GOVERNANCE AND THE EFFICIENCY OF ECONOMIC SYSTEMS

GESY

Discussion Paper No. 384

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July 2012

Financial support from the Deutsche Forschungsgemeinschaft through SFB/TR 15 is gratefully acknowledged.

NBER WORKING PAPER SERIES

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Working Paper 18166
http://www.nber.org/papers/w18166

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2012

This research was supported by the Behavioral and Social Research program of the National Institute on Aging (grants P01AG033559 and RC4AG039036), with additional support from the E. Morris Cox Fund at the University of California, Berkeley. We thank Mark Duggan for helpful comments, Patricia St. Clair for her support of the data construction effort, and Armando Franco and Sarah Axeen for additional assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 18166
June 2012
JEL No. C25,D12,H51,I11,I18

ABSTRACT

We study the Medicare Part D prescription drug insurance program as a bellwether for designs of private, non-mandatory health insurance markets, focusing on the ability of consumers to evaluate and optimize their choices of plans. Our analysis of administrative data on medical claims in Medicare Part D suggests that less than 10 percent of individuals enroll in plans that are ex post optimal with respect to total cost (premiums and co-payments). Relative to the benchmark of a static decision rule, similar to the Plan Finder provided by the Medicare administration, that conditions next year's plan choice only on the drugs consumed in the current year, enrollees lost on average about $300 per year. These numbers are hard to reconcile with decision costs alone; it appears that unless a sizeable fraction of consumers value plan features other than cost, they are not optimizing effectively.

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1. Introduction

Health-care systems with mandated health insurance financed from some combination of consumer, employer, and government sources are standard in all developed countries except the United States, where about 18 percent of the non-elderly population is currently uninsured (Gruber, 2008), and many of the insured face financially risky gaps in coverage. The health cost of incomplete coverage is substantial: In comparison with other countries, the United States ranks 25th in the survival rate from age 15 to age 60, which impacts the population of workers and young parents whose loss is a substantial cost to families and to the economy.[1] If the U.S. could raise its survival rate for this group to that of Switzerland, a country that has mandatory standardized coverage offered by private insurers, this would prevent more than 190,000 deaths per year. The elderly in the United States aged 65 and older do have universal coverage under the Medicare program, with prescription drug coverage (Medicare Part D) added in 2006. This may explain the somewhat better comparative performance of the United States for seniors, a rank of 14th in life expectancy at age 65. Since the U.S. has a population that at retirement has the poorest health in the developed world, this is a medical accomplishment, but it is very costly – U.S. health expenditures per capita are 50 percent higher than those in any other country.

Medicare Part D provides the Medicare-eligible population with universal access to a subsidized market for non-mandatory standardized prescription drug coverage through government-approved contracts sponsored by private insurance firms; see Bach and McClellan (2005). This new market is representative of a trend toward "consumer-directed healthcare" that relies on consumer behavior and competition among insurance firms to attain satisfactory allocation of health care resources with limited government regulation, and is one model for more comprehensive reform of health care insurance (see Newhouse, 2004; Buntin et al., 2006; Goodman, 2006; and the references therein). Overall, Medicare Part D is considered a success story: Despite a rocky start, enrollment rates are high[2], consumers have a broad choice of sponsors, and premiums are

[1] These statistics are based on World Health Organization data for 2006, and U.S. Census data on population by age in 2006.

[2] In the first year of Medicare Part D, more than 90% of the eligible population obtained prescription drug coverage, either from a Medicare Part D plan or a source with comparable coverage (Heiss, McFadden, and Winter, 2006).

lower than anticipated by policymakers and insurers (Heiss, McFadden, and Winter, 2006, 2007; Goldman and Joyce, 2008; Duggan, Healy, and Scott Morton, 2008).[3]

Despite these successes, making optimal, or even just reasonable, decisions in the Part D market is difficult for seniors. Typically, about 40 drug plans are in the choice set of an individual in most Medicare regions, once she has decided that she wants to enroll in a Part D stand-alone *Prescription Drug Plan* (PDP). When choosing among these plans, individuals face uncertainty with respect to their future health status and drug needs, and rather complicated benefit schedules and formularies with a coverage gap and other peculiar institutional features of the Part D program.[4] Plan choice was considered a major problem of Medicare Part D right from the beginning (see, e.g., Neuman and Cubanski, 2009), and the Medicare administration (the Centers for Medicare and Medicaid Services, or CMS) has undertaken an extensive program of outreach to provide relevant information and guidance to consumers. In particular, such efforts include its Plan Finder, an internet tool that gives the available plans, premiums, and out-of-pocket costs for a medicine cabinet specified by the consumer. A range of industry-specific factors – market concentration of insurers, jockeying by insurers in their formulary and benefit designs, their marketing to new and existing enrollees, and their bargains with pharmaceutical companies – all have the potential to reduce the social benefit of the Part D program. Management of these market features and orderly and efficient operation of the Part D market will require continuing vigilance from CMS.

How seniors decide whether to enroll in Medicare Part D, and what plans they select, is important not only for management of the Part D program, but also is an informative experiment on how consumers behave in real-world decision situations with a complex, ambiguous structure and high stakes, and may yield predictions for how they will handle plan choices in the new gen-

[3] We have pointed out elsewhere (Heiss, McFadden, and Winter, 2009) that variety in available levels of coverage has diminished sharply for individual buyers in the first three years of operation of the Part D market. Offerings of plans with the most comprehensive coverage have collapsed, and plans with intermediate coverage are at risk of a death spiral of rising premiums and falling enrollment, a phenomenon predicted for this market by Pauly and Zeng (2004) as a consequence of adverse selection, and observed in other health insurance markets; see Cutler and Reber (1998). Union and employer-provided retiree plans that are coordinated with Part D, and Medicare Advantage plans that bundle drug coverage with other medical services in an HMO-like setting, are not subject to the same selection pressures, and continue to offer a variety of coverage levels. However, health insurance provided under retiree plans is dropping in the working population, and individual policies for prescription drugs will become more important in the future.

[4] In addition to the monthly premium, features of PDP include deductibles, copayment percentage or copayment tiers in an initial coverage range up to an initial coverage limit, level of coverage in the gap (the doughnut hole between the initial coverage limit and a catastrophic coverage threshold), copayment rules above the catastrophic coverage threshold, formulary restrictions, etc., all explained in more detail later.

eral health insurance exchanges that will implement the Patient Protection and Affordable Care Act of 2010.

In this paper, we examine how well consumers did in choosing their Medicare Part D insurance plan. A number of papers have considered this issue, but mostly with rather specific or small samples, and also with somewhat inconsistent findings.

Abaluck and Gruber (2011) use comprehensive pharmacy data provided by Wolters Kluwer that cover almost one-third of all third-party prescription drug transactions. They match these data with information on the characteristics of all the plans available to the individuals in the dataset. Abaluck and Gruber find that in their plan choice, individuals place more weight on plan premiums than on expected out-of-pocket costs. Also, individuals value plan financial characteristics in excess of their possible impacts on financial expenses or risk, while placing almost no value on variance-reducing aspects of plans.

Ketcham et al. (2011) analyze a large data set from a "single insurer that sells Part D plans (PDPs) and administers PDPs sold by other companies". The data contain information on individuals' chosen and available plans, prescription drug use and spending, and other characteristics. Their analysis focuses on the issue of whether the choices of Medicare Part D enrollees improved over the first two years of the Medicare Part D program in terms of reducing overspending, defined as "the consumers annual *ex post* out-of-pocket (OOP) costs for insurance and prescription drugs above the cost of the cheapest alternative, where the alternatives include other Part D plans as well as having no coverage". They find large reductions in "over-spending" from 2006 to 2007, which they attribute mostly to plan switching. These findings contrast with those of Kling et al. (2011) who argue that consumers' choices are subject to substantial "comparison frictions" and arrive at a more pessimistic conclusion about consumers' ability to choose the best plans.

Our paper is the first to provide a comprehensive analysis of plan choice in the Part D market using a large random sample from the entire Medicare-eligible population. Our data, Part D claims records for three years, 2006–2008, combined with Parts A and B claims records for 2002-2008, have been provided by the Medicare administration (the Centers for Medicare and Medicaid Services, or CMS) under a special data use agreement. These records give administrative information on plan choice, drug use, health conditions, out-of-pocket costs, and premiums. The data on drug use are particularly detailed, thus avoiding the need to impute an individual's drug bill from self-reported survey data (as discussed in Winter et al., 2006). Using these Medi-

care A, B, D data, we study both enrollment choices in the first three years of Medicare Part D (2006–2008) and plan choice among those enrolled, conditional on previous year's drug use, in the years 2007 and 2008.

The remainder of this paper is structured as follows. In Section 2, we describe the data and the approach taken for simulating the relevant attributes of alternative plans available to each consumer. We use the administrative data on drug spending to characterize Part D enrollment decisions in Section 3. In Section 4, we present the analytical framework for analyzing *ex ante* and *ex post* optimization failures, along with the results. Section 5 concludes.

2. Data

2.1 Data sources and definition of working samples

Our study starts with a draw of all records from the Medicare denominator files for the years 2006, 2007, and 2008 that have an HIC code ending in the digits '0' or '5'. The denominator file is an administrative list of all persons in the United States who are eligible for Medicare benefits, and each person enrolled in Medicare for one or more days in a year has a unique identifier, the HIC code, that is associated with them for the duration of their enrollment in Medicare.[5] Then, this draw is in each year a 20 percent representative sample of all people enrolled in Medicare at some point in the year, and all persons enrolled in any year appear longitudinally across all the years in which they are enrolled by virtue of retaining their HIC code with the same terminal digit (or being tracked through a change in HIC code for their primary beneficiary). The 20 percent sample grows each year as new people become eligible (primarily by reaching age 65 or developing a qualified disability), and shrinks as people become ineligible (primarily through death or recovery from a qualified disability). Each record in the 20 percent sample is linked to (1) Medicare Parts A and B claims beginning in 2002, or date of enrollment if later, giving data on diagnoses and treatments, (2) a file giving Part D enrollment status and (encrypted) plan choice in each of the years 2006, 2007, and 2008, and (3) for those enrolled in stand-alone prescription drug plans (PDP), all prescription drug claims, including medication, benefits paid, total prescription cost, and copayments.

[5] When an individual moves from one household to another, and is not a primary beneficiary in either, the HIC code assigned to this beneficiary switches to reflect the new primary beneficiary, and will no longer necessarily end in '0' or '5'. However, as of 2006 these individuals are tracked through the HIC code change, their claims are retained in the 20 percent draw, and their claim records under their previous HIC code are retained. We have not yet obtained full documentation of these procedures, and this description may be modified to reflect actual practice.

The 20 percent representative sample includes 9,086,340 beneficiaries in 2006; 9,299,848 in 2007; and 9,530,609 in 2008. Table 1 shows how the working samples are constructed from the initial 20 percent samples by applying a number of exclusion criteria. The reduced sample comes primarily from (1) the exclusion of Part D non-enrollees and late enrollees, (2) the exclusion of dual-eligibles, people under 65 who are eligible due to disability, and people with low-income subsidies, many of whom were directed to Medicare Advantage plans that do not break out prescription drug use, and (3) the exclusion of people on retiree plans who do not have unrestricted plan choice. Most of these exclusions are part of the definition of our target population of consumers in stand-alone PDP where study of plan choice is of interest and drug claims records are available. For our final working samples, we also exclude people who do not have Part D coverage throughout the year, people not enrolled in stand-alone PDP plans throughout the year, people who switch plans during the year, people enrolled in employer group waiver (EGWP) plans, people not living in the United States, and people without prior year claims information. An appendix table gives a breakdown by age of the patterns of part and full year Medicare enrollment.

Because of the exclusion restrictions we apply, the numbers of beneficiaries in our working sample do not match up directly with published statistics. Consider the 20 percent sample in 2007. Of the 9,299,848 beneficiaries on the denominator file, 87 percent are identified as having some form of prescription drug coverage at some point in 2007. This is a little less than the 90 percent coverage rate targeted by CMS and achieved in various enrollment reports; the difference may be under-reporting in the denominator file of some forms of coverage that are counted by CMS in total coverage. The share of the 9,299,848 beneficiaries with Part D coverage at some point in 2007 is 56.1 percent, and with Part D coverage throughout the year is 48.7 percent. These shares reflect individuals with creditable or retiree coverage who are not enrolled in Part D, and individuals who move into Part D from non-Part D plans, in some cases because they become newly eligible during the year.

