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

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Abstract

Medicare Part D presents a novel privatized structure for a government pharmaceutical benefit. Incentives for firms to provide low prices and high quality are generated by consumers who choose among multiple insurance plans in each market. To date the literature has primarily focused on consumers, and has calculated how much could be saved if they chose better plans. In this paper we take the next analytical step and consider how plans will adjust prices as consumer search behavior improves. We use detailed data on enrollees in New Jersey to demonstrate that consumers switch plans infrequently and imperfectly. 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 high premiums are consistent with insurers profiting from consumer inertia. We use the demand model and a model of firm pricing to calculate how much lower Part D program costs would be if consumer inattention were removed and plans re-priced in response. Our estimates indicate that consumers would save $601 each over three years when firms' choice of markup is taken into account. Cost growth would also fall: by the last year of our sample government savings would amount to $224 million per year or 4.1% of the cost of subsidizing the relevant enrollees.

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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 (OOP or copayments) 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 consumer's choices would discipline plans into providing low prices and high quality, and that this would result in better outcomes than a government-run plan. Critically, these better outcomes require that market forces work, in that demand shifts to 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 those features.

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 consistently shop for price and quality when they do switch, reducing the effective demand elasticity faced by insurers. We provide evidence that, in the absence of strong disciplining pressures from consumers, insurers set price above the efficient level, allowing plans to extract high rents due to consumer inattention. Not only would better consumer search benefit consumers directly, it would also lead to plan re-pricing that would save both consumers and the government significant sums. Our results indicate that removing inattention and allowing price to adjust while leaving other choice frictions unchanged would reduce consumer expenditures by \$601 per enrollee over the three years 2007-9. Government program costs would fall by \$224 million per year by 2009 due to plan re-pricing. To our knowledge, this is the first paper to estimate the impact of better searching through both demand and supply-side channels. We find that the insurer response - lowering premiums - results in signifciant savings both to enrollees and taxpayers.

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) 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 program's inception, increases in pharmaceutical prices have been restrained, in part due to aggressive use of generics by many insurers. According to Congressional Budget Office estimates, drug costs under the basic Part D benefit increased by only 1.8% per beneficiary from 2007-2010 net of rebates. The remainder of plan expenditures - approximately 20% of total costs according to the CBO - consists of administration, 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 in our data were on average 62.8% higher in 2009 than they were in 2006, the first year of the program, which corresponds to a 17.6% compound annual growth rate. The CBO estimates indicate that plan profits and administrative expenses per beneficiary (combined) grew at an average rage of 8.6% per year from 2007 to 2010.

These figures raise 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. 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. Since the program is 75% subsidized by the federal government, any lack of effective competition would increase government expenditures as well as consumer costs.

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 conduct counterfactual simulations to investigate several possible policy interventions designed to increase competition in the Part D market. We find that removing inattention with fixed prices saves each consumer on average $170 over the years 2007-9. Choosing wisely among plans with the help of a pharmacist or similar expert could save enrollees a further $686. However, such calculations ignore the supply-side response of insurers to newly attentive consumers. In a market where consumers choose each year based at least partly on price and quality, our simulations show that average plan premiums fall substantially. Plan repricing would generate consumer savings of $601 per person on average, even without the help of the pharmacist, over three years. Growth in costs would also slow considerably. By 2009, the last year of our sample, the federal government would save $224 million per year, or 4.1% of the relevant program costs in that year.

The first section of the paper describes the Medicare Part D program and discusses reasons for search imperfections. Next we review the literature related to both Medicare Part D specifically and markets with choice frictions generally. The following section of the paper describes our dataset, which provides detailed information on the choices and claims of non-subsidized enrollees in New Jersey. We observe that consumers consistently make choices that are financially costly given their consumption patterns, and that this pattern of choosing expensive plans when cheaper ones are available does not appear to diminish with either experience in the program or time. Consumers seem to switch plans in response to "shocks" to their health or current plan characteristics, but are much less sensitive to changes in other plans.

Motivated by these findings, we develop a two-stage consumer decision model for estimation which accounts for inattention as a source of inertia. We identify the effect of consumer inattention separately from other potential sources of choice persistence, such as persistent heterogeneous unobserved preferences, using a detailed panel dataset which documents the choices of new entrants to the Part D program and then follows each individual's choices over time. Our identification strategy is similar to that utilized in recent related papers that investigate the reasons for consumer choice persistence in other health insurance programs (Handel (2013), Polyakova (2014)). The estimates indicate that inattention is an important part of the story and that switchers' preferences are affected by the shocks they experience.

Having established the behavior of consumers, we turn to analysis of the supply side of the Part D marketplace. Using a dataset of nationwide plan characteristics and enrollment, we show that premiums rise steadily over time and that plans with larger market shares set prices in a manner consistent with high choice frictions. We also document rapid growth in plan prices that is not accounted for by changes in costs, and high dispersion in relatively homogenous standard benefit plans that is indicative of search frictions. We write down the first order condition of a profit-maximizing insurer and show how insurer bids are related to premiums.

The final section of the paper simulates the evolution of the Part D marketplace under several different policy-relevant counterfactuals. First we fix plan prices but alter consumer behavior. We consider a counterfactual of fully attentive consumers who re-optimize their plan choices every year. We find that consumer spending would fall by approximately \$170, or 12.5% of the gap between the chosen and least costly plan, in 2007-9. However this policy does not address the issue that even attentive consumers do not choose their lowest-cost plan. Our second consumer counterfactual allows the enrollee's pharmacist to move them from their chosen plan to one of the 5 lowest-cost options available to them if this switch would save at least \$200. We find that 63% of total three-year gap in spending would be removed by this policy.

We then turn to the main contribution of the paper, which is the construction of a counterfactual that allows the supply side to adjust to the change in consumer behavior. We model plans as profit-maximizing insurers that take into account the elasticity of demand, including consumers attentiveness, when choosing a markup over cost. More attentive and price-elastic consumers will generate lower insurer margins. We use accounting data from the Part D program to estimate firm costs and then simulate the path of premiums under the counterfactual scenario where consumer inattention is removed. Removing inattention in the simulations makes the price-setting process static rather than dynamic; since firms no longer have an incentive to lock-in demand early and raise prices later, the path of prices should be flatter than in the data. We revise our predictions of consumer choices given these plan premium changes and use them to predict substantial total equilibrium savings from this change to the Part D program and to consumers. We estimate that at fixed prices removing inattention reduces over-spending by \$170; when we allow prices to adjust, this figure increases to \$601 over three years. These results indicate that even if consumers do not choose the lowest-cost plan for them, whether due to information processing costs or for other reasons, simply prompting them to choose a new plan every year has a substantial effect on costs through the channel of plan premiums. More aggressive plan pricing strategies also reduce government program costs by \$224 million per year by 2009, the last year of our data.

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 OOP 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 "protected" drug treatment classes, as well as two or more drugs within roughly 150 smaller key formulary types. The protected classes include many treatments that would identify very sick patients such as AIDS drugs, chemotherapy treatments, and antipsychotropics. Plans' placement of these drugs on their formulary is required, and the cost-sharing required of beneficiaries is carefully scrutinized by CMS to ensure plans are not discriminating against sick beneficiaries. Hence it is not straightforward for a plan to avoid the sickest enrollees, especially in the first years of the program when it was unclear which enrollees would have particular costs or utilization profiles and there was no usage history. Moreover, subsidy payments to plans for enrollees are risk-adjusted according to their enrollee's demographics and health status. There is an additional multiplier to increase the subsidy for LIS status and institutionalized status. Thus sponsors receive higher payments for sicker enrollees, reducing the incentive of plans to seek out healthy participants. In addition, plans must evaluate their OOP costs using particular actuarial models. This limits their ability to attract consumers by shifting costs to a part of the benefit that the enrollee has difficulty evaluating or will pay later. The result of this fairly tight regulatory environment is the the plan's premium emerges as its most salient characteristic for consumers, particularly for the defined standard benefit plan.[1] We will see in our later empirical work that consumers place high weight on a plan's premium when they make choices among plans. The deductible and other characteristics have an effect, but their empirical magnitude is much smaller than that of the premium.

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

[1] As we show in the paper, enrollees can do better by searching for the plan-specific OOP payments for the particular drugs they will consume.

of 74.5% of costs, so for the vast majority of seniors, enrolling is financially favorable (see Heiss 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.

Many observers have noted that the Part D choice problem is remarkably difficult and the empirical literature indicates that consumers do not choose plans that minimize their costs. In 2006 when the program began there were at least 27 plans offered in each county in the US. Enrollees had to consider how premiums varied across these plans, forecast their drug consumption in the year ahead and compare the OOP costs for that set of drugs across plans. In addition enrollees might receive an adverse health shock during the coming year that would change the set of medications demanded, necessitating the comparison of an expectation of possible expenditures across plans. Furthermore, no major program like this existed in the US at the time Part D began, so seniors likely had no experience attempting to make these calculations. Lastly, most Part D consumers are older Americans; outside the dual-eligible and disabled, Medicare eligibility begins at age 65. Finding a low-cost plan in 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 for seniors enrolled in the standard fee-for-service Medicare program (which does not cover drug costs). In 2006, 10.4 million people enrolled in PDPs. Medicare Advantage plans (MA-PD), for seniors who have opted out of standard Medicare, 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. MA-PD plans have particularly low enrollment in New Jersey, the state from which our data are taken: only 18-20% of NJ Part D enrollees were in MA-PD plans in 2006-9, compared to 32-38% in the U.S. overall. This paper focuses solely on PDPs and prescription drug coverage. We assume that PDP enrollees do not consider enrolling in an MA-PD plan. We justify this assumption by noting both the low share of NJ MA-PD plans and the fact that moving from a stand-alone PDP to an MA-PD plan incurs the substantial cost of changing coverage (and potentially providers) for hospital and physician services as well as prescription drugs.

A FFS Medicare enrollee can choose among all the PDPs 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-insurance rate for the next \$2000 in spending, no coverage for the next \$2850 (the "coverage gap"), and a five percent co-insurance rate in the "catastrophic region", when OOP 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 - no deductible but higher cost-sharing, for example. Enhanced plans have additional coverage beyond these levels and therefore higher expected costs and higher premiums.

The way in which sponsors bid to participate in the program is important to an analysis of competition. Sponsors have more freedom to choose their premium level than they do regarding details of the OOP price schedule described in the previous paragraph. Sponsors must apply to CMS with a bid at which each plan they wish to offer will 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.[2] The bid is supposed to reflect the applicant's estimate of its "average monthly revenue requirements" (i.e. 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 equally weighted, but in subsequent years the average slowly transitioned to 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%[3]. 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 (with the caveat that the premium is truncated at zero). This scheme makes the consumer bear higher premiums at the margin, which contributes to differences in premiums being important in consumer choice.

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

Enhanced plans provide coverage that is more generous than the defined standard benefit, and for which they charge correspondingly higher premiums.[4] Plan sponsors offering plans with

[2]CMS may not bargain with plans over their bids. The agency may disallow a bid if some aspect of the plan such as the formulary or the actuarial equivalence does not follow regulations.

[3]The sum of the government subsidy and the beneficiary premium percentage is over 100% because part of the government subsidy is used for plan reinsurance rather than as a direct subsidy to premiums.

[4]This added benefit typically takes the form of either additional coverage in the coverage gap, reduced copayments,

enhanced coverage must also offer a basic plan within the same region, and sponsors are prohibited from offering more than two enhanced plans in a given region. Enhanced plans do not receive higher subsidies, and any incremental costs are paid entirely by enrollees. The amount of this additional premium is negotiated between the CMS and the plan sponsor depending on their risk pool.

Two types of beneficiaries do not pay the full cost of Part D coverage. Approximately 6.3 million dual-eligible Medicaid recipients were automatically enrolled in Part D in 2006, as were an additional 2.2 million Low Income Subsidy (LIS) recipients. Premiums and OOP costs are fully paid by the government for the former, while the latter receive steep discounts. Part of this group is fully elastic, and part matches our model of consumer choice. None of the LIS beneficiaries pay the full cost of the plan they choose, so one might imagine they are less price sensitive than regular enrollees. However, foreseeing that potential inelasticity, the Part D regulations only provide a full subsidy for LIS recipients who choose a plan with costs below the benchmark for their region. For the first three years of the program, the benchmark was calculated as the equal-weighted mean basic PDP plan premium in a region. In later years the benchmark was constructed as an enrollment-weighted mean. Since lower cost plans have more enrollees, this policy change reduced the number of plans that qualified as benchmark over time. As plans lost benchmark status, their enrollees were reassigned. LIS and dual-eligible enrollees are automatically reassigned (equally across qualifying plans) to a benchmark plan in their region unless they choose to opt out.

Our demand model considers only non-LIS enrollees who are not dual eligible; modeling the auto-enrollment of the LIS population would introduce complexities that are beyond the scope of this paper. There is an obvious potential concern that, since carriers set a single premium for a plan that enrolls both LIS and non-LIS consumers, there are interactions between the two markets that should be accounted for in any study of Part D plans. For example, a strategy studied by Decarolis in the early years of Part D involved cycling of plans. A sponsor would raise the price of an existing plan above the benchmark, but introduce a new plan below the benchmark to catch auto-assigned LIS recipients, meanwhile keeping any choosers and other enrollees in the original plan. We note that this cycling strategy was not used by all insurers, and declined over time.[5] In section 7 below we find no evidence of this cycling behavior by plans in our New Jersey sample and we do not attempt to account for it in our model of supply.

One potential reason for this lack of premium cycling in the data is the fact that quite a large number of LIS enrollees opt out of automatic reassignment and therefore become “choosers” who are not auto-enrolled. A study that looked at the 2007-8 transition determined that 10% of 1.9 million LIS recipients who received a letter from CMS explaining that their old plan no longer qualified and they would be reassigned actively chose a new plan.[6] . The Kaiser study concludes that 23% of all LIS enrollees in 2010 must choose a different plan if they do not want to pay premiums. Choosers are never auto-assigned by CMS again, and thus the stock of choosers rises

or coverage of certain drug types excluded from normal Part D coverage, such as cosmetic drugs and barbiturates.

[5] For example, by 2010 the Kaiser study (page 7) reports that 92% of all auto-assignments were across corporate boundaries.

[6] KaiserLISreport

over time. Choosers are responsible for the incremental costs of their plan above the benchmark. The Kaiser Family Foundation [7] hypothesizes that LIS recipients who stay in a plan that loses benchmark status may not realize that they have lower cost choices available to them, and CMS does not routinely remind this group or provide them information. In addition, many states have a State Pharmacy Assistance Program (SPAP) that subsidizes the costs of Part D to low income residents. CMS does not reassign enrollees in this group, and therefore this is another source of subsidy recipients who may nonetheless be paying premiums because they have not changed to a qualifying plan. The Kaiser study reports that "those whose plans have recently lost benchmark status pay lower premiums, on average, than choosers who have remained in benchmark plans for several years. In 2010, these groups of choosers paid estimated average premiums of $2.39 and $11.36 respectively." This finding is exactly consistent with our model. Interestingly, in 2010 , the "AARP MedicareRX Preferred" plan was not a benchmark plan in any region in the United States – but had been a benchmark plan in 33 out of 34 regions in 2006. This plan enrolled 5% of LIS recipients in 2010 despite the fact that it charged premiums.

Our primary counterfactual analysis quantifies the price and spending effects of removing enrollee inattention. We simulate non-LIS enrollees' choices given the observed path of premiums, set by plans for both LIS and non-LIS enrollees, in our baseline scenario, and compare them to the outcome of the static premium-setting game where plans price only to fully attentive non-LIS recipients. This is a conservative estimate of the impact of removing inattention in the current system where the LIS and non-LIS markets are intertwined. It is conservative because, while the baseline premiums account for the existence of a group of highly elastic auto-enrolled LIS recipients who constrain non-LIS premiums, the simulated counterfactual premiums do not. An alternative approach would be to simulate the dynamic baseline path of premiums, accounting for inattentive non-LIS enrollees but ignoring LIS enrollees, and compare this to our counterfactual predictions. However, this would require making simplifying assumptions regarding the number of firms, the extent of firm and consumer heterogeneity, and the time horizon which would substantially limit the usefulness of the exercise. It would also ignore the important links between the LIS and non-LIS Part D programs in the current system. We return to these points below.

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 OOP costs. The website also enables prospective enrollees to estimate costs in each plan under three health statuses (Poor/Good/Excellent), to estimate costs in standard benefit plans based

[7] The Medicare Part D Low-income Subsidy Program: Experience to Date and Policy Issues for Consideration, Summer et al, 2010, p12

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 use the Planfinder website on behalf of the caller in order to locate a good choice. However, conversations with CMS representatives suggest that very few enrollees make full use of the website. Pharmacies, community service centers, and other advocates offer advice. Survey evidence (Kaiser Family Foundation (2006), Greenwald and West (2007)) indicates that enrollees rely on friends and family to help them choose a Part D plan, yet still find the choice process difficult.

3 Literature Review

The introduction of Part D immediately created a literature evaluating outcomes from the novel program structure. An important early paper documenting that the elderly do not choose optimally is that of Abaluck and Gruber (2011, hereafter AG). Using a subset of claims data from 2005 and 2006 and a similar methodology to our own, the authors show that only 12% of consumers choose the lowest cost plan; on average, consumers in their sample could save 30% of their Part D expenditure by switching to the cheapest plan. Consumers place a greater weight on premium than expected OOP costs, don't value risk reduction, and value certain plan characteristics well beyond the way those characteristics influence their measure of expected costs. These results have been largely corroborated by Heiss et al. (2013) and Ketcham et al. (2012) among others.

