample from CVS Caremark's plans in 2006 and 2007, which have switching rates double those in the population as a whole. They find that enrollees who switch reduce their overspending by $200 on average, although a sizeable majority of the consumers in their data, including most non-switchers and some switchers, are still not in the best plan in 2007. Polyakova (2013)[36] estimates a model of plan choice that features switching costs and adverse selection on the part of enrollees, with unobservably riskier beneficiaries choosing more comprehensive coverage. She uses the model to simulate the effect of closing of the "doughnut hole" on adverse selection and finds that switching costs inhibit the capacity of the regulation to eliminate sorting on risk. The presence of switching costs, adverse selection and consumer choice frictions has been documented in other health insurance markets by Handel (2012)[23] and Handel and Kolstad (2013)[24] among others.

There is a great deal of work both in psychology and in economics on consumer choice. For example, Iyengar and Kamenica (2010)[30] provide evidence that more options result in consumers making worse choices. In contrast to the prediction of a standard neoclassical model, more choice may not improve consumer welfare if it confuses consumers and leads them to seek simplicity. Furthermore, enrollees in Part D are either disabled or elderly, and as documented by Agarwal et al.(2009)[3], the ability to make sound financial decisions declines with age. Thus it would be reasonable to expect more mistakes from Part D consumers than that of the population as a whole. These types of results have led some critics of Part D to call for CMS to limit the number of plans available to seniors. On the other hand, using data on private-sector health insurance, Dafny et al. (2013)[13] show that most employers offer very few choices to their employees and that the employees would greatly value additional options. Thus while the inherent difficulty of choosing an insurance plan may lead consumers to make mistakes, it is not clear that limiting the number or range of options is the correct policy response.

Other authors have found evidence for inattention or lack of comparison shopping in complex and infrequent purchase decisions. In the auto insurance market, Honka (2012)[28] finds that consumers face substantial switching costs, leading them to change plans infrequently, and that search costs lead those who switch to collect quotes from a relatively small number of insurers. In related works, Busse et al. (2010)[10] and Busse (2013)[9] find that consumers are inattentive and use a limited number of "cues" such as price promotions and mileage thresholds to evaluate auto purchases rather than actual prices and qualities. Giulietti et al. (2005)[21] examine consumer choices and switching behavior among gas suppliers in the UK. They conclude that consumers could save significant amounts by switching, there are substantial switching costs, and that as a consequence of this behavior the incumbent supplier (British Gas) retains market power and a 60% market share two years after privatization. Ater and Landsman (2013)[5] present evidence against learning on the part of consumers in retail banking.

Ericson (2012)[17] is the primary paper in the literature that analyzes the insurer's problem in the face of Part D consumers who do not choose perfectly. He argues that firms exploit consumer switching costs by entering with low prices and raising prices rapidly over time (as in Klemperer (1987)[33]), gradually replacing their highest-priced plans with cheaper plans (cycling). The "invest then harvest" dynamic[19] induced by lock-in effectes has also been studied empirically in other markets with consumer switching costs, such as Kim et al. (2003)[32] in the case of retail banking, while the pricing incentives for firms facing consumers with choice frictions has been studied by Hortacsu and Syverson (2004)[29] in the case of mutual fund fees.

4 Data

The data we use for demand estimation are a sample of Part D enrollees from New Jersey. We have a random sample from 2006 and a random sample of new enrollees in 2007-9 that adds up to 250,000 enrollees in total. We obtained these data from CMS. We chose New Jersey because it has a very low percentage of MA-PD enrollees and the total number of enrollees that met our criteria was not far above the CMS cutoff of 250,000. In our request to CMS, we asked for enrollees who did not have LIS status at any time and also were enrolled in stand-alone PDPs, rather than MA plans. Limiting the sample to these enrollees reduced the sample size from all New Jersey enrollees in PDP plans, of which there were between 527,000 and 545,000 from 2006 to 2009, to between 300,000 and 325,000 over the same time period. We then took a random sample in each year so that the total sample size was just under 250,000. We made these choices because we wanted to focus on the decisions of consumers who had to pay the listed price for the plan, and therefore were not subsidized. We also wanted a setting where plans had relatively standardized quality. This is not true of MA-PD plans, where the pharmacy benefit is linked to all other medical care. The details of the sample definition and data cleaning procedure can be found in Appendix A.

Table 2 shows the number of enrollees in our dataset each year; this ranges from 127,000 in the first year of the program up to 160,000 in 2009. Just over 60% of enrollees are female, and about 90% of enrollees are white. The breakdown by age group is also shown in Table 2. The main change over our four years of data is that the entering cohort, ages 65-69, grows in size from under 20% to almost 28% of the sample. It may be that over time employers and their about-to-be-retired employees no longer make other arrangements for pharmaceutical coverage, but build in to the employee benefit that he or she will use Part D. An evolution of this type would cause the flow rate into Part D at retirement to increase over time. Because we have data from four years of the program we can study the behavior of enrollees who have three, two, one, and zero years of experience with the program. The proportions of enrollees with different amounts of experience are also shown in Table 2. About 10% of each cohort leaves the program each year, and between 27,000 and 30,000 new enrollees enter each year.

Table 2A: Sample Composition

	Count	% of Sample	% Female	% White
2006	127,654	21.98%	63.7%	91.1%
2007	141,987	24.43%	62.4%	90.8%
2008	151,289	26.05%	61.6%	91.0%
2009	159,906	27.53%	60.4%	90.9%

Notes: Summary statistics on composition of New Jersey data sample.

Table 2B: Age Distribution

	Under 65	65-69	70-74	75-79	80-84	Over 85
2006	5.82%	19.71%	19.51%	20.33%	17.27%	17.36%
2007	6.20%	22.28%	19.51%	18.63%	16.52%	16.85%
2008	6.15%	24.84%	19.85%	17.26%	15.66%	16.24%
2009	6.15%	24.84%	19.85%	17.26%	15.66%	16.24%

Notes: Summary statistics on age distribution of New Jersey data sample.

Table 2C: Part D Tenure

	New Entrants	1 Year	2 Years	3 Years
2006	127,654	0	0	0
2007	28,460	113,437	0	0
2008	26,802	24,745	99,742	0
2009	31,275	25,203	21,170	84,258

Notes: Summary statistics on composition of New Jersey data sample by number of years in Part D.

For each enrollee, we estimate counterfactual costs in each plan after discarding any small plans that constitute less than 5% of enrollees in aggregate. We use a methodology that combines some elements of that used in AG (2011)[2] with some from Ketcham et al. (2012)[31]. First we asked a physician to classify drugs as either chronic (drugs taken regularly over a prolonged period) or acute (other drugs). We assume that chronic drug consumption is perfectly predicted by the patient and calculate the total cost for each enrollee of the observed prescriptions using each plan's cost-sharing structure. For acute drugs we use a method analogous to AG; rather than assuming that acute drug usage is perfectly predicted by the consumer, we assign each individual to a group of ex-ante "similar" individuals and assume that the consumer expects to incur a total cost equal to the median within her group. Groups are defined by gender, age (four categories), race (white or non-white), income quartile, deciles of observed total days' supply of drugs in the previous year, a dummy for each of the nine largest plans (and another for "any other" plan), and a dummy for having one of seven common conditions (hypertension, mental illness, diabetes, high cholesterol, Alzheimers, chronic pain, thyroid problems and conditions requiring anti-coagulants). We then use a method similar to that in Ketcham et al. (2012)[31] to calculate overall expected out-of-pocket spending. We apply each plan's overall terms (deductible, copayment or coinsurance rate on each tier, gap coverage) to each individual and use his or her predicted total (chronic and acute) drug cost in each month to predict total out-of-pocket spending given these terms. This procedure yields estimates which closely track those for plan choices we observe in the data. Further details are provided in Appendix B. Note that, as in previous papers, our method assumes no moral hazard, and unlike Ketcham et al. (2012)[31] we assume no elasticity with respect to plan prices. Using these estimated costs, we measure a plan's "average price" as being the mean estimated out-of-pocket spending in that plan (over all enrollees in the data), which corrects for selection effects.

The quality of PDP plans nationally, as measured by the proportion of the 117 most-commonly prescribed chemical compounds "covered" by the plan, rises over time from 53% to 80%. When weighted by enrollment we see in Table 3 that consumers disproportionately choose plans that include more treatments. The enrollment-weighted average coverage begins at 59% and rises to 82% by 2009. One other dimension of quality that consumers might care about is customer service. CMS has a star rating system for enrollees to rate plans (with 3-5 stars available in between 11-19 categories). Consumers appear to prefer higher-rated plans. The method used to assign star ratings changed dramatically between 2007 and 2008, making comparison between the 2006-2007 and 2008-2009 period difficult.

Table 3: Average Plan Quality

	# Plans	% Top Drugs Covered Unweighted	% Top Drugs Covered Enrollment Weighted	% Quality Stars Unweighted	% Quality Stars Enrollment Weighted
2006	1,426	53%	59%	92%	96%
2007	1,866	68%	71%	95%	98%
2008	1,824	79%	80%	75%	77%
2009	1,687	80%	82%	67%	68%

Notes: Percent of 117 most-commonly prescribed drugs covered, and percent of possible stars achieved, in PDP plans in each year (national data).

If consumers do not like an aspect of their plan, they can switch in the open enrollment period. Table 4 reports summary statistics on enrollees who switch plans. Our data allow us to analyze three opportunities for consumers to switch. From 2006-7 a total of 19% of enrollees actively switch plans (there are consumers who passively switch in the sense that the firm retires their plan and automatically moves them into a different plan run by the same firm, and we do not count these as active switches). In 2007-8 a total of 24% of consumers switch plans. By 2008-9, however, active switching drops considerably, to 8%. For the first two years, women are about five percentage points more likely to switch plans than men, and non-whites are about three percentage points more likely to switch also. In 2008-9 those differences become minimal. The probability of switching increases monotonically with age. We create a group of those under-65 but eligible for Medicare due to disability. This group is similar in switching behavior to the 85+ group. Switching probability also decreases monotonically with income.

Table 4: Switching by Demographic Group

	2006-07	**2007-08**	**2008-09**
Whole Sample	19.10%	24.10%	8.20%
Female	20.90%	26.30%	8.50%
Non-White	21.70%	26.90%	8.80%
Income	**2006-07**	**2007-08**	**2008-09**
1st Quartile (low)	24.79%	30.68%	9.03%
2nd Quartile	19.85%	24.72%	8.15%
3rd Quartile	18.08%	23.25%	8.21%
4th Quartile (high)	13.89%	18.38%	7.45%
Age	**2006-07**	**2007-08**	**2008-09**
Under 65	28.99%	33.10%	11.05%
65-69	12.61%	17.99%	7.69%
70-74	15.30%	20.63%	7.57%
75-79	17.53%	22.53%	7.42%
80-84	21.84%	26.26%	7.74%
Over 85	27.96%	34.21%	10.18%

Notes: Percent of enrollees switching plans in NJ data, by year and demographic group.

5 Analyzing the Behavior of Part D Enrollees

5.1 The Nature of Enrollees' Mistakes

We begin our investigation of the behavior of Part D enrollees by considering their overpayment in their chosen plan given the other plans that are available to them. For the moment we refer to overspending interchangeably as consumer error or mistakes when choosing a plan. However we note that, if consumers have preferences for non-price characteristics, these may lead them to choose a plan other than the cheapest available without corresponding to errors in choice. We return to this issue in the discussion of our demand model and simulations below.

We define overpayment as the expected out-of-pocket payment (including premium) in the plan they chose less the minimum expected out-of-pocket payment in any other plan in their choice set. Table 5 summarizes the level of overspending by year in our sample. In 2006, the first year of the program, the average amount paid above the minimum expected out-of-pocket payment available to the enrollee, including premium, was \$397.61, or 37% of the total out-of-pocket payment. The percent and dollar amounts both fell in 2007 but then increased in both 2008 and 2009, to a level of \$436.96 or 36% of total spending in the final year of our sample. These numbers mask underlying variation for new enrollees compared to those with experience of the program. As shown in the table, new enrollees' overspending was lower in 2008 and 2009 than that of continuing enrollees, reaching a level of \$371.78 or 32% in 2009. 2006 enrollees (those who first entered the program in 2006 and remained in it throughout our sample) had bigger errors in every year than the average for the full sample; their overspending in 2009 was \$459.19, or roughly the same percentage of total cost (37%) as in 2006 despite their long exposure to the program. This suggests that overspending is not declining over time.

Table 5: Overspending by Part D Cohort

	Full Sample			**New Enrollees**			**2006 Enrollees**		
	Count	**\$ Error**	**% Error**	**Count**	**\$ Error**	**% Error**	**Count**	**\$ Error**	**% Error**
2006	127,654	\$397.61 (\$361.80)	37.20 (22.39)	127,654	\$397.61 (\$361.80)	37.20 (22.39)	127,654	\$397.61 (\$361.80)	37.20 (22.39)
2007	141,897	\$320.55 (\$302.50)	29.63 (18.59)	28,460	\$300.23 (\$314.53)	30.21 (19.27)	113,437	\$325.65 (\$299.19)	29.49 (18.42)
2008	151,289	\$381.80 (\$350.77)	32.98 (17.96)	26,802	\$333.96 (\$348.95)	30.83 (18.90)	99,742	\$390.77 (\$348.06)	33.08 (17.47)
2009	159,906	\$436.96 (359.44)	36.01 (16.49)	31,275	\$371.78 (\$371.34)	32.02 (18.44)	84,258	\$459.19 (\$353.25)	37.01 (15.61)

Notes: Predicted overspending (or error) by year. "%" is percent of enrollee's total OOP spending (including premium) in observed plan. Standard deviations in parentheses.