2.2 From prescription drug claims data to simulated plan choices

For each beneficiary, we observe a complete record of each prescription filled and submitted to Medicare for reimbursement in each of the years 2006, 2007, and 2008. Each claim includes detailed information on the payment for the particular drug and quantity dispensed, days supplied, which tier the insurance plan classifies the drug on, the benefit phase associated with

each claim, the national drug classification (NDC) code of the drug, and the prescription's date. This information forms the beneficiary's claim history that will be used to simulate their *out-of-pocket* (OOP) copayments for prescriptions, and the sum of their simulated OOP copayments and premiums, which we call *Consumer Inclusive Cost* (CIC), in each of the insurance plans available to them.

Our simulation predicts a beneficiary's out-of-pocket spending among each available stand-alone Part D plan in his region. There are two main parts to this simulation: (1) constructing the *formulary and benefit design* (FBD) for each plan, and (2) running each beneficiary's claim history through these FBDs and calculating out-of-pocket (OOP) spending based on each plan's various rules and copayment provisions.

2.2.1 Construction of empirical FBDs

CMS data confidentiality rules encrypt the identities of plans in our Part D data. Consequently, we cannot assign published plan formularies from public CMS records to these encrypted identifiers, and are unable to calculate from actual formularies the benefits and out-of-pocket costs for plans available but not chosen. As a substitute, we construct an empirical formulary for each insurance plan that is the union of all the NDC codes of claims of enrollees in our Part D data who are in plans with the same formulary identifier in a specified year. The most popular formulary in 2007 had almost 900,000 enrollees, while the median formulary had 7,385 enrollees. The chance that a formulary drug will be captured by this method is low for uncommon drugs in formularies with low numbers of enrollees.[6] Thus, the assumption that only drugs observed with claims are covered by each plan's formulary may make the coverage of smaller plans appear less generous than in reality.

There are five types of Part D stand-alone PDPs. A Standard plan has an administratively specified benefit schedule with four phases – an annual deductible, an initial coverage phase with a 25 percent copayment, a gap or doughnut hole with no coverage between an initial coverage limit (ICL) and a catastrophic coverage threshold (CCT), and a catastrophic phase above the CCT with a 5 percent copayment. In 2007, the deductible was $265, the ICL was $2400, and the CCT was reached when OOP costs reached $3850, attained at a drug bill of $5451.25. These limits are

[6] A drug ranked 500 in prescription frequency is used by about 0.21 percent of enrollees, and in the median enrollment empirical formulary is almost certainly captured; the probability is $1 - (1 - 0.0021)^{7385}$. For the drug ranked 1000, the prescription frequency is 0.03 percent , and the chance of capture is 90 percent, while for the drug ranked 2000, the prescription frequency is 0.003 percent and the chance of capture is 19 percent.

adjusted by CMS each year. Actuarially Equivalent plans differ from the Standard plan only by substituting copayment tiers for copayment percentages, keeping benefit generosity the same on average. Basic Alternative plans eliminate the deductible phase, and are required to be at least as generous as the Standard plan. Enhanced plans offer two types of gap coverage, either full coverage, or coverage of generic drugs only, at the equivalent of a 25 percent copayment rate. Enhanced plans reduce OOP costs through the gap phase, so that higher drug bills are required to reach the CCT.[7]

Our data identify plan types, and for each drug appearing in the empirical formulary of a plan, its branded/generic/preferred status classification and tier classification. Many beneficiaries in stand-alone PDP plans have one or more covered claims for drugs listed on a tier that is higher than the highest tier covered by the plan or a tier classified as "NA". The NDC claims for drugs so classified never appear on a regular tier in other claims for enrollees in the plan, indicating that they are in most cases benefits paid as the result of appeals rather than administrative coding errors or off-schedule purchases, such as replacements of lost prescriptions. After empirically examining the cost sharing associated with such claims by benefit phase, we assign "off-tier" claims no coverage in the deductible or doughnut hole, 25 percent coinsurance in the pre-ICL phase, and 5 percent coinsurance in the catastrophic phase. Roughly 20 percent of the sample has at least one off-tier claim so this is a pervasive phenomenon.

We estimate a benefit design for each plan based on drug classification, phase-dependent empirical tier copayment rate, days supplied, and the type of pharmacy that fills the prescription. These aspects of the benefit design, and other elements that we take into account, are summarized in Table 2. The steps described above then provide an empirical formulary and benefit design for each plan and year that can be used to estimate the annual OOP cost of any specified list of prescriptions supplied under that plan.

2.2.2 Simulation of OOP copayments for alternative plans

Each person in our working sample has realized OOP costs in the claims data in their chosen plan for the prescriptions they use during a year; we term the list of prescriptions filled their *medicine cabinet* (MC). To study the quality of plan choices, we must impute "what if" OOP

[7] For example, in 2007 a drug bill of $14,175 was required for an enrollee with full gap coverage to reach the CCT. Consequently, this enrollee co-paid at a 25 percent rate rather than the Standard plan 5 percent rate for drug bills between $5451.25 and $14,175, eventually repaying all the benefits received from gap coverage.

costs in the available plans that were not chosen. To do this, we impute adjusted OOP costs from our simulation of the formulary and benefit design of each plan, and use these imputed OOP costs for both the chosen and alternative plans. The imputation avoids some anomalies due to tier coding and off-schedule drug purchases, and potential bias in comparing actual and imputed OOP costs, but also misses some payment variations actually experienced. In this imputation, each person's claims history is run through the empirical FBD described above for a particular plan to estimate their OOP should they have been enrolled in that plan. The simulations are performed on each of the plans in the beneficiary's choice set determined by the Medicare-defined region (of 34) in which she lives. When claims straddle two or more benefit phases, we split the claim into parts corresponding to each benefit phase and apply the associated cost sharing for that component. We make five assumptions about prescription drug utilization:

A1 *Same order of drug utilization.* Individuals follow the same order of drug consumption in each alternative plan as is actually observed in their chosen plan. Any substitution is based only on the type of drug, but not the quantity or timing of utilization.

A2 *Sorting claims on the same date.* It is common for multiple prescriptions to be filled on the same day. The order in which such claims are processed may be important for calculating a patient's OOP if one of the claims straddles two benefit phases. To achieve replicable simulation results, some sorting rule must be imposed for claims occurring on the same day. We assume that multiple claims on the same day are sorted first based on the benefit phase recorded in the beneficiary's chosen plan and are then sorted second based on the total cost of the drug (from low to high).

A3 *Pharmacy choice to minimize OOP cost.* In reality, the choice of where to fill prescriptions is likely based on differences in both OOP cost and convenience. However, we assume that beneficiaries will always fill prescriptions at pharmacies and in quantities offering the lowest annual OOP cost. Our assumption assures comparability in costs across consumers and plans, and to the extent that higher OOP costs incurred at local pharmacies or for more frequent refills simply reflect consumers' valuations of the added convenience, our measure is the correct benchmark for OOP cost comparisons.

A.4 *Zero price elasticity of drug use.* We assume that if a consumer uses a drug in their chosen plan, then they will use the same quantity and dosage of this drug, or a therapeutic

equivalent, in any alternative plan, irrespective of price differences across plans and drugs.

A.5 *Drug substitution*. We simulate OOP costs under two alternative assumptions on drug substitutions. The first assumption is no drug substitution, so a specific drug used in the consumer's chosen plan would also be used if the consumer were enrolled in an alternative plan, even if it is on a different tier or is not covered in the alternative plan formulary.[8] This alternative may overstate the OOP cost of meeting the same therapy needs in alternative plans, and make chosen plans look better than they are. The second alternative assumption is that whenever a drug used in a chosen plan is not in the formulary of an alternative plan, then that drug is replaced in both the chosen and alternative plans by lowest-price therapeutic equivalents. The rules we adopt here are similar to those used by the CMS Plan Finder for calculating the costs of alternative plans.[9] Note that if a consumer uses a branded drug that is in the formulary of her current plan, and has a strict preference for this brand over an alternative brand classified as therapeutically equivalent, our calculation with drug substitution can understate the OOP cost to this individual of meeting her perceived drug needs under both the chosen and alternative plans.

2.2.3 Validity of the simulation

The simulation's internal validity is tested by examining the difference in actual OOP spending and simulated adjusted OOP spending (without drug substitution) for each beneficiary in their chosen plan. Actual OOP is defined as the sum of patient payments not reimbursed by a third party, all qualified third party payments, and patient liability reductions due to coordination of benefits from other payers. The median difference is $0, the mean difference is -$33, and the correlation coefficient exceeds 0.98. This compares favorably to a similar simulation check presented in Ketcham et al. (2011). Figure 1 below displays the distribution of this difference for beneficiaries with differences less than $1000 in absolute value, which make up more than 99.5 percent of the distribution. The small size of these differences for most beneficiaries suggests

[8] Under CMS rules, OOP payments for off-formulary drugs do not count in the accumulated "True OOP" (TrOOP) costs that determine qualification for catastrophic coverage. Our simulation does not account for this additional cost of alternative plans. In practice, this will have little influence on our analysis, as plans requiring off-formulary drugs are rarely cost competitive even without accounting for this potential added cost.

[9] One difference is that Plan Finder asks consumers which pharmacies they would like to use, without providing any cost information, and then bases cost estimates on those choices. Our simulation chooses the lowest cost pharmacy to calculate OOP cost since we cannot observe the consumer's preferences for different pharmacies.

that the simulation performs reasonably well and is likely accurate for predicting OOP spending in the plans not chosen. However, there are still some outliers for whom the difference between simulated and actual OOP is large. Figure 2 plots the empirical mean of simulated OOP cost against overall drug bill for consumers on various plans, and compares this with the designed standard plan benefit schedule. The figure indicates that the simulated benefits for Standard and Actuarially Equivalent plans conform well to the designed schedule over the phases where benefits are paid, but give somewhat higher OOP costs when drug bills are in the gap. This may be a statistical artifact, or may be evidence that consumers are being surcharged on drugs purchased in the gap where there is no coverage. The OOP costs for plans with brand and generic gap coverage show the expected reduction of OOP costs in the gap phase. The relatively higher OOP costs for plans covering only generics in the gap phase may suggest that branded drugs are the primary cost driver at that level of spending.

For comparability of chosen and non-chosen plans, we use hereafter annual imputed adjusted OOP costs of a medicine cabinet, with or without drug substitution, rather than a mix of observed OOP costs for the chosen plan and imputed OOP costs for alternative plans. An important measure for consumers is the sum of annual imputed adjusted OOP cost and premiums, which we term *Consumer Inclusive Cost* (CIC).

3. Enrollment choices

We begin our analysis of the administrative data on Medicare Part D by looking at the enrollment decision; this complements earlier research that used survey data such as Winter et al. (2009) and Heiss et al. (2006, 2009). The Part D program is heavily subsidized, with insurers reimbursed from government general revenues for about 75 percent of overhead and benefits paid out, with fairly tightly regulated formulary and benefit design and competitively determined premiums. As a result, the program is first-year actuarially favorable for most eligible people, even before considering the value of reducing risk and the option value of avoiding delayed enrollment penalties if a Part D plan becomes attractive in the future (Winter et al., 2006).

The marketing and information provided on Part D policies by insurers and by CMS focus on the expected benefits rather than on risk reduction. In particular, the CMS Plan Finder invites users to list current drugs, and then provides a list of available plans ranked by out-of-pocket cost if the current drug use continues through the coming year. While consumers could in principle

use Plan Finder on a "what if" basis by introducing counterfactual drugs and dosages, it would be cumbersome to do this and combine the results into an analysis of expected plan benefits and costs. No information is provided on the likelihood that the person will have different drug needs, the ability of plans to meet these needs, and the reduction in risk offered by plans with more generous coverage. As a result, consumers are nudged toward lowest cost plans under the static forecast that current drug use will continue without change, rather than being nudged toward overall risk management.