Other studies have examined infrequent switching between plans as an explanation for inefficient consumer choice in the Part D market. In a field experiment, Kling et al. (2012) show that giving Part D consumers individualized information about which plans will generate the most cost savings for them can raise plan switching by 11% (from 17% to 28%) and move more people into low-cost plans. Ketcham et al. (2015) use administrative data through 2010 to show that switching increases when more plans are available and that people become more responsive to large increases in their plans' costs over time. Polyakova (2013) estimates a model of plan choice featuring consumer switching costs and adverse selection, with unobservably riskier beneficiaries choosing more comprehensive coverage. She uses the model to simulate the effect of closing of the coverage gap on adverse selection and finds that switching costs inhibit the capacity of the regulation to eliminate sorting on risk. The presence of switching costs and consumer choice frictions has been documented in other health insurance markets by Handel (2013) among others.

Abaluck and Gruber followed up their results with a study of how enrollees' choices varied across the first four years of Part D (Abaluck and Gruber (2013), hereafter AG13). AG13 finds that consumers continue to make significant mistakes and that there is no measurable learning over time in their national sample. We also find that consumers behave this way in our New Jersey sample. In both sets of results consumers continue to be extremely sensitive to premiums. AG13 also shows, as we do, that consumers who make mistakes are purchasing generous coverage: "beneficiaries may be choosing plans whose coverage is too generous... but not for their mix of drugs." The empirical specification in AG13 is more reduced form than our model, but the two papers estimate similar levels of welfare loss from inertia. AG13 controls for brand fixed effects but still finds a strong role for inertia, concluding “rather than reflecting persistent unobserved factors of chosen plans, [inertia] reflect[s] either adjustment costs or inattention.” Our paper explores the inattention hypothesis in detail. Because AG13 includes the decision to switch as part of the reduced form choice model, they cannot ‘turn off’ inattention in their study to isolate its impact. Our specification separately models consumer inattention, consumer valuation of the insurer’s brand, and also persistent unobserved heterogeneity in preferences for a particular product. We continue to find an empirical role for inattention even in this sophisticated choice environment. AG13 concludes that choice inconsistencies are “driven by changes on the supply side that are not offset both because of inertia and because non-inertial consumers still make inconsistent choices.” By modeling the supply side, as we do in this paper, we can simulate how insurers will set premiums in response to changing consumer attention. This step is a key missing element in the current Part D literature.

There is a great deal of research in both psychology and economics literatures on consumer search and choice. Iyengar and Kamenica (2010) 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. A large literature studies the importance of information processing costs to explain deviations from the choices expected of computationally unconstrained agents (see Sims (2003) and Reis (2006) for examples). Models of consumer search with learning, where each consumer uses the observed price of a single product to infer the prices likely to be set by other firms, also indicate that consumers may incur excessive costs by searching either too little or too much (e.g. Cabral and Fishman (2012)). Agarwal et al.(2009) show that the ability to make sound financial decisions declines with age. Since Part D enrollees are either disabled or elderly, and seem likely to experience cognitive costs of processing information, it may be reasonable to expect less optimal behavior from Part D consumers than from 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) show that most employers offer very few choices to their employees and that employees would greatly value additional options. Moreover the results from Stocking et al. (2014) suggest that merely limiting the number of available plans would not be sufficient, as this would limit competition and lead to higher prices. Thus while the difficulty of choosing an insurance plan may lead consumers to choose expensive plans, it is not clear that limiting the 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 (2014) 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. Sallee (2014) uses the idea of rational inattention to explain why consumers under-weight energy efficiency when purchasing durable goods. Busse et al. (2010) 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. Hortaçsu et al (2015) examine consumer choices and switching behavior among retail electricity suppliers in Texas and conclude that high search frictions lead to a high market share for the incumbent supplier.

Several prior studies have considered firm behavior in the presence of choice frictions. Ericson (2012) and Ericson (2014) are the primary papers in the literature that analyze the insurer's problem in the face of Part D consumers who do not choose perfectly. These papers argue that consumer switching costs, which are exacerbated by a default of automatic renewal, lead firms to enter with low prices and raise prices rapidly over time (as in Klemperer (1987)), gradually replacing their highest-priced plans with cheaper plans (cycling). Decarolis (2015) and Decarolis et al (2014) study the supply side of the Part D market paying particular attention to the interaction of low-income subsidy and other enrollees. The "invest then harvest" pricing dynamic induced by consumer switching costs and other choice frictions has also been studied empirically in other markets, e.g. by Miller (2014) in the case of Medicare Advantage, and Cebul et al (2011) in commercial health insurance. Dube, Hitsch and Rossi (2008) show that as switching costs grow, they first lower and then raise equilibrium prices in the consumer product markets they study.

4 Data

Our primary data source, provided by the Centers for Medicare and Medicaid Services (CMS), contains information on prescriptions and plan choices for Part D enrollees from New Jersey in 2006-9. Our data consists only of enrollees who did not have LIS status at any time and who were enrolled in stand-alone PDPs, rather than MA plans. Limiting the study to these enrollees reduced the population 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 chose New Jersey partially because it has a very low percentage of MA-PD enrollees compared to the national average; 20% of NJ enrollees are in MA-PD plans while nationwide the percentage is 33 and the total number of enrollees that met our criteria was not far above the CMS cutoff of 250,000. From this subpopulation we drew a random sample in 2006 and a random sample of new enrollees in 2007-9 that added up to 250,000 enrollees in total. We limited the sample to unsubsidized PDP enrollees in order to focus on a setting where consumers had to pay the listed price for every plan and where plans had relatively standardized quality (not the case for MA-PD plans which include medical as well as pharmacy benefits). Details of the data cleaning procedure are provided in Appendix A.

Appendix Table A1 shows the number of enrollees in our dataset each year, ranging 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% are white. The breakdown by age group is also shown in the table. Over our sample period the entering cohort, ages 65-69, grows in size from under 20% to almost 28% of the sample.[8]

[8]It may be that over time employers and their about-to-be-retired employees no longer make other arrangements

Because we have data from four years of the program we can study the behavior of enrollees who have different numbers of years' experience in Part D. About 10% of each cohort leaves the program each year, and between 27,000 and 30,000 new enrollees enter each year.

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 51% to 80%. Appendix Table A2 summarizes the variation in this measure of quality across plans and over time. When weighted by enrollment we see that consumers disproportionately choose plans that include more treatments. The enrollment-weighted average coverage begins at 59% and rises to 82% by 2009. The significant change over time and across plans has been in utilization management. Many plans now require prior authorization for expensive drugs; the weighted average use of prior authorization is 22% of all drugs in 2014.[9][10] Preferred pharmacy networks were not a significant factor during our time period. Kaiser reports that only 6% of enrollees had a preferred pharmacy netwok in 2011, though they became popular shortly after that and expanded to 72% of enrollees by 2014.

For each enrollee, we estimate counterfactual costs in each plan (after discarding very small plans) holding consumption constant. While Einav et al (2015) have shown that moral hazard affects an enrollee's drug consumption and, in addition, an enrollee might be elastic across therapeutic substitutes when she changes plans, dealing with these issues is beyond the scope of the current paper. We follow the existing literature in our calculation of counterfactual costs. Our methodology, described in detail in Appendix B, combines elements of the techniques used in AG (2011) and Ketcham et al. (2012). First we asked a physician to classify drugs as either chronic (taken regularly over a prolonged period) or acute (all other). We assume that chronic drug consumption is perfectly predicted by the patient and calculate the total underlying drug cost for each enrollee of the observed chronic drug prescriptions. For acute drugs, as in AG (2011) we assign each individual to a group of ex-ante "similar" individuals and assume that the consumer expects to incur a total underlying drug cost equal to the median within her group. Following Ketcham et al. (2012), we then apply each plan's coverage terms (deductible, copayment or coinsurance rate on each tier, gap coverage) to each individual and use his or her predicted total (chronic plus acute) drug costs to predict total OOP spending given these terms. This procedure yields estimates which closely track those we observe in the data for chosen plans. While we expect there to be very little measurement error in the chronic OOP spending variable, since this is derived from observed utilization, there may be some measurement error in the acute OOP spending variable. Hence in much of the analysis we treat these variables separately.

If consumers do not like an aspect of their plan, they can switch in the open enrollment period. Table 2 reports summary statistics on enrollees who switch plans. Our data allow us to analyze

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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.

[9]Kaiser9thyear Medicare Part D in Its Ninth Year by Hoadley et al Kaiser Family Foundation 2014

[10]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 each of 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 2: Switching by Demographic Group

	2006-07	2007-08	2008-09
Whole Sample	19.08%	24.07%	8.16%
Female	20.86%	26.27%	8.54%
Non-White	21.68%	26.94%	8.83%
Income	**2006-07**	**2007-08**	**2008-09**
1st Quartile (low)	24.84%	30.60%	9.00%
2nd Quartile	19.84%	24.76%	8.18%
3rd Quartile	18.01%	23.20%	8.22%
4th Quartile (high)	13.99%	18.49%	7.43%
Age	**2006-07**	**2007-08**	**2008-09**
Under 65	29.28%	33.23%	11.32%
65-69	12.78%	18.08%	7.68%
70-74	14.71%	20.03%	7.55%
75-79	17.03%	22.33%	7.55%
80-84	20.65%	25.20%	7.64%
Over 85	27.45%	33.37%	9.80%

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

three opportunities for consumers to switch. From 2006-7 a total of 19% of enrollees switch plans[11]. In 2007-8 a total of 24% of consumers switch plans. By 2008-9, however, active switching drops considerably, to 8%. In every year, women and non-whites are more likely to switch plans than other enrollees. 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.

5 Analyzing the Behavior of Part D Enrollees

5.1 Consumer Overspending and Switching Behavior

We begin our investigation of the behavior of Part D enrollees by considering the amount they pay in their chosen plan given the costs of the other plans that are available to them. We refer to the gap between what the consumer spent and the lowest cost plan she could have chosen as "overspending" or gap spending. However, if consumers have preferences for non-price characteristics, these may lead them to choose a plan other than the cheapest available; such a choice would not be an "error," and therefore the term we use in the paper is "overspending." We return to the issue of brand preferences in the discussion of our demand model and simulations below.

We define the gap in payment as the expected OOP payment (including premium) in the chosen plan less the minimum expected OOP payment in any other plan in the choice set. Table

[11] 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 switches.

Table 3: Overspending Relative to the Minimum Cost Plan by Part D Cohort

	Full Sample			New Enrollees			2006 Enrollees		
	Count	**$ Error**	**% Error**	**Count**	**$ Error**	**% Error**	**Count**	**$ Error**	**% Error**
2006	127,654	$425.37 ($369.50)	37.28 (22.38)	127,654	$425.37 ($369.49)	37.28 (22.38)	127,654	$425.37 ($369.49)	37.28 (22.38)
2007	141,897	$320.08 ($301.97)	29.61 (18.59)	28,460	$299.03 ($313.16)	30.12 (19.25)	113,437	$325.36 ($298.87)	29.48 (18.41)
2008	151,289	$378.72 ($348.80)	32.83 (17.98)	26,802	$331.88 ($346.83)	30.74 (18.91)	99,742	$387.50 ($346.24)	32.92 (17.49)
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 spending above the minimum by year. "%" is percent of enrollee's total OOP spending (including premium) in observed plan. Standard deviations in parentheses.

Table 4: Spending Gap 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	27.97%	35.01%	-16.66%	-9.62%	-7.04%
2007	28.09%	42.98%	2.35%	17.24%	-14.89%
2008	25.83%	39.75%	-4.12%	9.80%	-13.92%
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	29.81%	29.81%	-5.55%	-5.55%	0.00%
2007	35.00%	35.00%	4.07%	4.07%	0.00%
2008	37.07%	37.07%	6.03%	6.03%	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.

3 summarizes the level of overspending by year in our sample[12].

In 2006, the first year of the program, the average amount paid above the minimum expected OOP payment available to the enrollee, including premium, was $425.37, or 37% of the OOP payments. 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. New enrollees' spending gap 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 above-average gaps in every year relative to the full sample; their level of spending above the lowest cost plan 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 high spending is not declining over time.

Part of the spending gap shown by Part D enrollees is a result of failing to choose a new plan each year. Column 1 of Table 4 shows that in every year, consistent with Ketcham et al. (2012),

[12]We include both chronic and acute payments in our measure of OOP spending; the qualitatitive results change very little when we exclude acute spending.

Table 5: Proportion Within X% of Lowest-Cost Plan

10%	Whole Sample	Switched Past Year	Didn't Switch
2006	14.81%	-	-
2007	15.67%	15.00%	16.04%
2008	10.39%	18.09%	6.50%
2009	7.67%	27.81%	4.05%
25%	**Whole Sample**	**Switched Past Year**	**Didn't Switch**
2006	28.06%	-	-
2007	42.82%	50.16%	40.85%
2008	35.27%	44.23%	30.83%
2009	21.74%	46.99%	17.12%

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

the spending gap is on average lower for consumers who have just switched plans. Moreover, the spending gap for the group switching decreases slightly over time, while that for non-switchers increases. Columns 2-5 of the same table show that switchers on average would have had a higher gap than non-switchers, and a larger increase in the spending gap year-on-year, if they had remained in the same plan. Table 5 considers the fraction of enrollees spending within 10% or 25% of their estimated lowest-cost plan and shows much the same pattern. By 2009, over a quarter of switchers spent less than 110% of their cheapest-plan cost, while only 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. While switchers continued to overspend even after switching plans, enrollees who had never switched overspent by more. By 2009 they spent on average about 40% more than they would in their lowest-cost plan; only 2% of them were within 10% of their lowest-cost plan. Overspending increases monotonically in years since last plan election. This suggests that the failure of consumers to switch plans is one important factor contributing to them spending well more than the lowest cost plan available.

There is a significant insurance literature that examines the question of risk-aversion and whether consumers over-insure themselves because they have great distaste for risk. This might be an explanation of our initial findings, and those of other Part D papers. However, in our data we do not find evidence to support this theory – that high spending by non-switchers is related to over-insurance, as would be the case if risk aversion was causing the observed overspending. Appendix Table A3 shows that the percentage of enrollees' total costs covered in the gap is much higher for switchers than for non-switchers, while premiums are on average lower for switchers. Coverage in the gap is a more generous level of insurance, and yet it is chosen by consumers who select lower cost plans. Thus higher coverage is chosen by people who overspend by less, rather than more, 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. Note that the coverage figures in Appendix Table A3 summarize the percent of costs covered for consumers enrolled in the relevant plan, not for the statistical average enrollee used for the CMS actuarial equivalence calculations.

The data do not imply that switchers choose plans that provide better coverage at a lower cost for everyone, but rather, that switchers' plans provide more coverage for their particular enrollees than do non-switchers' plans. Switchers are choosing good plans for them, ones that are both reducing risk and charging a low premium. We also run cross-sectional regressions of percent overspending, defined as the difference between the chosen and minimum cost plans divided by the chosen plan's cost, on plan and enrollee characteristics. The results are set out in Table 6. Having switched plans is negatively and significantly related to overspending, and whether or not we control for having switched plans, gap coverage is negatively related, and premiums and deductibles positively related to overspending conditional on observed OOP costs. Therefore we conclude that overspending is not associated with overinsurance.

Table 6: Predicted Overspending Regressions

	Without Switching Decision		**With Switching Decision**	
	Coeff.	**S.E.**	**Coeff.**	**S.E.**
Years in Program	-0.0254***	(0.0002)	-0.0017***	(0.0004)
Female	0.0026***	(0.0004)	0.00027	(0.00047)
White	0.0102***	(0.0007)	0.0089***	(0.0008)
Obs TrOOP ($)	-0.000011***	(3.97 E-07)	-0.000025***	(4.68 E-07)
Premium ($)	0.0007***	(2.52 E-06)	0.0006***	(2.71 E-06)
Deductible ($)	0.000068***	(1.85 E-06)	0.000084**	(2.40 E-06)
Gap Cov. (All)	-0.159***	(0.004)	-0.664***	(0.024)
Gap Cov. (Generic)	-0.128***	(0.001)	-0.099***	(0.001)
National PDP	-0.038***	(0.001)	-0.061***	(0.001)
Switched Plans	-	-	-0.005***	(0.0008)
Constant	0.324***	(0.001)	0.342***	(0.002)
N	580,746	-	366,555	-
R^2	0.378	-	0.412	-

Notes: Regressions of predicted overspending (relative to predicted lowest-cost plan) on plan characteristics. All specifications include deciles of days' supply of chronic drugs in the previous year, income quartiles and age group fixed effects. 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 spending relative to the minimum in the following year. The next key question is why people do not switch more frequently. If we conservatively define switching as the optimal choice whenever a consumer's current plan is expected to cost more than 125% of the cheapest plan's cost next year, then the optimal choice for about 83% of enrollees in 2008 was to switch plans. However, less than a tenth of that number actually switched.

One potential explanation for this behavior, which has been explored in numerous papers in this and other settings, is that consumers face switching costs which lead to inertia. If switching costs were important, the consumers choosing to switch would be those for whom the value of switching was high enough to compensate them for these costs. Our data appear consistent with this idea. On average over all years and plans, switchers would overspend relative to the minimum by $524 if they remained in their current plan, while the figure for non-switchers is $338 on average[13]. We decompose the difference between these overspending numbers into five categories: overspending in the current year, the increase in the current plan's premium and in its predicted out-of-pocket cost (TrOOP), and the reduction in the lowest-cost plan's premium and in its predicted TrOOP[14]. This decomposition, shown in Table 7, is illuminating.

Table 7: Decomposition of Difference in Next-Year Overspending if Remain in Current Plan, Switchers vs. Non-Switchers

Year	% from Change in Current Plan Prem	% from Change in Current Plan TrOOP	% from This Year Error	% from Change in Cheapest Plan Prem	% from Change in Cheapest Plan TrOOP
2006	29.35%	-64.92%	173.89%	-16.77%	-21.54%
2007	71.76%	-0.62%	-9.98%	10.59%	28.26%
2008	57.11%	2.63%	2.28%	2.04%	35.93%
Overall	68.94%	-19.94%	33.10%	-1.29%	19.19%

Notes: Decomposition of the difference between overspending of switchers vs non-switchers if they remain in their current plan. This difference is broken into five components: the current-year error (defined as overspending in current year relative to lowest-cost plan), the increase in current-plan premium and TrOOP, and the reduction in lowest-cost plan premium and TrOOP.