Much of the overspending by Part D enrollees is a result of failing to choose a new plan each year. Column 1 of Table 6A shows that, in every year, overspending is on average lower for consumers who have just switched plans than for those who have not. Moreover, errors for the group switching decrease slightly over time, while those for non-switchers increase over time. Column 2 of the same table shows that switchers on average would have had higher errors than non-switchers had they remained in the same plan. Table 6B considers the fraction of enrollees spending within 10% or 25% of their estimated optimal-plan cost and shows much the same pattern. By 2009, over a quarter of switchers spent less than 110% of their optimal-plan cost, while less than 4% of those not switching achieved this.

The disparity in overspending between switchers and non-switchers appears to be growing over time. By 2009, around 62,000 enrollees present in all four years, or just under half the original cohort (not adjusting for attrition) had never picked a new plan. These enrollees spent on average about 40% more than their optimal plan cost; only 2% of them spent under 110% of optimal plan cost. Overspending increases essentially monotonically in years since last active plan election. This suggests that the failure of consumers to switch plans is a major contributing factor to overspending.

Table 6A: Overspending by Switch Decision

Switchers	% Error, Next-Year Chosen Plan	% Error, Next-Year Same Plan	Δ% Error, Chosen Plan	Δ% Error, Same Plan	Δ% Error, Chosen Relative to Same
2006	28.05%	36.47%	-16.05%	-7.62%	-8.43%
2007	28.68%	44.18%	2.85%	18.35%	-15.50%
2008	25.83%	41.22%	-4.20%	11.19%	-15.39%
Non-Switchers	**% Error, Next-Year Chosen Plan**	**% Error, Next-Year Same Plan**	**Δ% Error, Chosen Plan**	**Δ% Error, Same Plan**	**Δ% Error, Chosen Relative to Same**
2006	30.90%	30.90%	-4.51%	-4.51%	0.00%
2007	35.96%	35.96%	4.98%	4.98%	0.00%
2008	39.15%	39.15%	5.80%	5.80%	0.00%

Notes: Predicted percent error in observed chosen plan, and under scenario where enrollee stays in previous-year plan, for both switchers and non-switchers.

Table 6B: Proportion Within X% of Optimal Spending

10%	Whole Sample	Switched Past Year	Didn't Switch
2006	14.91%	-	-
2007	15.66%	15.04%	16.00%
2008	10.18%	17.28%	6.56%
2009	7.67%	27.81%	3.98%
25%	**Whole Sample**	**Switched Past Year**	**Didn't Switch**
2006	28.20%	-	-
2007	42.75%	49.94%	40.81%
2008	34.98%	43.15%	30.90%
2009	21.74%	46.99%	16.69%

Notes: Estimated proportion of sample within 10% and 25% of spending in optimal plan, for full sample and separately for switchers and non-switchers.

We also find no evidence that errors are related to over-insurance, as would be the case if heterogeneity in risk preferences was causing the observed overspending. Each year, switchers choose plans that on average dominate the plans chosen by non-switchers. Table 7 shows that the premiums charged to those who switch plans are on average about 30% lower than those charged to non-switchers, while the percentage of total costs covered in the gap is dramatically higher for switchers. Thus higher coverage is chosen by people making smaller, rather than larger, errors on average. In addition, this increased gap coverage does not come at the expense of reduced coverage in the pre-ICL phase (the main coverage phase), as the percent of covered costs is actually higher in this phase on average for switchers as well. Finally we note that the differences between switchers and non-switchers do not reflect underlying differences in the type of plan that would generate the lowest costs for them. Panel 2 of Table 7 demonstrates that the characteristics of the lowest-cost plans for switchers and non-switchers are very similar. Overall we see that on average switchers choose plans that fairly closely resemble their lowest-cost plans, while non-switchers do not.

Table 7: Next-Year Plan Characteristics Choices

Observed Choices					Optimal Choices				
Switchers	**% Enhanced**	**Premium**	**% Pre-ICL Cvge**	**% ICL Cvge**	**Switchers**	**% Enhanced**	**Premium**	**% Pre-ICL Cvge**	**% ICL Cvge**
2006	14.64%	19.02	70.15%	12.15%	**2006**	19.82%	22.09	71.58%	12.63%
2007	24.00%	26.50	70.50%	29.29%	**2007**	55.71%	22.14	70.65%	14.50%
2008	37.53%	29.93	71.34%	29.60%	**2008**	46.76%	24.01	79.56%	27.33%
Non Switchers	**% Enhanced**	**Premium**	**% Pre-ICL Cvge**	**% ICL Cvge**	**Switchers**	**% Enhanced**	**Premium**	**% Pre-ICL Cvge**	**% ICL Cvge**
2006	28.28%	26.06	62.30%	10.30%	**2006**	15.50%	18.62	71.36%	12.32%
2007	33.54%	38.60	65.88%	6.53%	**2007**	55.97%	21.89	69.64%	13.23%
2008	37.45%	41.27	63.59%	11.09%	**2008**	49.37%	24.18	78.96%	25.48%

Notes: Comparison of observed to optimal plan characteristics, for switchers and non-switchers.

As a final test of the effect of risk aversion on overspending we run cross-sectional regressions of percent overspending each year on plan and enrollee characteristics. The estimated coefficients and standard errors are shown in Table 8. In 2008 and 2009, having switched plans is negatively related to overspending, and the estimated coefficient becomes more negative over time. Moreover, whether or not we control for having switched plans, gap coverage is negatively and premiums positively related to overspending. This suggests that errors are not driven by over-insurance, but may plausibly be driven by failure to switch plans. These results are broadly supportive of the finding in Ericson (2012)[17] that plans enter with low premiums and raise them over time. In such a scenario, overspending would be driven by enrollees failing to switch out of older plans as they raised their premiums, leading overspending to be related to inertia and premiums but not to gap coverage. We next investigate why enrollees choose, or do not choose, to switch plans.

Table 8: **Predicted Overspending Regressions**

	Without Switching Decision				With Switching Decision		
	2006	**2007**	**2008**	**2009**	**2007**	**2008**	**2009**
Years in Program	-	0.0010773 (0.0010116)	0.0025059*** (0.0004558)	0.006177*** (0.0002955)	-	0.0000882 (0.0009006)	0.0022513*** (0.0004513)
Hypert./Diab.	-0.0024821* (0.0014207)	0.0451368*** (0.0011881)	0.004755*** (0.0010869)	0.0001496 (0.0010744)	0.0445431*** (0.0012976)	0.0034357*** (0.0011782)	0.0001959 (0.0011409)
Alz/Mental Ill.	-0.0113808*** (0.0010839)	0.0030174*** (0.0009704)	-0.0082099*** (0.0008857)	-0.0074646*** (0.0008404)	0.0026534*** (0.0010514)	-0.007903*** (0.0009552)	-0.0069858*** (0.0008872)
Female	0.0007703 (0.0008828)	0.0006267 (0.0007932)	0.0001121 (0.0006822)	-0.0017273*** (0.0006542)	-0.0006384 (0.0008655)	0.0011001 (0.0007397)	-0.0016274*** (0.0006924)
White	-0.0021962 (0.0015382)	0.0134758*** (0.0013213)	0.0053273*** (0.0011794)	0.0145952*** (0.001124)	0.0144624*** (0.0014988)	0.0027161** (0.0012922)	0.0107309*** (0.0012324)
Under 65	0.0333286*** (0.0022703)	0.0536756*** (0.0019833)	0.0202563*** (0.0017354)	0.0156464*** (0.0016246)	0.0515434*** (0.0023837)	0.0218978*** (0.0020255)	0.0129585*** (0.0018836)
Over 80	0.0155229*** (0.0008733)	0.0276734*** (0.0008145)	0.0092578*** (0.0007427)	0.0071423*** (0.0007189)	0.0247906*** (0.00086)	0.0078899*** (0.0007763)	0.006811*** (0.0007405)
Pred. OOP ($)	0.0000283*** (0.000000848)	0.000016*** (0.00000078)	0.00000973*** (0.000000637)	0.00000226*** (0.000000536)	0.0000133*** (0.000000778)	0.0000108*** (0.000000735)	0.00000269*** (0.000000603)
Premium ($)	0.0012957*** (0.00000558)	0.0007056*** (0.00000538)	0.000632*** (0.0000051)	0.0006908*** (0.00000708)	0.0006816*** (0.00000569)	0.0006119*** (0.00000591)	0.0005344*** (0.00000691)
Deductible ($)	0.00006*** (0.00000645)	0.000018*** (0.0000046)	0.0002663*** (0.00000326)	0.0002561*** (0.00000331)	-0.0001353*** (0.00000603)	0.0002538*** (0.00000384)	0.0002372*** (0.00000351)
Gap Cov. (All)	-0.2857783*** (0.0041193)	-0.7050151*** (0.0171637)	-	-	-0.7875692*** (0.0246581)	-	-
Gap Cov. (Generic)	-0.2817112*** (0.0055148)	-0.0539567*** (0.0015226)	-0.0811792*** (0.0022641)	-0.1119702*** (0.0029374)	-0.0631379*** (0.0016752)	-0.0893012*** (0.0027987)	-0.060675*** (0.0030052)
National PDP	0.0095063*** (0.0015417)	-0.10214*** (0.0008585)	-0.0401159*** (0.0015888)	0.0585779*** (0.0014497)	-0.0972765*** (0.0009647)	-0.0518978*** (0.0016934)	0.0442879*** (0.0015037)
Switched Plans	-	-	-	-	0.0650212*** (0.0014838)	-0.0058346*** (0.0011704)	-0.0685957*** (0.0017385)
Income Qtiles	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spending Dciles	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	127,654	141,897	151,289	151,289	113,437	124,487	128,631
R^2	0.568	0.425	0.495	0.417	0.451	0.503	0.434

Notes: Regressions of predicted overspending (relative to predicted lowest-cost plan) on plan characteristics. Robust Standard Errors in Parentheses. "*" = 90% Significance, "**" = 95% Significance, "***" = 99% Significance

5.2 Who Switches and Why?

We have shown that switchers on average reduce their overspending in the following year. Table 9 goes further: it shows that not switching is rarely an optimal strategy. If we conservatively define switching to be the optimal choice whenever a consumer's current plan is expected to cost more than 125% of optimal-plan costs next year, then the optimal choice for about 85% of enrollees in 2008 was to switch plans, yet less than a tenth of that number actually did switch. A key question then is why people do not switch more frequently.

Table 9: Future Overspending in Current Plan

	% Overspending		
	Total	**Switchers**	**Non-Switchers**
2006	30.82%	36.47%	30.90%
2007	36.91%	44.18%	35.96%
2008	38.27%	41.22%	39.15%
	Within 10% of Optimal		
	Total	**Switchers**	**Non-Switchers**
2006	15.20%	11.79%	16.00%
2007	5.91%	4.01%	6.51%
2008	3.80%	4.08%	3.77%
	Within 25% of Optimal		
	Total	**Switchers**	**Non-Switchers**
2006	39.77%	35.39%	40.80%
2007	27.28%	16.05%	30.84%
2008	16.35%	15.75%	16.40%

Notes: Predicted overspending, relative to lowest-cost plan, for switchers compared to non-switchers.

One potential answer is that consumers are inattentive, and that in the absence of highly visible "prompts" they simply roll-over their current plan choice. Recall that overspending is a function of three variables: consumers' current plan characteristics, the characteristics of their optimal plan, and their drug consumption. We now consider whether the decision to switch plans places more weight on own-plan and personal characteristics, which are readily observable, than on optimal-plan characteristics, which require costly search. We construct three simple indicators for "shocks" to expected spending that depend only own-plan and personal characteristics. We define a "premium shock" as an increase in own-plan premiums next year of greater than the median increase across all consumers (about \$4 in 2007, \$7 in 2008, and \$4.50 in 2009) and a " coverage shock" as a decline in pre-ICL coverage of at least 3% or ICL coverage of at least 6% in the current plan. We think of these shocks as appropriate measures of rapidly increasing premiums and eroding coverage. Third, we define enrollees as receiving an "acute shock" if they are in the top quintile of total spending and also the top decile for either percent spending on acute drugs or deviation between predicted and observed spending.[1] This shock is meant to indicate unanticipated short-term illness, which may prompt the consumer to scrutinize her choice of insurance while also serving as signal of high expected future spending. The distribution of these shocks in the population and their correlation with the decision to switch plans are shown in Table 10.[2]

[1]Based on our estimation method the latter would result only if the consumer spent dramatically more on acute drugs than demographically-similar consumers.