This said, current drugs and annual drug bills *are* good predictors of one-year-ahead drug needs. The correlation of total drug bills in adjacent years is about 0.75, reflecting high persistence in patterns of use of individual drugs. As a result, persons with modestly high drug bills can expect to be ahead of the game by enrolling, even if they are not risk-adverse or concerned about the late enrollment penalty and future options. In addition, conditioned on this information there is significant risk reduction from enrollment. Figure 3 gives the cumulative distribution function of 2007 total drug bills. Table 3 gives descriptive statistics for this distribution, and also for the distribution of 2008 total drug bills, for the population that had full-year enrollment in a stand-alone prescription drug insurance plan in both years. The correlation of total drug bills in the two years is 0.7437.

Figure 4 gives the complementary cumulative distribution functions for 2008 total drug bills, conditioned on the 2007 drug bill percentiles. As the relatively high inter-year correlation implies, these CCDF are relatively tightly distributed around the 2007 levels, but with some regression to the mean. However, they have relatively thick right tails. Figure 5 plots the conditional mean of the 2008 total drug bill, and the contour giving the approximate 95th percentile, against the 2007 total drug bill. The scales are logarithmic, so that this graph shows substantial risk of large increases in drug bills over the previous year. Below a 2007 drug bill of $2317 (the 71st percentile), the 2008 conditional mean exceeds the 2007 drug bill, and above this level, the reverse is true, reflecting regression to the mean.

A myopic consumer who considers only first-year benefits from a Part D plan and is risk neutral should enroll if expected benefits received exceed the premium. Consider a Part D standard or equivalent plan in 2008, which had a typical premium of $30 per month. Figure 6 gives the probability, conditioned on 2007 total drug bill, that an enrollee in the standard plan will be ahead of the game in the first year, with benefits exceeding the annual premium. For 2007 drug bills above $690, this probability exceeds 50 percent. The probability peaks at a 2007 drug bill of

about $5000, and thereafter declines slightly, apparently due to elevated mortality risk for people with very high drug bills. Figure 7 gives the expected cost conditioned on the 2007 total drug bill for non-enrollment, enrollment in a Silver (i.e., standard or equivalent) plan, and enrollment in a Gold (i.e., generic drug coverage in the gap) plan with a premium at the national average of $63.34 per month. These curves assume that 50 percent of drug costs in the gap are generic. At a 2007 drug bill of $470, corresponding to a 2008 expected drug bill of $760, enrollment in a Silver plan breaks even with non-enrollment in terms of expected cost. Then, if risk aversion and an option value for avoiding a late enrollment penalty in future years are not considerations, 19.5 percent of the eligible population is best off not enrolling. At a drug bill of $3,744 in 2007, corresponding to an expected drug bill of $3,570 in 2008, the Silver and Gold plans break even in terms of expected cost. Then, the 9.5 percent of the eligible population with the highest 2007 drug bills is best off with a Gold plan. Moreover, if first-year payoff is the only criterion and risk is not a consideration, about 12 percent of those enrolling in Part D plans would choose a Gold plan.

In an earlier analysis of Part D enrollment choices using a national sample of about 2,500 eligible people, Heiss, McFadden, and Winter (2009) found that 23.8 percent of those not automatically enrolled in Part D through retiree plans or Medicaid chose to not enroll. CMS tabulations from the denominator file give 15.1 percent of the eligible population without drug insurance of some creditable form in 2008 – this will translate into a higher percentage of those who are active deciders with a personal choice of whether to enroll and if so what plan to choose; see Table 4. While these rates bracket the 19.5 percent that the simple analysis above would suggest if consumers are myopic and risk-neutral, the actual pattern of non-enrollment was much more random, including many who left money on the table in the first year as the result of their enrollment choice. The earlier finding was that non-enrollment was concentrated among those with low but above-poverty incomes, low education, and relatively low prior drug use. The earlier analysis also found that when the option value of Part D insurance without a late enrollment penalty is taken into account, only a few percent of very old people with little drug use should rationally choose to not insure. Then, the observed rates of non-enrollment indicate that myopia and inattention are significant, and are reducing prescription drug insurance participation rates below levels that are optimal for individuals.

In our Medicare 20 percent sample of all Part D eligible people, Gold plans (combined with the relatively unimportant Platinum plans with full gap coverage) have a 9.4 percent share of

those enrolled in Part D plans; see Table 5.[10] Thus, Gold plans appear to be slightly undersubscribed relative to their first-year actuarial value. The complexity of the valuation of Silver and Gold plans, the availability of plans at national average premiums, consumer errors in assessing the actuarial value of gap coverage and focus on premium costs over potential benefits, and our assumption on the share of generics in gap purchases are factors that may contribute to this difference in predicted and actual market share. What the numbers indicate is that risk aversion is apparently not strong enough to offset the (perceived) disadvantageous loading of extended benefits.

The analysis above did not condition on the demographic variables available in claims data, gender and age. We find that drug use does vary with these variables, but that conditioned on prior drug use, they have little explanatory power. Thus, further conditioning on these demographic variables does not alter our general conclusions on enrollment.

4. Models of plan choice behavior

In this section, we develop an analytical framework for comparing *ex ante* and *ex post* optimization failures of Part D enrollees, and present results for 2007 plan choices made at the end of 2006 and for 2008 plan choices made at the end of 2007.

4.1 Rational expectations and decisions

We make the reasonable assumption that at the time of their plan choice at the end of a year for the upcoming year, consumers know the drugs they have used over the current year, their health conditions, and their realized drug bill for the year, and they can calculate from public information (e.g., the CMS Plan finder) the projected CIC for each plan alternative they face and each medicine cabinet they may need. Since the open enrollment periods for 2007 and 2008 were mid-November to mid-December in the preceding year, this is a good but not perfect assumption, as end-of-year events that appear in our information measures may not be predictable by the individual, and no public source including Plan Finder makes it easy to carry through a sophisticated forecast of the likelihood and consequences of changes in health and drug needs. We assume in practice that the information that each consumer has in year t-1, denoted X_{t-1}, includes their age

[10] Our calculations are based on 253,080 beneficiaries enrolled in Gold and 23,468 enrolled in Platinum plans and 2,936,066 beneficiaries enrolled in Part D stand-alone PDP.

and gender, their medicine cabinet (MC_{t-1}, a high-dimensional vector that describes all the consumer's prescription claims over the year and includes information on each claim such as national drug code (NDC) and number of days supplied), their end-of-year chronic conditions (based on the CMS Chronic Condition Warehouse (CCW) inventory of chronic health conditions), their risk score for expected drug costs (based on the Hierarchical Condition Code (HCC) used by CMS for risk adjustment), their overall drug bill, their Part D plan (if any), and premium and realized OOP cost (and hence CIC) under this plan.

Each consumer is assumed to have sufficient information, from the CMS Plan Finder or otherwise, to determine the formulary and benefit design mapping, denoted $CIC_t = FBD(MC_t,k,t)$, for each Plan k available in year t in her region[11], and to have, from peers or otherwise, a personal conditional density $f(MC_t \mid k,X_{t-1})$ of year t medicine cabinets given year t-1 information. From this, we assume that the consumer can deduce the conditional distribution of CIC in t given X_{t-1} and k, and its mean and variance

$$\mu(k,X_{t-1}) = \sum FBD(MC_t,k,t)\, f(MC_t \mid k,X_{t-1}),$$
$$\sigma^2(k,X_{t-1}) = \sum [FBD(MC_t,k,t) - \mu(k,X_{t-1})]^2\, f(MC_t \mid k,X_{t-1}).$$

For a consumer with fully rational expectations, the density f will be statistically accurate. Consumers with less than fully rational expectations may have densities f that are not fully accurate, perhaps because they ignore available conditioning information or because they distort reality.

We assume that consumers have CARA utility functions $U = (1 - \exp(-\gamma + \alpha CIC_t))/\alpha$, where γ is a term that can vary across individuals due to variations in wealth and in other risky opportunities, and $\alpha > 0$ is a coefficient of risk aversion that approaches zero in the limiting case of risk neutrality. Rational consumers are assumed to choose plans k that maximize the expected value of U. To a first approximation for α small, this is equivalent to minimizing a certainty equivalent expected CIC, $\mu(k,X_{t-1}) + \alpha[\sigma^2(k,X_{t-1}) + (\gamma - \mu(k,X_{t-1}))^2]/2$. This utility formulation ignores the possibility of intertemporal optimization of a discounted stream of utilities. For plan choice, where the consumer is free to reoptimize in each annual open enrollment period, the conditions for separability of the intertemporal problem into a series of one-period decisions are largely

[11] In practice, only about 20 percent of Part D enrollees consult Plan Finder, and it is unclear how much information the remainder obtain indirectly.

met.[12] Note that fully rational choice requires (1) use of all available relevant information to form expectations, (2) statistically realistic processing of information, and (3) plan choice to maximize expected utility. Failure of full rationality could come from violation of any of these conditions, and in general it will be difficult to identify the conditions responsible for failures.

4.2 *Ex post* and *ex ante* optimization errors

Observed choices and alternatives can be compared *ex post*, the realized costs from the chosen plan against the "what if" calculation of what costs would have been after the fact if the least inclusive cost alternative had been chosen. This allows us to describe consumer "regret" from a choice that in retrospect was not optimal. However, an *ex ante* comparison is more relevant for judging the quality of consumer decision making. This requires comparing expected utility of the observed plan choice with the alternative that maximizes expected utility, conditioned on the information available to the consumer at the time plan choice for the following year is made. This analysis requires specification of the information available to the consumer at the time of decision, and of the formation of expectations regarding the distribution of CIC for each choice alternative. Choosing a plan that fails to maximize expected utility, and the certainty equivalent expected excess cost from this failure, are arguably indications of failure by consumers to protect their self-interest, although factors such as a mismatch of the consumer's actual information and our information assumption, our assumption on utility, our assumptions on the formation and measurement of expectations, plan features known to the consumer and not taken into account in our description of consumer information, such as convenience of pharmacies in the insurer's network, and mistakes that are economically insignificant, may also contribute to behavior that we classify as optimization failures.

First consider *ex post* comparisons. Similarly to Ketcham et al. (2011), we define *ex post excess cost* as the difference between CIC for the chosen plan and the lowest CIC for any available plan, given the realized medicine cabinet. This comparison ignores risk, in effect treating consumers as risk neutral. The *ex post* excess cost is an upper bound on the losses of risk-neutral consumers from non-optimal decisions, but it will not be a tight bound unless the consumer has perfect foresight on drug use in the coming year. More realistic *ex ante* assessments of the qual-

[12] Factors that could reintroduce an intertemporal element would be switching costs between plans, leading consumers to prefer plans with good expected long-term performance even if they are not first-year optimal, and non-separable intertemporal preferences in which habit and inertia enter the determination of consumer well-being.

ity of consumer decisions reflect their ability to marshal and process the information available at the time they make a plan choice, to assess their own risk preferences and beliefs regarding future drug needs, and to go through a decision-making process that evaluates the utility of alternative plans and picks an optimal plan. This assessment requires consideration of the information available to consumers at the time plan choices are made, the manner in which they form expectations conditioned on this information, and the decision rules they follow given these expectations. We consider several models of information, expectations, and decision rules:

(1) *Perfect foresight*: In year t-1, the consumer forecasts exactly her drug needs in year t. This model is of course unrealistic, but it should give a lower bound on excess cost which will be tight only if consumers actually do have perfect foresight.

(2) *Static*: The consumer chooses the plan that minimizes expected CIC, given the realized drug cabinet in year t-1. In effect, drug use in year t is expected to be the same as in year t-1. Let $CIC_{Skt} = FBD(MC_{t-1},k,t)$ denote this static expected CIC, and call it the Plan Finder Predicted CIC (PFPCIC). Brand and generic substitutions are made as described above. This expectations model should have zero excess cost when consumers follow the recommendation of the CMS Plan Finder, except for difference in OOP cost resulting from pharmacy choices (see footnote 9).

(3) *Diffuse* (or inattentive) *expectations*: The consumer chooses at random among available plans, with equal probability. In effect, all plans in year t are believed to have the same expected CIC, insofar as this is considered by the individual, so that economic premiums and OOP costs are irrelevant to choice. The diffuse expectations model should give an upper bound on expected excess cost.

(4) *Minimum premium*: A related decision rule prescribes that the plan with the *smallest premium* is chosen, in effect all plans are believed to have the same expected OOP costs, insofar as this is considered by the individual.

(5) *Herding rule*: Another decision rule that ignores CIC and OOP costs is to choose plans randomly, but with probabilities defined by plan market shares. This decision rule can be seen as consistent with herding, or with consumers picking plans because of their familiarity or salience (due to, say, advertising or endorsement by organizations such as AARP). The quality of herding rules depends on whether leader behaviour is opti-

mizing, and whether followers have idiosyncratic characteristics that make imitation sub-optimal.