Almost 70% of the difference between switchers' and non-switchers' overspending if they remain in the current plan comes from changes in their current plan's premium[15]. In other words, a key distinguishing feature of switchers is not just that their value of switching plans is high, but that they also receive a signal of this fact in the form of a large increase in their current plan's premium.

Given these findings, we propose a slightly different explanation for the infrequent switching observed in the data. Consumers may be inattentive and in the absence of highly visible "prompts"

[13]We exclude enrollees who enter or exit the program the following year from this analysis.

[14]Throughout the paper, TrOOP refers to "true out of pocket costs", or OOP costs excluding premium, while OOP is the equivalent figure including premium.

[15]Switchers also have larger errors in the current year than non-switchers. Their OOP spending the following year falls in both current and lowest-cost plans, consistent with enrollees who have experienced a health shock reverting back to normal the following year

may simply roll-over their current plan choice. We argue in Section 6.1 that this behavior can be generated by a model where consumers have a cost of obtaining and processing information regarding alternative plan options and choose to incur this cost only when prompted by "cues" that are freely observed. For now we investigate whether the data are consistent with this intuition. Recall that spending above the minimum is a function of three variables: consumers' current plan characteristics, the characteristics of their lowest-cost plan, and their drug consumption. We 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 the following year of greater than the weighted median increase across all consumers (about \$4 in 2007, \$7 in 2008, and \$4.50 in 2009).[16] Each year in the open enrollment period an existing enrollee receives a letter from his or her plan detailing changes in the coming year. To the extent the enrollee opens the letter and reads it, the premium increase becomes known and salient at a time when the enrollee can easily switch plans. A "coverage shock" is defined as occurring when either (a) the consumer's current plan drops coverage in the coverage gap or (b) the plan moves from the defined standard benefit pre-ICL (before hitting the coverage gap) to a tiered system in that region[17]. 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 in the current year. This shock is meant to capture 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.[18] The distribution of these shocks in the population and their correlation with the decision to switch plans are shown in Table 8.[19] These three shocks appear to explain switching behavior well; those who receive no shocks switch very infrequently, only 4% of the time, while those who receive multiple shocks are much more likely to switch plans[20]. Almost all switchers (87%) receive some shock in the year of the switch.[21]

Table 9 shows the results of probit regressions of decision to switch plans on own-plan, low-cost

[16]We have experimented with different cutoffs and the median does well in terms of simplicity and explanatory power.

[17]Recall that basic plans must meet a coverage standard and be actuarially equivalent to the tariff set out in the law. The declines we label as "shocks" are declines in one part of the benefit schedule, which we treat as appropriate measures of rapidly increasing premiums and eroding (or increasingly complex) coverage on some dimension.

[18]We do not have information on diagnoses because we only have data from Medicare Part D and not Parts A and B. However, a diagnosis - and in particular an inferred diagnosis - may be a less precise measure of how much pharmaceutical spending increases compared to actual utilization.

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

[20]These findings are corroborated by Hoadey et al. (2013), who find that premium increases and removal of gap coverage are the best predictors of switching behavior.

[21]One could interpret our shock model as a very general nonlinear function of the value of switching. All the shocks raise the return to searching and switching, and this form seems to explain behavior the best. The discrete nature of the nonlinear function lead us to conclude that attention matters in this market.

Table 8: Distribution of Shocks and Switching Likelihood

	Sample Distribution							
	No Acute Shock				Acute Shock			
	Neither	**Premium Only**	**Coverage Only**	**Both**	**Neither**	**Premium Only**	**Coverage Only**	**Both**
2006	50,503	49,954	3,212	2,824	3,138	3,082	170	554
2007	68,647	47,806	499	0	3,488	4,008	39	0
2008	78,980	37,081	5,640	643	3,651	2,400	213	23
	Distribution Among Switchers							
	No Acute Shock				**Acute Shock**			
	Neither	**Premium Only**	**Coverage Only**	**Both**	**Neither**	**Premium Only**	**Coverage Only**	**Both**
2006	1,729	16,327	252	1,134	260	1,688	16	234
2007	5,042	22,066	1	0	550	2,306	0	0
2008	1,358	7,444	819	11	96	745	29	0
	Switching Likelihood							
	No Acute Shock				**Acute Shock**			
	Neither	**Premium Only**	**Coverage Only**	**Both**	**Neither**	**Premium Only**	**Coverage Only**	**Both**
2006	3.42%	32.68%	7.85%	40.16%	8.29%	54.77%	9.41%	42.24%
2007	7.34%	46.16%	0.20%	-	15.77%	57.53%	0.00%	-%
2008	1.72%	20.07%	14.52%	1.71%	2.63%	31.04%	13.62%	0.00%
Overall	4.10%	33.99%	11.46%	33.03%	8.82%	49.94%	10.66%	40.55%

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.

plan and personal characteristics. If consumers prefer low premiums and high coverage but are inattentive, we expect them to switch more frequently when their current plan raises premium or reduces coverage than when other low-cost plans reduce premium or increase coverage. If they switch in response to acute shocks we expect those with high OOP spending to switch. The estimates in Table 9 are consistent with this intuition. In all specifications enrollees with high OOP spending and those with high premiums and deductibles and without gap coverage switch more than other consumers. Model 1 indicates that consumers' switching probability increases when their own plan's premium rises or when their own plan removes gap coverage. Model 2 adds the equivalent variables for the average of the five lowest-cost plans and shows that, to the extent changes in other-plan characteristics affect switching at all, the correlations run in the "wrong" direction. In particular it seems that consumers are more likely to switch when low-cost plans increase their premiums. Changes in low-cost plans' gap coverage have no significant effect[22].

Table 10 presents evidence that consumers who switch select plans with characteristics that vary depending on the shock that prompted the switch. Consumers who receive acute shocks, which we can think of as signals of future ill-health, tend to prefer higher coverage conditional on switching than those who do not. The same is true of those receiving coverage shocks. Consumers facing premium shocks tend to choose plans with lower premiums. 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, as in Busse et al. (2014).

[22] The results are insensitive to using either the lowest-cost plan available, the lowest-cost plan within-brand, or an average of the 5 lowest-cost plans.

Table 9: Probit Regressions on Switch Decision

	Model 1	Model 2	Model 3	Model 4
Years in Sample	-0.174***	-0.174***	-0.167***	-0.167***
	(0.0047)	(0.0047)	(0.0049)	(0.0049)
Alzheimers/Mental Illness	-0.016**	-0.017**	-0.014**	-0.015**
	(0.007)	(0.007)	(0.007)	(0.007)
Obs TrOOP ($)	0.00011***	0.00011***	0.00010***	0.00010***
	(4.76 E-06)	(4.88 E-06)	(4.79 E-06)	(4.81 E-06)
Premium ($)	0.0027***	0.0027***	0.0026***	0.0026***
	(0.000036)	(0.000036)	(0.000037)	(0.000037)
Deductible ($)	0.0041***	0.0041***	0.0042***	0.0042***
	(0.000026)	(0.00026)	(0.000027)	(0.000028)
Gap Coverage (All)	-0.944***	-0.951***	-0.853***	-0.861***
	(0.031)	(0.031)	(0.031)	(0.031)
Gap Coverage (Generic)	-1.628***	-1.628***	-1.515***	-1.516***
	(0.028)	(0.028)	(0.029)	(0.029)
National PDP	-0.332***	-0.334***	-0.327***	-0.329***
	(0.007)	(0.007)	(0.007)	(0.007)
Female	0.099***	0.099***	0.099***	0.099***
	(0.006)	(0.006)	(0.007)	(0.007)
White	-0.014	-0.014	-0.028	-0.029
	(0.011)	(0.011)	(0.011)	(0.011)
Premium Change (Own Plan)	0.0055***	0.0055***	0.0053***	0.0053***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Next-Year Gap Coverage Dropped (Own Plan)	1.895***	1.898***	-	-
	(0.087)	(0.087)		
% TrOOP Change (Own Plan)	-	-	-1.05 E-10	-6.44 E-11
			(7.11 E-11)	(7.90 E-11)
Premium Change (Avg. 5 Lowest-cost Plans)	-	0.0002***	-	0.0002***
		(0.00004)		(0.00004)
Next-Year Gap Coverage Dropped (% 5 Lowest-cost Plans)	-	-0.0397	-	-
		(0.0362)		
% TrOOP Change (Avg. 5 Lowest-cost Plans)	-	-	-	-1.31 E-10
				(1.61 E-10)
Constant	-2.685***	-2.693***	-2.587***	-2.596**
	(0.021)	(0.021)	(0.025)	(0.025)
N	366,555	366,555	337,477	337,477
Pseudo-R^2	0.310	0.310	0.311	0.311

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

Table 10: Next-Year Plan Choices and Overspending by Shock, Switchers Only

2006	**Acute Shock**	**No Acute**	**Premium Shock**	**No Premium**	**Cov Shock**	**No Cov**
% Gap Coverage	14.10%	7.13%	3.46%	45.41%	30.87%	5.95%
Premium	20.83	18.82	17.46	32.47	29.65	18.16
% within 25%	72.07%	49.55%	52.29%	47.98%	62.53%	50.96%
2007	**Acute Shock**	**No Acute**	**Premium Shock**	**No Premium**	**Cov Shock**	**No Cov**
% Gap Coverage	5.39%	3.20%	2.97%	5.29%	0.00%	3.41%
Premium	27.25	26.43	25.77	29.68	22.10	26.50
% within 25%	64.99%	42.20%	46.70%	34.20%	0,00%	44.37%
2008	**Acute Shock**	**No Acute**	**Premium Shock**	**No Premium**	**Cov Shock**	**No Cov**
% Gap Coverage	9.54%	4.34%	3.55%	9.12%	2.44%	4.98%
Premium	31.84	29.76	29.07	32.97	29.99	29.92
% within 25%	58.28%	46.56%	47.91%	46.18%	46.45%	47.63%
Overall	**Acute Shock**	**No Acute**	**Premium Shock**	**No Premium**	**Cov Shock**	**No Cov**
% Gap Coverage	9.23%	4.75%	3.25%	15.08%	21.07%	4.52%
Premium	25.54	24.36	23.19	31.05	29.76	24.26
% within 25%	66.63%	45.49%	48.98%	39.98%	56.97%	47.11%
N	5,924	56,183	51,955	10,152	2, 496	59,611

Notes: Summary of types of plans chosen by type of shock experienced. '% Gap Coverage' is average percent of plans chosen with gap coverage; 'Premium" is average premium per enrollee per month for chosen plan; '% within 25%' is percent of plans chosen that are within 25% of lowest-cost option available.

5.3 Alternative Explanations

We have discussed the role of risk aversion above. Consumers are not overspending in order to reduce variance; the plans they are not choosing have both lower premiums and more coverage on average. A second possible explanation for overspending is that it takes experience to learn how to shop in the Part D marketplace. Perhaps an enrollee's overspending falls over time as she learns. Table 3 above addresses this issue. 2006 enrollees - those who first entered the program in 2006 and remained in it throughout our sample - had higher overspending 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 with experience in Part D.

Table 10 also provides insight on whether the small number of consumers who switch despite not experiencing shocks are more sophisticated than those who switch due to highly visible prompts. In fact these consumers are *less* likely to choose a plan whose costs are within 25% of the lowest available level than are consumers who switch in response to a shock. It may be appropriate to think of consumers who switch without being prompted by an observed shock as responding to some unobserved random shock to the likelihood of switching along the lines of a friend or relative advising them to do so. We also consider whether consumers who switch plans on a regular basis are more sophisticated than other consumers. A small number of consumers (less than 4% of the sample) choose a different plan in every year of our data. They are enrolled in lower-cost plans on average in 2009 than the population as a whole in 2006. However, rather than being particularly sophisticated dynamic optimizers, it seems that these consumers are simply unlucky in terms of the number of shocks they receive over time. Virtually the entire segment receives a premium shock each year, and these consumers are also three times as likely as other consumers to receive acute shocks.

Lastly, limitations in the cognitive capability of consumers are clearly important in this market. However, this shows up in the choices of consumers conditional on actively choosing. Our model is able to separate this choice imperfection from the problem of consumer inattention.

6 A Model of Consumer Behavior

6.1 A Framework for Consumer Inattention

We outline a model under which the consumer inattention we observe in the data is caused by costs of processing information. Our framework draws from the models of rational inattention developed by Sims (2003) and Reis (2006) and from the models of consumer search and learning of Cabral and Fishman (2012) and Honka (2014) among others.

Consider a model with the following assumptions. A risk-neutral, myopic consumer i may choose from a set of plan options $j = 1, ..., J$. The consumer has a limited capacity for processing information: acquiring and processing the data needed to understand the characteristics of all plans in the choice set has a cost $\tilde{v}_{i,t} = f(Z_{i,t})$, where $Z_{i,t}$ are consumer characteristics such as age and sickness level which could affect, for example, the likelihood of a younger family member helping with the plan choice process. The consumer's utility from plan j if she was fully informed of its characteristics in period t would be

$$u_{i,j,t} = \beta X_{i,j,t} + \gamma c_{i,j,t} + \epsilon_{i,j,t} \tag{1}$$

where $c_{i,j,t}$ is the OOP cost paid by the consumer, $X_{i,j,t}$ are other plan characteristics relevant to the choice and $\epsilon_{i,j,t}$ is an i.i.d. shock known to the consumer but not to the researcher[23].

At the end of year t each consumer observes her own plan k's cost in the following year; this is sent to her in the mail. (We normalize any processing cost involved in reading the letter to zero and consider as "costs" activities more difficult than that.) After receiving this mailing she chooses whether to incur cost $\tilde{v}_{i,t}$ in order to observe all plans' terms and choose the plan that maximizes her utility, or whether to incur no cost and remain in plan k the following year. Under these assumptions the consumer will choose to pay the cost $\tilde{v}_{i,t}$ provided the expected benefit is greater than the cost:

$$E\left[\max_{j=1...J}(u_{i,j,t+1})\,|\bar{X}_{i,k,t+1}\right] - u_{i,k,t+1} > \tilde{v}_{i,t} = f(Z_{i,t}). \tag{2}$$

[23] We break out $c_{i,j,t}$ into its component parts in the model for estimation; it is condensed to a single variable in this section for simplicity of exposition. The utility equation may not be "rational" in the sense that agents weight premium and copays equally, for example. However we assume that $\gamma < 0$.

where $\bar{X}_{i,k,t+1}$ are the characteristics $(X_{i,k,t+1}, c_{i,k,t+1}, \epsilon_{i,k,t+1})$ of plan k in period $t+1$ and the expectation is taken over the characterstic she searches for: cost $c_{i,j,t+1}$ for all plans $j \neq k$.[24]

The literature on consumer search and learning indicates that, under these assumptions, the consumer may choose to default into her current plan until she experiences a sufficiently large shock to her own plan's cost or her own health. Cabral and Fishman (2012), the study most relevant for our application, shows that observing a high price or a large price increase has two effects: it increases the expected benefit from search (it's likely that a better deal can be found) but also reduces it since the consumer assumes firm prices will be correlated. Under reasonable assumptions, the first effect dominates, and a large increase in price prompts the consumer to search for alternatives.

A shock to the consumer's health may increase the probability of search and switching for two reasons. First it may decrease $\tilde{v}_{i,t}$, for example by prompting the senior's relatives to help evaluate the plans in her choice set. It could alternatively increase the variance of the consumer's expected distribution of costs $c_{i,j,t+1}$. Sallee (2014) shows that, in a similar model where consumers choose durable goods based partly on their expected lifetime fuel costs, an increase in the variance of the cost distribution (uncertainty) implies an increase in the expected benefit from search.

6.2 Model for Estimation

Having outlined a framework under which costs of processing information can generate the consumer inattention we observe in the data, we move on to specify a simple two-stage model of consumer decision-making for estimation. Consistent with the framework just developed, we abstract away from risk aversion and learning and assume that consumers are myopic in their choice of plans. We distinguish between two possible unobserved sources of choice persistence: persistent variation in unobserved preferences and inattention. We account for inattention using the following simple framework. We assume that each consumer ignores the plan choice problem until hit by a shock to the OOP costs of her current plan or to her health. These shocks are assumed to have additively separable effects on her decision to re-optimize her choice of plan. If she chooses to re-optimize, she makes choices according to a utility equation to be estimated.[25] We will use this simple decision 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.

Specification As in section 5.2, we consider three shocks to the consumer's own characteristics that could prompt her to incur the costs of search: two types of bad news concerning her current plan's characteristics for next year (the plan's premium will rise or coverage will fall noticeably)

[24] As we will discuss in detail later in the paper, consumers are able to perfectly forecast a significant fraction of the future OOP costs of any plan.

[25] Our consumers are "naive," in the sense that they do not realize that they are inattentive, and therefore their decisions do not take into account that they may not reoptimize again for a long time.

and an unusually high OOP payment driven by a health shock. As before we define a shock to premiums in the enrollee's current plan (v_p) as a premium increase of more than the weighted median increase in the relevant year. A coverage shock (v_c) is again defined as the plan dropping coverage in the coverage gap or moving from the defined standard benefit to a different (tiered) system in the Pre-ICL phase. An enrollee is defined as having an acute shock (v_h) when she is 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. Additionally, 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 this shock v_e. The sum of these shocks creates a composite shock received by consumer i at time t:[26]

$$v_{i,t} \quad = \quad v_{i,p,t}\beta_1 + v_{i,c,t}\beta_2 + v_{i,h,t}\beta_3 + v_{i,e,t} \tag{3}$$

where the weights β allow the different shocks to have different effects on the propensity to search (for example shocks to premiums may increase the likelihood of switching more than other shocks). We assume that the random shock $v_{i,e,t}$ is distributed IID Extreme Value Type 1.