[2]The acute shock has a cross-year correlation of around .5, which is considerably lower than the cross-year correlation of other measures of sickness. Total spending, total supply, and acute supply each have a cross-year correlation

Table 10: Distribution of Shocks and Switching Likelihood

	Sample Distribution							
	No Acute Shock				Acute Shock			
	Neither	**Premium Only**	**Coverage Only**	**Premium and Coverage**	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**
2006	51,175	28,017	2,540	24,761	3,129	1,411	179	2,225
2007	17,903	7,681	51,234	40,134	642	850	2,884	3,159
2008	77,028	5,165	7,592	32,559	3,465	337	399	2,086
	Distribution Among Switchers							
	No Acute Shock				**Acute Shock**			
	Neither	**Premium Only**	**Coverage Only**	**Premium and Coverage**	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**
2006	1,762	2,674	219	14,787	254	313	22	1,609
2007	861	1,259	4,173	20,816	60	135	489	2,172
2008	1,171	659	1,006	6,796	74	46	51	699
	Switching Likelihood							
	No Acute Shock				**Acute Shock**			
	Neither	**Premium Only**	**Coverage Only**	**Premium and Coverage**	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**
2006	3.44%	9.54%	8.62%	59.72%	8.12%	22.18%	12.29%	72.31%
2007	4.81%	16.39%	8.14%	51.87%	9.35%	15.88%	16.96%	68.76%
2008	1.52%	12.76%	13.25%	20.87%	2.14%	13.65%	12.78%	33.51%
Overall	2.60%	11.24%	8.80%	43.51%	5.36%	19.01%	16.23%	59.97%

Notes: Panel 1 sets out the number of enrollees with different types of shocks by year. Panel 2 presents the same information for switchers. Panel 3 summarizes switching probabilities by type of shock.

These three shocks appear to explain switching behavior well. Those who receive none of the three shocks switch very infrequently, a little more than 2% of the time, while those who receive all three shocks are considerably more likely to switch plans, doing so almost 60% of the time. Shocks also compound with one another, and the marginal effect of an additional shock is always to increase the likelihood of switching.

Table A1 in the Appendix provides evidence to suggest that the particular choice friction driving consumer inertia is inattention rather than an explicit search or switching cost. If switching costs were important, the consumers choosing to switch would be those for whom the value of switching, measured as expected future cost in their current plan less expected future cost in their optimal plan, was high. In our data the expected value of switching (as a percentage of current costs) is very similar for switchers and non-switchers: 38% of total out-of-pocket costs on average for switchers compared to 36% for non-switchers. The Table in the Appendix shows that the decision to switch is slightly negatively correlated with the expected value of switching. In addition, conditional on not receiving a premium shock, the expected value of switching plans is essentially uncorrelated with the decision to switch. These results are inconsistent with a model of consumer behavior in which the probability of switching plans is increasing in the value of switching.

A model of consumer inattention, where (consistent with Table 10) consumers use shocks to their own plan's premiums and coverage as a prompt to switch, explains these findings. The expected cost saving from switching plans is a function of expected changes in *optimal* plan costs as well as current-plan costs. If consumers are unable or unwilling to reference other plans in the marketplace when deciding whether to switch, then we should expect some profitable potential switches to be ignored. We investigate this idea further by analyzing the weights placed on different sources of cost savings (own- and other-plan changes in both premiums and true OOP costs) in enrollees' switching decisions. We find that though both switchers and non-switchers face similar expected savings on their premiums, the fraction of those savings attributable to own-plan changes is 85% for those who switch and just 47% for those who do not. This finding lends further support to our argument that consumers are basing their decision to switch on premium changes in their current plan, and not expected changes in the rest of their choice set[3].

To formalize the intuition that consumers do not actively shop for the best plan in their choice set, we run probit regressions of decision to switch plans on own-plan, optimal-plan and personal characteristics. Our hypothesis is that consumers prefer lower premiums and higher coverage but do not actively search for plans and hence are insensitive to changes in their optimal plan's characteristics. Thus we should expect consumers to switch more frequently when their current plan becomes less attractive by raising premia or eroding coverage but not when their optimal plan becomes more attractive by lowering premia or reducing coverage. In the context of a probit regression, we test this hypothesis via the coefficients on own-plan and optimal plan characteristics. Comparing the estimated coefficients and standard errors for Model 2 and Model 3 in Table 11, we

between .8 and .9, implying that the acute shock is substantially less persistent than underlying health status.

[3]This asymmetric response to current-product and alternative-product price changes can also be understood as a form of loss aversion as in Hardie et al. (1993)[25]

see that current-plan premium increases and eliminations of current-plan gap coverage significantly increase the likelihood of switching, while declines in optimal-plan premia and optimal plans adding gap coverage in general have no significant effect on switching. To the extent that they affect switching at all, the correlation often runs in the "wrong" direction. For example consumers are more likely to switch when the optimal plan drops gap coverage. We do find that consumers are more likely to switch when their optimal plan's deductible declines, but the estimated effect is very small: only 5% as large as the effect of an own-plan deductible change. Models 4 and 5, replace plan characteristics with the true OOP expenditure (TrOOP) in both current and optimal plans. Comparing these estimates, we see that consumers are significantly more likely to switch when their own plan raises its premium or true OOP costs but not when their optimal plan lowers them. This adds to the evidence that consumers do not consider the characteristics of other plans in deciding to switch, or that comparison shopping is minimal.[4]

There are two other important considerations for evaluating what effect this lack of comparison shopping has on the functioning of the market. First, is there any set of consumers that do actually comparison shop? Klemperer (1987)[33] suggests that if even a small fraction of the market faces no switching costs, the eventual result will be an efficient market with zero excess profit. Hence it is worth considering whether any set of consumers actually chooses to consider all their options and rationally choose a different plan each period. Second, how well do consumers who receive these shocks choose plans? The results in Busse et al. (2010)[10] suggest that consumers who decide based on a limited set of attention-grabbing shocks tend to make poor choices. If so we should not expect interventions aimed at increasing the frequency with which consumers re-optimize to solve problems with market functioning. We investigate these questions in the next section.

[4] These results are robust to comparing the consumer's current plan to an average of the 3-, 5- and 10-least-cost plans. Although only a fraction of switching consumers actually choose their optimal plan, this suggests that the result is not driven by restricting attention only to changes in the unique lowest-cost plan.

Table 11: Probit Regressions on Switch Decision

	Model 1	Model 2	Model 3	Model 4	Model 5
Years in Sample	-0.0247934***	-0.0294415***	-0.0314633***	-0.0248372***	-0.0182399**
	(0.0071761)	(0.007169)	(0.0071728)	(0.0071691)	(0.0073693)
Hypertension/Diabetes	0.0733129***	0.0798342***	0.080307***	0.0823364***	0.0790961***
	(0.0109065)	(0.0105009)	(0.0105133)	(0.0105091)	(0.0107192)
Alzheimers/Mental Illness	-0.0006917	0.0016514	0.0011363	-0.0020816	-0.0038301
	(0.0083146)	(0.0080086)	(0.0080228)	(0.008015)	(0.0081016)
Predicted OOP ($)	-0.00000666	-0.00000355	-0.00000469	0.000000978	-0.000000789
	(0.00000521)	(0.0000051)	(0.00000511)	(0.00000508)	(0.00000513)
Premium ($)	-0.0030395***	0.001489***	0.00148***	0.0012272***	0.001291***
	(0.0000612)	(0.0001185)	(0.0001186)	(0.0001094)	(0.0001142)
Deductible ($)	0.0004298**	0.0030066***	0.0029995***	0.0015065***	0.0013991***
	(0.0001927)	(0.0002211)	(0.0002212)	(0.000228)	(0.0002345)
Gap Coverage (All)	-1.188066***	-2.186089***	-2.189749***	-1.985019***	-2.009538***
	(0.0618919)	(0.1722554)	(0.1721852)	(0.081262)	(0.0831418)
Gap Coverage (Generic)	-1.620322***	-2.928265***	-2.923399***	-2.706543***	-2.760044***
	(0.0502069)	(0.1668769)	(0.1667854)	(0.0766255)	(0.0789347)
National PDP	0.1919726***	-0.111148***	-0.1130871***	-0.1035053***	-0.1142313***
	(0.009978)	(0.0110867)	(0.0110961)	(0.0110598)	(0.0114696)
% Overspending	0.1621421***	-0.002202	-0.0049825	0.0282952	0.0286192
	(0.0218353)	(0.0230459)	(0.0231305)	(0.0231461)	(0.0248564)
Female	0.1028543***	0.1041825***	0.1042258***	0.1052629***	0.10504***
	(0.0069641)	(0.0065628)	(0.0065636)	(0.0065552)	(0.0067686)
White	-0.0095315	-0.0114518	-0.0118292	-0.0111965	-0.0175775
	(0.011737)	(0.011112)	(0.0111145)	(0.0111034)	(0.0115039)
Premium Change (Own Plan)	-	0.0052918***	0.0052814***	0.0047289***	0.0047704***
		(0.000121)	(0.0001211)	(0.0001084)	(0.0001132)
Deductible Change (Own Plan)	-	0.0026001***	0.00259***	-	-
		(0.0003199)	(0.00032)		
Next-Year Gap Coverage Dropped (Own Plan)	-	3.414528***	3.411202***	-	-
		(0.14284)	(0.1428775)		
Next-Year Gap Coverage Added (Own Plan)	-	0.193063	0.1956484	-	-
		(0.1490678)	(0.1489341)		
% TrOOP Change (Own Plan)	-	-	-	0.0000589***	0.066935***
				(0.0000049)	(0.0045806)
% Next-Year Error (Own Plan)	-	0.1316546***	0.1366389***	0.137364***	0.1531454***
		(0.0068874)	(0.0070427)	(0.0071095)	(0.0073229)
Premium Change (Optimal Plan)	-	-	0.0000245	-	0.0000041
			(0.0000197)		(0.0000153)
Deductible Change (Optimal Plan)	-	-	-0.0001234***	-	-
			(0.000022)		
Next-Year Gap Coverage Dropped (Optimal Plan)	-	-	0.044478**	-	-
			(0.0197525)		
Next-Year Gap Coverage Added (Optimal Plan)	-	-	0.0099427	-	-
			(0.0239145)		
% TrOOP Change (Optimal Plan)	-	-	-	-	-0.0003736
					(0.0005723)
Constant	0.7597976***	-2.788946***	-2.797083***	0.4495404**	0.4325211**
	(0.1845319)	(0.2643028)	(0.2643399)	(0.1881253)	(0.1910365)
N	365,185	365,185	365,185	365,185	343,736
R^2	0.353	0.372	0.372	0.370	0.372

Notes: Probit regressions to predict probability of switching. All specifications include spending deciles, income quartiles and age group, year and insurer fixed effects. White HCE Standard Errors in Parentheses. "*" = 90% Significance, "**" = 95% Significance, "***" = 99% Significance

5.3 Where Do Switching Consumers Go?

Though shocks to health and current-plan characteristics dramatically increase the likelihood of switching plans, a small number of consumers who do not face these shocks switch as well. Table 12 addresses the question of whether this set of switchers is more sophisticated than the set of consumers who switch due to highly visible prompts. Comparing the optimality of plans chosen by switchers with and without shocks each year, we see that those who switch in response to shocks actually end up in better plans on average than other switchers. In particular, consumers who switch in reponse to a premium or acute shock are more likely to choose a plan whose costs are within 25% of the optimal level than are switchers who did not receive a shock (although consumers who switch after a coverage shock are somewhat less likely to come close to the optimal plan because of their preference for high-coverage plans). Consumers who switch following a shock also on average choose plans that offer more coverage with lower premiums. This suggests that the small measure of consumers who switch without being prompted are not in fact optimizers or fully-attentive comparison shoppers. Rather, it may be more appropriate to think of these consumers as responding to an unobserved random shock to the likelihood of switching along the lines of a friend or relative advising them to do so.[5]

Table 12 also presents evidence that consumers who switch select plans with characteristics that vary depending on the shock that prompted the switch. Consumers may be evaluating plans based on salient features, so that for instance a consumer who switched to avoid rising premiums would place more weight on premiums in making her choice, while a consumer who switched to avoid declining coverage would evaluate plans more closely on the coverage dimension. Several such patterns are apparent in Table 12. First, consumers who receive acute shocks, which we can think of as signals of future ill-health, tend to prefer higher coverage conditional on switching, especially in the gap phase, than those who do not. The same is true of those receiving coverage shocks, although their choice differ from those receiving acute shocks in that they tend to choose lower premiums as well. Second, consumers facing premium shocks tend to choose plans with lower premiums, although there is no clear pattern with respect to their preferred coverage levels. This suggests that consumers treat shocks to their health status and plan characteristics not only as prompts to switch but also as "cues" to search for particular plan attributes. These results are consistent with a model of "projection bias" in consumer preferences, as in Busse et al. (2012)[8], where consumers assume that their current needs will persist far into the future rather than predicting their future needs.

Although in aggregate overspending increases over time, consumers who switch plans on a regular basis actually make better choices in 2009 than the population as a whole in 2006. A key question is whether there is anything special about this group of consumers. Table A3 in the Appendix shows that they are observably very similar to other enrollees. The consumers who

[5]The results in Table 12 compare those receiving a shock to those not receiving it pairwise without distinguishing between the other shocks they receive. Appendix Table A2 shows the same breakdown using 8 comparison groups (with and without each of three shocks), and all of the same patterns are visible in the marginal effect of an additional shock.