(6) *Rational expectations*: We assume that consumers form rational expectations, statistically realistic forecasts of $\mu(k,X_{t-1})$ and $\sigma^2(k,X_{t-1})$, for relevant information X_{t-1}, and that they choose a plan k to minimize $\mu(k,X_{t-1}) + \alpha[\sigma^2(k,X_{t-1}) + (\gamma - \mu(k,X_{t-1}))^2]/2$, the certainty equivalent expected CIC.

The rational expectations model is the ultimate benchmark for "good" consumer decision-making in our analysis, but is also richest and computationally most burdensome alternative in that it requires specification of the information in year t-1 available to and considered by the individual, and calculation of the conditional forecasts $\mu(k,X_{t-1})$ and $\sigma^2(k,X_{t-1})$. Because of the high dimensionality of X_{t-1} when it includes MC_{t-1}, it is impractical to estimate nonparametrically the conditional density $f(MC_t \mid k,X_{t-1})$ and use this to estimate directly the moments $\mu(k,X_{t-1})$ and $\sigma^2(k,X_{t-1})$. Instead, we use a "method of sieves" and a one-dimensional "sufficient statistic" for the impact of last year's medicine cabinet to estimate these moments semiparametrically. Our method does not take advantage of the known fine structure of the nonlinear mapping $CIC_t = FBD(MC_t,k,t)$, but with sufficient flexibility in the sieve specification we can recover the relevant aspects of this structure from the data. To implement this procedure, we assume first that the static expectation $CIC_{Skt} = FBD(MC_{t-1},k,t)$ is a sufficient statistic for the information conveyed by a consumer's prior medicine cabinet MC_{t-1}, and second that CIC_{Skt} and a limited number of other demographic and health characteristics in X_{t-1} influence the conditional density of MC_t through a single linear index $H(k,X_{t-1})\beta_{kt}$, where H is a vector of transformations of X_{t-1} and β_{kt} is a vector of parameters for each plan and year. This implementation is also consistent with an "adaptive expectations" model in which consumers start with the static expectation and adjust toward the CIC for consumers with similar demographic and health attributes.

We consider a number of alternative "rational" decision models with various variables included in X_{t-1}, as described in Table 6. These variables and transformations are defined as follows:

1. PFPCIC (Plan Finder predicted CIC), the static expectation $CIC_{Skt} = FBD(MC_{t-1},k,t)$, appearing in H either linearly or in a cubic spline
2. Age linear spline

3. Gender
4. CCW, a vector of indicator functions of 22 chronic conditions derived from the Chronic Conditions Warehouse (CCW) as well as HIV/AIDS. The CCW employs algorithms based on International Classification of Disease Version 9 (ICD-9) codes, the type of claim (inpatient, outpatient, physician services, etc.), and the number of claims within a given time period.[13]
5. CCW score, equivalent to the Hierarchical Condition Category (HCC) risk score calculated by Center for Medicare and Medicaid Services (CMS). The HCC risk score is a measure of expected drug costs based on diagnosis codes and demographic factors and is used by CMS to adjust Medicare Parts C and D payments to insurance plans.[14]

In each version of X_{t-1} in the rational decision models we consider, we use the method described above to estimate $\mu(k,X_{t-1})$, and $\sigma^2(k,X_{t-1})$, and then predict the choice k that minimizes the certainty equivalent conditional mean. We have investigated the effect of risk aversion by varying α in these calculations, but do not find evidence for a significant influence of risk aversion on plan choice. We report results only for the case of risk neutrality, $\alpha = 0$.

For any of these expectations models, our primary measure of the quality (loosely speaking) of the consumer's plan choice is the *ex ante* expected excess cost, obtained by taking the difference of the conditional mean (or conditional mean adjusted for risk preference) CIC associated with the chosen plan and the alternative with the lowest conditional mean CIC in year *t,* given the information assumed available at the time of plan choice in *t*-1, and the model of how the consumer processes this information. In the case of the rational expectations model, these means are taken over the sample of individuals with the same information set in *t*-1. In general, one could use kernel or nearest neighbor estimates of these conditional expectations. In the current analysis, we condition only on categorical subpopulations, a simple form of nearest neighbor estimation.

A secondary measure of the quality of consumers' plan choices is the "regret" the consumer will have after the fact, given by the difference of the simulated adjusted CIC for actual

[13] The 22 CCW conditions include chronic obstructive pulmonary disease and brochiectasis, depression, diabetes, glaucoma, heart failure, hip/pelvic fracture, hyperlipidemia, hypertension, ischemic heart disease, osteoporosis, rheumatoid arthritis/osteoarthritis, stroke/transient ischemic attack, breast cancer, colorectal cancer, prostate cancer, lung cancer, and endometrial cancer. For detailed information on the construction of the chronic conditions, see www.ccwdata.org/cs/groups/public/documents/document/ccw_conditioncategories2011.pdf We code the presence of each chronic condition as of December 31 of the year that plan choices are made.

[14] For more information on the construction of the HCC score, see http://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/Risk_adjustment.html

plan choice for year t less the simulated adjusted CIC for the optimal plan choice for year t obtained from *ex ante* optimization with a specified expectations model, both evaluated at the actual year t medicine cabinet. This is a *retrospective excess cost* for the specified *ex ante* optimal choice. This is an imperfect criterion for judging decision-making quality, except in the case of perfect foresight, as it replaces the *ex ante* difference in expectations with the difference of the CIC under the chosen and *ex ante* best plan, evaluated at the realized 2007 or 2008 medicine cabinets which are random draws from the empirical distributions of expected CIC. However, this measure averaged over a subpopulation with the same *ex ante* information will coincide with the full *ex ante* excess cost measure under rational expectations, so that across subpopulations with different information sets, these measures will be highly correlated. The retrospective excess cost will also provide a measure of "realized pain" that may influence the attention that consumers pay to their Part D plan choices, and may nudge them to consider switching plans.

Summarizing, we have three valuation criteria, *ex post* excess cost, *ex ante* expected excess cost, and retrospective excess cost; and in addition to the benchmark perfect expectations model, thirteen expectations models: static, diffuse, minimum premium, herding, and nine variants of the rational model with various specifications of the conditioning information X_{t-1}.

4.3 Results

All simulations reported in this sections are conducted for the entire working samples of 2007 and 2008 (data from 2006 is used to construct the t-1 variables that serve as state variables in the decisions made at the end of year t-1 for year t). Due to the large samples, statistical sampling errors are negligible, and are not reported.

We begin by characterizing optimal plan choices *ex post*. Table 7 reports the sample proportions of simulated plan choices (given data for t-1) that are *ex-post* optimal after the year t medicine cabinet has been realized. It also reports the sample proportion of individuals whose actual plan choice is better *ex post* than the plan choices predicted by our simulated decision rules. The top panel ignores drug substitution, the bottom panel implements drug substitution as discussed earlier. First, we observe that the plans that individuals chose for 2007 and 2008 were rarely *ex post* optimal – only 5.8 percent in 2007 and 7.4 percent in 2008. Taking account drug substitution, these numbers change slightly. In general alternatives to a chosen plan will have

lower cost if substitutions are assumed, but there can be exceptions when a drug is in the alternative plan formulary, but on a higher tier than in the chosen plan formulary, or when a drug in the chosen plan is much more expensive than the least cost therapeutic equivalent in this plan. A decision rule based on static expectations – essentially, following the strategy used by the CMS Plan Finder – does much better: The sample proportion of individuals who would have chosen the *ex post* optimal plan if they followed that rule is 41.7 percent in 2007 and 46.0 percent in 2008 without drug substitution; with drug substitution these numbers are 60.3 percent and 54.6 percent for 2007 and 2008, respectively. Interestingly, none of rational expectations rules does better by this criterion than following the static rule. This holds both without and with drug substitution. Rational models that include PFPCIC in X_{t-1} must by construction do at least as well as PFPCIC alone in terms of the criterion of minimizing expected CIC, implying that the gain from these rational models comes primarily from shrinking the upper tail of the conditional distribution of CIC. However, the additional gain is small compared to the gain from moving from actual to optimal choices under static expectations.

Next, we turn to actual choices. Corresponding to the numbers just mentioned, most individuals could have done better by following one of the rules we considered – those who show up in the "worse than" columns of the table. With a simple rule such as "pick the plan with the smallest premium", 68.3 percent (2007) and 71.1 percent (2008) could have done better. Even by picking a plan randomly, about a quarter could have done better than with the plan they actually have chosen. These numbers are for the case without drug substitution and even higher with drug substitution. One immediate interpretation is that individuals are willing to pay higher premiums for features of plans that do not enter our cost calculation, such as convenience. It will be easier to assess this interpretation by looking at the monetary losses implied by not choosing plans optimally or at least by some simple rule such as "pick the lowest premium". We turn to this analysis in Tables 8 and 9.

An upper bound on the losses an individual incurs by not choosing her plan optimally is given by comparing the total cost of the chosen plan, and of the plans predicted by our hypothetical decision rules, with the cost that obtains for the plan chosen under perfect foresight. These numbers are reported in Table 8. At the mean over our working sample, these losses are, for the actually chosen plan, $399 and $435 dollars in 2007 and 2008, respectively. Medians are lower at $249 and $327. To put this into perspective, the median loss as a percentage of realized CIC is 27

percent in 2007, and the mean loss is 30 percent. These are substantial numbers, but of course perfect foresight is only an abstract benchmark. Among the hypothetical decision rules we consider, the diffuse decision rule (random plan choice) and the herding rule generate higher losses at the mean and the median. All other decision rules imply smaller losses relative to perfect foresight than actual choices. Again, the static rule that conditions only on the current year's medicine cabinet when making plan choices for the next year implies surprisingly small losses of $137 and $105 at the mean, and $24 and $16 at the median (all without drug substitution). These low numbers are explained, in part, by the fraction of individuals with zero or low drug expenditures in both years. For example, just over 1 percent of beneficiaries have zero claims, over 9 percent of beneficiaries have claims totalling less than $100 in out-of-pocket costs, and almost a quarter paying less than the deductible. With drug substitution, the simulated losses incurred by following our hypothetical decision rules are even smaller, and zero at the medium for the static decision rule. Overall, the diffuse and herding rules do rather poorly – choosing one's prescription drug plan randomly certainly is not a good idea. The rational decision rules generate losses relative to perfect foresight at about the order of magnitude of the static decision rule.

Finally, Table 9 reports means and medians of the distribution of savings that the individuals in our working samples could have realized *ex post* by following our hypothetical decision rules rather than their actual decision rule. (The numbers reported for the perfect foresight rule are the same as in Table 8.) Again, the static decision rule fares well: On average, individuals could have saved $261 or $330 in 2007 and 2008, respectively, had they picked the plan that is optimal given previous year's drug cabinet (i.e., if they followed the strategy used by Plan Finder). Medians are lower at $159 and $242 but still sizeable. In 2007, this translates into savings of 20 percent of the actual CIC for the mean and 18 percent for the median. Allowing for drug substitutions increases these hypothetical savings dramatically to $579 (2007) and $438 (2008) at the mean; medians are again lower. Even a simple "minimum premium" decision rule would have resulted in savings of above $100 per year on average. As before, the rational decision rules do, overall, as well as the static rule – some slightly better, some slightly worse. The conclusion here is that following a rather sophisticated decision rule that requires a rational expectations prediction of future drug costs does not, in this particular market, bring systematic monetary and thus utility gains, even if one excludes the potentially large costs associated with making such predictions.

Another important result of these simulations is that the monetary costs associated with the plans the individuals in our sample chose, relative not only to the perfect foresight decision, but also relative to the simple static rule are substantial – about $159 and $242 at the median in 2007 and 2008, even if one does not allow for drug substitution (with which they would be around $300 in both years). It is hard to reconcile these monetary losses—about 12 percent and 25 percent of realized CIC with and without drug substitution, respectively, in 2007—with just the implicit decision costs associated with using a tool such as Plan Finder. In fact, Medicare might take a lesson from Geico's popular advertisement for its car insurance: "12 minutes with Plan Finder could save you 12 percent or more on your prescription drugs." As suggested above, another interpretation is that individuals value plan features other than those we consider in our analysis, such as convenience and customer service.