When the composite shock $v_{i,t}$ is large enough, i.e. when:

$$v_{i,t} \quad \geq \quad \tilde{v}_{i,t}, \tag{4}$$

then the consumer becomes aware and decides to re-optimize her plan election. Here $\tilde{v}_{i,t}$ is a function of consumer demographics related to health status and sensitivity to changes in plan characteristics: age groups, income quartiles, gender and race. In our model consumers are not heterogeneous in the weights they place on the three different shocks. Heterogeneity in search costs, however, is an important part of the model and the data, as can be seen for example in Table 2[27]. We also include year fixed effects in $\tilde{v}_{i,t}$ to account for differences in the environment across our three different enrollment periods. We expect that the amount and nature of advertising and of pharmacy and government outreach affected consumer attentiveness, and we expect these factors varied over time.

The second stage of the model examines how consumers who have decided to re-optimize choose whether to switch and to which plans. We assume that if equation (4) holds then consumer i makes a choice from the full choice set (including her current plan) based on the following utility from

[26] In a comparable analysis of the Texas retail electricity market, Hortaçsu et al (2015) use bill size, brand dummies and seasonality to explain awareness.

[27] Note that $\tilde{v}_{i,t}$ should not be strictly interpreted as a search cost since we have not fully specified a first stage in which the consumer re-optimizes when the expected benefit of search is greater than its cost. However it has a similar interpretation: it is the level above which shocks to the consumer's attention will lead to search.

choosing plan j in year t:

$$
\begin{aligned}
u_{i,j,t} &= Tr\hat{O}OP_{i,j,t}\beta_1 + Premium_{j,t}[\beta_{2,1} + v_{i,p,t}\beta_{2,2}] + Ded_{j,t}\beta_{3,1} \\
&+ Gap_{j,t}[\beta_{4,1} + v_{i,c,t}\beta_{4,2} + v_{i,h,t}\beta_{4,3}] + X_{j,t}\beta_{5,i} + \epsilon_{i,j,t} \\
&= \delta_{i,j,t} + \epsilon_{i,j,t} \qquad (5)
\end{aligned}
$$

where expected OOP spending excluding premium ($Tr\hat{O}OP_{i,j,t}$) is calculated using the method described in Section 4, $Premium_{j,t}$ and $Ded_{j,t}$ are annual premiums and deductibles and $Gap_{j,t}$ is an indicator for any coverage in the gap. $X_{j,t}$ are non-price plan characteristics including an indicator for enhanced plans and brand fixed effects (defined at the carrier rather than the plan level) and $\epsilon_{i,j,t}$ is an IID extreme value type 1 error term (assumed to be independent of $v_{i,e,t}$).

In the reported specifications we use chronic TrOOP as our measure of out of pocket costs, since acute TrOOP may be measured with error while this is unlikely to be the case for chronic TrOOP.[28] Note that a consumer who could calculate expected costs perfectly would value a given change in either TrOOP equally, and with the same weight as premium, as they are all measured in dollars. We do not include a term for the variance of chronic TrOOP since consumers are assumed to predict their chronic drug costs with certainty. While in principle a risk-neutral consumer should not put any weight on other plan financial characteristics after correctly calculating TrOOP, we know from past research that they do. Therefore we include other financial characteristics of the plan (the size of the deductible and an indicator for coverage in the gap) in the utility equation to help us predict consumer choice. Significant coefficients on these characteristics may reflect consumer risk aversion, the salience of particular publicized plan characteristics, or other choice frictions that we do not not formally model. In addition we allow consumers prompted to search by shocks to premiums to place additional weight on premiums. Consumers experiencing shocks to coverage, or acute shocks, are permitted to place additional weight on the plan offering gap coverage.

We model persistent unobserved preference heterogeneity by including normally-distributed random coefficients $\beta_{5,i}$ on fixed effects for the three dominant brands, which together have over 80% market share in 2006, and on the enhanced plan fixed effect. The model therefore allows choice persistence (such as a lack of switching away from a particular plan even when other plans reduce their premiums) to be caused either by heterogeneous preferences (some consumers have a very strong valuation for this brand that makes it worthwhile to remain enrolled even at a high relative price) or by inattention (consumers who are not affected by any of the previously-defined shocks are unaware of other plan premium reductions). One of our objectives in estimating this equation is to distinguish between these two effects.[29]

[28] In robustness tests we show that including acute TrOOP as a separate input to the utility equation has very little impact on the results.

[29] We choose not to model a third possible source of choice persistence: the existence of switching costs defined to be distinct from the attention and search costs here. While switching costs has been a focus of some previous papers on health insurance markets (e.g. Handel (2013) and Polyakova (2014)), we find it difficult to separate out what those might be (time, effort, searching) and whether they overlap with the cognitive effort of paying attention to a particular decision and investing in optimization. The evidence presented above indicates that inattention is an important source

The model is estimated using a random coefficients simulated maximum likelihood approach similar to that summarized in Train (2009). The likelihood function for each enrollee is predicted for a sequence of choices from entry into the Part D program until the end of our data panel. Details of the methodology are provided in Appendix D.

Identification The intuition for identification of this model is now fairly standard in the literature (see for example Handel (2013) and Polyakova (2013)). We use the panel structure of the data, which implies that we can track individuals making consecutive choices over several years, together with the fact that new enrollees in the program enter the data in every year. These new enrollees are assumed to choose without inertia; we also assume that the normally distributed random coefficients fully capture the unobserved heterogeneity in their preferences. The parameters governing the unobserved preference heterogeneity (the distribution of the random coefficients) can therefore be estimated from the choices made by new enrollees in the program. Other determinants of the decision to switch, most importantly the parameters governing inattention, are identified from consumers' observed sequences of choices in the years following entry. The initial conditions problem (e.g., Heckman (1991)) does not arise in our data because we observe the first Part D choices for all individuals in the estimation sample.

Endogeneity issues are of course also relevant for identification. A classic endogeneity problem would occur if a plan's additional coverage was valued in ways we did not observe and this additional coverage was correlated with the plan's premium. An insurer with an unobservably good plan that wanted to charge a higher price could 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 this 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 possible ways to differentiate in an unobservable dimension are limited. Here we consider unobservable quality appearing through the formulary, additional benefits, and customer service. Anecdotally, customer service does not appear to be a very important force in this market. We predict consumer OOP payments using observed chronic drug utilization and demographic and utilization types, as described in Appendix B. If there is some error in this calculation, we may predict OOP costs that differ from consumers' own predictions, implying that consumers may perceive some plans to be more attractive than is indicated by our OOP spending variable. In this case the error may be correlated with the premium, leading to downward bias in the premium and premium shock coefficients. 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 systematically over-estimate OOP costs

of search frictions in our data. We focus on identifying the effects of inattention separately from persistent unobserved preferences, choosing not to attempt the notoriously difficult empirical task of also distinguishing between the effects of asymmetric search costs (inattention) and switching costs.

for that plan. If premiums are increased to account for this "unobserved generosity", the estimated premium coefficient will be biased towards zero. We address this concern by including carrier fixed effects in all specifications, as formularies are almost always fixed across plans within a carrier[30]. The fact that formularies are nearly always constant across an insurance carrier's plans is helpful for us because it means that unobserved quality related to the formulary is picked up with our brand fixed effects. The last possible endogeneity problem we consider is the additional coverage offered by enhanced plans, which is subject to less tight regulatory scrutiny than that of basic plans. We include enhanced plan fixed effects in all specifications and add enhanced-year interactions to account for time variation in the quality of enhanced plan coverage in some specifications. The typical unobserved quality dimension correlated with premium, as in Berry (1994), is therefore unlikely to play a major role in our data.

6.3 Demand Estimates

The estimated coefficients and standard errors for four separate demand specifications are shown in Table 11; the means and standard deviations of the variables used in estimation are reported in Appendix Table A8. Model 1 uses a simple specification where only chronic TrOOP, premium, brand fixed-effects and an enhanced plan fixed effect, with random coefficients as specified above, are included in the utility equation. We add variables incrementally in the following columns; Model 4 is our full specification. In all models 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. Women, 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 in Table 9 and also with intuition. Failing to choose the lowest-cost plan is more costly for older enrollees who already spend a higher fraction of their income on drugs, and for lower-income enrollees for whom the excess spending is more burdensome. For this reason they tend to require smaller prompts in order to re-optimize their choice.

The third panel of Table 11 sets out the estimated choice coefficients. As noted in the previous literature, if consumers are risk neutral and perfectly predict their expected OOP costs, we expect the coefficients on TrOOP and premium to be negative and approximately equal in magnitude. Consistent with AG, our estimates do not satisfy this criterion. Consumers are estimated to place a much greater weight on premiums than on chronic TrOOP.[31]. If we ignore shocks for simplicity, the model 4 estimates imply that a one-standard-deviation (or \$241) increase in premium for a single plan, holding all other plans' characteristics fixed, generates an average reduction in the probability that the plan is chosen of 8.5%, while a one-standard-deviation increase in chronic TrOOP, which is a much larger dollar increase of \$935, leads to a 7.6% reduction in probability of choice. Consumers also put significant weights on both gap coverage and deductibles. Model

[30]We also included carrier-year fixed effects, in a simpler specification without random coefficients on the brand fixed effects, with little effect on the estimates.

[31]Evidence for consumers over-weighting premiums and other plan variables relative to expected costs in other insurance markets is presented in Handel (2013).

Table 11: Estimated Structural Demand Coefficients

	Model 1		Model 2		Model 3		Model 4	
Switch Parameters Threshold Shifters	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Year (2007)	3.73***	0.03	3.73***	0.04	3.72***	0.04	3.74***	0.04
Year (2008)	3.17***	0.03	3.19***	0.03	3.26***	0.03	3.27***	0.03
Year (2009)	4.38***	0.04	4.38***	0.04	4.35***	0.04	4.34***	0.04
Female	-0.26***	0.02	-0.26***	0.02	-0.26***	0.02	-0.26***	0.02
Nonwhite	-0.04	0.03	-0.04	0.03	-0.06*	0.03	-0.06*	0.03
Q1 Income	-0.52***	0.03	-0.52***	0.03	-0.52***	0.03	-0.52***	0.03
Q2 Income	-0.29***	0.02	-0.29***	0.02	-0.29***	0.02	-0.29***	0.02
Q3 Income	-0.22***	0.02	-0.22***	0.03	-0.22***	0.02	-0.22***	0.02
Age 70-74	-0.15***	0.03	-0.15***	0.03	-0.14***	0.03	-0.14***	0.03
Age 75-79	-0.35***	0.03	-0.35***	0.03	-0.36***	0.03	-0.36***	0.03
Age 80-84	-0.50***	0.03	-0.49***	0.03	-0.50***	0.03	-0.49***	0.03
Age U-65	-0.49***	0.05	-0.48***	0.05	-0.52***	0.05	-0.52***	0.05
Age O-85	-0.76***	0.03	-0.76***	0.03	-0.76***	0.03	-0.75***	0.03
Shocks	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Premium Shock	2.38***	0.01	2.40**	0.02	2.36***	0.03	2.38***	0.02
Coverage Shock	0.70***	0.05	0.69**	0.05	0.68**	0.05	0.68**	0.05
Acute Shock	0.58***	0.04	0.58**	0.05	0.57***	0.05	0.56***	0.05
Choice Parameters	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Chronic TrOOP	-1.58***	0.01	-1.51***	0.05	-1.46***	0.02	-1.34***	0.02
Annual Premium	-5.81***	0.08	-7.51***	0.12	-6.14***	0.03	-6.44***	0.08
Deductible	-	-	-0.35**	0.16	-1.67***	0.08	-1.77***	0.24
Gap Coverage	-	-	1.44***	0.08	1.44***	0.07	1.62***	0.08
Premium Shock x Prem	-	-	-	-	-10.33***	0.17	-10.08***	0.25
Coverage Shock x Gap Cov	-	-	-	-	0.61	1.24	0.43	1.94
Acute Shock x Gap Cov	-	-	-	-	0.95**	0.37	0.94**	0.28
Enhanced: Mean	-0.22***	0.10	-0.60***	0.02	-0.59***	0.04	-1.30***	0.07
Enhanced: Variance	2.81	-	2.81	-	3.40	-	4.09	-
Enhanced (2007)	-	-	-	-	-	-	0.78***	0.08
Enhanced (2008)	-	-	-	-	-	-	0.44**	0.10
Enhanced (2009)	-	-	-	-	-	-	1.83***	0.12
Lge Brand 1: RC Mean	3.26***	0.02	3.07***	0.06	3.01***	0.03	2.92***	0.06
Lge Brand 1: RC Variance	3.31	-	4.01	-	3.88	-	1.72	-
Lge Brand 2: RC Mean	2.47***	0.05	2.51***	0.09	2.67***	0.02	2.77***	0.03
Lge Brand 2: RC Variance	2.07	-	1.10	-	0.45	-	3.12	-
Lge Brand 3: RC Mean	1.22***	0.15	0.91***	0.09	1.02***	0.03	1.18***	0.04
Lge Brand 3: RC Variance	4.65	-	3.96		1.56	-	3.53	-
Fixed Effects	**Brand**		**Brand**		**Brand**		**Brand**	
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 OOP 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

4 implies that, for plans offering coverage in the gap, eliminating that coverage has an equivalent effect to a $252 increase in annual premium, a $915 increase in the deductible, or a $1211 increase in chronic TrOOP. The significant coefficients on gap coverage and deductibles could be due to consumer risk aversion or the salience of these easily-observed plan characteristics, as noted above. These variables may also absorb the effect of expected acute OOP costs which are not included in our primary specifications.[32]. Overall we conclude that a plan's premium is clearly the most important characteristic affecting demand.

The random coefficient estimates are intuitive. While our data agreement prevents us from specifying the names of individual insurers, we can say that the three largest brands have a combined market share of over 80% in 2006-7. Consistent with this large enrollment, all three random coefficients are estimated to have positive and significant means. Those for large brands one and two, the largest in the sample, are particularly high and have variances of the same order of magnitude as the means. The third large brand has a relatively low premium which helps rationalize its high market share; its brand fixed effect has a somewhat lower mean and relatively higher variance compared to the others. The remaining brand dummy variables (not reported) indicate that consumers are willing to pay on the order of $500 to move from the second-lowest-value plan to one of the three largest brands. Conditional on all other plan variables, consumers show a slight aversion to enhanced plans on average, although the variance of this random coefficient is three times larger than its mean. When we break out the enhanced plan coefficient by year in Model 4, we see that enhanced plans became increasingly attractive over time; the overall coefficient is positive by 2009.[33]

The choice equation also identifies a second source of frictions in consumer decision-making. Consistent with the evidence presented above as well as that in Busse et al. (2014), consumers switching plans following a shock to premiums place additional weight on premiums in making their choice, while those switching following a health shock place additional weight on gap coverage. The magnitudes of these interaction terms indicate substantial effects. In particular, the weight placed on premiums by consumers who have experienced a premium shock is more than twice that for other consumers[34].

These findings suggest that while consumer inattention, and the extra weight placed on pre-

[32] Acute TrOOP is excluded from the main specifications because of measurement issues: it is generated from an average within a group defined by demographics and utilization and thus does not pick up private information regarding idiosyncratic cost variation within the group, which is likely to be an important factor in consumers' choice of plan. Appendix Table A9 shows that when we add acute TrOOP to models 1 and 2 its coefficient has the wrong sign but most of the other estimates change very little.

[33] Some of the effect of enhanced benefits could be subsumed in the estimate for gap coverage which many enhanced plans provide and many basic plans do not.

[34] We also estimate 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; it estimates preferences by averaging over the behavior of inattentive and attentive consumers. The results are shown in Table A9. Consistent with AG, the average consumer under-weights TrOOP relative to premiums, deductibles and gap coverage. Adding a first-stage switching model makes the coefficient on enhanced plans become less negative (more "rational" in the sense of risk-neutral fully-informed agents choosing the utility-maximizing option) and the variance of the random coefficients decrease. That is, including consumer inattention in the model helps explain the choice behavior identified in AG on these dimensions.

Table 12: New Jersey Part D Market Summary Statistics

Year	Num Plans	Enrollmnt	CR-4	HHI	Entering Plans	Enhanced Plans	Enhanced Mkt Share	DSB Plans	DSB Mkt Share
2006	44	281,128	0.862	0.259	44	17	12.27%	6	12.89%
2007	56	298,978	0.780	0.217	19	27	24.32%	8	10.49%
2008	57	304,198	0.617	0.157	9	29	28.62%	7	5.31%
2009	52	317,997	0.637	0.154	1	27	30.63%	5	0.48%
2010	46	329,178	0.660	0.163	2	24	30.43%	5	2.48%
2011	33	333,553	0.751	0.285	1	15	22.46%	4	2.53%
2012	30	343,886	0.753	0.281	3	14	24.00%	3	0.38%

Notes: Summary statistics on New Jersey Part D plans. Source: aggregate CMS data, generously provided by Francesco Decarolis. Total number of plans includes enhanced, Defined Standard Benefit (DSB), and other standard plans not following DSB coverage terms exactly. The latter are not listed separately in the table.

miums and coverage by enrollees experiencing related shocks, explain some of the choice frictions identified in the previous literature, some other sources of remain. For example consumers display a substantial willingness-to-pay for access to particular brands. 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. 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)) 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) 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 (2015)) from CMS files on plans, ownership, enrollment, premiums, formularies, and other characteristics. It covers all plans in all regions of the US (34) for the years 2006-2012[35]. We focus largely on stand alone Part D PDPs in New Jersey, as these are the plans which serve the consumers modeled in the previous section.

[35]See Decarolis (2015) for a detailed description of the data.

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 quite highly 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. Our data agreement does not allow us to provide names for the large plans in our data. However, a table containing publicly available CMS information on the names and market shares of the five largest PDP plans in New Jersey in 2006, together with their brands, is provided in Appendix Table A10. There was little change in the rankings of these top five plans over the period of our data[36].