Table 12: Next-Year Plan Choices and Overspending by Shock, Switchers Only

2006	**Acute Shock**	**No Acute Shock**	**Premium Shock**	**No Premium Shock**	**Coverage Shock**	**No Coverage Shock**
% Pre-ICL Coverage	69.83%	70.18%	70.90%	63.63%	71.98%	64.05%
% ICL Coverage	12.78%	12.07%	12.06%	12.93%	12.38%	11.34%
Premium	20.83	18.82	17.46	32.47	15.97	29.19
% Within 25% of Optimal	57.73%	49.06%	50.56%	44.62%	49.37%	51.83%
2007	**Acute Shock**	**No Acute Shock**	**Premium Shock**	**No Premium Shock**	**Coverage Shock**	**No Coverage Shock**
% Pre-ICL Coverage	72.42%	70.29%	69.82%	73.47%	70.69%	68.22%
% ICL Coverage	34.60%	28.73%	27.02%	39.21%	30.84%	10.77%
Premium	27.25	26.43	25.78	29.69	26.18	30.32
% Within 25% of Optimal	53.85%	42.02%	45.38%	33.40%	42.56%	50.19%
2008	**Acute Shock**	**No Acute Shock**	**Premium Shock**	**No Premium Shock**	**Coverage Shock**	**No Coverage Shock**
% Pre-ICL Coverage	75.94%	70.92%	72.56%	66.97%	72.16%	67.72%
% ICL Coverage	41.69%	28.51%	32.82%	18.16%	32.13%	18.50%
Premium	31.84	29.76	29.07	32.97	28.73	35.19
% Within 25% of Optimal	56.55%	46.13%	48.70%	40.92%	48.25%	41.49%

Notes: Summary of types of plans chosen by type of shock experienced.

choose a different plan every year seem simply to have been unlucky in terms of the number of shocks they received over time. Virtually the entire segment received both premium and coverage shocks each year, and they were also twice as likely to receive acute shocks.

We have presented several key trends in the data that inform our understanding of consumer behavior in Part D plans. First, consumers appear to be inattentive, in that they switch plans infrequently and only in response to clear prompts based on health status and changes to their current plan. Their mistakes are related to not changing plans on a regular basis, and they do not appear to comparison shop until prompted to do so by shocks to their attention. Giulietti et al. (2005)[21] refers to this as "awareness." Without being aware, the consumer does not search and therefore does not choose. Furthermore, switching consumers' revealed preferences for plan characteristics appear to depend on the shocks they observe, indicating that they use these shocks as cues to search for particular product attributes. Finally, consumers do not appear to learn over time, nor is there a significant measure of consumers who rationally re-optimize their plan selection each year. Almost all switching behavior is prompted by shocks to own-plan characteristics and health status, and consumers who switch without receiving these shocks do not appear to make choices reflective of heightened understanding of the Part D system. Motivated by these observations, in the next section we specify a model of consumer plan choice which differs from previous models in that it accounts directly for these features.

6 A Model of Consumer Behavior

Rather than assuming, as in Handel (2012)[23], that consumers make an active choice every year but display inertia in their choices, we posit that each consumer ignores the choice problem entirely until hit by one of several types of shocks. The first two represent bad news concerning the enrollee's current plan characteristics for next year: the plan's premium will rise or coverage will decline dramatically. A third type of shock is an unusually high out of pocket payment driven by a health shock. This shock causes the enrollee to need more medication, triggering payments and increased awareness of the choice option. Lastly, a consumer i could simply receive a random shock that causes awareness, for example from a younger relative visiting the consumer and reviewing her plan choices. We label these shocks respectives v_p, v_c, v_h, and v_e. The sum of these shocks creates a composite shock received by consumer i at time t.[6]

$$v_{i,t} = v_{i,p,t} + v_{i,c,t} + v_{i,h,t} + v_{i,e,t} \qquad (1)$$

When the composite shock $v_{i,t}$ is large enough, the consumer becomes aware and decides to

[6] In a comparable analysis of the UK deregulated gas market, Giulietti et al. (2005)[21] use bill size, tenure, education, income, and payment method, among others, to explain awareness.

re-optimize her plan election. That is, if:

$$v_{i,t} \quad \geq \quad \tilde{v}_{i,t} \tag{2}$$

then the enrollee re-optimizes. Here $\tilde{v}_{i,t}$ is a function of consumer demographics related to health status and sensitivity to changes in plan characteristics, such as age, income, and number of chronic prescriptions. This captures the idea that consumers who rely more heavily on their Part D coverage for treatment require less prompting to consider the implications of their plan choice. Heterogeneity in search costs is an important part of the model and the data, as can be seen for example in Table 4.

The second stage of the model examines how consumers choose to switch and to which plans. For the purposes of this model we assume that consumers who elect to re-optimize their plan choice will with certainty switch to a new plan. As shown in Table 9, the fraction of consumers for whom it is optimal to continue in their current plan is small, and smaller still for those consumers facing shocks to their current-plan characteristics or health[7]. The first stage is then a decision to switch, which we treat as equivalent to re-optimization, and $\tilde{v}_{i,t}$ includes all costs of the switch decision. We assume that once the consumer has become aware and decided to switch plans there is no additional switching cost or other friction to be estimated.

The shocks to premiums, health and coverage are allowed to affect the choice of plan conditional on switching in addition to the decision to switch. Consumer i's subjective utility in plan j, conditional on shocks, is then:

$$u_{i,j,t} = X_{i,j,t}\beta_1 + X_{i,j,t}v_{i,p,t}\beta_2 + X_{i,j,t}v_{i,c,t}\beta_3 + X_{i,j,t}v_{i,h,t}\beta_4 + \epsilon_{i,j,t} \tag{3}$$

where $X_{i,j,t}$ are person-specific plan characteristics (including expected OOP payments, premium and brand and enhanced fixed effects) and the β terms capture the additional weights consumers with shocks place on certain plan characteristics.

Our model is parsimonious: we do not estimate a full dynamic model that tries to separate the costs of search and switching. Furthermore, we abstract away from risk aversion and learning because we find no evidence in the data that they are important. We will use this consumer model to predict the behaviors that will affect the optimal plan strategies: consumers' decisions to switch in response to different changes in the market and in their own health and the types of plans to which they switch after each type of shock. Then we will use the estimates to explore how firms respond to this consumer behavior and simulate market outcomes under counterfactual consumer choices.

[7]This assumption is also helpful for estimation since we observe switching in the data but do not observe search. If aware consumers are able to remain in their current plan, then awareness would be identified from functional form rather than immediately from the data.

6.1 Empirical Model

For the empirical model, we parameterize observable heterogeneity in $\tilde{v}_i$ using age groups, income quartiles, gender, and race. If we assume that the random shock $v_{i,e,t}$ is distributed IID Extreme Value Type 1, then the probability that a consumer i in plan j switches plans is:

$$
\begin{aligned}
P^S_{i,j,t} &= P(v_{i,t} \geq \tilde{v}_{i,t}) \\
&= P(v_{i,p,t}\beta_1 + v_{i,c,t}\beta_2 + v_{i,h,t}\beta_3 + v_{i,e,t} \geq Z_{i,t}\delta \\
&= \frac{1}{1 + e^{Z_{i,t}\delta - v_{i,p,t}\beta_1 - v_{i,c,t}\beta_2 - v_{i,h,t}\beta_3}} = \frac{1}{1 + e^{X_{i,j,t,S}\theta_S}} \qquad (4) \\
v_{i,e,t} &\sim \Lambda(v) \qquad (5)
\end{aligned}
$$

where $Z_{i,t}$ are demographic variables and sickness measures used to parametrize $\tilde{v}_{i,t}$, δ is the effect of those demographic variables on $\tilde{v}_{i,t}$, $X_{i,j,t,S}$ is a vector containing all variables relevant to the switch decision of consumer i in plan j at time t (i.e. shocks to awareness and the variables in $Z_{i,t}$), and θ_S is the set of parameters governing the effect of those variables on the decision to switch.

The first three shocks listed in Equation (3) represent shocks to premiums (v_p), coverage (v_c) and health status (v_h). Their definitions are consistent with the analysis in Section 5.2. As before we define a premium shock as an increase in premiums under the enrollee's current plan of more than \$4 in 2007, \$7 in 2008, or \$4.50 in 2009. A coverage shock is again defined as a decline in the percent of costs covered by the current plan of at least 3% in the Pre-ICL phase or at least 6% in the ICL phase. Finally an enrollee is defined as having an acute shock when they are in the top quintile of total drug cost as well as the top decile of either percent spending on acute drugs or deviation between predicted and observed spending. These shocks are allowed to have varying effects on the propensity to switch, as captured by β. For example this allows shocks to premiums to increase the likelihood of switching differently from other shocks (consistent with our findings in Table 10).

We postulate that the subjective utility of person i from choosing plan j depends on predicted OOP spending, premiums, deductibles, coverage rates (an indicator for any coverage in the gap), indicators for whether the plan is a national brand or an enhanced plan, and brand fixed effects. Expected OOP spending excluding premium (TrOOP) is calculated using the method described in Section 4 and Appendix B, and brands are defined at the carrier level (i.e. the insurance company) rather than the plan level. In some specifications we permit predicted chronic TrOOP costs to enter the utility function separately from acute costs, as the consumer may have different expectations over the two sources of TrOOP spending. We also allow for brand-year fixed effects in certain specifications to account for the time-varying value of particular carriers' benefits (for example as new drugs are introduced). Consumers prompted to search by prior shocks to premiums are permitted to place additional weight on premiums. Consumers with prior shocks to coverage, or acute shocks, are permitted to place additional weight on the plan offering gap coverage (for any type of drug).

Our utility specification, shown in Equation (6), is linear in all these variables:

$$\begin{aligned} u_{i,j,t} &= Tr\hat{O}OP_{i,j,t}\beta_1 + Premium_{i,j,t}[\beta_{2,1} + v_{i,p,t}\beta_{2,2}] + Ded_{i,j,t}\beta_{3,1} \\ &+ Gap_{i,j,t}[\beta_{4,1} + v_{i,c,t}\beta_{4,2} + v_{i,h,t}\beta_{4,3}] + X_{i,j,t}\beta_5 + \epsilon_{i,j,t} \\ &= X_{i,j,t,C}\theta_C + \epsilon_{i,j,t} = \delta_{i,j,t} + \epsilon_{i,j,t} \qquad (6) \\ \epsilon_{i,j,t} &\sim EV(1) \qquad (7) \end{aligned}$$

where $X_{i,j,t}$ are other plan characteristics, $X_{i,j,t,C}$ are all variables and interactions relevant to a consumer's plan choice when she is in plan j, θ_C governs their effect on plan choice, and $\delta_{i,j,t}$ is the utility of consumer i in plan j before receiving the shock $\epsilon_{i,j,t}$. Recall that this specification allows the type of shock received to affect the weight the consumer places on the premium and/or coverage offered by the plan; we found clear evidence for this in the data analysis above[8]. Under the assumption in (7) of Extreme Value Type 1 error in utility, and an additional assumption that the errors in equations (4) and (6) are independent, the choice probability conditional on choosing to switch becomes:

$$P^C_{i,j,t} = \frac{e^{X_{i,j,t,C}\theta_C}}{\Sigma_{m \neq j} e^{X_{i,m,t,C}\theta_C}} \qquad (8)$$

where m denotes the enrollee's plan choice in the previous year. The analogous expression for consumers entering the market for the first time is similar, although the denominator is summed over all plans. We treat consumers whose plans exit the market as if they are choosing for the first time, since they have no default and are forced to actively choose a new plan.

We estimate the parameters (θ_s, θ_c) using full-information maximum likelihood; further details of the empirical procedure are contained in Appendix E. Before presenting our preliminary estimates we note that some of the variables included in the utility equation may be correlated with unobserved plan characteristics that also affect consumers' choice of plans. Our strategy to address this issue is to control for important unobserved characteristics using fixed effects. The most plausible endogeneity concern is the fact that we predict consumer out of pocket payments using observed chronic drug utilization and demographic and utilization types, as described in Appendix B. If, as seems likely, there is some error in this calculation, it means we predict an out of pocket cost for particular consumers that is different from their own prediction. This could mean that some plans are perceived to be more attractive by particular consumers than is indicated by our OOP spending variable. Although in the aggregate the predictions of the out-of-pocket payment model are accurate, if these expectations are mis-estimated in a systematic way for a particular plan, the error may be correlated with the premium and this could lead to bias in the premium

[8] An alternative would be to allow for correlation between the errors $v_{i,e,t}$ and $\epsilon_{i,j,t}$.

coefficient. For example, if a plan offers a low-priced version of a chronic drug, many consumers might choose to switch to it if they enroll in that plan. Our OOP cost measure assumes that consumers do not switch chronic drugs, so we would predict a higher OOP cost of the plan than their perception. If premiums are increased to account for this "unobserved generosity" of the plan, the estimated premium coefficient will be biased towards zero. We include carrier fixed effects in all specifications to address this issue (since the formulary is usually fixed across plans within a carrier), and in certain specifications we also include carrier-year fixed effects.

A second possible endogeneity issue is the classic problem that occurs when an enhanced plan's additional coverage is valued in ways we do not observe, and this additional coverage is correlated with the plan's premium. An insurer with an unobservably good plan who wants to charge a higher price would submit a higher bid to CMS, and this would show up as a higher premium. However, the institutional features of the Part D setting reduce the endogeneity concern considerably. Because plans must meet the CMS' actuarial standards for coverage for an average statistical person, insurers are not permitted to offer plans with the types of unobservable quality typical in other differentiated products markets. What consumers purchase is a tariff; any given treatment does not vary in its characteristics across plans, and coverage is regulated by CMS; hence the only way to differentiate in an unobservable dimension is via customer service, which anecdotally does not appear to be a very important force in this market[22]. Moreover, the persistent presence of overspending even by consumers switching plans, as well as the lack of dependence on OOP costs shown in Table A1 and Figure 1 suggests that individual firm-specific variation in OOP costs is not driving consumer choices. Hence the typical unobserved quality dimension correlated with premium, as in Berry (1994)[7], is unlikely to play a role in this market. To account for time-variation in the quality of enhanced plan coverage, in some specification we include enhanced-year fixed effects.