This brings us to our final question: What predicts individuals' actual plan choices? To answer this question, we ran multinomial logit models in which the chosen plan is the dependent variable. The choice set is the set of all (30-50 or so) plans in the corresponding Medicare region (the number of available plans is around 40 but varies between regions). For computational reasons, we ran these regressions on a 5 percent random sample of our 2007 and 2008 working samples, and then used a one-step linearization to obtain our estimators. The results are shown in Tables 10a and 10b for 2007, and 2008, respectively.[15] The plan-specific explanatory variables are the plan premium and additional variables that capture expected costs, computed under the rules we just discussed.

We begin with the 2007 results (Table 10a). The first specification (column 1) contains only the plan premium, the CIC associated with the plan, and the PFPCIC – that is, it corresponds to the static decision rule where predictions of next year's drug costs are conditioned on the drugs used in the current year. All three variables are highly statistically significant (not surprising given the sample size) and have negative signs. The pseudo R^2 measure of determination is 0.028.

The remaining 18 specifications (columns 2–19) include each of the 9 rational expectations CIC predictions, where the specific expectations models are those described in Table 6 above. For each of the 9 CIC measures, we estimated one specification that includes the premium, the predicted CIC and the variance of the predicted CIC, and a second specification that

[15] The numbers of observations reported in these tables refer to the number individual-plan combinations. They vary slightly between different specifications because of missing values in some variables that are used to construct the predictors.

includes current CIC in addition. Other than the variance measure, whose effect is not always statistically significantly different from zero at the 1 percent level, all other predictors are highly statistically significant in all specifications. As one would expect, the premium and (where included) current CIC always have a negative effect on the probability of choosing a plan (and the magnitudes of these effects are stable across the different specifications).

There are three specifications that have pseudo R^2 measures that are noticeably larger than those of the baseline and most other specifications (around 0.033 compared to 0.028 in the baseline specification). These are all specifications that include current CIC; the rational-expectations predictions of the CIC in these specifications come from models "rational 1", "rational 6", and "rational 7" – the models that use only sex and age splines, the CCW score alone, and the CCW score together with CCW conditions to predict the CIC. The other specifications which are based on rational expectations predictions that condition on the PFPCIC do not bring an improvement in explanatory power of the predictive regressions.

The results for 2008 (Table 10b) are similar overall. Note that every coefficient reported in the table is statistically significant at the 1 percent level. The sizes of the coefficients for the premium are smaller than those in the regressions for 2007, and they change their sign between specifications. However, note that in these regressions, PFPCIC and predicted CIC are included. By definition, these also include the premium. So the coefficient of the premium captures the *additional* effect, which explains the sign change. Most importantly, as in the 2007 regressions, the largest pseudo R^2 values are obtained for the specifications that use predicted CICs based on the rules "rational 1", "rational 6", and "rational 7".

5. Conclusions

This paper shows that there is potentially great scientific benefit in using the detailed information on health, drug use, Part D plan choice, premiums, and OOP costs in Medicare A, B, D claims data. To deal with the inability to link encrypted plan information in the Part D claims data to CMS public files on plan characteristics, we have constructed empirical formularies and benefit designs using data from the sub-sample of individuals enrolled in each plan. This effort is successful in reproducing the OOP costs of chosen plans, and appears to be valid for calculating the CIC for both chosen and alternative plans.

Our analysis of enrollment and choice between levels of plan generosity suggests that the share of eligible consumers without drug insurance is in the range one would expect if risk reduction and the option value of avoiding late enrollment penalties in the future are ignored and the only criterion is whether enrollment is first-year actuarially favorable. In choice between Silver (e.g., standard) and Gold (e.g., generic gap coverage) plans, the evidence is that consumers are undersubscribing to Gold plans. This result is consistent with the finding by others (*inter alia*, Abaluck and Gruber, 2011) that consumers pay more attention to premiums than to benefit generosity, so that they are nudged toward low-premium standard or equivalent plans.

Calculations of the *ex post* costs for all available plans, without and with drug substitution, and of the optimal choices under various expectations models and decision rules for each individual, suggest that less than 10 percent of individuals enrolled in plans that are *ex post* optimal with respect to consumer inclusive cost (premiums and co-payments). Relative to the benchmark of a static decision rule, similar to the Plan Finder provided by CMS, that conditions next year's plan choice only on the drugs consumed in the current year, enrollees lost about $300 per year, on average. While these losses are rather modest when compared to the losses associated with not enrolling at all, an issue we have studied extensively in earlier research, they are difficult to reconcile with decision costs alone. It appears that a sizeable fraction of consumers either value plan features that are not reflected in total cost, or else do not optimize effectively. Our results then do not support the proposition that consumers can make and benefit from good choices in private health insurance markets, and direct health care resources to their best use.

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Table 1: Construction of the working samples, 2006–2008

	2006		2007		2008	
	Number	%	Number	%	Number	%
Total	9,086,340	100	9,299,848	100	9,530,609	100
U.S. residents aged 65+	7,120,960	78	7,235,063	78	7,403,722	78
Enrolled in Part D	3,764,474	41	4,003,149	43	4,215,955	44
Non-dual eligible	2,727,638	30	2,951,936	32	3,154,861	33
Enrolled in standalone Part D Plan (PDP)	1,730,371	19	1,814,568	20	1,865,320	20
Non-low income subsidy	1,618,365	18	1,661,073	18	1,719,953	18
Non-employer group waiver plan	1,484,007	16	1,540,757	17	1,579,152	17
Did not switch plans during year	1,415,563	16	1,497,138	16	1,535,887	16
Prior year PDP claims available	NA		1,253,683	13	1,350,726	14

Note: Sample constructions starts with a random 20% sample of Medicare beneficiaries.

Table 2: Plan characteristics

Characteristics fixed by plan

- Whether the first prescription is free
- Whether the plan applies the deductible to generics (and if so, the copayment for generics in the deductible)
- Deductible amount
- The pre-initial coverage limit (pre-ICL) amount
- Whether drugs in the pre-initial coverage limit are subject to Medicare-defined coinsurance levels or cost-sharing tiers
- The type of coverage in the gap (none, generics only, generics and preferred brands, generics and brands, or all formulary drugs)
- The out-of-pocket threshold amount
- Whether the plan charges the lesser of cost sharing or the total cost

Characteristics specific to drugs within a plan

- The copayment or coinsurance rate associated with each drug based on:
    - Number of days supplied
    - Pharmacy type (in-network preferred, in-network non-preferred, out-of-network, or mail-order)

Table 3: Descriptive statistics for observed total drug bills in 2007 and 2008

	Total drug bill, 2007	**Total drug bill, 2008**
Mean	1,871.7	1,941.8
s.d.	2,221.0	2,524.2
1st percentile	28.1	23.5
5th percentile	111.9	118.4
10th percentile	229.5	239.4
25th percentile	648.8	647.0
Median	1,440.0	1,463.0
75th percentile	2,490.1	2,556.2
90th percentile	3,740.1	3,850.2
95th percentile	4,860.3	5,063.6
99th percentile	8,360.3	9,114.4

Note: Tabulations for all persons in the working sample with full-year coverage in a stand-alone PDP in 2007 with positive Part D claims. The table is not corrected for Part D enrollees in 2008 who were not enrolled in Medicare in 2007, for enrollees with part-year coverage in 2008, or for enrollees with no claims. Bills are in current dollars.

Table 4: Medicare Part D enrollment in December, 2006–2008 (Denominator File)

	2006			2007			2008		
	Total	65+	Pct	Total	65+	Pct	Total	65+	Pct
Total	43,338,571	36,316,594		44,263,111	36,965,846		45,411,883	37,896,079	
No Part D, Retiree Drug Subsidy, or Creditable Coverage	7,801,239	6,516,882	17.9%	7,053,805	5,799,802	15.7%	6,980,480	5,726,326	15.1%
Part D Enrolled									
Total	22,854,973	18,368,305	50.6%	24,477,276	19676031	53.2%	25844675	20,790,368	54.9%
With Creditable Coverage	2,663,377	2,172,276	6.0%	2,922,694	2,406,994	6.5%	2,174,420	1,831,963	4.8%
Without Creditable Coverage	20,191,596	16,196,029	44.6%	21,554,582	17,269,037	46.7%	23,670,255	18,958,405	50.0%
Retiree Drug Subsidy									
Total	6,838,613	6,552,456	18.0%	7,009,702	6,715,950	18.2%	6,655,834	6,380,143	16.8%
With Creditable Coverage	676,496	637,207	1.8%	703,149	659,076	1.8%	624,879	584,305	1.5%
Without Creditable Coverage	6,162,117	5,915,249	16.3%	6,306,553	6,056,874	16.4%	6,030,955	5,795,838	15.3%
Creditable Coverage (No Part D or Retiree Drug Subsidy)	5,843,746	4,878,951	13.4%	5,722,328	4,774,063	12.9%	5,930,894	4,999,242	13.2%
Creditable Coverage Without Regard to Part D or Retiree Drug Subsidy	9,183,619	7688434	21.2%	9348171	7840133	21.2%	8730193	7415510	19.6%

Source: Centers for Medicare and Medicaid 2007-2009 Statistical Supplements, Table 14.4

Table 5: Counts by Part D enrollment status of 20% sample and working sample

	2006	%	2007	%	2008	%
Panel A. 20% Sample: Part D Enrollment Status in December						
Not enrolled in Part D with creditable coverage	1,295,192	14.3	1,292,191	13.9	1,312,470	13.8
Not enrolled in Part D without creditable coverage	2,769,583	30.5	2,685,661	28.9	2,630,485	27.6
Enrolled in Medicare Advantage plan	1,311,554	14.4	1,507,154	16.2	1,724,249	18.1
Enrolled in employer-provided retiree plan (starting Jan 2007)	NA	NA	25,024	0.3	25,349	0.3
Enrolled in Part D stand-alone basic (silver) plan	3,121,961	34.4	3,136,343	33.7	3,223,848	33.8
Enrolled in Part D stand-alone enhanced (gold) plan	93,125	1.0	253,080	2.7	236,295	2.5
Enrolled in Part D stand-alone full gap coverage (platinum)	95,856	1.1	23,468	0.3	75	0.0
Enrolled in Part D stand-alone plan for which coverage could not be determined	24,410	0.3	1	0.0	1	0.0
NEC	374,659	4.1	376,926	4.1	377,837	4.0
Total, 20% Sample	9,086,340	100	9,299,848	100	9,530,609	100
Panel B. Working Sample Enrollment throughout year						
Enrolled in Part D stand-alone basic (silver) plan	1,106,503	89.8	1,062,131	84.1	1,113,201	86.7
Enrolled in Part D stand-alone enhanced (gold) plan	81,748	6.6	182,897	14.5	171,110	13.3
Enrolled in Part D stand-alone full gap coverage (platinum)	44,380	3.6	18,280	1.4	45	0.0
Total, Working Sample	1,232,631	100	1,263,308	100	1,138,105	100

Note : The top panel displays the enrollment status in December of the particular year, providing a snapshot for all beneficiaries on the denominator file. The bottom panel tabulates the type of gap coverage for our working sample, which is constructed as shown in Table 2. Since our sample is restricted to people enrolled in the same PDP plan throughout the year, these coverage counts remain constant throughout the year.