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 36 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 43 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 12, suggest an oligopolistic market characterized by increasing product differentiation and increasing concentration.

7.2 Insurer Pricing Strategies

We now consider the effect of consumer inattention, coupled with product differentiation and imperfect competition, on insurer pricing strategies in the Part D marketplace. In particular, we focus on the insurer's choice of premium. This is partly because the premium is by far the most important characteristic for consumer choice. It is also the metric CMS uses to approve plans, calculate a region's benchmark, etc. (As already mentioned, other plan characteristics are tightly regulated.) Other characteristics of the plan's strategy, such as the design of the formulary (which is also regulated) or gap coverage options are possible areas for future research, but are beyond the scope of the current paper. One would expect a profit-maximizing insurer to set its premiums in a way that took advantage of consumer choice frictions. In this section we note that the patterns in the data are consistent with this intuition. We also assume, as is traditional in IO research, that the insurers have rational expectations and are able to study the market in advance and choose an optimal strategy.

Theoretical models of search frictions have fairly clear predictions for prices. Papers such as Varian (1980) 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

[36]The market shares listed in Table 12 and Table A10 are slightly different from the shares of the plans in the data used for our analysis, because as noted in Appendix A, we drop very small plans from our sample.

"become informed" (perhaps by paying a cost) and at that point know all prices. This model fits the situation where a consumer who has experienced a shock 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. 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. Each plan offers exactly the same financial tariff and any given medicine is exactly the same in each plan. The plans differ by formulary, customer service, and brand. Different formularies will create differences in expected costs across individuals, but formularies are regulated by CMS to ensure that every therapeutic category has sufficient coverage and utilization management tools are appropriate – so the average value of each plan will be similar. Nevertheless, Table A11 in the Appendix 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 close-to-homogeneous product by 2012.

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) captures the main intuition of the firm's problem. If consumers enter the market in period t and choose among firms in that period without frictions, the firm has an interest in capturing them with a low price ("invest"). In later periods there are two offsetting effects: an incentive to increase prices ("harvest") because the firm's installed base has to pay a cost to switch, and an incentive to keep prices low to attract new entrants to the market and switchers from other firms. The first effect usually dominates. In the Part D setting the prediction of consistent price increases is even more stark because the second, offsetting effect is very small: consumer inattention (or asymmetric search costs) imply that enrollees in one plan rarely notice other plans' prices[37]. A critical element of these models 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. In a further complication, there are LIS consumers in the marketplace, some of whom are very elastic. The firm's problem is to set a single price for the searching consumers, the inattentive consumers (LIS and non-LIS), and the auto-assigned LIS consumers.

Table 13 shows that, consistent with the predictions above, 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. The second panel of Table 8 flags plans that raise premiums by more than \$10. 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.

[37]The papers on consumer search and learning referenced above (e.g. Cabral and Fishman (2012)) also consider how firms price in response to consumer search. They contain similar intuition and make the point that the equilibrium outcome for prices depends on the size of the search cost relative to the variation in firm costs of production.

Table 13: 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	33.33%	40.74%	0.33%	10.53%
2008	\$4.65	\$11.50	\$5.93	\$14.45	39.29%	55.17%	24.10%	39.82%
2009	\$6.20	\$7.12	\$3.68	\$4.39	24.00%	33.33%	0.83%	39.31%
2010	\$5.06	\$1.77	\$2.92	\$5.44	21.74%	29.17%	1.19%	35.08%
2011	\$1.04	\$14.33	-\$3.09	\$2.84	11.11%	73.33%	6.50%	24.48%
2012	-\$1.24	\$6.52	\$1.97	\$2.02	12.50%	42.86%	0.16%	16.38%

Notes: Summary of premium changes ($ per enrollee per month) over time for New Jersey PDPs, by Year and Plan Type

Table 14: Estimated Coefficients from Regression on Annual Premium Increases ($)

	Model 1		Model 2		Model 3		Model 4	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Lagged Premium	-0.177***	0.008	-0.165***	0.008	-0.177***	0.008	-0.165**	0.008
Lagged # Tier 1 Drugs	0.040***	0.005	0.037**	0.005	0.035**	0.005	0.031***	0.005
Lagged Deductible	-0.009***	0.001	-0.008***	0.001	-0.009***	0.001	-0.007***	0.001
Lagged Enhanced	1.448***	0.334	1.617***	0.335	1.442***	0.333	1.623***	0.334
Lagged Gap Coverage	5.773***	0.395	5.552***	0.396	5.750***	0.394	5.505***	0.396
Lagged Market Share	-	-	6.227***	1.220	-	-	6.716***	1.228
Enrollment Growth Rate	-	-	-	-	-3.288**	1.148	-4.011**	1.154
Brand FE?	Yes		Yes		Yes		Yes	
Region FE?	Yes		Yes		Yes		Yes	
N	7,796		7,796		7,796		7,796	
R^2	0.274		0.276		0.274		0.277	

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

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 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), but rather in premium changes. It is the increase in price that becomes more lucrative with an increase in installed base. We 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 14 reports the results of the main specification. When we control 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. The estimates also indicate 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) and Farrell and Klemperer (2007).

A further issue is that firms can sponsor more than one plan to offer more than one price. The work of Ericson (2012) and Decarolis (2015) leads us to investigate whether there is evidence of segmentation of consumers and price discrimination. In particular, the entry of basic "sister" plans may allow an existing plan to convert to enhanced status and raise its premium. The low-priced sister plan could enable the insurer to "catch" some enrollees who are auto assigned, or actively switch, to a low-priced plan. If carriers engage in this kind of consumer segmentation and "cycling", we should see higher premium growth of an existing plan when a new plan is added to the carrier's portfolio. The results of specifications including indicators for "sister" plan entry are provided in Appendix Table A12. We consider the impact of adding any "sister" plan and also the effect of adding a low-cost option: a plan whose premium is the lowest offered by the relevant carrier in the market. In both specifications, the relevant coefficient is negative and significant, implying that on average plan premiums actually *fall* when a sister plan is introduced. We conclude that, in contrast to Ericson (2012) and Decarolis (2015), in our sample there is no evidence of higher-than-average premium increases when the carrier adds a new plan to the portfolio. Therefore, we will not model this cycling behavior in the simulations below.

7.3 Insurer Cost Estimates

Our next step is to use accounting data (our claims data from New Jersey) to estimate each plan's average cost per enrollee. These costs will be used as an input to the counterfactual premium simulations in the following section.

The claims data indicate the gross drug cost for every claim, including the drug ingredient cost plus the dispensing fee and sales tax paid to the pharmacy, but not accounting for manufacturer rebates or plan administrative costs. For each branded drug we find the average gross drug cost of a thirty-day supply across all plans and all encounters in the relevant year and apply a 20% rebate to that average cost. For generic drugs we assume a $4 cost per 30 day supply for all plans[38]. We use these figures, and the observed drug utilization for each enrollee, to predict an average drug cost net of rebates per enrollee per year. Our methodology also accounts for the fact that, as part of its risk-adjustment strategy, the government covers 80% of all drug costs in

[38] A study by the Department of Health and Human Services Inspector General (Levinson (2011)) found that, in 2009, rebates reduced Part D drug expenditures by 19% on average for the 100 highest-volume brand name drugs. Our assumption regarding generic drug costs is based on Walmart's well known "$4 for any generic prescription" program.

the catastrophic phase so that the plan pays at most 20% of these costs.[39] We winsorize these estimated per-person costs at the 2.5% level (i.e. replace the top and bottom 2.5% with the 2.5^{th} and 97.5^{th} percentile, respectively), as there are several large outliers that would otherwise skew the average figure. We then compute the average per-person drug cost of the plan's beneficiaries. Finally we need to account for plan administrative costs. Sullivan (2013) notes that the National Health Expenditure Accounts (NHEA) includes the administrative costs of Medicare Advantage plans and Part D plans in its report of total Medicare administrative costs. We use this fact, and data from the NHEA for 2006-2010, to back out administrative expenses of 14-16% of total costs - or 16-19% of non-administrative costs - for Parts C and D combined. We therefore inflate the estimated average plan-level drug cost per enrollee per year by 120% to account for administrative costs. Additional details on the construction of the cost estimates is provided in Appendix D.

Table 15: Bids and Estimated Plan Costs for New Jersey PDP Plans

	Observed Bid	**Observed Premium**	**Predicted Cost**	**Pred. Cost net of TrOOP**
2006	\$65.03 (\$26.68)	\$24.00 (\$10.23)	\$145.56 (\$39.10)	\$75.00 (\$26.23)
2007	\$64.93 (\$25.76)	\$25.05 (\$11.92)	\$162.24 (\$37.78)	\$84.86 (\$19.01)
2008	\$92.28 (\$31.04)	\$35.29 (\$15.83)	\$153.18 (\$43.43)	\$85.60 (\$33.00)
2009	\$100.97 (\$29.90)	\$40.34 (\$15.22)	\$154.03 (\$40.69)	\$87.90 (\$40.53)

Notes: Summary of weighted average observed bids, observed premiums, predicted costs to the plan, and predicted costs net of enrollee out-of-pocket payments. All figures are per enrollee per month. Weighted standard deviations in parentheses; weighted by enrollment.

The resulting plan costs per enrollee are summarized in Table 15. We report weighted averages and standard deviations of both the total cost per enrollee and the estimated cost net of enrollee out-of-pocket payments[40]. The latter will be the cost variable used as an input into the premium-setting simulations below. Finally we report for comparison the weighted average observed bid and observed premium separately for each year of our data. Observed bids are about \$10 lower than predicted costs net of TrOOP on average in 2006, the first year of the program. Observed bids fall slightly in the second year, and this together with an increase in estimated costs implies a lower average markup. Bids increase much faster than predicted costs in the following two years.

The plan markup does not equal the bid less the cost and for this reason we do not report a markup estimate based on these data. Plan revenues also include an additional premium amount for enhanced plans plus reinsurance payments from CMS. The plan profit equation in Section 8 provides more details of these elements of revenue. For now we note that the estimates in Table 15 clearly indicate that plan margins did not converge towards zero over the first few years of the program.

[39]In most cases the beneficary pays a 5% copay in the catastrophic phase, so for branded drug events we assume the plan pays 15%. Fewer than 5% of enrollees reach this phase so this has little effect on predicted plan costs.

[40]We truncate the plan-level average cost net of OOP payments at zero; this step involves only a few plans.

8 Counterfactual Simulations

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. (2012) provide information to Part D enrollees regarding their best plan choice, and find that it increases the probability of switching by 11 percentage points.[41] Abaluck and Gruber (2013) 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 simulate the impact of policy experiments that "switch off" particular components of consumer choice frictions. Perhaps more importantly, they do not account for plans repricing in response to changes in consumer behavior, potentially further lowering program costs. In this section we address both issues.

Our demand model allows us to remove the different sources of consumer choice error. We then use the firm cost data set out in the previous section, together with a model of firm behavior, to consider price changes in response to the changes in consumer choices. The key insight is that when consumers choose more easily or more wisely, the insurer chooses to set a different price. In particular, more elastic (attentive) consumers will cause plans to set lower prices. The impact of more attentive consumers will appear not just in out of pocket costs, but in reduced premiums that plans choose to charge in order to attract those consumers. These lower premiums affect overall program costs and are therefore very important to take into account when assessing any policy change that affects choice frictions.

We conduct two sets of simulations. The first predict the effect of reduced consumer inattention holding plan prices fixed. The second allow plans to adjust their prices in response to the changes in consumer behavior. We make some modeling choices that apply to both simulations. We simulate consumer and plan choices using the entire New Jersey PDP sample, but report premium and spending changes for a fixed set of 40 plans that entered the New Jersey market in 2006; we follow each plan through to its exit from the market[42]. By limiting ourselves to these 40 plans we ensure that the reported numbers focus only on within-plan price and spending changes[43].

Our baseline simulations, which predict spending in the world where consumers are inattentive, use our demand estimates to predict inattentive consumers' choices conditional on the premiums we observe in the data. We compare the predicted spending from this exercise to that from a counterfactual where we predict *both* premiums and consumer choices when consumers become attentive. We note that this approach has the limitation that we compare an outcome from observed premiums (in the baseline) to predicted premiums (in the counterfactual scenario). To the extent

[41] While the rather modest efficacy of this experiment may in part be explained by the relatively low dollar amounts at stake in Medicare Part D and the reduced cognitive capacity of older beneficiaries, Cronqvist and Thaler (2004) document similar experiences with an advertising campaign intended to deter people from selecting the default option following a redesign of the Swedish pension system. The confirmation of these results among younger participants with greater stakes suggest that they are not a feature unique to Medicare Part D.

[42] There were actually 44 PDP plans in New Jersey in 2006 (Table 12); as noted in Appendix A, we drop the smallest plans in the sample, so we focus on 40 of these 44. 31 of the 40 plans were still active in 2009.

[43] Results using the entire sample of New Jersey PDP plans in every year, available from the authors, generate very similar percent savings estimates.

that the observed path of premiums increases over time for reasons other than the invest-then-harvest incentive that is our focus, the results in section 8.2 will over-estimate the price effects of removing inattention. Possible reasons for such premium increases include LIS cycling as in Decarolis (2015); insurer learning over time after mis-pricing (setting lower-than-optimal premiums in early years from the insurer's point of view); and low pricing in early years to attract enrollees with the goal of switching them to MA plans. However, we showed in the previous section that there is no evidence of premium cycling in our sample. Similarly, the MA plan market share is low in New Jersey, at 18% of total PDP enrollment in 2006, and it increased very little in the period of our sample. Another possible cause of premium increases is firm learning. Estimated firm costs net of TrOOP (Table 15) increased by 13% from 2006-7 and then were flat or increasing over time. In contrast firm bids, which determine their premiums, fell substantially from $90.52 in 2006 to $79.64 in 2007 (Table 19). We infer from this sharp reduction in bids, despite the cost increase, that there was substantial uncertainty among insurers regarding their costs in the initial period which led to *higher*-than-optimal bids in 2006. Since bids fell in 2007 and then increased fairly smoothly over time, it seems likely that the majority of firm learning took place in the first year of the program. Our savings estimates therefore exclude the year 2006. To the extent that firms were still learning, and still over-bidding in early years relative to optimal levels, this should reduce the premium growth in the data and therefore make our estimates conservative. We conclude that, while it is still possible that other explanations for our estimated savings numbers exist, the leading alternative explanations to our inattention story are unlikely to generate upwards bias on our estimates.

One alternative approach to our counterfactuals would have been to simulate the dynamic path of premiums in the baseline model with inattention. However, predicting the equilibrium of a dynamic pricing game with many firms is difficult. Papers on the methodological frontier have either considered very simple markets with two firms and small numbers of consumer types (e.g. Dube et al (2010)) or made other simplifying assumptions, e.g. of a finite time horizon, or the simplification that markets are large enough that the random evolution of individual firms "averages out" and each firm can be assumed to respond to a long-run average industry state rather than the predicted current choices of its competitors (Weintraub et al (2008) and applications such as Miller (2014)). None of these assumptions seems reasonable in our setting, and making them would have prevented us from assessing the effect of inattention on the whole PDP market. In addition, the existence of low-income subsidy enrollees makes our application even more complex. It would not be feasible to include their effect in a simulated dynamic baseline model, so this approach would ignore them entirely. By using the observed path of premiums as a baseline we ensure that LIS enrollees' impact on firm pricing in the baseline scenario is taken into account. Our counterfactual price simulation without inattention has premiums that are likely to be biased up because it ignores the effect of highly elastic auto-enrolled LIS recipients. Our estimate of the savings from moving to the counterfactual is therefore probably biased down. Thus our method allows us to conclude - as the alternative approach would not - that our overall estimates provide a conservative measure of the cost savings from removing inattention in the current, complex system where the LIS and non-LIS programs are connected through plan pricing.

8.1 Simulations Holding Prices Fixed

We begin with the simple counterfactuals that hold premiums fixed at their observed levels. We simulate the effect of changing the Part D plan choice mechanism in a way that makes consumers actively re-optimize their plan choices each year (i.e. removes the effect of consumer inattention). This could potentially be accomplished by replacing the existing default, under which each consumer remains in her current plan unless she chooses to switch, with the default that she exits the program[44]. Choices are predicted using the estimated preferences from Table 11 except that we suppress the effect of past shocks on preferences: shocks no longer have any effect when all consumers re-optimize each year[45]. In order to compare simulated-to-simulated choices, we also predict choices under the full frictional model specified in Section 6.2 and treat these estimates as the "baseline".[46]

Our next 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 the average of her five lowest expected-cost plans, if moving would save her at least $200 on average. We consider this policy for two reasons. First it removes all sources of consumer overspending rather than just inattention. By involving a pharmacist in the choice process, who is assumed to use the online CMS plan finder tool, we remove all choice frictions and unambiguously place the enrollee in one of the lowest expected-cost plans (although we note that, due to acute shocks, it may not turn out ex post to be the cheapest plan in the current year).[47] Our simulation assumes the pharmacist is independent of all insurers, and has no mechanism to let the insurer compensate or incentivize the pharmacist. Other enrollees, whose choices are predicted to be within $200 of the optimal choice, continue to make choices based on our two-stage demand model. While eliminating inattention and restricting poor choices may be an unrealistically low-cost simulation, we want to highlight how this market would work if the shoppers in it were both skilled and attentive. This is important because there are policy choices the government can make that would also change these attributes and we wish to investigate their economic impact.

Finally we conduct a slightly different pharmacist-based simulation. Here we address an issue with the previous counterfactual: the allocations made by the pharmacist in that simulation

[44]Heiss et al. (2006) suggests that few consumers would choose to exit the program rather than re-optimizing.

[45]This is consistent with a model where the increased importance of a plan characteristic following a shock is due to its relevance in prompting the consumer to re-optimize. However, we note that the results are similar if shocks are allowed to interact with preferences.