The estimated coefficients and standard errors for four separate demand specifications are shown in Table 13; the means and standard deviations of the variables used in estimation are reported in Appendix Table A5. Columns 3 and 4 of Table 13 report the estimates from the main specifications. Model 1 uses brand fixed-effects while Model 2 uses brand-year fixed effects; both models separate TrOOP costs into a chronic and an acute component. The switch parameter estimates indicate that consumers are more likely to switch plans if they receive premium or coverage shocks or have an acute shock to their health. Females, as well as nonwhite, lower-income and older enrollees have lower threshold values to trigger awareness, and hence are more likely to switch. These results are consistent with the probit regression estimates shown in Table 11 and also with intuition. Overspending mistakes are more costly for older enrollees who spend a higher fraction of their income on drugs and for lower-income enrollees for whom the excess spending is more burdensome. Since the Medicare Part D plan choice is more salient for these consumers, they tend to require smaller prompts in order to re-optimize their choice.

The estimated choice coefficients are consistent with the previous literature. Consumers prefer plans with lower premiums, lower OOP costs, lower deductibles and those with gap coverage. The brand fixed effects (not reported) are also often significant. As in AG[2], consumers place

Table 13: Estimated Structural Demand Coefficients

	No Switch 1		No Switch 2		Model 1		Model 2	
Switch Parameters Threshold Shifters	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Constant	-	-	-	-	4.660***	0.024	4.579***	0.021
Female	-	-	-	-	-0.27***	0.011	-0.24***	0.011
Nonwhite	-	-	-	-	-0.11***	0.018	-0.14***	0.018
Q1 Income	-	-	-	-	-0.46***	0.016	-0.48***	0.015
Q2 Income	-	-	-	-	-0.25***	0.017	-0.26***	0.014
Q3 Income	-	-	-	-	-0.19***	0.015	-0.21***	0.015
Age 70-74	-	-	-	-	-0.24***	0.018	-0.25***	0.016
Age 75-79	-	-	-	-	-0.45***	0.017	-0.48***	0.017
Age 80-84	-	-	-	-	-0.56***	0.016	-0.61***	0.018
Age U-65	-	-	-	-	-0.73***	0.023	-0.69***	0.023
Age O-85	-	-	-	-	-0.79***	0.016	-0.80***	0.017
Shocks	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Premium Shock	-	-	-	-	1.950***	0.012	1.905***	0.012
Coverage Shock	-	-	-	-	1.583***	0.012	1.486***	0.012
Acute Shock	-	-	-	-	0.589***	0.019	0.626***	0.019
Choice Parameters	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
TrOOP (Chronic)	-1.09***	0.01	-0.95***	0.009	-1.08***	0.006	-0.74***	0.014
TrOOP (Acute)	0.22***	0.01	-0.01	0.02	0.308***	0.017	-0.08***	0.019
Deductible	-3.01***	0.02	-3.87***	0.01	-1.85***	0.032	-0.97***	0.044
Premium	-3.35***	0.01	-4.08***	0.003	-5.43***	0.027	-4.34***	0.008
Premium Shock x Premium	-	-	-	-	-3.75***	0.034	-3.08***	0.039
Coverage Shock x Gap Cov	-	-	-	-	0.017	0.015	-0.08***	0.018
Acute Shock x Gap Cov	-	-	-	-	0.621***	0.028	0.498***	0.028
Gap Coverage	0.38***	0.01	0.86***	0.01	0.957***	0.011	0.834***	0.009
Enhanced	-0.57***	0.005	-	-	-0.18***	0.010	-	-
Enhanced (2006)	-	-	-0.72***	0.01	-	-	-0.01	0.014
Enhanced (2007)	-	-	-1.05***	0.008	-	-	0.117***	0.011
Enhanced (2008)	-	-	-0.83***	0.007	-	-	-0.50***	0.012
Enhanced (2009)	-	-	-0.41***	0.008	-	-	0.765***	0.013
Fixed Effects	**Brand**		**Brand-Year**		**Brand**		**Brand-Year**	
N	580,746		580,746		580,746		580,746	

Notes: Estimates from two-stage demand model. Threshold Shifters and Shocks are variables that affect the probability of switching. Choice Parameters are variables that affect preferences for plans conditional on switching. TrOOP is predicted out-of-pocket cost excluding premium. TrOOP, Deductible and Premium are in $000 per year. Gap Coverage is an indicator for any coverage in the gap. White HCE Standard Errors. "*" = 90% Significance, "**" = 95% Significance, "***" = 99% Significance more weight on premiums than would be rational for risk neutral consumers in an expected-cost-minimization framework (where the coefficients on premium and on TrOOP should be equal in magnitude). They also over-weight gap coverage and deductibles, both of which should have zero coefficients since their expected impact on out-of-pocket costs is already included in the TrOOP variable[9]. Perhaps due to the inherent difficulty in forecasting acute health expenditures, the coefficient on expected acute TrOOP costs is positive in Model 1. It becomes negative when we add brand-year fixed effects in Model 2, but even then is considerably smaller in magnitude than the coefficient on chronic TrOOP costs. The previous literature treats these sources of expenditures equivalently, though we find no evidence that consumers do so.

The choice equation also identifies a second source of frictions in consumer decision-making, beyond the inattention already discussed. Consistent with the evidence presented in Table 12 as well as that in Busse et al. (2012)[8], consumers who switch plans following a shock to premiums in the previous year place additional negative weight on premiums in making their choice. Likewise consumers place additional positive weight on gap coverage following a shock to their health status (although not following a shock to their previous plan's coverage). Finally, conditioning on all other plan variables, consumers show a slight aversion to enhanced plans on average. When we break out the enhanced plan coefficient by year in Model 2 the coefficient becomes positive and significant in 2007 and 2009; it is negative and significant only in 2008.[10]

The first two columns of Table 13 present for comparison the results of estimating the choice model without an initial stage where consumers experience shocks and choose whether to switch. This specification is very similar to that in AG[2]. Essentially the model estimates the preferences derived from averaging over the behavior of both inattentive and attentive consumers. Consistent with AG, the estimates indicate that the average consumer over-weights premiums, deductibles and gap coverage; in addition the coefficient on enhanced plans is negative in every year. Comparing across columns, when we add the first stage switching model the coefficients on enhanced plans and deductibles become less negative (more "rational" in the sense outlined above), while those on premiums and gap coverage become larger in magnitude (less "rational"). We explain these changes as follows. The upwards shift in the enhanced plan coefficients is consistent with inattentive consumers not noticing that increasingly attractive enhanced plans are being offered over time and therefore not switching to them; the single-stage model interprets this as a negative utility from enhanced plans, whereas in reality this lack of switching is due to inattention. The upwards shift in the deductible coefficient is similar. In the single-stage model this coefficient is "too" negative; it suggests that consumers irrationally over-weight deductibles when making choices. When we add switching to the model we see that this "over-weighting" is partly caused by inattentive consumers not considering moving into the other (high-deductible) plans available to them. Thus these two variables, whose coefficients in the single-stage model seem to indicate irrational behavior, are at

[9]Evidence for consumers over-weighting premiums and other plan variables relative to expected costs in other insurance markets is presented in Handel (2012)[23] and Ericson and Starc (2013)[18].

[10]Some of the effect of enhanced benefits could be subsumed in the estimate for gap coverage, which many enhanced plans provide and which by 2008 and 2009 had all but vanished from basic plans.

least partly rationalized by consumer inattention.

The coefficients on premium and gap coverage are different. These characteristics seem to be over-weighted in the single-stage model and become even more over-weighted when we add switching. That is, averaging over attentive and inattentive consumers generates a smaller, rather than a larger coefficient. This is consistent with inattentive consumers not switching out of their plans when their premiums rise or gap coverage falls relative to others in the choice set. The single-stage model interprets this as a relatively low (although still over-emphasized) weight on premiums and coverage whereas in fact it is due to inattention regarding other-plan characteristics. When we add the switching stage we see that switchers actually over-weight these characteristics more than the single-stage model would suggest.

These findings suggest that while consumer inattention, and the extra weight placed on premiums and coverage by enrollees experiencing related shocks, explain some of the choice frictions identified in the previous literature, some other sources of overspending remain. Some are related to preferences for non-price characteristics (captured, for example, by the brand and enhanced fixed effects in our model) while others may be related to consumer choice errors. Switchers seem to substantially over-weight premiums and gap coverage, in particular, even conditional on predicted out-of-pocket costs. In the counterfactual analyses below we explore the implications of these findings for the cost savings derived from policies that reduce consumer inattention relative to policies that address the other frictions as well, for example by allowing pharmacists to make choices for some consumers. Before conducting these analyses, however, we consider the supply side of the market.

7 The Supply Side of the Part D Market

The estimated model of consumer demand for Part D plans presented above contains substantial choice frictions, both due to consumer inattention (as described in Farrell and Klemperer (2007)[19]) and for other reasons. The frictions caused by inattention induce a tradeoff for insurance providers between (in the words of those authors) “harvesting” and “investing”. “Investing” is the process of building up market share via low prices in order to increase future profits, while “harvesting” is the process of reaping those profits by raising prices on an installed base. Ericson (2012)[17] finds evidence of this dynamic at work in the Part D market. In this section we present evidence consistent with this model of insurer pricing behavior.

7.1 The New Jersey Part D Market

To analyze the supply-side of the Part D market, we make use of the dataset of Part D plans generously provided by Francesco Decarolis (Decarolis (2012)[14]) from CMS files on plans, ownership, enrollment, premiums, formularies, and other characteristics. It covers all plans in all regions of the US (34) for 7 years from 2006-2012[11]. In this part of the paper we focus only on the data

[11] See Decarolis (2012)[14] for a detailed description of the data.

covering stand alone Part D PDPs in New Jersey, as these are the plans which serve the consumers modeled in the previous section.

There were 44 PDP plans active in New Jersey in 2006, the first year of the Part D program; this is in line with an average of 42.2 plans per region nationwide. The New Jersey market is fairly concentrated in every year of our data: measured in terms of enrollees, the 4-firm concentration ratio begins at 0.862 and declines to .617 in 2008 before rising again to .753 in 2012. Herfindahl indices show the same pattern, declining from 0.259 to 0.154 between 2006 and 2009 before peaking at .285 in 2011. There was some plan entry in New Jersey in the first several years of the program but subsequent entry was limited. A total of 19 plans entered in 2007, joining 38 continuing from 2006, and 9 others entered in 2008, but from 2009 to 2012 no more than 3 plans entered in any year. After 2008 plan attrition reduced the number of active firms in every year from 57 down to 30 by 2012. In the first few years of the program enhanced plans proliferated rapidly, going from 17 of 44 plans with a combined 12% market share in 2006 to 27 of 52 plans with a combined 31% market share in 2009. This coincided with a near-continuous shift away from Defined Standard Benefit plans; by 2012, only 3 such plans remained in the market, down from 8 in 2007. These statistics, presented in Table 14, suggest an oligopolistic market characterized by increasing product differentiation and increasing concentration.

7.2 Insurer Pricing Strategies

We now consider what effect consumer inattention, coupled with product differentiation and imperfect competition, has on insurer pricing strategies in the Part D marketplace. One would expect a profit-maximizing insurer to set its premiums in a way that takes advantage of consumer choice frictions. In this section we note that the patterns in the data are consistent with this intuition.

Theoretical models of search frictions have fairly clear predictions for prices. Papers such as Varian (1980)[39] feature search in an environment of a homogeneous product, multiple sellers, and heterogeneous consumers. In this model, consumers do not engage in sequential search but rather "become informed" (perhaps by paying a cost) and at that point know all prices. A consumer who has experienced a shock and decides to re-optimize her plan choice, enters her ZIP code and medications in the Part D website and then has access to all firms and prices fits this model well. The equilibrium symmetric outcome of Varian's model is price dispersion - which we certainly see in the Part D marketplace. In particular, Defined Standard Benefit plans are so tightly regulated as to represent a nearly homogeneous product; the only dimensions in which they differ are customer service and the particular drugs offered within each Key Formulary Type, though they are constrained a choice a treatments for each. Nevertheless, Table 15 shows that price dispersion persists among Defined Standard Benefit plans. Though the difference between the minimum and maximum premium is falling over time, there is still considerable variation in the cost of this essentially homogeneous product by 2012.

Table 14: New Jersey Part D Market Summary Statistics

Year	# Plans	Enrollment	CR-4	HHI	Entering Plans	Enhanced Plans	Enhanced Market Share	DSB Plans	DSB Market Share
2006	44	281,128	0.8615	0.2588	44	17	12.27%	6	12.89%
2007	57	298,978	0.7804	0.2165	19	27	24.32%	8	10.49%
2008	57	304,198	0.6169	0.1571	9	29	28.62%	7	5.31%
2009	52	317,997	0.6371	0.1543	1	27	30.63%	5	0.48%
2010	47	329,178	0.6601	0.1630	2	24	30.43%	5	2.48%
2011	33	333,553	0.7505	0.2847	1	15	22.46%	4	2.53%
2012	30	343,886	0.7525	0.2805	3	14	24.00%	3	0.38%

Notes: Summarys statistics on New Jersey Part D plans. Source: aggregate CMS data, generously provided by Francesco Decarolis.