Table 6: Hypothetical decision rules and expectations models used in the plan-choice simulations

Shorthand	Description	Notes
Perfect foresight	*Ex post* minimum CIC plan	
Static	Optimal given previous year's PFPCIC	
Minimum premium	Smallest premium plan	
Diffuse	Random choice of plan	equal probabilities
Herding rule	Random choice of plan	probabilities proportional to market share
Rational 1	Rational choice with risk neutrality	sex, age spline
Rational 2	Rational choice with risk neutrality	PFPCIC (linear)
Rational 3	Rational choice with risk neutrality	PFPCIC (cubic spline)
Rational 4	Rational choice with risk neutrality	PFPCIC (linear) + sex, age spline
Rational 5	Rational choice with risk neutrality	PFPCIC (cubic spline) + sex, age spline
Rational 6	Rational choice with risk neutrality	CCW score
Rational 7	Rational choice with risk neutrality	CCW score + CCW conditions
Rational 8	Rational choice with risk neutrality	PFPCIC (linear) + sex, age spline + CCW score
Rational 9	Rational choice with risk neutrality	PFPCIC (linear) + sex, age spline + CCW score + CCW conditions

Table 7: Simulated plan choices implied by the hypothetical decision rules vs. actual choices

Without drug substitution

	Simulated choices are *ex-post* optimal [%]		Actual choice is … better than [%]		same as [%]		worse than [%]	
Rule	**2007**	**2008**	**2007**	**2008**	**2007**	**2008**	**2007**	**2008**
Actual choice	5.8	7.4						
Perfect foresight	100.0	100.0	0.0	0.0	5.8	7.4	94.2	92.6
Static	41.7	46.0	13.1	9.8	6.9	5.9	80.0	84.3
Minimum premium	13.8	13.1	21.8	28.5	9.9	0.4	68.3	71.1
Diffuse			74.5	74.5	0.0	0.0	25.5	25.5
Herding rule			66.5	60.8	0.0	0.0	33.5	39.2
Rational 1	11.2	26.0	27.8	15.4	4.5	10.3	67.7	74.3
Rational 2	38.8	44.6	13.6	8.2	6.7	8.3	79.7	83.5
Rational 3	38.9	42.6	14.5	8.9	5.9	7.7	79.6	83.4
Rational 4	38.8	44.6	13.6	8.2	6.7	8.3	79.7	83.5
Rational 5	38.9	42.8	14.5	8.9	5.8	7.7	79.6	83.4
Rational 6	12.3	26.7	26.3	14.7	5.2	10.3	68.5	75.0
Rational 7	13.4	26.9	25.0	14.3	5.5	10.2	69.4	75.6
Rational 8	38.1	44.0	13.5	8.2	6.8	8.4	79.7	83.4
Rational 9	37.9	44.1	13.4	8.3	6.8	8.3	79.8	83.5

With drug substitution

	Simulated choices are *ex-post* optimal [%]		Actual choice is … better than [%]		same as [%]		worse than [%]	
Rule	**2007**	**2008**	**2007**	**2008**	**2007**	**2008**	**2007**	**2008**
Actual choice	1.9	8.2						
Perfect foresight	100.0	100.0	0.0	0.0	1.9	8.2	98.1	91.8
Static	60.3	54.6	5.9	6.9	2.6	8.2	91.5	84.9
Minimum premium	37.7	15.0	16.8	35.8	1.6	4.3	81.6	59.9
Diffuse			61.8	72.3	0.0	0.0	38.2	27.7
Herd rule			62.8	57.9	0.0	0.0	37.2	42.1
Rational 1	44.5	27.9	12.4	15.2	1.9	8.8	85.7	75.9
Rational 2	56.3	51.7	6.8	6.4	2.5	8.6	90.7	85.0
Rational 3	60.3	54.1	5.6	6.1	2.6	8.5	91.8	85.4
Rational 4	56.1	51.8	6.9	6.4	2.5	8.6	90.6	85.0
Rational 5	59.7	54.1	5.7	6.1	2.5	8.5	91.7	85.4
Rational 6	44.6	28.3	12.2	15.0	1.9	8.9	85.8	76.1
Rational 7	44.7	28.4	12.1	14.8	1.9	8.7	85.9	76.4
Rational 8	55.1	51.3	7.0	6.4	2.4	8.7	90.6	84.9
Rational 9	55.5	51.1	6.9	6.4	2.4	8.7	90.7	85.0

Table 8: *Ex-post* losses relative to the perfect foresight rule ($ per year)

Without drug substitution				
	Mean		**Median**	
Rule	**2007**	**2008**	**2007**	**2008**
Actual choice	399	435	249	327
Static	137	105	24	16
Minimum premium	268	281	139	193
Diffuse	486	533	365	468
Herding rule	433	454	304	358
Rational 1	227	193	138	113
Rational 2	130	100	32	19
Rational 3	132	101	32	28
Rational 4	129	100	32	19
Rational 5	131	100	32	27
Rational 6	216	187	132	108
Rational 7	209	183	126	106
Rational 8	125	100	33	22
Rational 9	124	100	34	21

With drug substitution				
	Mean		**Median**	
Rule	**2007**	**2008**	**2007**	**2008**
Actual choice	653	541	389	360
Static	75	104	0	0
Minimum premium	215	442	83	268
Diffuse	632	629	437	482
Herding rule	650	553	403	372
Rational 1	97	264	31	102
Rational 2	69	102	0	0
Rational 3	66	98	0	0
Rational 4	70	101	0	0
Rational 5	66	98	0	0
Rational 6	98	259	30	98
Rational 7	97	254	30	97
Rational 8	71	101	0	0
Rational 9	70	101	0	0

Table 9: *Ex-post* gain relative to the actually chosen plan ($ per year)

Without drug substitution				
	Mean		**Median**	
Rule	**2007**	**2008**	**2007**	**2008**
Perfect foresight	399	435	249	327
Static	261	330	159	242
Minimum premium	130	154	90	129
Diffuse	-88	-98	-120	-127
Herding rule	-34	-18	-55	-41
Rational 1	172	243	93	179
Rational 2	269	335	159	247
Rational 3	267	335	159	246
Rational 4	269	336	159	247
Rational 5	267	335	159	246
Rational 6	183	249	97	182
Rational 7	189	253	101	184
Rational 8	273	335	159	247
Rational 9	275	336	159	247

With drug substitution				
	Mean		**Median**	
Rule	**2007**	**2008**	**2007**	**2008**
Perfect foresight	653	541	389	360
Static	579	438	328	293
Minimum premium	439	99	226	62
Diffuse	22	-88	-64	-116
Herding rule	3	-12	-40	-34
Rational 1	556	277	303	199
Rational 2	584	440	332	293
Rational 3	588	443	335	296
Rational 4	584	440	331	293
Rational 5	587	443	334	296
Rational 6	556	283	303	201
Rational 7	557	287	303	203
Rational 8	583	440	328	293
Rational 9	583	441	329	293

Table 10a: Conditional logit regressions predicting plan choice (5 percent sample, 2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Premium	**-0.0022**	**-0.0025**	**-0.0022**	**-0.0022**	**-0.0021**	**-0.0021**	**-0.0021**	**-0.0022**	**-0.0021**	
CIC	**-0.0010**		**-0.0009**		**-0.0009**		**-0.0008**		**-0.0009**	
PFPCIC	**-0.0002**									
CIC_hat_1		**-0.0012**	**-0.0006**							
CIC_var_1		**-1.54E-06**	**-1.32E-06**							
CIC_hat_2				**-0.0011**	**-0.0004**					
CIC_var_2				-1.12E-08	-3.62E-09					
CIC_hat_3						**-0.0012**	**-0.0005**			
CIC_var_3						-6.84E-10	-5.00E-09			
CIC_hat_4								**-0.0011**	**-0.0004**	
CIC_var_4								**-1.13E-08**	-3.82E-09	
Pseudo R2	0.028	0.029	0.033	0.026	0.028	0.027	0.029	0.026	0.028	
Log Likeli-hood	-226342	-246212	-245230	-226766	-226305	-226577	-226224	-226764	-226305	
N	3,229,641	3,517,853	3,517,853	3,229,641	3,229,641	3,229,641	3,229,641	3,229,641	3,229,641	

	(10)	(11)	(12)	(13)	(14)	(15)	('16)	(17)	(18)	(19)
Premium	**-0.0021**	**-0.0021**	**-0.0022**	**-0.0020**	**-0.0022**	**-0.0020**	**-0.0022**	**-0.0021**	**-0.0022**	**-0.0021**
CIC		**-0.0008**		**-0.0009**		**-0.0009**		**-0.0009**		**-0.0008**
PFPCIC										
CIC_hat_5	**-0.0012**	**-0.0005**								
CIC_var_5	-4.71E-10	-4.74E-09								
CIC_hat_6			**-0.0017**	**-0.0009**						
CIC_var_6			**-7.72E-07**	**-7.13E-07**						
CIC_hat_7					**-0.0018**	**-0.0010**				
CIC_var_7					**-3.98E-07**	**-3.81E-07**				
CIC_hat_8							**-0.0012**	**-0.0004**		
CIC_var_8							-1.17E-08	-4.92E-09		
CIC_hat_9									**-0.0012**	**-0.0004**
CIC_var_9									-1.05E-08	-4.54E-09
Pseudo R2	0.027	0.029	0.029	0.033	0.029	0.032	0.027	0.028	0.027	0.028
Log Likeli-hood	-226574	-226223	-245528	-244582	-245593	-244685	-226375	-225939	-226367	-225938
N	3,229,641	3,229,641	3,506,354	3,506,354	3,506,354	3,506,354	3,224,563	3,224,563	3,224,563	3,224,563

Note: Coefficients that are statistically significant at $p < 0.01$ are printed in bold.

Table 10b: Conditional logit regressions predicting plan choice (5 percent sample, 2008)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Premium	**-0.0008**	**0.0002**	**0.0006**	**-0.0003**	**-0.0001**	**-0.0002**	**-0.0001**	**-0.0003**	**-0.0001**
CIC	**-0.0013**		**-0.0006**		**-0.0007**		**-0.0006**		**-0.0007**
PFPCIC	**0.0004**								
CIC_hat_1		**-0.0037**	**-0.0035**						
CIC_var_1		**4.71E-06**	**4.62E-06**						
CIC_hat_2				**-0.0021**	**-0.0015**				
CIC_var_2				**5.16E-06**	**5.08E-06**				
CIC_hat_3						**-0.0018**	**-0.0012**		
CIC_var_3						**3.04E-06**	**2.88E-06**		
CIC_hat_4								**-0.0021**	**-0.0015**
CIC_var_4								**5.17E-06**	**5.09E-06**
Pseudo R2	0.017	0.038	0.039	0.027	0.028	0.023	0.024	0.027	0.028
Log Likeli-hood	-251712	-246715	-246329	-249192	-248807	-250158	-249855	-249156	-248771
N	3,490,225	3,496,126	3,496,126	3,490,225	3,490,225	3,490,225	3,490,225	3,490,225	3,490,225

	(10)	(11)	(12)	(13)	(14)	(15)	('16)	(17)	(18)	(19)
Premium	**-0.0002**	**-0.0001**	**0.0001**	**0.0004**	**0.0001**	**0.0004**	**-0.0004**	**-0.0002**	**-0.0004**	**-0.0002**
CIC		**-0.0006**		**-0.0005**		**-0.0005**		**-0.0007**		**-0.0007**
PFPCIC										
CIC_hat_5	**-0.0018**	**-0.0012**								
CIC_var_5	**3.11E-06**	**2.95E-06**								
CIC_hat_6			**-0.0033**	**-0.0030**						
CIC_var_6			**3.73E-06**	**3.61E-06**						
CIC_hat_7					**-0.0032**	**-0.0030**				
CIC_var_7					**3.75E-06**	**3.65E-06**				
CIC_hat_8							**-0.0019**	**-0.0013**		
CIC_var_8							**5.13E-06**	**5.05E-06**		
CIC_hat_9									**-0.002**	**-0.001**
CIC_var_9									**5.18E-06**	**5.11E-06**
Pseudo R2	0.023	0.024	0.033	0.034	0.033	0.034	0.025	0.027	0.025	0.027
Log Likeli-hood	-250100	-249790	-247163	-246857	-247131	-246854	-249207	-248855	-249231	-248883
N	3,490,225	3,490,225	3,485,940	3,485,940	3,485,940	3,485,940	3,485,940	3,485,940	3,485,940	3,485,940

Note: Coefficients that are statistically significant at $p < 0.01$ are printed in bold.