[46]Details of how these choices are simulated are provided in Appendix D.

[47]Note that the real-world logistics of this policy simulation would not be difficult. A well-organized pharmacy chain would run optimization software based on the previous year's utilization on each customer due to collect a prescription. When the customer arrived in the store the customer's record would prompt the pharmacist to say, "Mrs Smith, you know you could save $400 next year if you changed to XYZ plan? Sign here." We abstract from the possibility that the pharmacist's choice would be constrained by pharmacy networks. Likely a consumer is at the pharmacy because it is geographically convenient, so this may be a reasonable assumption.

overrode consumer choices that were partly due to preferences for non-price characteristics (e.g. the brand and enhanced fixed effects in our model) which may have led to overspending by our definition but did not correspond to choice mistakes. To address this we consider an analogous policy, except that now the pharmacist is paid \$50 for moving enrollees to another plan *within the same brand* if this would save over \$200 in expectation. This simulation removes overspending due to consumer choice frictions while respecting their preferences for particular insurance carriers.

8.2 Allowing Insurers to Change Prices

The second set of counterfactuals allows plans to change their prices. We focus on the simple counterfactual where consumer inattention is removed and preferences are not affected by shocks experienced in the previous year. 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 in our simulations than in the data.

It is important at this point to fix ideas concerning the pricing freedom Part D insurers have. Recall that each insurer submits a bid for each plan. That bid determines the price consumers face (by the amount over the base beneficiary premium). Importantly, each basic plan must offer actuarially equivalent coverage if it does not follow the tariff set out by law. This means that for a statistical person, the mean of OOP charges must be the same in expectation for all basic plans, so plans cannot respond to increased consumer premium sensitivity by reducing premiums while increasing average OOP charges. Additionally, the subsidy for each enrollee is risk-adjusted depending on age, chronic conditions, LIS, and institutional status. While the risk-adjustment mechanism is potentially manipulable, risk-adjusted subsidies plus the high share of catastrophic costs paid by CMS (80%) mean it will be difficult for firms to immediately determine if LIS enrollees are profitable or not, and the computation will be complex. In all years we see many plans setting premiums that seem designed to qualify for LIS benchmark status, so we infer that this segment is not unprofitable. This assumption allows us to abstract from selection issues as we model the behavior of insurers. We model insurers' choices of bids while holding the schedule of OOP charges fixed.

We write plan j's variable profit in year t as:

$$\pi_{j,t} = (B_{j,t} + E_{j,t} - C_{j,t})N_{j,t} \tag{6}$$

where $B_{j,t}$ is the bid made to CMS reflecting the plan's average monthly revenue requirement per enrollee in a basic plan (including profit), $E_{j,t}$ is the additonal amount charged to enrollees in an enhanced plan (the "enhanced premium"; this is zero when j is a basic plan), $C_{j,t}$ is the plan's cost per enrollee net of enrollee OOP payments and $N_{j,t}$ is its number of enrollees.

The premium charged to enrollees in a basic plan is the difference between the bid and the proportion of the NAMBA that is subsidized by the government:

$$Premium^{Basic}_{j,t} = B_{j,t} - \gamma_t NAMBA_t = (1 - \frac{\gamma_t}{J_t})B_{j,t} - \frac{\gamma_t}{J_t}\Sigma_{k \neq j} B_{k,t} \qquad (7)$$

where γ_t is the proportion of the NAMBA that is paid by the government and J_t is the number of Part D plans included in the average in year t.[48] This expression reflects the fact that, in the first two years of the program, the NAMBA was an unweighted national average of bids for all MA and PDP plans. From 2008 on, CMS phased in the implementation of a weighted average, where the weight was the plan's enrollment.[49]

We take several steps to account for CMS's risk adjustment strategy. The government subsidy, which is written into law at 74.5% of the NAMBA, is split between a premium subsidy and reinsurance or risk adjustment payments. The latter include a commitment to pay 80% of the total cost of drugs above each enrollee's catastrophic threshold and payments to keep plans within symmetric risk corridors that limit their overall losses and profits. We adjust our measure of plan costs per enrollee to take account of the catastrophic drug subsidies as described in the previous section. We use the true proportion of the NAMBA that is paid by the government in every year (which is observed in our data, e.g. 66% in 2006) as an input to the premium calculation in equation (7). We assume that the remaining risk adjustment payments neutralize the effect of enrollee selection on plan costs, i.e. the cost per enrollee does not change with enrollees' plan choices in our simulations.

We implement the "no inattention" assumption by considering a single-stage consumer demand system. We use the estimated parameters of the choice equation in model 4 of Table 11 but set the coefficients on premium, coverage and acute health shocks to zero. The resulting utility equation can be written as:

$$\begin{aligned} u_{i,j,t} &= Tr\hat{O}OP_{i,j,t}\beta_1 + Premium_{j,t}\beta_{2,1} + Ded_{j,t}\beta_{3,1} + Gap_{j,t}\beta_{4,1} + X_{j,t}\beta_{5,i} + \epsilon_{i,j,t} \\ &= \lambda_{i,j,t}(\beta_{5,i}) + \beta_{2,1} Premium_{j,t} + \epsilon_{i,j,t} \\ &= \delta_{i,j,t}(\beta_{5,i}) + \epsilon_{i,j,t} \qquad (8) \end{aligned}$$

where $Premium_{j,t}$ includes the enhanced premium where relevant. $\lambda_{i,j,t}(.)$ includes all consumer and plan-specific variables in the estimated utility equation except the premium; it is a function of $\beta_{5,i}$, the random coefficients on the three dominant brands and the enhanced plan fixed effect. This

[48] CMS requires that the basic premium never fall below zero. This constraint is not binding for PDPs in our data because MA-PDs, which bundle prescription drug insurance with Medicare Part C insurance and whose bids are included in the NAMBA, often have very low premium bids. However we account for this truncation in the simulations that predict equilibrium bids when inattention is removed.

[49] The premium charged to enhanced plan enrollees is the basic premium defined in equation (7) plus the enhanced premium $E_{j,t}$. The enhanced premium is negotiated between the carrier and CMS and is meant to comprise the average additional cost of enhanced benefits provided to enrollees in the plan. It is not subsidized by CMS. We observe this variable in the data for every plan-year and account for it in our simulations under the assumption that it does not change in response to simulated changes in enrollee behavior.

utility equation can be used to predict plan enrollment $N_{j,t}$ under any set of plan characteristics:

$$\begin{aligned} N_{j,t} &= \sum_{i=1}^{N_t} \int_{\beta_{5,i}} \frac{e^{\delta_{i,j,t}(\beta_{5,i})}}{\sum_{k=1}^{J_t} e^{\delta_{i,k,t}(\beta_{5,i})}} \, \partial F(\beta_{5,i}) \\ &= \sum_{i=1}^{N_t} \int_{\beta_{5,i}} \Lambda_{i,j,t}(\lambda_{i,j,t}(\beta_{5,i}), \lambda_{i,-j,t}(\beta_{5,i}), Premium_{j,t}, Premium_{-j,t}) \, \partial F(\beta_{5,i}). \end{aligned} \tag{9}$$

Here $\Lambda_{i,j,t}(.)$ is the predicted probability that consumer i chooses plan j in period t; it is a function of all plan characteristics including their premiums. We consider plans' optimal choices in the static bid-setting game that results from removing consumer choice frictions. The first-order condition for plan profits with respect to the bid $B_{j,t}$ is:

$$(B_{j,t} + E_{j,t} - C_{j,t}) \frac{\partial N_{j,t}}{\partial B_{j,t}} + N_{j,t} = 0. \tag{10}$$

Calculating the derivative $\frac{\partial N_{j,t}}{\partial B_{j,t}}$ requires us to predict the effect of a change in the bid $B_{j,t}$ on the premium. We use the expression in equation (7) under the assumption that the NAMBA is an (unweighted) national average for MA-PD and PDP plans and that plans internalize their impact on the NAMBA, and therefore on the government subsidy, when choosing their bids[50]. We predict the resulting effect on enrollment using equation (9). The first order condition simplifies to:

$$\begin{aligned} N_{j,t} + (B_{j,t} + E_{j,t} - C_{j,t}) \Big\{ \Sigma_{i=1}^{N_t} \beta_{2,1} [\int_{\beta_{5,i}} \Lambda_{i,j,t}(.)(1 - \Lambda_{i,j,t}(.)) \, \partial F(\beta_{5,i})] \frac{J_t - \gamma_t}{J_t} \\ + \Sigma_{k \neq j} \beta_{2,1} [\int_{\beta_{5,i}} \Lambda_{i,j,t}(.) \Lambda_{i,k,t}(.) \, \partial F(\beta_{5,i})] \frac{\gamma_t}{J_t} \Big\} &= 0 \end{aligned}$$

where we omit the arguments of $\Lambda_{i,j,t}(.)$ for ease of exposition. All plans' bids enter this equation through $\Lambda_{i,j,t}(.)$ as well as through $B_{j,t}$. We solve this system of equations to obtain the implied new equilibrium for bids.[51]

8.3 Simulation Results

The simulation results are set out in Tables 16-19. Table 16 considers the impact of altering consumer behavior without allowing premiums to change in response. The column labeled "baseline" in Table 16 shows the cross-enrollee average of annual premium costs and OOP costs (including premiums) predicted by our demand model including all frictions.[52] The second column ("Lowest Predicted Cost") shows the same simulated costs when every enrollee chooses the plan with the

[50] We account for the fact that a change in one plan's bid will affect all plans' premiums via the subsidy. We use national NAMBA figures published in annual press releases as an input to this analysis. The bid-setting game is solved for NJ PDP plans, holding fixed the bids of other plans that contribute to the NAMBA.

[51] Additional details of this derivation are provided in Appendix D.

[52] The "baseline" in Table 16 is slightly different from the panel labeled "Full Sample" in Table 4 because the baseline in Table 16 uses predicted choices from our demand model rather than the choices observed in the data.

Table 16: Simulated Per-Person Spending Holding Premiums Fixed

	Baseline		Lowest Pred. Cost		Lowest 5 Average		No Inattention	
	Premium	**OOP**	**Premium**	**OOP**	**Premium**	**OOP**	**Premium**	**OOP**
2006	$304.21	$1,206.20	$124.54	$790.20	$214.20	$948.40	$304.21	$1,206.20
2007	$330.49	$1,230.30	$232.74	$857.32	$270.22	$949.72	$312.29	$1,200.00
2008	$468.96	$1,288.80	$261.53	$820.94	$282.30	$900.24	$404.41	$1,203.90
2009	$479.15	$1,336.80	$290.19	$819.75	$338.94	$954.02	$449.60	$1,282.00
Total '07-09	$1,278.60	$3,855.90	$784.46	$2,498.01	$891.46	$2,803.98	$1,166.30	$3,685.90
Saving	-	$0	-	$1,357.89	-	$1,051.92	-	$170.00
% Fixed	-	0%	-	100%	-	77.5%	-	12.5%

Notes: Results of counterfactual simulations holding premiums fixed at observed levels. Simulated OOP costs are cross-enrollee averages per enrollee per year including premiums. Premiums include both basic and enhanced premium.

lowest predicted costs to her in the relevant year; this is the lowest-cost outcome possible. Column 3 shows the average simulated costs from the average of the five lowest predicted-cost choices for each enrollee. Column 4 shows costs simulated using the "no inattention" model. In each column, the row labeled "Total" provides cumulative spending per enrollee over the three years 2007-9[53]. "Saving" is the difference between that cumulative three-year spending and the spending in the baseline scenario, and "% Fixed" is the proportion of the saving from moving every consumer to her lowest-cost plan that is achieved by the relevant counterfactual.

Substantial savings could be achieved in every year if enrollees could be switched to their lowest-cost plan. Cumulative savings over the three year period from this change would be approximately $1,358 per person, or 35% of the total baseline OOP cost. The total saving from moving each enrollee to the average of her five lowest-cost plans is $1,052 or 78% of the total current excess spending of the enrollee. The savings from removing inattention begin in 2007 with a total saving of approximately $30 per person and rise to $85 per person in 2008 and $54 per person in 2009. Overall the model predicts that the average consumer saves $170 cumulatively across the three years when frictions are removed, or 12.5% of total excess spending. While these savings are non-trivial, they represent a fairly small proportion of the total amount the consumer could save. This is unsurprising given that consumers rarely choose the lowest-cost plan available when they do actively choose. We should not expect our simulations to bring overspending below the level reached by observed switchers in the data; that level, defined as a percent of total spending, is approximately 26-28% (Table 4) and our simulations generate errors of a comparable magnitude. We also note that, since our demand estimates indicate consumers respond strongly to premiums, a substantial part of the savings from removing inattention should come from consumers choosing low-premium plans. Consistent with this intuition, 66% of the savings from removing inattention come from lower premiums. Savings are concentrated in later years when the baseline choices are most affected by inattention.

[53]We ignore potential savings in the first year of the program since consumers or firms needed to guess at entry strategies and were likely still learning.

Table 17: Simulated Per-Person Spending, Premiums Fixed, Pharmacist Simulations

	Baseline		Lowest Pred. Cost		Pharma		Pharma w/in-Brand	
	Premium	OOP	Premium	OOP	Premium	OOP	Premium	OOP
2006	$304.21	$1,206.20	$124.54	$790.20	$224.17	$990.94	$279.09	$1,126.41
2007	$330.49	$1,230.30	$232.74	$857.32	$271.00	$1,010.04	$284.50	$1,112.49
2008	$468.96	$1,288.80	$261.53	$820.94	$314.24	$968.95	$383.56	$1,125.56
2009	$479.15	$1,336.80	$290.19	$819.75	$368.05	$1,021.18	$440.69	$1,193.26
Total '07-09	$1,278.60	$3,855.90	$784.46	$2,498.01	$953.29	$3,000.17	$1,108.75	$3,431.31
Saving	-	$0	-	$1,357.89	-	$855.73	-	$424.59
% Fixed	-	0%	-	100%	-	63.0%	-	31.3%

Notes: Results of counterfactual simulations holding premiums fixed at observed levels. "Pharma" is pharmacist. Simulated OOP costs are cross-enrollee averages per enrollee per year including premiums. Premiums include both basic and enhanced premium.

Table 17 repeats the baseline and lowest-cost estimates for comparison and shows the simulated outcomes in the policy experiments where pharmacists are involved in plan choice. The OOP costs include the $50 payment to the pharmacist per switched enrollee. In column 3 the pharmacist can move the enrollee to any plan[54]; in column 4 she can be moved only to other plans within the same carrier. The "no inattention" counterfactual demonstrated that approximately 13% of spending above minimum levels was due to consumer inattention. The "pharmacist" counterfactuals address the remaining 87% which is attributable to other factors such as enrollees placing a high weight on particular characteristics (e.g. brand, premium or gap coverage) rather than minimizing overall costs. As shown in Columns 3 and 4 of Table 17, pharmacists are very effective in reducing costs. Even though the payments made to pharmacists are included in the OOP costs, the first pharmacist counterfactual generates savings of $856 per enrollee over the three year period, or 63% of the total baseline error. Approximately 65% of enrollees are switched to low-cost plans by the pharmacist. While we note 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. We also note that, when the pharmacist is restricted to moving enrollees to other same-carrier plans, the savings fall to 31% of the total baseline error. While consumers may have preferences for particular brands, and this may be one reason why they do not choose the lowest-cost plan available, the benefit to the enrollee from staying within-brand may not be as great as the cost.

Tables 18 and 19 report our key results. Here we see the "no inattention" simulations when we allow prices to adjust. Consider first the cross-plan unweighted average bids reported in columns 1 and 2 of Table 19[55] Recall that theory predicts plans should respond to consumer inattention by setting a low price initially and then increasing prices substantially every year. Removing inattention (i.e. increasing search) should lead to a higher year-1 price but a lower rate of price

[54] We use the average of the five lowest-cost plans for each enrollee. The savings from moving enrollees to the single lowest cost plan are approximately four percentage points higher.

[55] We report unweighted rather than weighted average bids because the predictions of theory relate to the prices set by firms, rather than sales-weighted prices.

Table 18: Simulated Per-Person Spending With Premium Adjustments

	Baseline (Fixed Premium)		Lowest Pred. Cost (Fixed Premium)		No Inattention (Fixed Premium)		No Inattention (Premium Change)	
	Premium	**OOP**	**Premium**	**OOP**	**Premium**	**OOP**	**Premium**	**OOP**
2006	$304.21	$1,206.20	$124.54	$790.20	$304.14	$1,206.10	$151.34	$1,067.70
2007	$330.49	$1,230.30	$232.74	$857.32	$312.29	$1,200.00	$251.78	$1,136.80
2008	$468.96	$1,288.80	$261.53	$820.94	$404.41	$1,203.90	$232.75	$1,054.20
2009	$479.15	$1,336.80	$290.19	$819.75	$449.60	$1,282.00	$191.15	$1,063.50
Total '07-09	$1,278.60	$3,855.90	$784.46	$2,498.01	$1,166.30	$3,685.90	$675.68	$3,254.50
Saving	-	$0	-	$1,357.89	-	$170.00	-	$601.40
% Fixed	-	0%	-	100%	-	12.5%	-	44.3%

Notes: Results of counterfactual simulations allowing premiums to adjust to changes in consumer behavior. Simulated OOP costs are cross-enrollee averages per enrollee per year including premiums. Premiums include both basic and enhanced premium.