Table 15: Premium Dispersion in New Jersey DSB Plans

	Mean, Equal	Std. Dev., Equal	Mean, Weighted	Std. Dev., Weighted	Minimum	Maximum
2006	\$26.33	\$11.33	\$9.27	\$9.41	\$4.43	\$35.49
2007	\$31.28	\$12.44	\$10.37	\$1.70	\$10.20	\$47.40
2008	\$32.51	\$17.61	\$31.28	\$5.73	\$19.20	\$69.00
2009	\$42.88	\$18.08	\$29.84	\$9.36	\$26.60	\$72.70
2010	\$37.66	\$4.88	\$32.84	\$1.97	\$32.00	\$42.90
2011	\$39.73	\$5.73	\$37.26	\$2.75	\$34.20	\$47.60
2012	\$38.37	\$4.20	\$37.32	\$3.66	\$34.80	\$43.00

Notes: Summary of premium dispersion in NJ plans. "Weighted" means weighted by enrollment.

Another important feature of the Part D marketplace is the existence of switching frictions. We model these frictions as limited attention rather than an explicit switching cost but the effect on insurer behavior is similar. The classic switching cost model of Klemperer (1987)[33] captures the main intuition of the firm's problem. If consumers enter the market in period t and choose among firms in that period (and by assumption pay no switching costs in the first period), the firm has an interest in capturing them with a low price (invest). The switching cost the consumer must pay in order to change plans later causes her to be unwilling to switch in response to small price differences. Thus the firm can raise price by a small amount in period $t+1$ without losing the consumer (harvest). A critical element of this model is that firms cannot discriminate between new and old consumers; likewise, in Medicare Part D the firm must choose one price for both types of consumers. [12]

Table 16 shows that, consistent with this prediction, premiums increase on average almost every year. The average annual premium increase for basic plans (weighted by enrollment) is small, less than \$6 per month in every year. Premiums for enhanced plans increase more quickly; in 2008, the weighted-average premium increase for enhanced plans is over \$14 per month, and in 2011 and 2012 smaller enhanced plans post large premium increases. We flag plans that raise premiums by more than \$10. These are tabulated in the second panel of Table 16. Enhanced plans always have a higher probability of a jump in a given year than basic plans. For three years from 2008 to 2010, at least a third of enrollees in enhanced plans face large premium shocks, although the rate is lower in other years.

We can also use the intuition from the theory to predict differences in premium growth across insurers. First, the change in profit for a given change in price is a function of both the intensive margin (profit per enrollee) and the extensive margin (number of enrollees). Since larger firms have a larger intensive margin, we should expect large firms to raise prices more than smaller firms all else equal. Second, we should expect slower premium growth when the number of consumers purchasing for the first time is high relative to the size of the installed base. Thus premiums should

[12]Since firms can sponsor more than one plan, we might expect to see segmentation of consumers and price discrimination as in Ericson (2012)[17]. In our supply-side model we simplify by abstracting away from multi-product strategies and concentrate on the invest versus harvest tradeoff.

Table 16: Average Premium Increase and % of Plans with $10 Premium Increase

	Premium Increase				**$\geq$ $10 Premium Increase**			
	Equal, Basic	**Equal, Enhanced**	**Weighted, Basic**	**Weighted, Enhanced**	**Equal, Basic**	**Equal, Enhanced**	**Weighted, Basic**	**Weighted, Enhanced**
2007	-$2.94	$1.01	-$2.20	$7.20	0.00%	7.41%	0.00%	8.24%
2008	$4.65	$11.50	$5.93	$14.45	28.57%	34.48%	22.59%	36.98%
2009	$6.20	$7.12	$3.68	$4.39	20.00%	33.33%	0.81%	39.31%
2010	$5.06	$1.77	$2.92	$5.44	21.74%	20.83%	1.19%	33.02%
2011	$1.04	$14.33	-$3.09	$2.84	5.56%	73.33%	0.19%	24.48%
2012	-$1.24	$6.52	$1.97	$2.02	6.25%	28.57%	0.13%	7.71%

Notes: Summary of premium changes over time for New Jersey PDPs, by Year and Plan Type rise more slowly in years with high attrition (e.g. high death rates) or large cohorts aging into the Part D program. Because of our focus on shocks to consumers' attention and the dynamics of pricing, we do not estimate our motivating regression in levels like Polyakova (2013)[36], but rather in premium changes. It is the increase in price that becomes more lucrative with an increase in installed base. We therefore estimate regressions of annual premium increases on lagged market shares, growth rates, and other plan variables that might affect costs for all PDP plans in the national dataset.

Table A4 in the Appendix reports the coefficients. In Models 2 and 4, controlling for region and carrier fixed effects and coverage variables that may affect costs, lagged market shares significantly predict future increases in premiums, providing evidence in support of the first hypothesis. Also, in Models 3 and 4 we see that the growth rate of enrollment in the region, which we treat as a proxy for new enrollment, is negatively associated with price increases. This result provides evidence for the third hypothesis, that price competition is more aggressive (with smaller price increases) when there are relatively more unattached consumers to compete for. Taken together, the results of these models provide suggestive evidence in favor of firms pursuing pricing strategies similar to those in Klemperer (1987)[33] and Farrell and Klemperer (2007)[19].[13]

A potential alternative explanation for the patterns observed in the data is that premiums are mean-reverting; the firm prices low in one year, attracting a large market share, and upon realizing a loss increases prices in the next year, leading to the observed correlation. However, this does not explain why some firms maintain large market shares even after increasing premiums quite steeply. Moreover, this strategy would not be profit-maximizing unless choice frictions of the type described above were present.

8 Counterfactual Simulations

Medicare Part D is difficult for consumers to navigate, and as already noted, previous studies have considered the effects of various interventions designed to ease the decision-making process. For example, in a randomized experiment, Kling et al.[34] provide information to Part D enrollees regarding their best plan choice, and find that it increases the probability of switching by 11

[13]The observed pattern of price increases could potentially be due to unobserved quality; plans with higher quality are more attractive to enrollees, leading to higher market shares, and are also able to raise prices as a result. For several reasons this is unlikely to account for the observed price increases. First, the model controls for brand fixed-effects, and thus accounts for any unmodeled dimension of quality which is fixed at the carrier-level (and as discussed we believe this covers most such dimensions). Second, the coefficient on lagged market share is still positive even when we restrict the sample to Defined Standard Benefit plans (although due to lack of power the coefficient is not significant). As mentioned before these DSB plans represent an essentially homogeneous product, suggesting that the harvesting dynamic is active even among non-differentiated plans. Third, individual plans switch between "investing"' and "harvesting" over time in ways that are inconsistent with time-invariant unobserved heterogeneity. For example the SilverScript/CVS Caremark enhanced plan reduced premiums by \$19 from 2006-7 and by \$8 between 2007-8, resulting in substantial increases in market share. Over the next four years the plan's premium growth was well above the market growth rate. Over the same time period the Humana enhanced plan pursued the reverse strategy, raising premiums by \$23 and \$26 in 2007 and 2008 and then switching to below-market price increases in 2009. We interpret these patterns as evidence that particular plans switch from being "investors" to "harvesters" over time in response to changes in market share.

percentage points. Abaluck and Gruber predict that if an intervention could make consumers fully informed and fully rational, they would choose plans that reduced their costs by about 27%. However these papers do not estimate sufficiently detailed models of consumer demand to permit simulations of the impact of policy experiments that "switch off" particular components of consumer choice frictions. Perhaps more importantly, they do not account for the issue that plans are likely to change their pricing strategies in response to changes in consumer behavior, potentially further lowering program costs. In this section we will address both issues. Our demand model allows us to remove each of the different sources of consumer choice error in turn. In the next iteration of the paper we will use accounting data on firm costs, together with a model of firm behavior and our demand estimates, to consider price changes in response to the changes in consumer choices. That is, we will estimate the impact of reducing consumer inattention on overall program costs, taking into account plans' price responses to this change.

Our choice model identifies several sources of frictions: inattention, which prevents switching until the consumer experiences a shock to her health or her own plan's price or coverage; the impact of shocks on preferences when choosing a new plan; and the fact that switchers place a larger weight on characteristics like premium and gap coverage than would be the case for risk-neutral consumers choosing the plan with the lowest expected costs. The simulations described below predict the effects of different counterfactual policies that address some or all of these frictions under the assumption that all lead to errors that the social planner would wish to correct. However we note that the third friction may or may not generate errors; it could simply point to the existence of some aspect of consumer preferences that is not captured in our demand model. The same comment applies to preferences for non-price characteristics (e.g. the brand fixed effects in our model); these too are likely to lead to overspending by our definition but do not correspond to choice mistakes. The results of our simulations should be interpreted with this in mind.

We begin by simulating the effect on consumer and program costs of replacing the existing default (that each consumer remains in her current plan unless she chooses to switch) with the default that she exits the program. Under the assumption that no consumer chooses to exit (consistent with the evidence in Heiss et al (2006)[27]), this has the effect in our model of prompting all consumers to consider switching in every year, i.e. removing consumer inattention. However actual choices will still be made with the estimated preferences from Table 13; for example they are affected by the shocks experienced in the previous year and over-weight certain characteristics. We also consider the additional savings that would be generated if consumers could be persuaded to make choices that were not affected by their shocks - although it is less clear what policy could generate this behavior, and we show that the incremental savings from this change are small.

Our third counterfactual policy addresses the issue that even attentive consumers do not make cost-minimizing choices. We simulate the impact of a policy that pays the pharmacist \$50 each time he moves an enrollee to her lowest-cost plan from the previous year, if moving would have saved her at least \$200 in that year. We consider this policy for two reasons. First it removes all sources of consumer overspending rather than just inattention. By involving a pharmacist, who is assumed to use the online CMS plan finder tool, in the choice process we remove all choice frictions and unambiguously place the enrollee in the plan that was cheapest for her the previous year (although we note that, due to acute shocks, it may not turn out to be the cheapest plan in the current year).[14] This policy simulation also avoids a potential problem that was assumed away in the first counterfactual: some consumers might respond to the "no default" policy by exiting the program. We assume that enrollees who are moved by their pharmacist do not switch away from the pharmacist's chosen plan. Other enrollees, whose choices the previous year were within $200 of the optimal choice, continue to make choices based on our two-stage demand model.

In the current version we run the simulations holding prices fixed. The next iteration will use accounting data on plan costs per enrollee as an input to a simulation of supply side changes in response to the change in consumer behavior.[15] We note that while the firm pricing problem in the observed data is dynamic, the dynamics come only from consumer inattention, i.e. the fact that consumers are "sticky" so a plan's price in one period affects its enrollment in future periods. Removing inattention makes the price-setting process static rather than dynamic, implying that the new equilibrium prices can be predicted (as a function of costs) using a simple system of static first-order conditions. Since capturing demand today to "harvest" tomorrow is no longer important in the static problem, we expect the path of prices to be flatter - and average prices potentially also lower - in our simulations than in the data. This will generate a second cost effect of changing consumer behavior, which will affect the cost of the program for both enrollees and the government.

For the moment, however, our simulations hold prices fixed. The results are set out in Table 18. The panel labeled "baseline" shows total premium costs and out-of-pocket costs (including premiums) predicted by our demand model including all frictions. The second panel shows the same simulated costs when every enrollee chooses the plan with the lowest realized costs to her in the relevant year; this is the lowest-cost outcome possible. Column 3 shows costs simulated with the "no default" model (i.e. there is no inattention). Column 4 removes both inattention and the effect of shocks on preferences when the consumer chooses her plan. Finally the fifth column shows the simulated outcome in the policy experiment where pharmacists are involved in plan choice; the out-of-pocket costs include the $50 payment to the pharmacist per switched enrollee. In each column, the row labeled "Total" provides cumulative spending over the four years we consider. "Saving" is the difference between that cumulative spending and the spending in the baseline scenario, and "% Fixed" is the proportion of the total saving from moving every consumer to her lowest-cost plan that is achieved by the relevant counterfactual.

In the first year of the program the choices in the "no inattention" counterfactual are the same as the baseline (since there can be no inattention; all consumers are entering the program). Even in that year, however, savings of approximately $410 per person would be generated if enrollees could be switched to their lowest-cost plan. Cumulative savings over the four year period from

[14] It is also possible that the pharmacist's choice would be constrained by the pharmacy network offered by each plan. For now we abstract away from this issue.

[15] We cannot use our claims data to generate plan costs since the drug costs recorded there do not account for rebates, which are likely to be large for large carriers.

moving everyone to the lowest-cost plan would be approximately $1852 per person, or 36% of the total baseline out-of-pocket cost. The savings from removing inattention begin in 2007 with a total saving of approximately $275 per person and fall to $169 per person in 2008 and $139 per person in 2009. Overall the model predicts that the average consumer saves $736 cumulatively across the four years when inattention is removed, or 39% of the total error. Comparing the fourth column to the third we see that removing the additional friction caused by consumers placing a greater weight on characteristics that were previously shocked results in very small additional savings. The average cumulative saving increases by only $7 to $744.