Figure 1: Distribution of differences between actual and simulated OOP costs

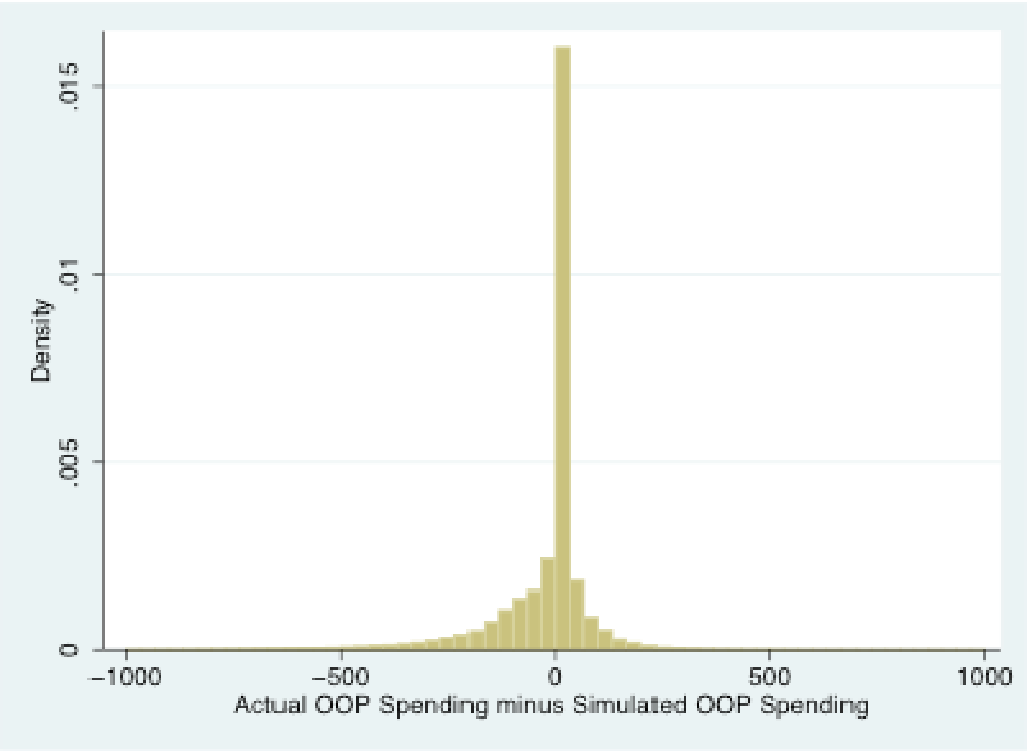


Figure 2: Empirical means of 2007 simulated OOP costs for alternative plan types and the Part D standard plan designed benefit schedule, conditioned on annual drug bill

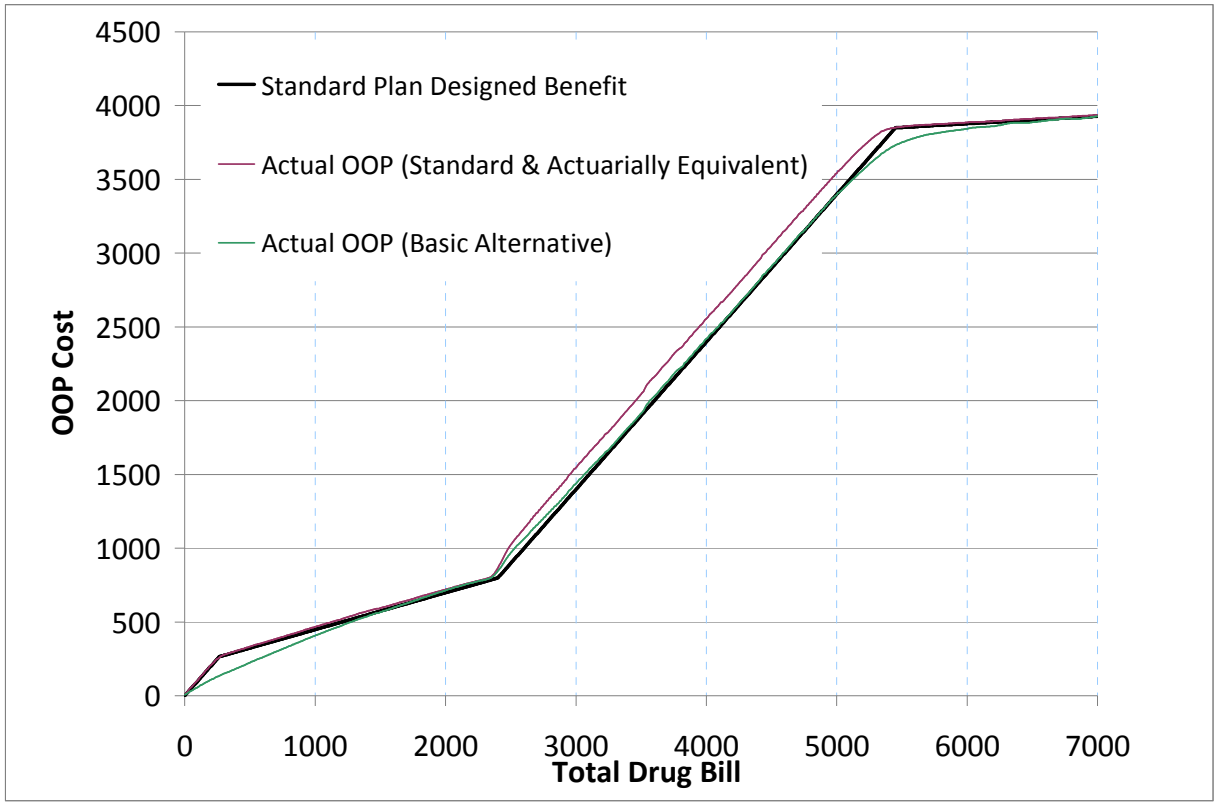


Figure 3: Cumulative distribution function of 2007 total drug bill

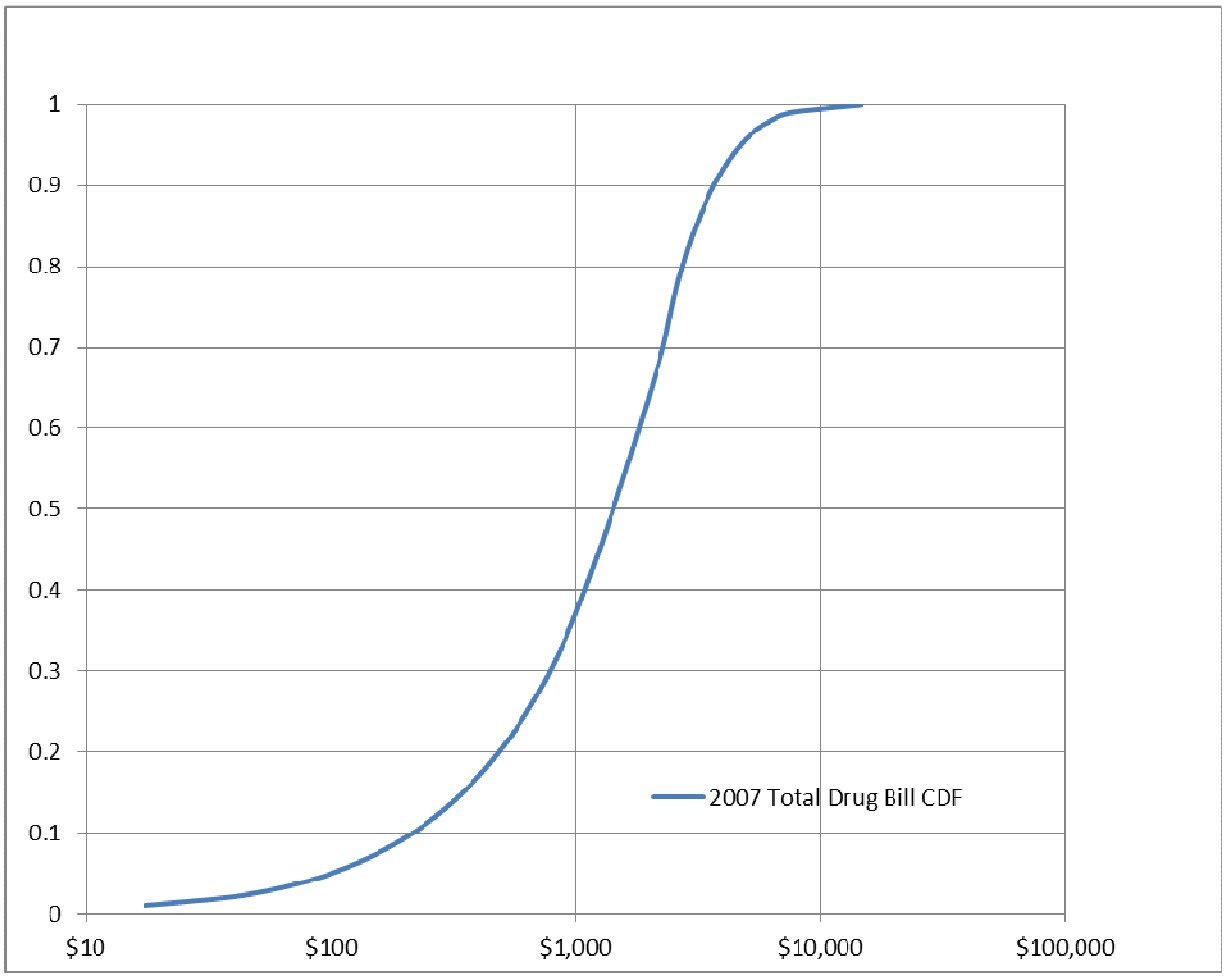


Figure 4: Complementary cumulative distribution functions of 2008 total drug bill conditioned on 2007 total drug bill percentile

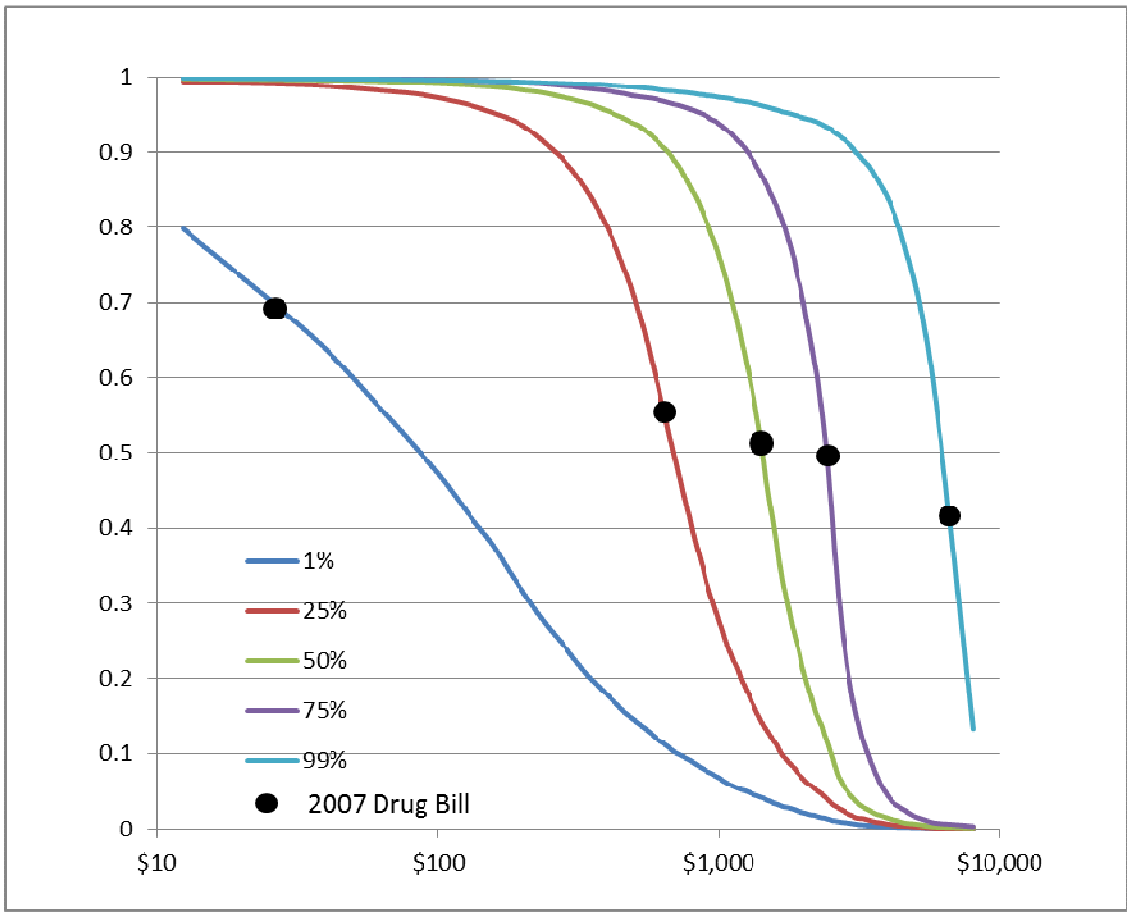


Figure 5: Mean and 95th percentile of 2008 total drug bill, conditioned on 2007 total drug bill