Table 19: Counterfactual Government Savings

Year	Observed Bid (Unw. Ave)	Simulated Bid (Unw. Ave)	γ_t	Annual ($) Ave Savings	Non-LIS Enrollment	Savings ($ million)
2006	$90.52	$77.79	0.65			
2007	$79.74	$79.22	0.66	$4.18	8,120,524	$34 million
2008	$85.45	$87.23	0.65	-$13.86	8,413,202	-$117 million
2009	$93.22	$89.82	0.64	$26.11	8,572,910	$224 million

Notes: Results of Program Cost Savings Calculation. Columns 1 and 2 are unweighted average bids, observed and simulated, for PDP plans in NJ, measured in $ per enrollee per month. Per-member average savings are the difference between the two average bids scaled by the proportion paid by the government and annualized. Non-LIS enrollment reported in national plan data generously provided by Francesco Decarolis. γ_t is defined in Section 7.

increases in later years. The observed and simulated bids reported in Table 19 for 2007-2009 are consistent with this intuition. The average simulated bid in 2007 is very similar to the average observed in the data for NJ PDP plans; both are approximately $79 per enrollee per month. Simulated bids then increase by 13% between 2007-2009, while the observed version has higher growth (particularly in 2008-9), increasing by 17% over the same time period. The bids for the year 2006, in contrast, are not consistent with the theory. The observed bid, which we expect to be low in 2006, is much higher than the simulated version ($90.52 compared to $77.79 in the simulation without inattention). This strongly suggests that firms were bidding based on limited information about their costs, and competitor pricing strategies, in the first year of the program. It is the reason why we exclude the year 2006 from our savings estimates.

Table 18 translates the bids into average per-enrollee premium and OOP spending figures analogous to those in Table 16. The first three columns are repeated from Table 16 for ease of comparison: these are the baseline, the lowest-cost plan and the no inattention scenarios, all holding prices fixed. Column 4 reports the results when we allow plans to re-optimize prices. Simulated premiums are lower than the fixed price level in every year for two reasons: the difference between observed and simulated bids (Table 19) and the fact that enrollees choose low-premium plans (particularly when inattention has been removed)[56]. These results indicate a large saving from the simulated changes in consumer behavior. While removing inattention resulted in only small reductions in costs, once premiums are allowed to adjust the savings are substantial. Plans respond to the newly attentive, premium-sensitive enrollee market by reducing their premiums and consumers move to the new low-premium plans. The results in the fourth column of Table 19 indicate a total out-of-pocket cost saving (including premiums) of $601.40 per enrollee over three years or 44% of total spending above the minimum.

Given that consumers choose plans so poorly, it is somewhat surprising that their overall saving is so large. The reason is that consumers put a heavy weight on premiums in the utility equation. Newly attentive choosers are attracted to plans with low premiums even if they are unable to locate the lowest cost plan for themselves. Savings are particularly large in cases where the cross-plan variance in premiums is high, making it relatively easy for attentive consumers to find a low-premium plan.[57]

If we are willing to assume that our New Jersey estimates can be extrapolated to the entire nation, we can calculate the implied government savings for enrolled consumers over the years 2007-9. These savings are substantial. Program cost savings result mostly from the slower growth in plan bids, of which the government pays a sizeable proportion. As shown in Table 19, bids in the counterfactual grow more slowly than in the baseline, and by 2009 the average bid is roughly $41 lower per year in the counterfactual than in the baseline. Applying the conservative assumption that reinsurance costs remain fixed so that the government saves a fraction of the difference in average bids equal to one minus the Base Beneficiary Percentage (γ_t in Section 8.2), we find that government savings come to $26.11 per covered life by 2009.[58] Assuming further that low-income subsidy payments are unaffected and multiplying this figure by the non-LIS PDP population in each year generates an estimate of the government's total savings from reduced bids. In the first one to two years the savings are small but they increase over time: by 2009 we predict savings of $224 million, or 4.1% of the government's cost of this part of the program[59]. Clearly we have made multiple assumptions to arrive at these numbers. However, when combined with the theoretical results discussed in Section 7, our estimates are sufficient to provide clear evidence that removing

[56]The Table 19 bid numbers are unweighted averages across plans, consistent with the method used to calculate government program costs in the first few years of the program. In contrast Table 18 reports averages across enrollees rather than plans. Consumers tend to choose lower-premium plans, particularly in the simulations without inattention.

[57]This helps explain the much larger consumer savings in the "Premium change" simulation than in the "fixed premium" version without inattention. For example, in 2009, the unweighted average observed premium is $47.48 per month (standard deviation $23.06). The unweighted average simulated premium, from the scenario without inattention, is $42.89 per month (standard deviation $35.42). The difference in unweighted averages is only around $5 per month or $60 per year, but the larger variance in simulated premiums allows attentive consumers to endogenously choose lower-premium plans in the second scenario.

[58]We use unweighted average bids for this calculation, consistent with the use of unweighted averages to calculate the NAMBA in the first few years of the program. Projected savings would be larger if we used weighted averages.

[59]This simple calculation assumes that, if inattention is removed nationally, the reduction in the NAMBA will be the same as the average predicted reduction in bids in NJ. The $220 million saving is 4.1% of the government's cost of subsidizing PDP premiums for non-LIS enrollees nationally.

inattention would lead to substantial savings by the third year after the change.

The CBO calculated that from 2007-10 the cost of the drug component of the basic benefit increased by 2.8% per annum on average for Part D enrollees while administrative costs and profits rose at 6.7%.[60] Premiums increased from a weighted average of $25.93 to $37.25 from 2006 to 2010 according to the Kaiser Family Foundation (Hoadley (2015)). This is the environment we explore with our data and seek to explain as rational pricing in the face of consumer inattention. Interestingly, the environment changed significantly in the second five years of the program. From 2010 to 2014 the rate of generic penetration increased significantly and the introduction of new branded blockbuster drugs slowed. National pharmaceutical expenditure actually fell in nominal terms in 2012 and 2013 according to IMS data (Schumock et al (2014)). However, from 2010 to 2015 stand alone Part D premiums rose from $37.25 to a high of $38.54 in 2013 and then declined to $37.02 by 2015 (Hoadley (2015)). Because drug costs fell modestly in those years, it is not clear what happened to the margins of the insurers participating in Part D. Ideally, what we would like to see from effective regulation is a reflection of costs in prices. That is, falling drug costs should benefit consumers in the form of falling premiums if a program is delivering the competitive benefits society expects. The available evidence suggests that this did not happen, adding weight to our hypothesis that consumer inattention limits the effectiveness of competition in this market. It may be the case that the underlying cost environment has changed again recently, as several sources report significant increases in specialty drug spending for 2014.[61] For example, the 2015 headline advice to consumers is: "Enrollees would face average 13 percent premium increase unless they switch plans."[62] Further research into the impact of consumer choice in Part D on competition is clearly warranted.

9 Conclusions

In this paper we have developed a model of consumer choice in the Part D program and have analyzed how firms set prices in response to the presence or absence of those behaviors. We find that the data support a model where consumers face costs of processing information. This leads them to avoid making new choices, rolling over their plan selections from one year to the next unless shocked by a change to their current plan or their current health. When making choices they place a substantial weight on brand; they may also under-weight predicted OOP payments relative to plan characteristics that are easier to observe such as premiums and gap coverage.

We provide evidence that firms' premium choices are responsive to consumers' search frictions. In particular, when consumers are attentive, firms are incentivized to lower their margins, resulting in lower premiums. Using our estimates of consumer behavior and a model of firm price-setting we simulate the cost effects of different counterfactual policies that could be used to address these issues. The benefit of removing inattention at fixed prices is fairly small, perhaps because consumers

[60]Figure 2-1 page 21 CBO report "Competition and the Cost of Medicare's Prescription Drug Program 2014".

[61]e.g. Express Scripts 2014 Drugs Trend Report

[62]Kaiser Family Foundation press release October 13, 2015

continue to face cognitive costs when making their new plan choice. However, when we simulate plans' premium choices, we predict a large price response to this change in behavior. Ironically, consumers' overweighting of premiums works to their advantage; as long as consumers are attentive, an effective way for plans to attract customers is by lowering premiums. Our simulations indicate that the combination of the demand- and supply-side changes would reduce the amount consumers spend relative to their lowest-cost options by 44%, even without addressing other choice frictions. The natural plan response of increasing other components of the price, like the OOP cost schedule, is constrained by the tightly regulated standard benefit levels. We also consider counterfactuals that involve the pharmacist in the plan choice process, particularly for those enrollees who overspend the most. These simulations predict even larger reductions in spending, although at the cost of overriding choices that reflect consumer preferences for non-price characteristics.

The role of plan re-pricing in response to more frequent and effective consumer search has not been analyzed to the best of our knowledge in the Medicare Part D economics literature to date. It is an important element in the evaluation of any policy that would help consumers choose better plans. In particular, while clearly the extrapolation of our New Jersey estimates to the national level should be interpreted with some caution, the implied government savings from consumer choice – $224 million per year by 2009 - indicate how important well-designed insurance marketplaces can be. Indeed, without effective consumer choice that puts market pressure on insurers, a policy of privatizing the delivery of benefits can be very expensive. This cost of privatization should be taken into account by policy makers. The Affordable Care Act creates health insurance exchanges that have similar characteristics to Medicare Part D. Policy makers may wish to choose features of market design in a way that helps generate competitive outcomes in light of our results.

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APPENDICES FOR ONLINE PUBLICATION

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 (OOP) 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

We partition the set of prescribed drugs into 464 common chronic drugs and all others. We assume that all other drugs treat acute conditions. We define the total cost per month supply for each common chronic drug in each plan to be the sample average cost per month for drug events where the supply length is between 7 and 90 days. This plan-specific average captures the effects of bulk discounts that particular plans negotiate with drug manufacturers.[63]

We approximate acute drug costs using a different method. We classify individuals into one of 7,040 "severity" 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 days' supply of chronic drugs, 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 drug cost 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.

We do not observe plan formularies; our next step is therefore to approximate the true formulary 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 has still not been assigned a tier, but it is observed for a plan offered by the same carrier, 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

[63]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).

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.

Finally, to generate counterfactual spending under each plan we step through the simulated sequence of drug events and generate counterfactual benefit phases and patient OOP payments according to the plan's stated cost structure, the estimated formulary, and cumulative spending for the year. Counterfactual OOP payments for each plan are estimated as the sum of OOP payments for the observed chronic drugs and simulated acute events for each beneficiary in each large plan every year. Note that, as in previous papers, our method assumes no moral hazard, and unlike Ketcham et al. (2012) we assume no elasticity with respect to plan prices for chronic drug consumption, in that patients take the same sequence of prescription drugs in every plan regardless of the costs they face. The plan-specific medians allow for some price elasticity for acute drugs for large plans. For simplicity we 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 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.

C Details on Demand Model Estimation

We estimate the model using simulated maximum likelihood. Let X_S and θ_S denote respectively the observed variables and parameters governing the decision to search, with X_C and θ_C analogously denoting the observed variables and mean values of the parameters governing the individual's choice of plan. Further let $\tilde{\theta}^R_{C,i}$ denote the R individual-specific random preference parameters, with associated observed variables X^R_C. We assume $\tilde{\theta}^R_{C,i} \sim MVN(\theta^R_C, \Sigma I_R \Sigma')$, where $\theta_C = \{\theta^R_C, \theta^{NR}_C\}$. Then for some individual-specific $R-$dimensional IID-$\mathcal{N}(0,1)$ vector ν_i, we can express utility as:

$$\begin{aligned}
u_{i,j,t} &= X_{C,i,j,t}\theta^{NR}_C + X^R_{C,i,j,t}\tilde{\theta}^R_{C,i} + \epsilon_{i,j,t} \\
&= X_{C,i,j,t}\theta^{NR}_C + X^R_{C,i,j,t}\nu_i\Sigma + \epsilon_{i,j,t} \\
&= \delta_{i,j,t} + \epsilon_{i,j,t}
\end{aligned}$$

The parameters to be estimated are then $\Theta = \{\theta_C, \theta_S, \Sigma\}$.

Estimation is complicated by two problems. First, the individual-specific component of preferences, $\nu_i\Sigma$, is unobserved. Second, we do not observe the individual's decision to search, only to switch plans, and must hence must estimate the probability of remaining in the current plan as a mixture over cases in which the individual searched and chose their current plan and cases in which the individual did not search. We can account for the second problem directly by writing the likelihood conditional on ν_i and Θ as a mixture:

$$\begin{aligned}
\mathcal{L}_{i,j,t}|\nu_i,\Theta &= \frac{e^{\delta_{i,j,t}}}{\Sigma_{k=1}^{K_t} e^{\delta_{i,k,t}}} \text{ if New Entrant} \\
\mathcal{L}_{i,j,t}|\nu_i,\Theta &= \underbrace{\frac{1}{1+e^{X_{S,i,t}\theta_S}}}_{\text{P(Search)}} \underbrace{\frac{e^{\delta_{i,j,t}}}{\Sigma_{k=1}^{K_t} e^{\delta_{i,k,t}}}}_{\text{P(Choose } j\text{)}} \text{ if Switching} \\
\mathcal{L}_{i,j,t}|\nu_i,\Theta &= \underbrace{\frac{e^{X_{S,i,t}\theta_S}}{1+e^{X_{S,i,t}\theta_S}}}_{\text{P(No Search)}} + \underbrace{\frac{1}{1+e^{X_{S,i,t}\theta_S}}}_{\text{P(Search)}} \underbrace{\frac{e^{\delta_{i,j,t}}}{\Sigma_{k=1}^{K_t} e^{\delta_{i,k,t}}}}_{\text{P(Choose } j\text{)}} \text{ if Not Switching}
\end{aligned}$$

where K_t is the number of plans offered in Year t. Let $C^1_{i,t}$, $C^2_{i,t}$, and $C^3_{i,t}$ be indicator functions for the chosen plan j being selected by respectively a New Entrant, Switcher, or Non-Switcher. We can thus account for the first problem by writing the likelihood conditional on Θ as the integral over all possible values of ν_i, which we assume is constant across years for a given individual:

$$\begin{aligned}
\mathcal{L}_{i,j,t}|\Theta &= \int_{\nu_i} [\frac{e^{\delta_{i,j,t}}}{\Sigma_{k=1}^{K_t} e^{\delta_{i,k,t}}}]^{C^1_{i,t}} + [\frac{1}{1+e^{X_{S,i,t}\theta_S}} \frac{e^{\delta_{i,j,t}}}{\Sigma_{k=1}^{K_t} e^{\delta_{i,k,t}}}]^{C^2_{i,t}} \\
&+ [\frac{e^{X_{S,i,t}\theta_S}}{1+e^{X_{S,i,t}\theta_S}} + \frac{1}{1+e^{X_{S,i,t}\theta_S}} \frac{e^{\delta_{i,j,t}}}{\Sigma_{k=1}^{K_t} e^{\delta_{i,k,t}}}]^{C^3_{i,t}} \, \partial\Phi(\nu_i)
\end{aligned}$$

We approximate this likelihood using simulation. Specifically, we take $S = 10$ $R-$dimensional fully independent draws $\{\nu_i^s\}_{s=1}^S$ from a standard normal distribution for each individual i and apply them to the individual for all years in which they are active in the data. At Step m of the likelihood maximization routine, for the current guess of $\Theta^{(m)}$ we compute $\mathcal{L}_{i,j,t}|\nu_i^s,\Theta^{(m)}$ for the individual's observed choice j and each ν_i^s and approximate the integral above with the sample average over the S draws. We then maximize the likelihood using KNITRO maximization software. In general the likelihood and integral are not exchangeable, and thus the gradient does not have a convenient closed-form expression; in particular the gradient is not in general equal to the integral over ν_i of the gradient conditional on ν_i. Hence in the maximization routine we use numerical gradients. However at the optimal maximum-likelihood parameter estimate $\hat{\Theta}$ the likelihood is linear in parameters, hence we can exchange the integral and gradient in order to compute standard errors directly, approximating the Hessian with the cross-product of the gradient as in Berndt et al (1974).

D Details on Counterfactual Simulation

In order to simulate plan pricing in the counterfactual, we first must construct an estimate of plan costs. In each year for each drug observed in the prescription drug event file, we categorize the drug as either branded or generic. For drugs that cannot be categorized, we label them as generic if their average cost is below the median among uncategorized drugs. Then for each branded drug and each year we generate the average cost per day's supply of the drug and apply it to each observed prescription, scaled by the observed supply length. We assume the cost net of rebates is 80% of this amount[64]. For generic drugs, we assume the cost is \$4 per month's supply and scale by the observed supply length[65]. For drug events in the catastrophic phase, we assume the plan pays 15% and the beneficiary pays 5%, while for all other events we treat the beneficiary's TrOOP payment as known. We sum these drug costs over beneficiaries to generate an estimated annual cost figure and annual TrOOP for each beneficiary. Then within each plan and year we winsorize by replacing estimated annual costs and annual TrOOP for the bottom 2.5% of beneficiaries with the 2.5% quantile, and analogously for the top 2.5%. These winsorized annual figures are then averaged within plan and year to generate estimates of benefit cost and TrOOP per covered life. Applying an administrative cost assumption of 16% of drug costs[66], we generate an estimate of total costs per covered life net of TrOOP, which treated as $C_{j,t}$ in Equation (6).

The second step in our simulation is to refine our estimates of each individual's unobserved type by using the information from their observed choices. Each individual i has random preferences $\tilde{\theta}^R_{C,i} \sim MVN(\theta^R_C, \Sigma I_R \Sigma')$. Denoting the distribution of random preferences as a function of our estimated parameters as $F(\tilde{\theta}^R_{C,i}|\hat{\theta}_C, \hat{\Sigma})$ with associated density f and the observed sequence of (possibly multiple) choices for individual i as C^{Obs}_i, we can write the conditional distribution of the individual's type as:

$$P(\tilde{\theta}^R_{C,i}|C^{Obs}_i) = \frac{P(C^{Obs}_i|\tilde{\theta}^R_{C,i}, \hat{\Theta}) f(\tilde{\theta}^R_{C,i}|\hat{\theta}_C, \hat{\Sigma})}{\int_{\tilde{\theta}^R_C} P(C^{Obs}_i|\tilde{\theta}^R_C, \hat{\Theta})\, \partial F(\tilde{\theta}^R_C|\hat{\theta}_C, \hat{\Sigma})}$$

Given $\hat{\Theta}$ and $\tilde{\theta}^R_{C,i}$ we can compute the likelihood of a given sequence of choices C^{Obs}_i directly using the formulas from Appendix C. We use this approach to construct the conditional density using simulation, approximating the integral in the denominator with $S' = 50$ simulation draws and drawing $S = 10$ values $\{\tilde{\theta}^{R,s}_{C,i}\}^S_{s=1}$ from the conditional distribution for each individual.