Table 18: Simulated Per-Person Costs

	Baseline		Lowest Cost		No Inattention		No Frictions		Pharmacist	
	Premium	**OOP**	**Premium**	**OOP**	**Premium**	**OOP**	**Premium**	**OOP**	**Premium**	**OOP**
2006	$335.41	$1,157.10	$134.55	$747.37	$335.41	$1,003.30	$331.82	$1,001.70	$149.78	$803.25
2007	$419.88	$1,326.10	$232.74	$857.34	$361.72	$1,051.20	$350.90	$1,046.50	$249.11	$926.56
2008	$428.33	$1,316.00	$261.53	$820.94	$392.05	$1,147.10	$385.09	$1,150.10	$289.85	$891.02
2009	$432.62	$1,298.00	$290.17	$819.75	$381.18	$1,159.20	$374.82	$1,155.40	$314.84	$885.38
Total	$1,616.24	$5,097.20	$918.99	$3,245.40	$1,470.36	$4,360.80	$1,442.63	$4,353.70	$1,003.58	$3,506.21
Saving	-	$0	-	$1,851.80	-	$736.40	-	$743.50	-	$1,590.99
% Fixed	-	0%	-	100%	-	39.8%	-	40.2%	-	85.9%

Notes: Results of counterfactual simulations. Simulated per-person costs are out-of-pocket costs including premiums

The "no inattention" counterfactual demonstrates that approximately 40% of overspending in our setting is due to consumer inattention. The remaining 60% is attributable to other factors such as consumers placing a high weight on particular characteristics (e.g. brand, premium or gap coverage) rather than minimizing overall costs. The "pharmacist" counterfactual addresses these remaining frictions, and as shown in Column 5 of Table 18, it is remarkably effective in reducing costs. Even though the payments made to pharmacists are included in the OOP costs, the counterfactual results in savings of almost $1600 over the four year period, or 86% of the total baseline error. Approximately 68% of enrollees are switched to low-cost plans by the pharmacist, and since those making the largest errors are the ones targeted, the cost of the pharmacist payments are small relative to the savings. While we stress that not all the frictions removed here are necessarily due to consumer errors - they may represent heterogeneous preferences that the social planner would not wish to ignore - the magnitudes of the cost savings from this counterfactual are considerable.

9 Conclusions

In this paper we have developed a model of consumer choice in the Part D program and have considered firm pricing decisions. We find that the data support a model of consumer inattention; consumers roll over their plan choices from one year to the next unless shocked by a change to their current plan or their health. Such attentive consumers then make a more optimal choice, although their preferences are affected by the types of shocks they have experienced and they overweight some characteristics such as premiums and gap coverage. We provide evidence that firms are responsive to consumers' search frictions. Using our estimates of consumer behavior we can simulate the cost effects of different counterfactual policies that could be used to address consumer inattention. While preliminary, our estimates indicate the importance of consumer search behavior in privatized markets such as Part D. The Affordable Care Act creates health insurance exchanges that have similar characteristics to Part D. Policy makers may wish to choose features of market design in a way that helps generate competitive outcomes in these kinds of settings.

References

[1] Abaluck, J., & Gruber, J. (2013). Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance. (No. w19163) National Bureau of Economic Research.

[2] Abaluck, J., & Gruber, J. (2011). Heterogeneity in Choice Inconsistencies Among the Elderly: Evidence from Prescription Drug Plan Choice. *The American Economic Review*, 101(3), 377-381.

[3] Gabaix, X., Agarwal, S., Laibson, D., & Driscoll, J. C. (2010). The Age of Reason: Financial Decisions over the Life Cycle and Implications for Regulation. *Brookings Papers on Economic Activity*: Fall 2009, 51.

[4] Altman, Drew E., John Benson, Robert Blendon, Mollyann Brodie, & Claudia Deane (2006). Survey Finds Few Seniors Expect to Switch Medicare Drug Plans for 2007. Kaiser Family Foundation and the Harvard School of Public Health.

[5] Ater, I., & Landsman, V. (2013). Do Customers Learn from Experience? Evidence from Retail Banking. *Management Science*.

[6] Berndt, E. K., Hall, B. H., & Hall, R. E. (1974). Estimation and Inference in Nonlinear Structural Models. *Annals of Economic and Social Measurement*, Volume 3, number 4 (pp. 103-116). NBER.

[7] Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics*, 242-262.

[8] Busse, M. R., Pope, D. G., Pope, J. C., & Silva-Risso, J. (2012). Projection Bias in the Car and Housing Markets (No. w18212). National Bureau of Economic Research.

[9] Busse, M. R., Lacetera, N., Pope, D. G., Silva-Risso, J., & Sydnor, J. R. (2013). Estimating the Effect of Salience in Wholesale and Retail Car Markets (No. w18820). National Bureau of Economic Research.

[10] Busse, M. R., Simester, D. I., & Zettelmeyer, F. (2010). "The Best Price You'll Ever Get": The 2005 Employee Discount Pricing Promotions in the US Automobile Industry. *Marketing Science*, 29(2), 268-290.

[11] Anna Cook (2013). Costs Under Medicare's Prescription Drug Benefit and a Comparison with the Cost of Drugs Under Medicaid Fee-for-Service. Congressional Budget Office.

[12] Cronqvist, H., & Thaler, R. H. (2004). Design Choices in Privatized Social-Security Systems: Learning from the Swedish Experience. *The American Economic Review*, 94(2), 424-428.

[13] Dafny, L., Ho, K., & Varela, M. (2013). Let Them Have Choice: Gains from Shifting Away from Employer-Sponsored Health Insurance and Toward an Individual Exchange. *American Economic Journal: Economic Policy*, 5(1), 32-58.

[14] Decarolis, F. (2012). Pricing and Incentives in Publicly Subsidized Health Care Markets: the Case of Medicare Part D.

[15] Dub, J. P., Hitsch, G. J., & Rossi, P. E. (2010). State Dependence and Alternative Explanations for Consumer Inertia. *The RAND Journal of Economics*, 41(3), 417-445.

[16] Duggan, M. G., & Morton, F. S. (2011). The Medium-Term Impact of Medicare Part D on Pharmaceutical Prices. *The American Economic Review*, 101(3), 387-392.

[17] Ericson, K. M. M. (2012). Consumer Inertia and Firm Pricing in the Medicare Part D Prescription Drug Insurance Exchange (No. w18359). National Bureau of Economic Research.

[18] Ericson, K. M. M., & Starc, A. (2013). How Product Standardization Affects Choice: Evidence from the Massachusetts Health Insurance Exchange (No. w19527). National Bureau of Economic Research.

[19] Farrell, J., & Klemperer, P. (2007). Coordination and Lock-In: Competition with Switching Costs and Network Effects. *Handbook of Industrial Organization*, 3, 1967-2072.

[20] Fudenberg, D., & Tirole, J. (1984). The Fat-Cat Effect, the Puppy-Dog Ploy, and the Lean and Hungry Look. *The American Economic Review*, 74(2), 361-366.

[21] Giulietti, M., Price, C. W., & Waterson, M. (2005). Consumer Choice and Competition Policy: a Study of UK Energy Markets. *The Economic Journal*, 115(506), 949-968.

[22] Greenwald, Leslie M. & Nathan West (2007). Medicare Part D Demonstration Focus Group Report. Research Triangle Institute.

[23] Handel, B. (2012). Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts. *American Economic Review*, forthcoming.

[24] Handel, B. R., & Kolstad, J. T. (2013). Health Insurance for Humans: Information Frictions, Plan Choice, and Consumer Welfare.

[25] Hardie, B. G., Johnson, E. J., & Fader, P. S. (1993). Modeling Loss Aversion and Reference Dependence Effects on Brand Choice. *Marketing Science*, 12(4), 378-394.

[26] Heiss, F., Leive, A., McFadden, D., & Winter, J. (2012). Plan Selection in Medicare Part D: Evidence from Administrative Data (No. w18166). National Bureau of Economic Research.

[27] Heiss, F., McFadden, D., &Winter, J. (2006). Who Failed to Enroll in Medicare Part D, and Why? *Health Affairs*, vol. 25 no. 5 w344-w354.

[28] Honka, E. (2012). Quantifying Search and Switching Costs in the US Auto Insurance Industry.

[29] Hortacsu, A., & Syverson, C. (2004). Product Differentiation, Search Costs, and Competition in the Mutual Fund Industry: A Case Study of S&P 500 Index Funds. *The Quarterly Journal of Economics*, 119(2), 403-456.

[30] Iyengar, S. S., & Kamenica, E. (2010). Choice Proliferation, Simplicity Seeking, and Asset Allocation. *Journal of Public Economics*, 94(7), 530-539.

[31] Ketcham, J. D., Lucarelli, C., Miravete, E. J., & Roebuck, M. C. (2012). Sinking, Swimming, or Learning to Swim in Medicare Part D. *The American Economic Review*, 102(6), 2639-2673.

[32] Kim, M., Kliger, D., & Vale, B. (2003). Estimating Switching Costs: the Case of Banking. *Journal of Financial Intermediation*, 12(1), 25-56.

[33] Klemperer, P. (1987). Markets with Consumer Switching Costs. *The Quarterly Journal of Economics*, 102(2), 375-394.

[34] Kling, J. R., Mullainathan, S., Shafir, E., Vermeulen, L. C., & Wrobel, M. V. (2012). Comparison Friction: Experimental Evidence from Medicare Drug Plans. *The Quarterly Journal of Economics*, 127(1), 199-235.

[35] MacLeod, W. (2003). Planning Costs and the Theory of Learning by Doing. USC CLEO Research Paper, (C03-16).

[36] Polyakova, M. (2013). Regulation of Insurance with Adverse Selection and Switching Costs: Evidence from Medicare Part D.

[37] Rothschild, M. (1974). Searching for the Lowest Price when the Distribution of Prices is Unknown. *The Journal of Political Economy*, 82(4), 689-711.

[38] Stahl, D. O. (1989). Oligopolistic Pricing with Sequential Consumer Search. *The American Economic Review*, 700-712.

[39] Varian, H. R. (1980). A Model of Sales. *The American Economic Review*, 70(4), 651-659.

[40] Zhou, C., & Zhang, Y. (2012). The Vast Majority of Medicare Part D Beneficiaries Still Dont Choose the Cheapest Plans That Meet Their Medication Needs. *Health Affairs*, 31(10), 2259-2265.

Appendix

A Sample Definition

The original sample consists of 249,999 Medicare Part D beneficiaries from the years 2006 to 2009. The panel is unbalanced, with some beneficiaries entering and others exiting throughout the sample, so the number of observations for each of the four years are, respectively, 209,827, 220,716, 226,501, and 227,753. We restrict the sample only to beneficiaries residing in New Jersey who, for any four consecutive months during the year were enrolled in a Medicare PDP but were neither Medicaid-eligible nor on low income subsidy. We also exclude beneficiaries whose Medicare termination code or ZIP code is unobserved. We then discard data from any month in which a beneficiary is Medicaid-eligible, low-income subsidized, or either not Part D enrolled or not enrolled in a Medicare PDP (e.g. in an MA plan or employer-sponsored coverage). New Jersey sponsors a prescription-drug assistance program for the elderly, PAAD, which caps out-of-pocket payments at either \$5, \$6 or \$7 (depending on the year and the drug type) so long as the beneficiary opts into the program and enrolls in an eligible low-cost plan. We infer the presence of this benefit, which is unobserved in the data yet severely restricts the set of possible plan choices, and exclude any beneficiaries enrolled in PAAD. We define a beneficiary as PAAD-enrolled if they enroll in a PAAD-eligible plan (as defined by the plan-type specific New Jersey premium thresholds) without gap coverage or deductible coverage and at least 95% of events occurring in the deductible phase or the coverage gap phase (where beneficiaries should pay the entire amount out-of-pocket) with total cost greater than the PAAD maximum copay result in the beneficiary paying the PAAD copay. As the plan formularies must be inferred from the drug event data, we cannot precisely estimate formulary structure for plans without a sufficient number of observed drug events. Hence we restrict the number of plans to 64 large plans covering around 95% of the sample and exclude any beneficiary ever enrolled in a different plan. Finally, we also exclude any beneficiaries observed only in non-consecutive years, since these observations do not assist in identifying the determinants of switching plans. This yields a final sample of 214,191 unique beneficiaries with the observations for each of four years, respectively, as 127,654, 141,897, 151,289, and 159,906.

We supplement the data with several additional variables from outside sources. First, we map beneficiary ZIP codes to census tracts using ArcGIS. We then define the income and percent college educated of each ZIP code as the tract median income and percent with a bachelor's degree or higher from the 2000 Census. In cases where a ZIP code mapped to multiple census tracts, the associated income and education levels were defined as unweighted averages across the tracts. We then convert these measures of income and education level into quartiles at the ZIP code level. Next, we obtain a list of commonly-prescribed drugs covering 92% of the events observed in our sample and classify these according to whether they are branded or generic and whether they are used for chronic or acute care. Of these, 464 distinct brand names for chronic drugs, representing 13.8 million of the 19.1 million events in our sample, are classified according to the condition they are most-commonly prescribed to treat using the website Epocrates Online. We then defined indicators for the 20 most common chronic conditions for which Medicare patients are prescribed medication based on whether the beneficiary was observed taking a drug to treat that condition. Finally, we generate estimated costs under a variety of counterfactual plan choices, a more detailed description of which is contained in the following section.

B Counterfactual Cost

First we partition the set of prescribed drugs into 464 common chronic drugs and all others. We treat all others as if they were for acute conditions, although some are still treatments for chronic conditions. Next we separate individuals into deciles of days' supply of acute drugs on an annual basis. We then classify individuals into one of 7,040 bins. Whites, who are over-represented in the sample, are classified on the basis of gender, four age groups (¡ 65, 65-75, 75-85, ¿ 85), income quartiles, deciles of spending, ten plan indicators (the largest nine plans plus "all other") and an indicator for receiving medication for any of hypertension, high cholesterol, diabetes or Alzheimer's. Nonwhites are classified on the basis of the same criteria, excepting plan indicators, for which there are not enough observations. Within each of these 7,040 bins, per-month acute spending is estimated as the median per-month amount. We divide these estimated per-month acute shocks into a branded and generic amount based on the percent of acute drug spending on generic drugs each year and generate an estimated sequence of acute drug events with two drug events (one branded, one generic) on the 15th of each month in which the beneficiary is observed in-sample. To this we add the observed sequence of chronic drug events and treat this as the estimated sequence of drug events.