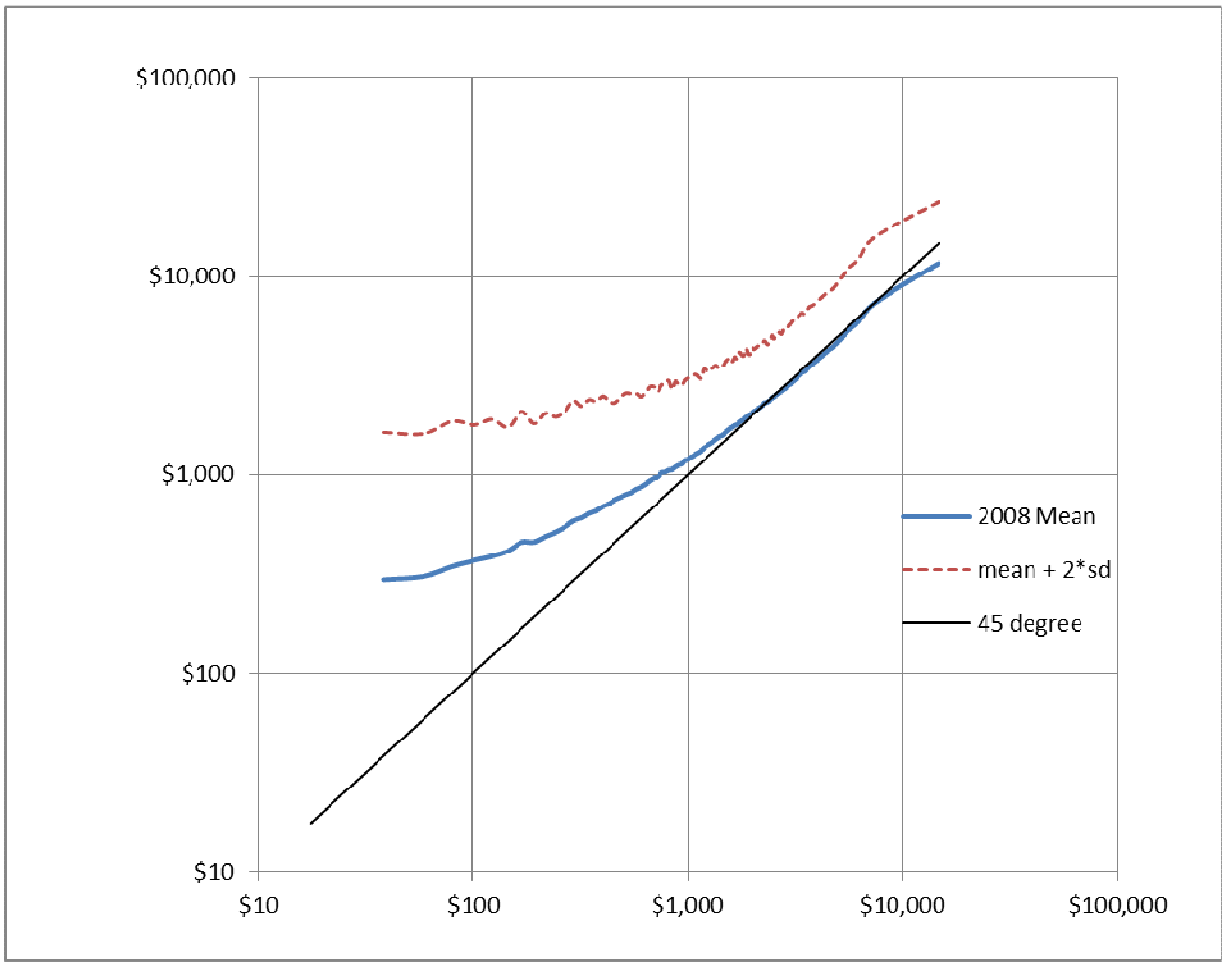


Figure 6: Probability that standard plan enrollment in 2008 at a $30 per month premium gives lower consumer cost than non-enrollment, conditioned on total drug bill in 2007 (log scale)

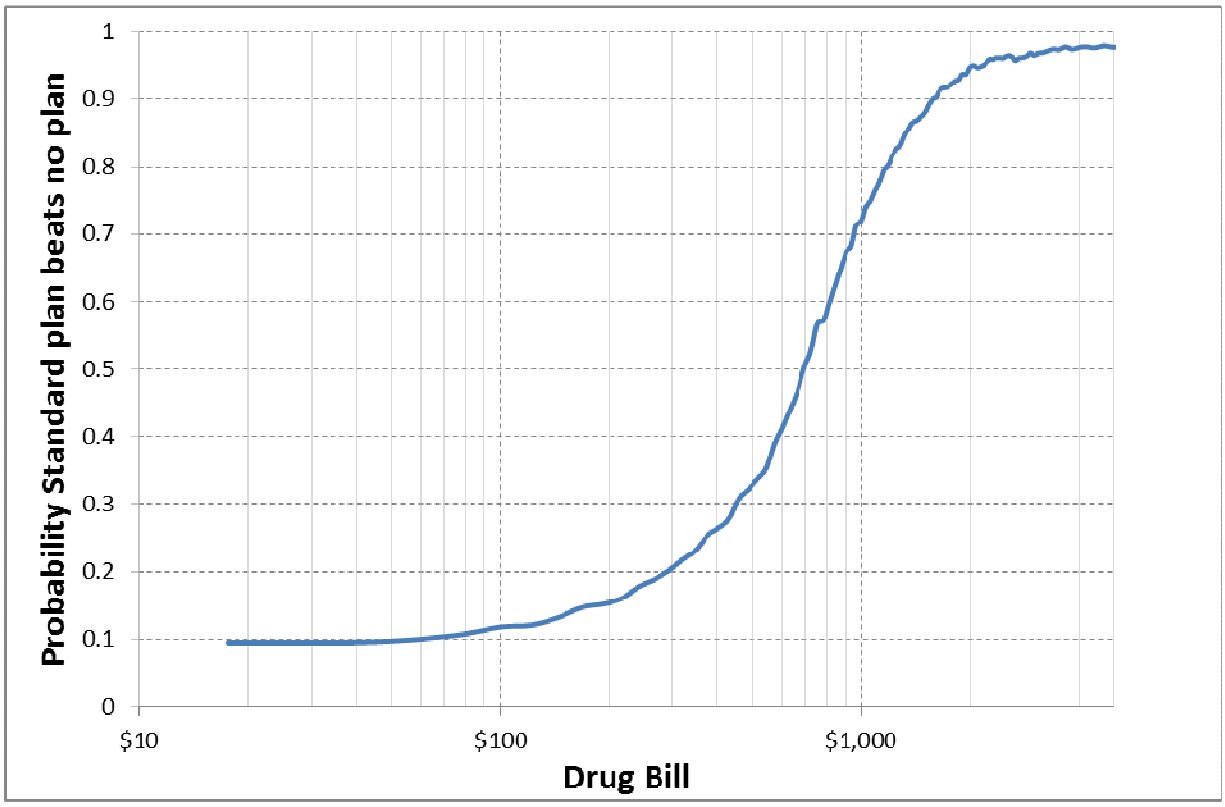
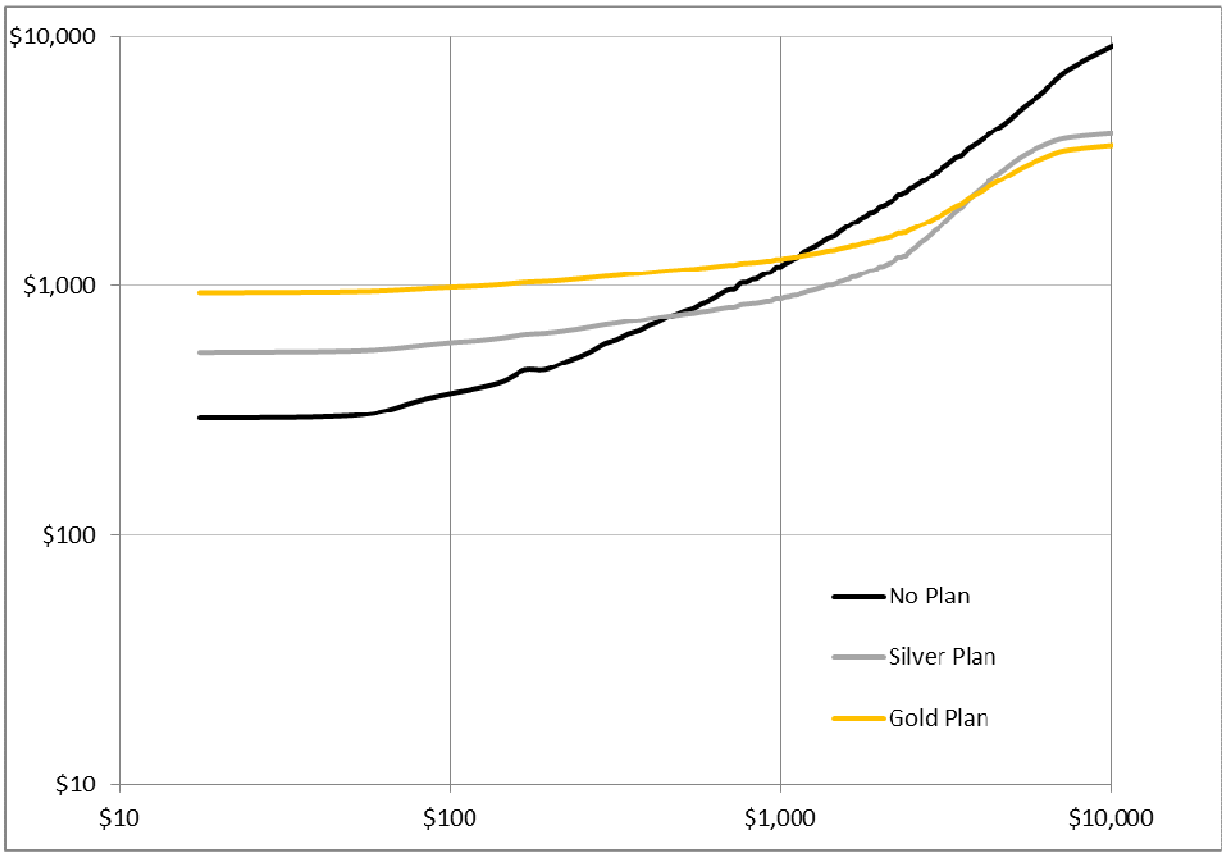


Figure 7: 2008 expected consumer OOP plus premium cost of "No Plan", "Silver" (Standard) plan, and "Gold" (gap generic coverage) plan choices, given 2007 total drug bill



Appendix: Medicare enrollment by age in 2007

Age January 2007	stayers	entrants	leavers (death)	Leavers (other)	entrants and leavers (other)	entrants and leavers (death)
Start:	January	After January	January	January	After January	After January
Stop:	December	December	Before December	Before December	Before December	Before December
64	98,214	393,088	2,704	24	71	1,435
65	444,480	4,720	5,934	88	17	9
66	421,186	2,016	6,198	79	9	6
67	402,074	1,243	6,193	70	11	7
68	395,671	972	6,753	77	5	3
69	374,095	831	6,985	66	5	3
70	355,531	602	7,258	58	7	6
71	345,095	535	7,784	77	9	2
72	330,193	435	8,298	86	6	2
73	306,904	355	8,434	73	5	1
74	306,732	357	9,154	80	5	4
75	295,700	324	9,600	86	2	4
76	293,876	250	10,578	102	8	2
77	273,060	221	10,660	76	7	5
78	265,997	211	11,437	82	2	2
79	256,164	146	12,335	87	0	4
80	237,797	125	12,633	91	4	2
81	223,355	124	13,321	70	0	2
82	210,338	99	13,925	73	1	4
83	189,343	81	13,754	77	0	2
84	171,297	56	13,977	75	2	2
85	157,259	65	14,348	63	0	2
86	134,761	41	13,946	57	0	2
87	108,484	39	12,474	45	1	0
88	95,107	23	12,449	36	0	1
89	77,746	23	11,273	25	1	0
90+	295,594	63	60,510	41	0	3

Source: Tabulations from 20% sample of Medicare enrollees