The next input to our analysis is a simulation of individuals' choices under various price regimes. For the purposes of simulating choices under the no inattention counterfactual, we can generate logit choice probabilities using the estimated demand model with frictions removed and sum across beneficiaries to generate market shares. The static nature of the choice problem makes this computation straightforward. For simulating choices under the baseline, the strong path-dependence implied by inattention makes simulating every possible path (of which there are $K_{2006} \times K_{2007} \times K_{2008} \times K_{2009} =$

[64] A study by the Department of Health and Human Services Inspector General (Levinson (2011)) found that, in 2009, rebates reduced Part D drug expenditures by 19% on average for the 100 highest-volume brand name drugs. We assume a slightly lower percentage to account for potentially lower rebates for lower-volume drugs.

[65] Our assumption for generic drug costs is based on Walmart's well known "\$4 for any generic prescription" program.

[66] Sullivan (2013) notes that the National Health Expenditure Accounts (NHEA) includes the administrative costs of Medicare Advantage plans and Part D plans in its report of total Medicare administrative costs. We use this fact, and data from the NHEA for 2006-2010, to back out administrative expenses of 14-16% of total costs - or 16-19% of non-administrative costs - for Parts C and D combined.

7,076,160) computationally infeasible. Instead, we opt for a Monte Carlo approach in which we generate choice probabilities in the initial year, randomly assign beneficiaries to plans according to these choice probabilities, generate shocks and switching probabilities using these simulated choices, and simulate forward. We draw $S'' = 10$ such sequences of choices and shocks for each beneficiary and average across simulation draws to construct our estimates.

Finally we use these inputs to solve for each plan's optimal bid under the counterfactual of no search frictions. With no frictions and conditional on their unobserved type $\tilde{\theta}^R_{C,i}$, the choice probability of each individual for each plan is of the simple logit form:

$$\tilde{\Lambda}_{i,j,t} = \frac{e^{X_{C,i,j,t}\theta_C^{NR} + X^R_{C,i,j,t}\tilde{\theta}^R_{C,i}}}{\Sigma_{k=1}^{K_t} e^{X_{C,i,k,t}\theta_C^{NR} + X^R_{C,i,k,t}\tilde{\theta}^R_{C,i}}}$$

while the unconditional probability is the integral over the filtered distribution from step 2:

$$\Lambda_{i,j,t} = \int_{\tilde{\theta}^R_{C,i}} \tilde{\Lambda}_{i,j,t}\, P(\tilde{\theta}^R_{C,i}|C_i^{Obs})\, \partial\tilde{\theta}^R_{C,i}$$

Plan j's enrollment in year t under the counterfactual is therefore:

$$N_{j,t} = \Sigma_{i=1}^{N_t} \Lambda_{i,j,t}$$

where N_t is the number of beneficiaries active in year t.

Denote the bid, base premium, enhanced premium and costs for plan j in year t by $B_{j,t}$, $P_{j,t}$, $E_{j,t}$, and $C_{j,t}$, respectively. Plan profits are a function of the bid, enhanced premium, costs, and enrollment, and plans choose their bid to maximize profit:

$$B_{j,t} = \underset{B}{ARGMAX}\ \pi_{j,t} = (B + E_{j,t} - C_{j,t})N_{j,t}$$

subject to the restriction that their premiums, and thus in part their enrollment, are determined by the Medicare Part D bidding mechanism, and are constrained to lie above zero:

$$\begin{aligned} P_{j,t} &= B_{j,t} - NAMBA_t + BBP_t + E_{j,t} \\ BBP_t &= BPP_t \times NAMBA_t \\ NAMBA_t &= \frac{1}{J_t}\Sigma_{k=1}^{J_t} B_{k,t} \\ P_{j,t} &\geq 0 \end{aligned}$$

Under the assumption that the Base Premium Percentage (BPP_t), enhanced premium and costs are exogenous, we can write the plan's premium in terms of its own and all other plans' bids, yielding an expression for the derivatives of plan premiums with respect to own- and other-plan bids:

$$\begin{aligned}
\frac{\partial P_{j,t}}{\partial B_{j,t}} &= \frac{J_t - (1 - BPP_t)}{J_t} \\
\frac{\partial P_{k,t}}{\partial B_{j,t}} &= \frac{-(1 - BPP_t)}{J_t}
\end{aligned}$$

Conditional on $\tilde{\theta}^R_{C,i}$, the derivative of the choice probability with respect to plan premiums is of the usual logit form:

$$\begin{aligned}
\frac{\partial \tilde{\Lambda}_{i,j,t}}{\partial P_{j,t}} &= \beta_{2,1} \tilde{\Lambda}_{i,j,t}(1 - \tilde{\Lambda}_{i,j,t}) \\
\frac{\partial \tilde{\Lambda}_{i,j,t}}{\partial P_{k,t}} &= -\beta_{2,1} \tilde{\Lambda}_{i,j,t} \tilde{\Lambda}_{i,k,t}
\end{aligned}$$

where $\beta_{2,1}$ is the utility parameter for plan premiums.

Combining the expressions above, we can write the plan's optimal bidding problem as:

$$\begin{aligned}
& \underset{B}{MAX}\ (B + E_{j,t} - C_{j,t}) \times (\Sigma_{i=1}^{N_t}\, \Lambda_{i,j,t}) \\
s.t. \quad & B \geq -E_{j,t} + \frac{1 - BPP_t}{J_t} \Sigma_{k=1}^{J_t}\, B_{k,t}
\end{aligned}$$

where $E_{i,t}$, BPP_t and J_t are given. Ignoring complementarity, we can derive a first-order condition for the plan's bidding decision as:

$$\frac{\partial \pi_{j,t}}{\partial B_{j,t}} = (B_{j,t} + E_{j,t} - C_{j,t}) \frac{\partial N_{j,t}}{\partial B_{j,t}} + N_{j,t} = 0$$

where

$$\begin{aligned}
\frac{\partial N_{j,t}}{\partial B_{j,t}} &= \Sigma_{i=1}^{N_t}\, \beta_{2,1} [\int_{\tilde{\theta}^R_{C,i}} \tilde{\Lambda}_{i,j,t}(1 - \tilde{\Lambda}_{i,j,t})\, P(\tilde{\theta}^R_{C,i} | C_i^{Obs})\, \partial \tilde{\theta}^R_{C,i}] \frac{J_t - (1 - BPP_t)}{J_t} \\
&+ \Sigma_{k \neq j}\, \beta_{2,1} [\int_{\tilde{\theta}^R_{C,i}} \tilde{\Lambda}_{i,j,t} \tilde{\Lambda}_{i,k,t}\, P(\tilde{\theta}^R_{C,i} | C_i^{Obs})\, \partial \tilde{\theta}^R_{C,i}] \frac{(1 - BPP_t)}{J_t}
\end{aligned}$$

We solve for each plan's choice of bids, and hence premiums, by solving the system of first-order conditions expressed above using Gauss-Jacobi and SQP. In each step, we solve each plan's constrained optimization problem using the current-iterate bids and the expressions for the bidding mechanism above, and then generate choice probabilities and update the bid accordingly. Choice probabilities are generated using Model 4 from Table 11, where we assume that the shock interaction effects are all zero, and we use the observed Base Premium Percentage in each year.

Some of the inputs to this analysis need to be imputed from the data. We observe PDP plan total and basic premiums for NJ and infer enhanced premiums as the difference between the two. The NAMBA, Base Beneficiary Premium and Base Premium Percentage are published annually by the

CMS, and in the years over which we simulate, they were, respectively, ($92.30, $32.20, 34.88%) in 2006, ($80.43, $27.35, 34.00%) in 2007, ($80.52, $27.93, 34.68%) in 2008, and ($84.33, $30.36, 36.00%) in 2009. For the purposes of determining monthly per-member subsidies, plan bids are actually scaled by a risk metric (RxHCC) that varies depending on the average demographic and chronic conditions of the insurer's risk pool. We ignore this metric, assuming that the government reinsurance program removes any incentives that may result from the scaling, and assume that each plan is paid their bid ($B_{j,t}$) plus their enhanced premium ($E_{j,t}$). For the baseline simulations our premium measure is the observed total premium for each plan. For the simulations where we allow the bid to adjust, we assume the enhanced premium is held fixed at observed levels. The NAMBA is a national average over all MA-PD and PDP plans. We use our NJ data, and the observed total number of plans included in the NAMBA, to back out the sum of bids for all plans except NJ PDPs and hold that "other market" component of the NAMBA fixed in our simulations. This implies an assumption that, while NJ PDPs respond to changes in their competitors' bids, plans outside this group do not.

In order to estimate government savings under the counterfactual, we construct average bids under the "baseline" and "no frictions" counterfactuals. Bids in the "no inattention" case are predicted as the outcome of the bid-setting game. We back out bids in the "baseline" scenario from the observed premium and the NAMBA data using the formula in equation (7). We make the simple assumption that, if inattention is removed nationally, then the NAMBA will fall by the same amount as the predicted average reduction for NJ. The government therefore saves a fraction of the difference in average bids equal to 1 minus the observed Base Premium Percentage, or γ_t, per person per month. Scaling this figure up to the year and multiplying by the observed number of non-LIS enrollees in PDP plans generates a conservative estimate for annual savings, assuming no change in the low-income subsidy and reinsurance components of program costs.

E Appendix Tables

Appendix Table A1A: 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.

Appendix Table A1B: 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	6.27%	27.68%	20.08%	16.13%	14.54%	15.28%

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

Appendix Table A1C: 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.

Appendix Table A2: Average Plan Quality

	# Plans	% Top Drugs Covered Unweighted	% Top Drugs Covered Enrollment Weighted	% Quality Stars Unweighted	% Quality Stars Enrollment Weighted
2006	1,426	51%	59%	92%	96%
2007	1,866	67%	71%	95%	98%
2008	1,824	80%	81%	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).

Table A3: Following-Year Plan Characteristics Choices, Switchers and Non Switchers

Switchers	% Enhanced	Premium	% Pre-ICL Cvge	% ICL Cvge
2006	14.64%	19.02	70.15%	12.15%
2007	24.00%	26.50	70.50%	29.29%
2008	37.53%	29.93	71.34%	29.60%
Non Switchers	**% Enhanced**	**Premium**	**% Pre-ICL Cvge**	**% ICL Cvge**
2006	28.13%	26.02	62.29%	10.29%
2007	33.62%	38.63	65.85%	6.52%
2008	31.58%	38.31	62.40%	9.07%

Notes: Comparison of observed plan characteristics, for switchers and non-switchers. '% Pre-ICL Cvge' is average observed percent of costs covered by the plan in Pre-ICL phase for that plan's enrollees; '% ICL Cvge' is analogous figure for costs in the coverage gap.

Table A8: Descriptive Statistics for 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	-0.024	0.154
Acute Shock	-0.037	0.189
Choice Parameters	**Variable Mean**	**Standard Deviation**
Chronic TrOOP($000)	0.784	0.935
Acute TrOOP ($000)	0.105	0.128
Premium ($000)	0.471	0.241
Deductible ($000)	0.095	0.126
Gap Coverage	0.235	0.424
Premium Shock x Premium	0.127	0.247
Coverage Shock x Gap Coverage	0.006	0.079
Acute Shock x Gap Coverage	0.010	0.098
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.

Table A9: Demand Robustness Tests

	No Switch 1		No Switch 2		Model 5		Model 6	
Switch Parameters Threshold Shifters	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Year (2007)	-	-	-	-	3.73***	0.04	3.73***	0.05
Year (2008)	-	-	-	-	3.17***	0.03	3.20***	0.04
Year (2009)	-	-	-	-	4.38***	0.04	4.38***	0.05
Female	-	-	-	-	-0.26***	0.02	-0.26***	0.02
Nonwhite	-	-	-	-	-0.04	0.03	-0.04	0.03
Q1 Income	-	-	-	-	-0.52***	0.03	-0.52***	0.03
Q2 Income	-	-	-	-	-0.29***	0.02	-0.29***	0.03
Q3 Income	-	-	-	-	-0.22***	0.03	-0.22***	0.03
Age 70-74	-	-	-	-	-0.15***	0.03	-0.15***	0.03
Age 75-79	-	-	-	-	-0.35***	0.03	-0.35***	0.03
Age 80-84	-	-	-	-	-0.50***	0.03	-0.50***	0.03
Age U-65	-	-	-	-	-0.48***	0.05	-0.48***	0.03
Age O-85	-	-	-	-	-0.76***	0.03	-0.76***	0.04
Shocks	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Premium Shock	-	-	-	-	2.39***	0.03	2.40***	0.03
Coverage Shock	-	-	-	-	0.70**	0.05	0.69**	0.05
Acute Shock	-	-	-	-	0.58**	0.05	0.58***	0.05
Choice Parameters	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Chronic TrOOP	-1.20***	0.01	-1.11***	0.01	-1.59***	0.01	-1.52***	0.03
Acute TrOOP					0.61**	0.06	0.60**	0.11
Annual Premium	-3.91***	0.01	-3.92***	0.01	-5.81***	0.12	-7.51***	0.27
Deductible	-0.33**	0.03	0.07	0.06	-	-	-0.38**	0.17
Gap Coverage	0.66***	0.03	0.76***	0.07	-	-	1.44**	0.20
Premium Shock x Prem	-	-	-	-	-	-	-	-
Coverage Shock x Gap Cov	-	-	-	-	-	-	-	-
Acute Shock x Gap Cov	-	-	-	-	-	-	-	-
Enhanced: Mean	-0.74***	0.01	-1.52***	0.09	-0.18	0.13	-0.61***	0.13
Enhanced: Variance	47.85	-	45.19	-	5.08	-	2.68	-
Enhanced (2007)	-	-	0.58**	0.11	-	-	-	-
Enhanced (2008)	-	-	0.71**	0.02	-	-	-	-
Enhanced (2009)	-	-	1.32**	0.10	-	-	-	-
Lge Brand 1: RC Mean	2.55***	0.04	2.62***	0.02	3.13***	0.11	3.17***	0.15
Lge Brand 1: RC Variance	5.57	-	4.92	-	2.83	-	3.85	-
Lge Brand 2: RC Mean	1.11***	0.01	1.10***	0.01	2.44***	0.13	2.55**	0.22
Lge Brand 2: RC Variance	67.04	-	61.84	-	2.74	-	1.10	-
Lge Brand 3: RC Mean	1.05***	0.02	1.03***	0.04	1.25***	0.05	0.99**	0.10
Lge Brand 3: RC Variance	3.02	-	5.87	-	4.03	-	3.96	-
Fixed Effects	**Brand**		**Brand**		**Brand**		**Brand**	
N	580,746		580,746		580,746		580,746	

Notes: Estimates from demand robustness tests. 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 OOP 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

Table A10: The Five Largest New Jersey PDP Plans, 2006

Insurer Name	Plan Name	Market Share
United Healthcare	AARP MedicareRx Plan	27.63%
Horizon Blue Cross Blue Shield of NJ	Horizon Medicare Rx Plan 2	25.40%
Humana Insurance Company	Humana PDP Standard S5884-062	10.13%
First Health Premier	First Health Premier	4.56%
Humana Insurance Company	Humana PDP Enhanced S5884-003	4.15%

Notes: Publicly available data on names and market shares of the five largest New Jersey PDP plans in 2006. Source: CMS.

Table A11: 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	$10.52	$4.43	$35.49
2007	$31.28	$12.44	$10.37	$1.86	$10.20	$47.40
2008	$32.51	$17.61	$31.28	$6.19	$19.20	$69.00
2009	$42.88	$18.08	$29.84	$10.46	$26.60	$72.70
2010	$37.66	$4.88	$32.84	$2.21	$32.00	$42.90
2011	$39.73	$5.73	$37.26	$3.17	$34.20	$47.60
2012	$38.37	$4.20	$37.32	$4.48	$34.80	$43.00

Notes: Summary of premium dispersion in NJ Defined Standard Benefit plans. Premiums are in $ per enrollee per month. "Weighted" means weighted by enrollment.

Table A12: Annual Premium Increases ($), Accounting for "Sister" Plan Entry

	Model 1		Model 2		Model 3	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Lagged Premium	-0.165***	0.008	-0.154***	0.009	-0.162***	0.008
Lagged # Tier 1 Drugs	0.031***	0.005	0.028**	0.005	0.030**	0.005
Lagged Deductible	-0.007***	0.001	-0.008***	0.001	-0.008***	0.001
Lagged Enhanced	1.623***	0.334	1.322***	0.338	1.529***	0.335
Lagged Gap Coverage	5.505***	0.396	5.194***	0.399	5.418***	0.397
Lagged Market Share	6.716***	1.228	6.749***	1.225	6.725***	1.227
Enrollment Growth Rate	-4.001**	1.154	-3.558***	1.154	-3.735**	1.155
Enter "Sister" Plan	-	-	-2.038***	0.342	-	-
Enter low-prem "Sister" Plan	-	-	-	-	-1.876***	0.516
Brand FE?	Yes		Yes		Yes	
Region FE?	Yes		Yes		Yes	
N	7,796		7,796		7,796	
R^2	0.274		0.276		0.274	

Notes: Regression of premium increase (in $) on previous-year plan characteristics (national data). Enrollment growth rate is rate of growth for region's Part D program. Lagged market share is for this plan. Enter "Sister" plan is an indicator for same carrier adding a new plan in the relevant year; Enter low-prem "Sister" plan is an indicator for adding a new plan whose premium is the lowest in the market for that carrier.