Next we infer the formularies for each plan. In many cases, the tier on which a drug is categorized is observed for the plan, and when this is the case we use the observed tier. If the tier is unobserved (i.e. there are no instances in the data of a prescription written for a given drug in a given plan in a given year), we classify it as either a branded or generic drug based on the observed classification in other similar plans and fill in the tier accordingly. For generic drugs, we place the drug on the plan's generic-drug tier if such a tier exists. For branded drugs, if the drug is not observed for any plan in that contract, we assume the drug is not covered by the plan. These assumptions are based on consideration of the actual formularies used by 5 of the largest Part D providers, which share a common list of covered drugs for all plans sponsored by the provider and typically cover any generic drug but not all branded drugs. If the drug is observed for a plan in the same contract, we fill in the tier as the corresponding drug-type tier for the plan. If none of these cases apply, we assume the drug is uncovered if at least 33% of plans do not cover the drug in that year; otherwise, we classify it on either the " Generic" or "Branded" tier according to the drug type. For simplicity we assume that the Pre-Initial Coverage Limit and Gap phases employ the same formulary structure, as they do for the few plans with Gap tiers, and we ignore the effect of specialty tiers as only one of the 464 most-commonly prescribed chronic drugs is a specialty treatment.

We then estimate the total cost per month supply for each of the 464 most-common chronic drugs in each plan as the sample average cost per month for drug events where the supply length is between 7 and 90 days. This drug-cost shifter captures the effects of bulk discounts that particular plans negotiate with drug manufacturers. Then for each event in the simulated drug sequence we adjust the total cost of the drug under each plan accordingly if the observed days supply is between 7 and 90 days (otherwise the observed total cost is left unchanged). Finally, to generate counterfactual spending under each plan we step through the simulated sequence of drug events and generate counterfactual benefit phases and patient out-of-pocket payments according to the plan's stated cost structure, the estimated formulary, and cumulative spending for the year. Counterfactual out-of-pocket payments for each plan are estimated as the sum of out-of-pocket payments for the observed chronic drugs and simulated acute events for each beneficiary in each large plan every year. We assume no price elasticity for chronic drug consumption, in that patients take the same sequence of prescription drugs in every plan regardless of the costs they face. Consumption of acute drugs is shifted for the largest plans based on observed usage to control for price elasticity. For simplicity we also ignore the effect of prior authorization requirement, step therapy regimens and quantity restrictions.

The estimated payments, which represent the "True Out-of-Pocket Payments", are added to a premium payment for each month in which the beneficiary is enrolled in the plan to create a counterfactual "Total Payment" variable for each beneficiary in each plan. These numbers are then scaled up to a 12-month equivalent for each beneficiary enrolled for fewer than 12 months. The minimum cost plan for each beneficiary is defined as the plan with lowest "Total Payment" in each year, and the error is defined as the difference between the estimated total payment in the observed-choice plan and the minimum-cost plan. Scaled variables and scaled TrOOP payments are defined analogously, and percent error is defined as the error as a percentage of estimated total payments in the observed choice plan.

C Shocks and Plan Selection

Table A1: Correlations Between Switching and Change in Key Variables

	Correlation
Premium Shock	0.3974
Premium Increase	-0.2579
OOP Cost Increase ($)	0.0263
OOP Cost Increase (%)	0.0472
Optimal Switch Value	-0.1312
Top-3 Switch Value	-0.1411
Top-5 Switch Value	-0.1458
Top-10 Switch Value	-0.1520
Coverage Shock	0.3617
Gap Coverage Increase	0.1538
Pre-ICL Coverage Increase	0.1147
Acute Shock	0.0756
Unanticipated Acute Costs	-0.0013

Notes: Correlation between change in plan characteristics and probability of switching. Changes are in own-plan characteristics except for switch values, which are expected savings from moving to plan that has lowest cost in expectation the following year. Top-3 Switch Value is expected saving from moving to average of the 3 lowest-cost plans. Premium shock, coverage shock and acute shock are defined as in Section 5.2.

Table A2: Next-Year Plan Choices and Overspending by Shock, Switchers Only

	No Acute Shock				**Acute Shock**			
2006	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**
% Pre-ICL Coverage	63.85%	64.30%	64.11%	72.09%	61.55%	65.11%	65.78%	72.12%
% ICL Coverage	12.73%	9.89%	10.67%	12.40%	16.35%	11.71%	11.45%	12.43%
Premium	32.16	26.10	27.36	15.79	39.11	30.92	31.81	15.84
% Error, Next-Year Chosen Plan	29.28%	23.48%	28.18%	29.30%	32.19%	22.05%	23.11%	23.34%
% Within 10% of Optimal	5.09%	40.47%	11.57%	8.90%	18.28%	31.11%	17.88%	20.81%
% Within 25% of Optimal	30.71%	62.06%	36.26%	42.35%	49.06%	59.11%	54.75%	57.93%
2007	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**
% Pre-ICL Coverage	69.09%	67.57%	74.38%	69.69%	68.57%	68.59%	73.99%	72.41%
% ICL Coverage	13.31%	8.51%	44.25%	27.48%	16.69%	13.05%	44.58%	34.19%
Premium	30.41	29.62	29.23	25.51	33.69	34.78	31.82	25.57
% Error, Next-Year Chosen Plan	26.44%	25.07%	34.70%	28.38%	28.34%	26.35%	28.00%	23.32%
% Within 10% of Optimal	23.39%	8.06%	2.79%	9.53%	27.26%	6.24%	15.50%	20.32%
% Within 25% of Optimal	56.73%	25.76%	30.78%	26.72%	54.98%	30.47%	47.85%	47.93%
2008	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**	**Neither**	**Premium Only**	**Coverage Only**	**Premium and Coverage**
% Pre-ICL Coverage	67.94%	67.30%	65.73%	72.56%	68.65%	66.64%	66.83%	77.99%
% ICL Coverage	20.67%	14.02%	14.75%	33.31%	23.68%	19.33%	19.87%	46.66%
Premium	33.67	35.85	30.83	28.33	46.13	46.77	40.16	28.74
% Error, Next-Year Chosen Plan	28.28%	28.78%	28.01%	25.24%	31.46%	33.63%	31.96%	19.97%
% Within 10% of Optimal	4.72%	3.72%	3.65%	8.08%	11.40%	10.68%	9.52%	19.99%
% Within 25% of Optimal	19.03%	14.06%	10.99%	18.56%	38.27%	26.11%	28.07%	41.37%

Notes: Summary of plan choices the following year for enrollees who switch.

Table A3: Shock Probability by # of Plans Actively Chosen as of 2009

	Choose 4 Times				Choose < 4 Times			
	Acute Shock	Premium Shock	Coverage Shock	% Error	Acute Shock	Premium Shock	Coverage Shock	% Error
2006	9.75%	97.49%	90.15%	45.34%	6.02%	48.44%	24.46%	36.84%
2007	12.30%	98.09%	96.82%	26.90%	5.90%	40.24%	77.79%	29.81%
2008	12.53%	98.02%	97.25%	30.18%	4.71%	29.62%	31.62%	33.15%

Notes: Shock probabilities for enrollees switching 4 times in 2006-2009, compared to those who switch less than 4 times.

D Premium Increase Regressions

Table A4: Estimated Coefficients from Regression on Annual Premium Increases ($)

	Model 1		Model 2		Model 1		Model 2	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Lagged Premium	-0.171***	0.026	-0.154***	0.024	-0.171***	0.026	8.792**	4.042
Lagged # Tier 1 Drugs	0.035***	0.012	0.028**	0.012	0.027**	0.013	-0.154***	0.024
Lagged Deductible	-0.005**	0.003	-0.004	0.003	-0.005**	0.003	0.020	0.013
Lagged Enhanced	1.867***	0.698	2.1***	0.666	1.887***	0.694	-0.004	0.003
Lagged Gap Coverage	5.741***	1.469	5.422***	1.417	5.717***	1.457	2.135***	0.660
Lagged Market Share	-	-	8.311**	4.028	-	-	8.792**	4.042
Enrollment Growth Rate	-	-	-	-	-6.002*	3.125	-6.686**	3.134
Brand FE?	Yes		Yes		Yes		Yes	
Region FE?	Yes		Yes		Yes		Yes	
N	7,796		7,796		7,796		7,796	
R^2	0.2732		0.2766		0.2748		0.2787	

Notes: Regression of premium increase (in $) on previous-year plan characteristics. Enrollment growth rate is rate of growth for NJ Part D program. Lagged market share is for this plan.

E Details on Demand Model Estimation

We estimate the model using full-information maximum likelihood. Let θ_C denote parameters governing the choice of plan, θ_S parameters governing the decision to search, X_C and X_C respectively. Further let $(c_{i,t,1}, c_{i,t,2}, c_{i,t,3})$ be indicators denoting the type of observation, in order, (1) choosing the same plan as last year (2) choosing a different plan from last year (3) choosing a plan as a new entrant to the market or when one's previous plan exited. For each individual i and chosen plan k in year t, one of these cases applies, and the likelihood differs case-by-case. The log-likelihood function is:

$$
\begin{aligned}
l_{i,k,t} &= c_{i,t,1}[X_{i,t,S}\theta_S - log(1+e^{X_{i,t,S}\theta_S})] \\
&+ c_{i,t,2}[\delta_{i,k,t} - log(1+e^{X_{i,t,S}\theta_S}) - log(\Sigma_{j\neq m}\, e^{\delta_{i,j,t}})] \\
&+ c_{i,t,3}[\delta_{i,k,t} - log(\Sigma_j\, e^{\delta_{i,j,t}})] \qquad (1) \\
L &= \Sigma_t\, \Sigma_{i,k\in K_t}\, l_{i,k,t} \qquad (2)
\end{aligned}
$$

where m denotes the enrollee's plan choice in the previous year. The score function of the likelihood is:

$$
\begin{aligned}
\frac{\partial l_{i,k,t}}{\partial \theta_{S,a}} &= -(c_{i,t,1}+c_{i,t,2})\frac{X_{i,t,S,a}e^{X_{i,t,s}\theta_S}}{1+e^{X_{i,t,s}\theta_S}} + c_{i,t,1}X_{i,t,S,a} \qquad (3) \\
\frac{\partial l_{i,k,t}}{\partial \theta_{C,a}} &= (c_{i,t,2}+c_{i,t,3})X_{i,k,t,C,a} - c_{i,t,2}\frac{\Sigma_{j\neq m}\, X_{i,j,t,C,a}e^{\delta_{i,j,t}}}{\Sigma_{j\neq m}\, e^{\delta_{i,j,t}}} - c_{i,t,3}\frac{\Sigma_j\, X_{i,j,t,C,a}e^{\delta_{i,j,t}}}{\Sigma_j\, e^{\delta_{i,j,t}}} \qquad (4) \\
\nabla_L &= [\Sigma_{i,k,t}\, \frac{\partial l_{i,k}}{\partial \theta_{S,a}}, \ldots, \frac{\partial l_{i,k}}{\partial \theta_{S,R_S}}, \Sigma_{i,k,t}\, \frac{\partial l_{i,k}}{\partial \theta_{C,a}}, \ldots, \frac{\partial l_{i,k}}{\partial \theta_{S,R_C}}] \qquad (5)
\end{aligned}
$$

where R_S and R_C denote respectively the number of switching and choice parameters. We maximize the likelihood in Equation (2) via the score function in Equation (5) using KNITRO maximization software. The standard errors reported in the paper are from BHHH estimates of the Hessian using the score in Equation (5) evaluated at the maximum likelihood estimates.

Table A5: Structural Demand Model Variables

Switch Parameters		
Threshold Shifters	**Variable Mean**	**Standard Deviation**
Constant	1.000	0.000
Female	0.619	0.486
Nonwhite	0.091	0.287
Q1 Income	0.225	0.417
Q2 Income	0.269	0.443
Q3 Income	0.255	0.436
Age 70-74	0.198	0.398
Age 75-79	0.179	0.383
Age 80-84	0.159	0.365
Age U-65	0.061	0.240
Age O-85	0.163	0.370
Shocks	**Variable Mean**	**Standard Deviation**
Premium Shock	-0.266	0.442
Coverage Shock	-0.307	0.461
Acute Shock	-0.037	0.189
Choice Parameters	**Variable Mean**	**Standard Deviation**
TrOOP (Chronic) ($000)	0.784	0.935
TrOOP (Acute) ($000)	0.095	0.121
TrOOP (Total) ($000)	0.879	0.984
Deductible ($000)	0.095	0.126
Premium ($000)	0.471	0.241
Premium Shock x Premium	0.127	0.247
Coverage Shock x Gap Coverage	0.080	0.271
Acute Shock x Gap Coverage	0.010	0.098
Gap Coverage	0.235	0.424
Enhanced	0.472	0.499
Enhanced (2006)	0.072	0.258
Enhanced (2007)	0.122	0.328
Enhanced (2008)	0.135	0.342
Enhanced (2009)	0.143	0.350

Notes: Summary statistics for variables included in two-stage model of choice and switching. Premium, Coverage and Acute Shocks defined in Section 5.2. Gap Coverage is an indicator for any coverage in the gap.